Outward FDI determinants in large N and T panels under model uncertainty: the case of Japan and the US

Doctoral Dissertation

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Castelló de la Plana
April 2022

UNIVERSITAT JAUME I

Programa de Doctorado en Economía y Empresa

Escuela de Doctorado de la Universitat Jaume I

Outward FDI determinants in large N and T panels under model uncertainty: the case of Japan and the US

Dissertation presented by Sergi Moliner Clemente to opt to a doctoral degree

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Funding received

PhD contract: Conselleria d'Educació, Investigació, Cultura i Esport of the Generalitat Valenciana through the project "Economic and social effects of real and financial integration processes", PROMETEO/2018/102.

Research stay abroad: Conselleria d'Innovació, Universitats, Ciència i Societat Digital of the Generalitat Valenciana through a grant for PhD students stay in research centres outside the Comunitat Valenciana, BEFPI/2021/063.

I would like to thank the Generalitat Valenciana for the funding received.

Chapters published

Chapter 2 "Japan's FDI drivers in a time of financial uncertainty. New evidence based on Bayesian Model Averaging" and Chapter 3 "Is there a euro effect in the drivers of US FDI? New evidence using Bayesian model averaging techniques" of the present doctoral dissertation has been published in the following Journal Citation Reports (JCR) journals:

Camarero, M., Moliner, S., and Tamarit, C. (2021a). Is there a euro effect in the drivers of US FDI? New evidence using Bayesian model averaging techniques. Review of World Economics, 157:881-926. JCR ECONOMICS (2019), 0.767, Q3. **DOI:** 10.1007/s10290-020-00405-y

Camarero, M., Moliner, S., and Tamarit, C. (2021b). Japan's FDI drivers in a time of financial uncertainty. New evidence based on Bayesian Model Averaging. Japan and the World Economy, 57:101058. JCR ECONOMICS (2019), 0.939, Q3. **DOI:** 10.1016/j.japwor.2021.101058

The coauthors of the publications mentioned above are the supervisors of the present Doctoral Dissertation and have waved the right to include them as a part of other Doctoral Dissertation.

Agradecimientos

Me gustaría aprovechar estas líneas para agradecer, de la mejor manera posible, a todos aquellos que de una manera u otra han contribuido a la realización de la presente Tesis Doctoral.

En primer lugar, dar las gracias a mis directores de Tesis, Mariam Camarero y Cecilio Tamarit, por depositar su confianza en mí y acogerme en su grupo de investigación Joint Research Unit in Economic Integration (INTECO), y darme la oportunidad de trabajar con ellos llevando a cabo esta Tesis Doctoral. Destacar su constante profesionalidad, disponibilidad y dedicación y paciencia en todo momento a lo largo de estos tres años, permitiendo formarme como investigador y persona. También agradecerles su apoyo al resto de integrantes del grupo INTECO, y en especial a Laura Montolio y Alejandro Muñoz, por su ayuda en todo lo que he necesitado para el desarrollo de mi Tesis, y a Emili Tortosa, por ser mi tutor de Tesis y darme la oportunidad de iniciarme también en el mundo de la docencia.

También quiero darle las gracias a la Generalitat Valenciana, y más concretamente, a la Conselleria d'Educació, Investigació, Cultura i Esport, por financiar la realización de esta Tesis Doctoral durante los años 2019 a 2021 a través del proyecto "Efectos económicos y sociales de los procesos de integración real y financiera", PROMETEO/2018/102, y a la Conselleria d'Innovació, Universitats, Ciència i Societat Digital por financiar mi estancia en el extranjero a través de la subvención BEFPI/2021/063.

Expresar mi gratitud a Inmaculada Martínez Zarzoso por su cordial acogida durante mi estancia en el extranjero en el Ibero-America Institute for Economic Research en Göttingen, así como a Andreas Fuchs, Felicitas Nowak-Lehmann y demás compañeros del Departamento de Economía de la Universidad de Göttingen, por ayudarme en todo lo que he necesitado durante mi estancia. También darles las gracias a mis compañeros de despacho, Armando Torres y Luis Díaz Pávez, por su cálida acogida durante toda la estancia en Alemania, haciéndome sentir como uno más.

También me gustaría extender mi agradecimiento a todos mis conpañeros del Departamento de Economía de la Universitat Jaume I, Alba Ruíz, Álex Barrachina, Anabel Doñate, Daniel Aparici, David Vidal, Diego De Mingo, Jaume García Segarra, Lidia Vidal, Marko Petrovic, Omar Blanco, Simone Alfarano, Vicente Orts y Jordi Ripollés por su continuo apoyo y sabios consejos en esta etapa de mi vida. Igualmente, dar las gracias a Miguel Ginés, Aurora García Gallego y Gabriele Tedeschi por su total disponibilidad y ayuda en todos los asuntos de gestión del Doctorado.

Por último, quisiera dedicarles estas líneas a mis padres y hermano, por su constante apoyo y cariño, e inculcarme los valores del esfuerzo y perseverancia desde pequeño, permitiéndome llegar donde hoy estoy y conseguir todos los objetivos que me proponga.

A todos, muchas gracias de corazón.

Sergi Moliner Clemente

List of acronyms

ADF Augmented Dickey-Fuller

AIC Akaike Information Criterion

ARDL Autoregressive-distributed lag

ASEAN Association of Southeast Asian Nations

BEA Bureau of Economic Analysis

BIC Bayesian Information Criterion

BMA Bayesian Modelling Averaging

BRIC Brazil, Russia, India and China

CADF Cross-Sectional Augmented Dickey-Fuller

CCE Common Correlated Effects

CIPS Cross-Sectional Im Pesaran Shin

CSD Cross-section dependence

DCCE Dynamic Common Correlated Effects

DCCEPMG Dynamic Common Correlated Effects Pooled Mean Group

DECM Dynamic Error Correction Model

EA Euro Area

EBA Extreme Bound Analysis

ECM Error Correction Model

EEC European Economic Community

EMU European Monetary Union

EU European Union

FAS Foreign affiliate sales

FDI Foreign direct investment

FMD Financial market development

FTA Free trade agreement

GATT General Agreement on Tariffs and Trade

GDP Gross domestic product

GFI Greenfield investment

GLS Generalized Least Squares

GVC Global value chains

HCI Human Capital Index

HFDI Horizontal foreign direct investment

JETRO Japan External Trade Organization

KK Knowledge-capital

LR Likelihood Ratio

M&A Mergers and acquisitions

MCMC Markov Chain Monte Carlo

MENA Middle East North Africa

MERCOSUR Mercado Común del Sur

MG Mean Group

MNC Multinational company

MSB Modified Sargan-Bhargava

NAFTA North American Free Trade Agreement

OECD Organization for Economic Co-operation and Development

OFDI Outward foreign direct investment

OLI Ownership, Location and Internalization

OLS Ordinary Least Squares

PIP Posterior inclusion probability

PMG Pooled Mean Group

PPML Pseudo Poisson Maximum Likelihood

RESET Ramsey Regression Equation Specification Error Test

SURE Seemingly Unrelated Regression Equations

TBMA Tobit Bayesian Modelling Averaging

UK United Kingdom

UNCTAD United Nations Conference on Trade and Development

US United States

VFDI Vertical foreign direct investment

WTO World Trade Organization

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Abstract

For the last three decades, there has been a significant reduction of international trade and investment barriers, fact that has led to an unprecedented growth of transnational operations throughout the world. Within this global context, the main investor countries have been Japan, the United States (US) and the European Union (EU). Therefore, the analysis of the foreign direct investment (FDI) location determinants for these three regions is a matter of general interest. In the present Dissertation, we focus on the cases of Japan and the US as investors and the EU as one of the leading destination regions.

The aim of this Doctoral Dissertation has been to study the determinants of Japanese and US outward FDI (OFDI), dealing with the problem of variable selection and applying an efficient estimator suitable for large long-memory panels. The first two Chapters of the Thesis use a Bayesian Modelling Averaging (BMA) analysis to solve the variable selection problem. Moreover, in the case of the US, we also focus on the effect of the euro. The general results in Chapters 2 and 3 indicate that many of the potential FDI determinants mentioned in the literature are not robust. Furthermore, our findings also reveal that both horizontal FDI (HFDI) and vertical FDI (VFDI) strategies coexist in the destination countries as investment motivations for Japanese and US OFDI. In addition, in the case of US OFDI, the euro has mainly favoured VFDI strategies.

Lastly, in Chapter 4, we study the long-run determinants of US OFDI using a suitable estimator to work efficiently with panel data. In particular, we apply the Dynamic Common Correlated Effects Pooled Mean Group (DCCEPMG) estimator. We extend this methodology to include a common structural break endogenously determined to capture changes in the long-run relationships due to external events or to the deepening of the integration process in the EU. The main findings of this Chapter suggest that there is a cointegration relationship between US OFDI and host country's characteristics. Additionally, there is also evidence that due to the growing economic interdependence and integration, some host country determinants have a long-run homogeneous effect on US OFDI.

Resumen

Durante las últimas tres décadas, se ha producido una importante reducción de las barreras internacionales comerciales y de inversión, hecho que ha provocado un crecimiento sin precedentes de las operaciones transnacionales en todo el mundo. En este contexto global, los principales países inversores han sido Japón, Estados Unidos (EEUU) y la Unión Europea (UE). Por lo tanto, el análisis de los determinantes de localización de la inversión extranjera directa (IED) para estas tres regiones es un tema de interés general. En la presente Disertación, nos centramos en los casos de Japón y EEUU como inversores, y la UE como una de las principales regiones de destino.

El objetivo de esta Tesis Doctoral ha sido estudiar los determinantes de la IED saliente de Japón y Estados Unidos, abordando el problema de la selección de variables y aplicando un estimador eficiente adecuado para paneles largos. Los dos primeros Capítulos de la Tesis utilizan un análisis Bayesian Modelling Averaging (BMA) para resolver el problema de selección de variables. Además, en el caso de EEUU, también nos centramos en el efecto del euro. Los resultados generales de los Capítulos 2 y 3 indican que muchos de los posibles determinantes de la IED mencionados en la literatura no son robustos. Además, nuestros resultados también revelan que las estrategias de IED horizontal (IEDH) y vertical (IEDV) coexisten en los países de destino como motivaciones de inversión para la IED saliente japonesa y estadounidense. Además, en el caso de la IED saliente americana, el euro ha favorecido principalmente las estrategias de IEDV.

Por último, en el Capítulo 4, estudiamos los determinantes de largo plazo de la IED de EEUU utilizando un estimador adecuado para trabajar eficientemente con datos de panel. En concreto, aplicamos el estimador Dynamic Common Correlated Effects Pooled Mean Group (DCCEPMG). Ampliamos esta metodología para incluir endogenamente un cambio estructural para captar los cambios en las relaciones a largo plazo debido a acontecimientos externos o a la profundización del proceso de integración en la UE. Los resultados principales de este Capítulo sugieren que existe una relación de cointegración entre la IED estadounidense y las características del país anfitrión. Además, debido a la creciente interdependencia e integración económica, algunos determinantes del país receptor tienen un efecto homogéneo a largo plazo sobre la IED estadounidense.

Chapter 1

Introduction

FDI is a significant part of international capital transactions in the world economy. Companies that engage in FDI have the opportunity to expand to new markets, take advantage of factor cost differences, and secure new technologies, modes of financing, and skills. In turn, host countries are provided with inflows of capital, more advanced technologies, more sophisticated production processes and techniques, management skills, job opportunities and economic development and prosperity.

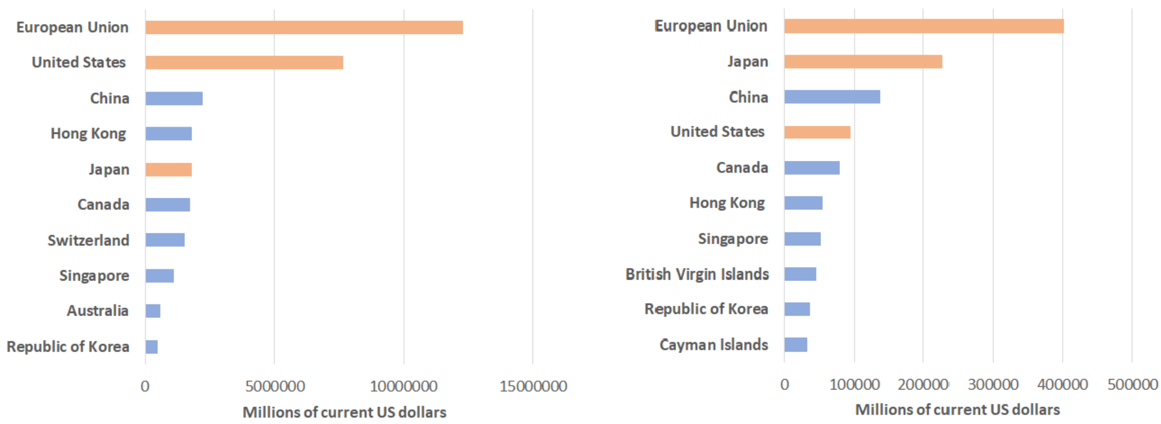
The conclusion of the Uruguay Round at the beginning of the 1990s and the consequent creation of the World Trade Organization (WTO) was a crucial event for the spread and increase of trade and investment flows in a context of growing economic globalization. Moreover, the considerable reduction of trade and investment barriers in that decade led to the growth of transnational operations without precedents. Against this background, the establishment of multilateral and regional free trade agreements (FTA) gained relevance, giving rise to a more integrated and interconnected world.

Economic integration has contributed to a deepening of linkages between countries, facilitating access to new markets and favoring the reorganization of international production processes within the so-called global value chains (GVC), where the different stages of production are located across different countries. However, this process has taken place unevenly since the bulk of capital flows has primarily concentrated in three economic blocs: North America, East Asia, and Europe.

At the same time, there have also been considerable differences among these three major investment hubs. In North America and Southeast Asia, the regional and bilateral agreements had the form of FTAs around the US and Japan. Moreover, most of them were a response to the deep and long integration process that, in the European case, started in 1957 and that established the Single Market in 1992 as a common market. Only seven years later, in 1999, a group of them created the European Monetary Union (EMU) with the euro as a common currency. Therefore, the relevance of these agreements constitutes a crucial explanatory factor of the increasing inward and outward FDI (OFDI), both with origin within these areas and from third countries.

From a historical point of view, the most prominent world investors have been the US, Japan, and the EU. This group is commonly known as the economic Triad. Traditionally, these countries dominated the world economy until the last decade of the twentieth century. However, new actors have irrupted the international panorama at the turn of the century, such as Brazil, Russia, India, and China (also known as BRIC countries). Despite this fact, the role of the Triad in world investment remains central. Indeed, according to United Nations Conference on Trade and Development (UNCTAD), both in terms of stock and flows, these three countries are still among the top 10 world investors in 2019 (see Figure 1.1). Therefore, the study of which factors determine the location of OFDI for these regions is a matter of general interest. In the present Doctoral Dissertation, we focus on the cases of Japan and the US as investors and the EU as one of the leading destination regions.

Figure 1.1: Top 10 investor countries in 2019



(a) Outward FDI stocks (b) FDI outflows

Source: Own elaboration. Data obtained from UNCTAD statistics.

Most researchers have used the gravity equation to analyze FDI, the most common approach applied in the trade literature. Its origins date back to Tinbergen (1962), who modeled bilateral trade flows as being proportional to the product of the economic size of the trading partners (as measured by their Gross domestic products (GDPs) and inversely proportional to the geographic distance between the countries. Unfortunately, early empirical applications of the gravity equation lacked firm theoretical foundations. However, from the seminal paper of Anderson (1979), essential steps were taken in filling this gap, as the early contributions of Bergstrand (1989, 1990) and Deardorff (1998). Nevertheless, Anderson and Wincoop (2003) were the first to develop a method that consistently and efficiently estimated a theoretical gravity equation and calculated the comparative statics of trade frictions. More recently, other papers have significantly contributed to consolidating the academic foundations in the modelization of trade and investment. This is the case of Bergstrand and Egger (2007), Head and Ries (2008), Kleinert and Toubal (2010), Yotov et al. (2016), and Anderson et al. (2020).

In this context or similar specifications, there is abundant empirical literature using multiple FDI drivers related to country characteristics. The reason is that also exist different theoretical approaches to FDI. Therefore, there is no consensus on which variables are the potential FDI determinants. Researchers generally focus on a predetermined set of variables depending on the theoretical framework they adopt. However, this practice could lead to misleading results when estimating a regression model due to the inclusion of insignificant variables or the omission of relevant ones. The latter would affect the estimation of the parameters of the covariates considered in a particular specification (Blonigen and Piger, 2014).

From a methodological point of view, the improvement in data availability has increased the panels' dimension in terms of N (number of cross-sectional units) and T (number of time periods). Traditional panel methods were designed for a large cross-section dimension but dealt with the time-series dimension using time dummies. However, this approach is not valid as the time dimension grows, as the variables may be non-stationary, and the probability of structural breaks increases. Moreover, if the groups of countries are highly integrated, the degree of cross-section dependence (CSD) could also be pervasive and should be accounted for. In addition, as N grows, the slope homogeneity assumption can be difficultly hold. Therefore, we adopt an alternative methodology suited for panels with large N and T dimensions.

In this Dissertation, we start trying to solve the problem of model uncertainty in variable selection for the particular case of FDI. In addition, we apply an efficient estimator suitable for large panels when studying FDI determinants. The Thesis is divided into three main chapters. In Chapter 2, we study the determinants of Japanese OFDI using a BMA analysis for variable selection. In Chapter 3, the focus is on US OFDI and on whether the euro's effect has attracted more investment to Europe compared to other areas. Finally, in Chapter 4, we build on the variables considered robust in the previous Chapter to analyze the long-run determinants of US OFDI, focusing mainly on the Eurozone. For this aim, we apply cointegration techniques that permit us to work efficiently with panel data.

This Doctoral Dissertation makes several contributions to the previous literature. In this Introduction, we will summarize them Chapter by Chapter. We describe here, from a methodological point of view, which are the main novelties of our approach. First, the use of FDI stock data instead of flows. This choice is because stocks are more predictable and stable, while flows are volatile and influenced by short-run factors. FDI stocks are, instead, compatible with the long-run approach we adopt. Second, to the best of our knowledge, no study has attempted to solve the problem of variable selection in the study of Japanese OFDI and the *euro effect* on US OFDI. In our case, this issue is addressed by applying a BMA analysis and, in particular, the proposal of García-Donato and Forte (2015) to obtain robust determinants of FDI in both cases. Third, we apply an econometric approach suitable for panels with large time series and cross-sectional dimension. We apply the DCCEPMG estimator, which accounts for CSD and permits a flexible specification. Thanks to this methodology, we can estimate the long-run model for FDI based on cointegration relationships without imposing homogeneous long-run parameters on all the variables. In addition, the model has flexible dynamics, and we obtain an error correction representation. We extend this methodology to allow for structural breaks in the long-run relationships we obtain endogenously. To the best of our knowledge, no previous work has adopted this methodology to analyze the long-run determinants of US foreign investment. Finally, the methodology adopted allows us to study the whole group of countries in each case and separate, smaller, and more homogeneous groups.

In the remaining of this Chapter, we describe the logical steps followed in the research that lead to this Dissertation. Following this introduction, in Chapter 2, we analyze the determinants of Japanese OFDI. Japan has a relevant role as an investor, especially in the other two members of the Triad and the neighboring Asian countries. We use a sample of 27 host countries for the period 1996-2017, those available with a reasonable time-series dimension. This sample covers important events that may have affected Japanese FDI, such as the two financial crises, one regional (in 1997 in Asia), the second with a world dimension (in 2008), and the establishment of Japan's bilateral trade agreements with Association of Southeast Asian Nations (ASEAN) countries. First, we study the whole group, composed of 27 countries from different continents. Subsequently, we distinguish between developed and emerging countries. The question is whether the reasons for Japanese FDI in the latter countries, of growing importance in GVCs, differ from more traditional Japanese investment in developed host economies. In addition, we also study smaller and more integrated groups, such as the EU and East Asian countries, a critical group due to the proximity of the source country.

Two reasons make the study of Japanese FDI investment in ASEAN countries relevant. First, most Japanese OFDI in this region consists of labor-intensive manufactures looking for inexpensive labor costs. GVCs in the area has favored the fragmentation of production processes of Japanese multinational companies (MNCs) across ASEAN countries and China since the 1980s. However, East Asian financial markets are underdeveloped. After the Asian financial crisis, ASEAN countries have implemented significant reforms to strengthen their financial markets. For this reason, we will also explore if those countries with better financial conditions attract more Japanese FDI.

Concerning the empirical methodology, in this Chapter, we apply the BMA approach developed by García-Donato and Forte (2015) to select the main determinants of Japanese FDI. We do not focus on a specific model or gravity setting, and we diverge from most of the previous literature by including 48 different potential covariates. The use of these techniques to solve the problem of model uncertainty has also been applied to other economic areas, such as inflation, trade, law, or energy. In the case of FDI, Blonigen and Piger (2014) were the first to use this approach and apply Bayesian statistical techniques to select the most relevant FDI determinants for a group of Organization for Economic Co-operation and Development (OECD) countries, as well as for the world economy, in 2000.

The main findings suggest that many of the variables considered by previous literature are not robust FDI determinants of Japanese OFDI. Furthermore, there is evidence of horizontal and vertical strategies in all country groups. However, HFDI strategies are more important in developed and, mainly, EU countries, whereas, for East Asian and emerging countries, VFDI prevails. Lastly, Japanese investment is attracted by those countries with a higher level of financial development. Thus, we confirm that these two reasons (low labor costs and relatively developed financial markets) are key determinants of FDI in ASEAN countries.

In Chapter 3, we study the role played by the creation of the EMU and the euro on US

OFDI. Historically, the EU has been one of the leading destinations of US OFDI. In parallel, since its beginning, the EU has experienced a progressive path of economic integration, culminating with the introduction of the euro. As a result, the circulation of the common currency has supposed to adopt a common monetary policy between EMU member states and the consequent elimination of intra-area currency risks and reduction of trade and investment costs. These conditions creates an attractive macroeconomic environment for potential investors. Therefore, due to the importance of the EU as a recipient of US OFDI, it is particularly relevant to know whether the inception of the euro has had an effect on FDI originating in the US and, if so, how it has changed the US investment patterns.

Most of the empirical literature agrees on the euro's role in the increase of FDI from within the EU and from third countries. Moreover, the reduction of trade costs and the subsequent creation of production networks and GVCs participation may have been encouraged by the common currency, favoring intra-European VFDI while discouraging HFDI. Moreover, third countries could take advantage of higher economic integration and lower trade costs within the EU to set an export platform in one country and serve neighbor markets through exports.

In this Chapter, our sample contains the stock of US OFDI in 56 countries from 1985 to 2017, which represents around the 70% of total US FDI stock in 2017. Therefore, our research starts with the study of a group of 56 countries, those with data available on US FDI. Then, we include many countries from different world regions to assess if the euro's inception has changed the patterns of US FDI at a worldwide level and whether the EMU countries have become a more attractive destination. Subsequently, we include the EU intending to compare the Eurozone countries with those on the Single Market but decided not to adopt the euro. Finally, within the EMU countries, we distinguish between the so-called core and periphery since the effect of the common currency and the determinants of US OFDI may differ between both groups of countries.

In the same vein as in Chapter 2, we do not focus on a specific set of predetermined variables, and we include 63 potential determinants available for the 56 OFDI destinations or host countries and the time range analyzed in our sample. Next, we apply the BMA approach of García-Donato and Forte (2015). To measure the *euro effect*, we construct a variable euro that captures the whole process of monetary integration in Europe, that is, the different stages prior to the adoption of the common currency. Moreover, to study if the common currency has changed the drivers of US OFDI, we interact this variable with proxies for market size, labor costs, and trade.

The main results show that the number of robust determinants is relatively small. Moreover, the introduction of the euro seems to have played a significant role in encouraging US FDI in Europe. Furthermore, we find that it is especially relevant in integrating the Euro Area (EA) periphery to the core. In addition, our results indicate that the adoption of the common currency has favored VFDI, that is, the participation in GVCs, to the detriment of market-seeking HFDI.

In Chapter 4, we estimate a model for the long-run determinants of US FDI, with a particular focus on the EMU countries. Historically, the US and the EU have had persistent bilateral investment linkages. Initially, most of the US FDI in the EU was aimed to serve host markets and avoid trade costs, a strategy consistent with HFDI. However, with the deepening of economic integration and the inception of the common currency, other strategies have arisen, such as the growing participation in GVCs. The latter has implied more VFDI, as well as export-platform FDI. Therefore, the consolidation of the investment relationship between the two parts and the increasing economic interdependence in the region make it especially interesting to analyze the long-run determinants of US FDI in the EU and, in particular, in the Eurozone.

From an econometric point of view, we test for the existence of long-run relations between the variables that explain US FDI for the different groups of countries and that we selected in the previous Chapter. Moreover, we estimate these relations using techniques that permit us to account for CSD while obtaining information about the models' dynamics. Furthermore, one of our primary motivations in this Chapter is searching for similarities across country groups in the long run. Therefore, we combine the Chudik and Pesaran (2015) Dynamic Common Correlated Effects (DCCE) and Pesaran et al. (1999) Pooled Mean Group (PMG) approaches and apply the DCCEPMG estimator allowing for one structural break. This estimator permits us to combine heterogeneous and homogeneous parameters across countries in our estimation. In our empirical estimation, we also apply state-of-the-art econometric techniques in panel data to test CSD, non-stationarity, slope homogeneity, and the search for structural breaks.

Our panel contains data for 54 countries during the period 1985-2019. As in Chapter 3, we start our analysis with the study of this largest group. Additionally, we separate EU and EA countries, and within this last group, we distinguish between the core and the periphery. Moreover, as we divide the countries into groups, we search for common characteristics that could attract or deter US FDI. We expect to find more evidence in favor of homogeneity for our smaller and more homogeneous groups, as is the case of the EU, Eurozone, and EA core and periphery. For our analysis, we start from the variables considered robust in the BMA analysis of the previous Chapter. Additionally, in this case, we are not only interested in the effect of the euro but also in the impact of all critical events of the period analyzed that might have changed the patterns of US FDI, such as the establishment of the Single Market, the 2004 EU enlargement, or the 2008 financial crisis. To this aim, we endogenously allow for structural breaks in our model.

The main findings of this Chapter suggest that the structural breaks are related to both the 2008 economic crisis and institutional changes in European integration, such as the introduction of the euro and the 2004 EU enlargement. Moreover, there is evidence of both HFDI and VFDI strategies in all country groups, although this last strategy prevails in more homogeneous groups. Lastly, we also find that some variables have a homogeneous effect on US FDI. This evidence is stronger for the smaller and more homogeneous groups.

Chapter 2

Japan's FDI drivers in a time of financial uncertainty. New evidence based on Bayesian Model Averaging

2.1 Introduction

In contrast to the European experience, regional integration in East Asia has followed a bottom-up approach in the absence of a formal institutional framework. East Asia's integration has been market-driven through increasing cross-border trade, investment and finance. Japan's OFDI has played a catalytic role in the rapid economic growth achieved by the East Asian economies over the last fifty years. In contrast to the networks in other parts of the world, international fragmentation of production in East Asia started with Japanese firms when they shifted their labour-intensive assembly operations to other Asian countries. The Plaza Accord in 1985 was a watershed event. The substantial reordering of exchange rates and the appreciation of the Japanese yen against the US dollar (70% between the 1985-95) encouraged Japanese companies to relocate their assembly lines across the world (Thorbecke, 2011). Since then, the analysis of the determinants driving Japanese OFDI has been the subject of an abundant, and sometimes, controversial literature.

As the world's third largest economy, Japan has established extensive trade and investment linkages with the rest of the world. Notably, the motivations of Japanese direct investors have varied by industry and region comprising, among others, trade facilitation, securing and expanding markets, the creation of supply chains for the manufacturing sector (energy, resources and inputs) and the control of foreign proprietary assets or international distributional networks. Yet, irrespective of the reason considered, there is an increasing consensus on that financial market development (FMD) has played a salient role as a general catalyst for the aforementioned drivers of Japanese OFDI.[1] FDI involves particularly high fixed costs upfront since an affiliate has to be established or acquired in the host country. Highly productive firms may cover these fixed costs at least partly through internal financing. However, the availability of external financing clearly renders it easier to cover the fixed costs of undertaking FDI. As access to external financing depends on FMD, it is to be expected that better developed financial markets in the source and/or host country results in higher OFDI (Desbordes and Wei, 2017). In the specific case of Japan, Klein et al. (2002) find that the links between MNCs and troubled banks at home help explain the decline of Japanese OFDI in the US in the 1990s.

[1] For many years, most theories of the determination of FDI focused on industrial organization motives but the striking correlation between real exchange rates and FDI that developed during the 1980s led to include the role of imperfect capital markets in describing the pattern of movements in FDI.

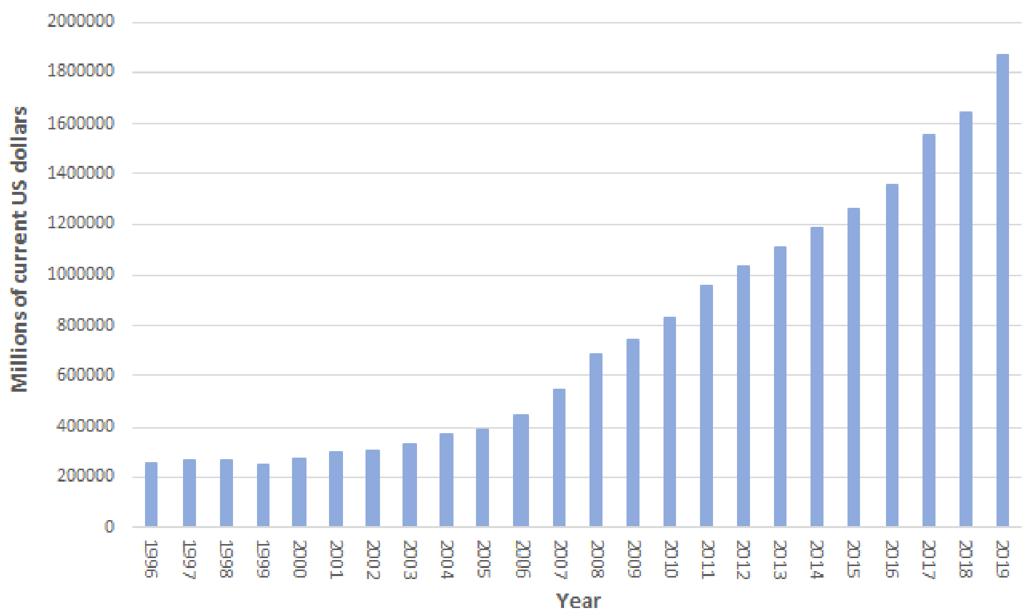
In this Chapter we analyze the potential determinants of Japanese OFDI stock for the period 1996-2017. To this aim, we consider a large set of candidate variables based on the theory as well as on previous empirical analysis. The sample considered can be especially interesting to test different theories as it comprises two financial crises. The Asian financial crisis of 1997-98 revealed the fragility of the region's prevailing exchange rate arrangements and highlighted the urgent need for a stronger regional financial architecture. Since the crisis, growing efforts have been made to promote regional monetary and financial cooperation in the area. Indeed, corporate activities were supported by public efforts to promote trade and investment under the General Agreement on Tariffs and Trade (GATT)/WTO multilateral framework as well as increasing number of FTAs in a process of "open regionalism" that includes both the real and, increasingly, the financial sector. The deepening of East Asian regional economic interdependence contrasts with the relatively underdeveloped financial markets. Weak financial inter-mediation within the region has meant that ample savings in Asia seem to be less utilized than its potential. In financing investment, Japan had to depend on short-term, dollar-denominated foreign funds, which created mismatches both in maturity and currency. Under these conditions, the financial turmoil generated by the Great Recession, again prompted negative effects on the OFDI issued by Japan. In general, countries with good institutions and developed financial markets tend to benefit more from financial integration. Therefore, countries in Western Europe and North America as well as those more developed in East Asia are more likely to meet these conditions compared to developing countries (Osada and Saito (2010)). Moreover, a higher FMD in the host country may attract FDI as well for a variety of reasons[2]. In a similar vein, Fernández-Arias and Hausmann (2001) argue that countries that are riskier, less financially developed and have weaker institutions tend to attract less capital but more of it in the form of FDI.

Although the Japanese OFDI stock-to-GDP ratio has been relatively low by international standards, it has been rising steadily since the mid-2000s. Indeed, Japan has become one of the most important reference investors for many countries, together with the US, China and the EU. Concretely, according to UNCTAD, it was the fifth largest world investor in 2019 in terms of OFDI stock, after the US, the Netherlands, China, Hong Kong and the United Kingdom (UK) (see Figure 1.1).

[2]See Alfaro et al. (2010), Kinda (2010) or Desbordes and Wei (2017).

The surge in Japanese OFDI, together with the fact that FDI outflows outweigh corresponding inflows by an order of magnitude, has resulted in a rapid net movement of Japanese productive capacity abroad. Japanese OFDI stock has noticeably increased during the last three decades, that is consistent with the rise of MNCs activity and the consequent increase of FDI operations around the world. Particularly, we can observe in Figure 2.1 that the OFDI stock grew slowly between 1993 and 1999, and even for some years decreased. Yet, since 1999 on wards it has kept a steady increasing pace. In fact, in 1999 the Japanese OFDI stock was about 250 billion US dollars, and in 2019 around eight times more, that is, close to 2,000 billion US dollars.

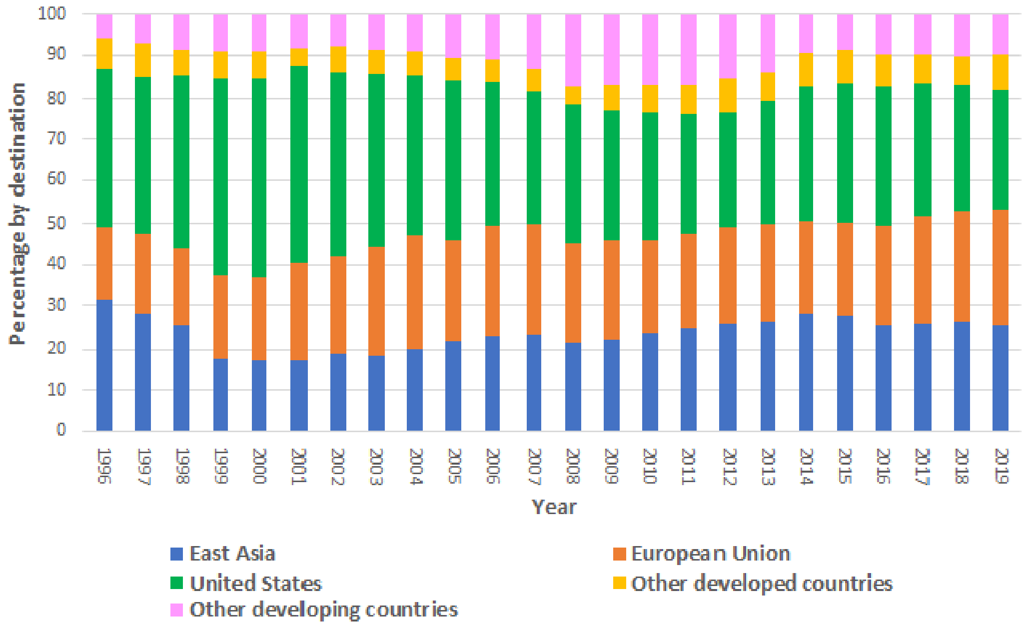
Figure 2.1: FDI outward stock from Japan



Source: Own elaboration. Data obtained from JETRO.

Concerning its geographical distribution, as we can observe in Figure 2.2, at the end of the 1990s the US was by far the main destination for Japan's MNCs. On the other hand, East Asian countries experienced an important decline due to the impact of the financial crisis. Subsequently, these countries and the EU have gained a significant importance as host country regions, and nowadays, together with the US, are the main recipients of Japanese OFDI.

Figure 2.2: FDI outward stock from Japan by regions



Source: Own elaboration. Data obtained from JETRO.

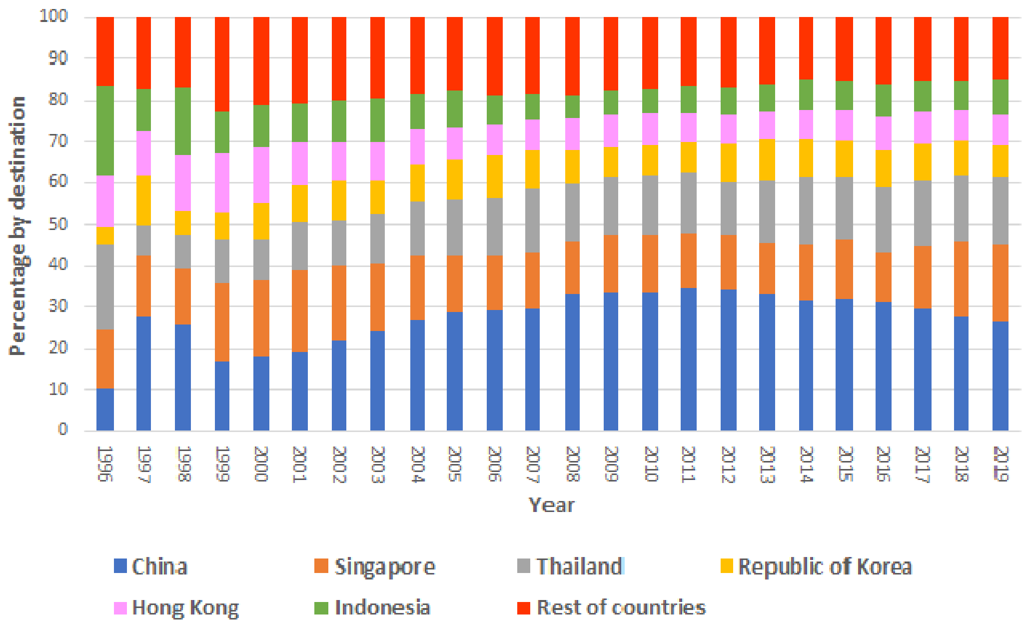
In East Asian countries, according to Thorbecke and Salike (2013), the appreciation of the Japanese yen after the Plaza Accord in September 1985 was the most important factor for the surge of Japanese OFDI in the late 1980s. There are two reasons for this. First, the 70 percent appreciation of the yen reduced drastically the competitiveness of the Japanese economy, especially in labor-intensive activities, reducing exports of these goods. Second, Japanese firms became wealthier in host countries because of such appreciation and were able to finance their investment more cheaply relative to the foreign competitors. Consequently, in line with Abe (2016), Japanese manufacturing firms moved plants massively to East Asia. It was this expansion toward overseas production that initially created the Asian GVCs that currently exist. High-value and high-technology production were kept at home, or shifted to other advanced economies, the so-called "four dragons"[3], and production of low-value and intermediate-value goods were concentrated on China and the ASEAN region[4]. According to the Japan External Trade Organization (JETRO), as shown in Figure 2.3, the main destinations of Japanese OFDI in the East Asia region have traditionally been

[3]These countries are South Korea, Hong Kong, Taiwan and Singapore.

[4]These countries are Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thai-land and Vietnam.

China, Singapore, Thailand, the Republic of Korea and Hong Kong. The increasing growth of China as Japanese OFDI destination stand outs.

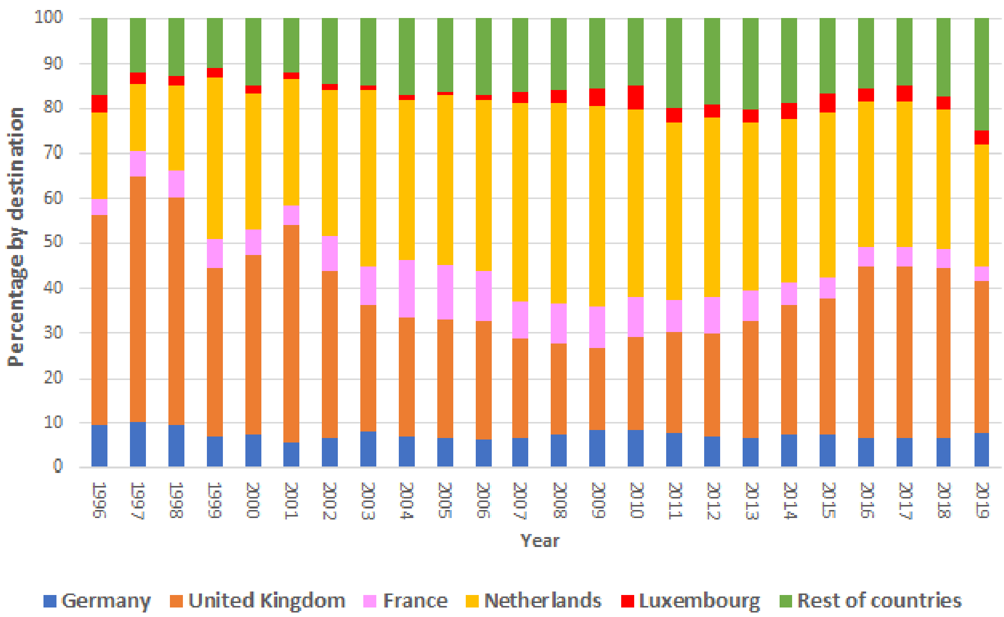
Figure 2.3: FDI outward stock from Japan by East Asian countries



Source: Own elaboration. Data obtained from JETRO.

Regarding the EU, as reported by Watanabe (2013), from the 1990s through the early 21st century, the progress of European integration was an important step for attracting Japanese direct investment. The trade liberalization within the community and the total removal of quantitative restrictions targeting Japanese goods, carried out by the European Commission, motivated the expansion of Japanese businesses in Europe Currently, the EU constitutes without any doubt an attractive destination for Japanese OFDI. According to the EU-Japan Centre for Industrial Cooperation (2014), the reasons that make this area a prominent recipient of investments are a single market maintained throughout the EU by means of a common regulatory framework applied in every single one of its Member States; a modern and well-maintained transportation infrastructure; and an investment policy which provides investors with better market access, legal certainty, and a stable, predictable, fair and properly regulated environment. In line with the JETRO, as displayed in Figure 2.4, the EU countries which have received the largest amount of Japanese OFDI have mainly been the UK and the Netherlands, followed by Germany, France and Luxembourg.

Figure 2.4: FDI outward stock from Japan by European Union countries



Source: Own elaboration. Data obtained from JETRO.

On 1 February 2019 the EU and Japan's Economic Partnership Agreement entered into force after several years of negotiations between both parts. According to the European Commission (2018), this agreement will further strengthen the position of EU exporters and investors on Japan, through the guarantee of EU protection standards and impulsing Europe's leadership in setting global trade rules. Furthermore, the text promotes investment between the two parts reiterating their right to regulate and pursue legitimate policy objectives.

As for the US, according to Cooper (2014), Japan's OFDI surged in the 1980s and become the main investor in this country. These investment flows were mainly driven by consumer electronics firms and auto producers. However, at the beginning of the current century, Japan dropped to the fourth-largest source of FDI in the US, far behind the UK and France, and slightly above the Netherlands. However, Japanese investments in the North American country have increased since then, being Japan the third most important source of FDI in 2018 (OFII - Global Investment Grows America's Economy, 2019).

Against this backdrop and given the importance of Japan in the present investment worldwide landscape, the analysis of the Japanese OFDI determinants has regained increasing interest both in academic and political grounds.

There are many location determinants that influence FDI decisions. Traditionally, empirical studies have adopted a gravity equation approach and examined the patterns of FDI as a function of country characteristics such as market size, distance and frictions measured with different proxies. Moreover, with the development of new theories, additional factors have been introduced such transportation cost, tariffs, corporate taxes, natural resources, factor endowment, institutional quality and exchange rate among others. Consequently, a wide range of different variables has been used in the empirical literature.

Studies that have reviewed the impact of location factors on foreign investment have generally focused on regression models involving specific sets of variables determined ex-ante by the researcher depending on the particular theoretical approach adopted. This practice ignores uncertainty regarding the model specification itself, which can have dramatic consequences on inference. Particularly, inference regarding the effects of the covariates considered in a specification can depend critically on the remaining or even omitted variables.

Consequently, the existence of many potential determinants and the heterogeneity of regression models chosen by different authors constitute an enormous challenge for the researcher that tries to obtain the best model specification of FDI location determinants. Different econometric techniques have been proposed to select from a large number of candidate variables those that are the best to explain FDI activity. Among such methods are Bayesian statistical techniques.

In this Chapter, we select from a large set of 48 candidates those variables most likely to be determinants of OFDI from Japan implementing BMA techniques. To this aim, we study Japanese OFDI stock in a sample of 27 countries during the period 1996-2017. We also analyze country-groups including developed, emerging, EU and East Asian countries. The main findings are that Japanese OFDI can be explained by a wide variety of variables, including not only the usual suspects in a gravity setting, as GDP, population or distance but also some others as factor endowment, trade, previous investment and macroeconomic stability, together with institutional quality and financial development and integration.

Moreover, Japan's OFDI is explained by both horizontal and vertical motives in all country groups. However, in developed, and in particular, EU countries, HFDI strategies are predominant, whereas for East Asian and emerging countries, there is more evidence in favour of VFDI.

The rest of the Chapter is organized as follows. Section 2.2 includes a review of the theoretical and empirical literature on the location determinants of FDI. Section 2.3 presents the econometric methodology, Section 2.4 describes our database and discusses the estimated results, whereas the final Section concludes.

2.2 The underlying literature

2.2.1 Types and decisions of FDI

The analysis of FDI determinants is complex because of the diversity of MNCs and the different reasons the firms have to invest abroad. The eclectic Ownership, Location and Internalization (OLI) paradigm, proposed by Dunning (1980), has been a relevant analytical framework for accommodating a variety of operationally testable economic theories of the determinants of FDI and the foreign activities of MNCs. It maintains that FDI decisions of MNCs are determined by the interaction of three sets of interdependent variables: Ownership, location and internalization advantages. Consequently, Dunning (2000) distinguishes four types of FDI: Market-seeking FDI or HFDI, resource-seeking FDI or VFDI, efficiency-seeking FDI and strategic asset-seeking FDI. Market-seeking motives imply FDI oriented to satisfy a particular foreign market, or set of foreign markets; resource-seeking FDI is designed to gain access to natural resources, agricultural products or unskilled labor; efficiency-seeking FDI promotes a more efficient division of labor or specialization of an existing portfolio of foreign and domestic assets by MNCs; and strategic-asset seeking FDI protects or augments the existing ownership specific advantages of the investing firms and/or reduces those of their competitors by acquiring specific technological competence or qualified human capital not available at home.

In general, the literature has traditionally focused on two forms of FDI, namely, HFDI, motivated by market access, and VFDI, encouraged by comparative advantage. According to the theory of HFDI, a firm invests abroad by replicating a part of its activities or production processes in another country so as to avoid transportation costs, tariffs and other types of trade costs. This strategy is referred to as market access motive and was introduced by Markusen (1984) and Markusen and Venables (1998, 2000). In HFDI models, exports and FDI are substitutes, and the decision to serve a market via exports or setting up an affiliate company abroad constitutes a proximity-concentration trade-off.

On the other hand, firms engage in VFDI when they fragment their production process across countries. The main reason for such vertical fragmentation is the cost considerations arising from countries' factor cost difference. Firms are encouraged to fragment production and locate a production stage in a country where the factor used intensively in that stage is abundant. This strategy is known to as the comparative advantage motive and was introduced by Helpman (1984) and Helpman and Krugman (1985). More recently, the globalization of the world economy has relied on GVCs and the fragmentation of production as a new form of specialization. FDI activities and GVCs are linked, as argued by Amendolagine et al. (2017) and Amador and Cabral (2014). In fact, according to Baldwin (2017) the current comparative advantage has been denationalized.

More recent strands of the literature suggest other foreign investment strategies, alternatives to HFDI and VFDI, such as the knowledge-capital (KK) model (Markusen et al., 1996; Carr et al., 2001; Markusen and Maskus, 2002). Overall, under the KK model, similarities in market size, factor endowments and transport costs were determinants of HFDI, while differences in relative factor endowments determined VFDI. The KK model has recently been extended to explain other forms of FDI such as export-platform FDI (Ekholm et al., 2007; Bergstrand and Egger, 2007) which is used to serve the neighboring markets of the host country. To sum up, while recent Eaton-Kortum (Ricardian) type models have been extended to motivate gravity equations for multinational production, theoretical foundations for FDI per se are limited primarily to Bergstrand and Egger (2007).[5]

In order to discriminate between competing theoretical approaches of FDI determinants, the estimation of gravity equation has been successfully applied in the empirical literature. In this case, as in gravity models applied to trade flows, the gravity approach to FDI describes the volume of bilateral FDI between two countries as positively related to their economic

[5] While Markusen and Maskus (2002) KK model is about foreign affiliate sales (FAS), Bergstrand and Egger (2007) is about both, FAS and proper FDI.

sizes and negatively to the distance between them. During the last decade, some of the literature on FDI tried to generalize the use of the gravity approach to analyze FDI patterns (Brainard, 1997; Eaton and Tamura, 1994). Nonetheless, there was a lack of theoretical foundation for the gravity equations for FDI. Since Bergstrand and Egger (2007) such a theoretical foundation does exist. They extend the 2x2x2 KK model in Markusen and Maskus (2002), by adding an extra factor and country, and derive a specification for the FDI gravity equation that explains its empirical fit to the data. This paper, together with the one by Head and Ries (2008), are considered the only two formal general equilibrium theories for FDI. Subsequently, more research followed and the theoretical justification of the gravity model for FDI is not longer questioned. Kleinert and Toubal (2010) illustrate how an aggregate FDI equation can be derived from different theoretical models. In particular, we adopt here the 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:

$$AS_{ij} = s_i(\tau D_{ij}^{\eta 1})^{(1-\sigma)(1-\epsilon)} m_j \tag{2.1}$$

where AS_{ij} are aggregate sales of foreign affiliates (FAS) 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 2.1 can be log-linearized as

$$ln(AS_{ij}) = \alpha_1 + \zeta_1 ln(s_i) - \beta_1 ln(D_{ij}) + \xi_i ln(m_j) \tag{2.2}$$

This type of expression is the one commonly used in the gravity models for FDI as well. Next, we will see that most of the postulated covariates can be related either with some measurement of economic distance or with market size.

2.2.2 Choosing FDI determinants using Bayesian techniques: a short literature review

Most of the factors mentioned above are related to location determinants. Many empirical studies have adopted a gravity equation approach from the international trade literature and examined the patterns of FDI as a function of country characteristics such as market size, distance, factor endowment, transportation cost, tariffs, corporate taxes, natural resources institutional quality and exchange rate among others[6]. Consequently, a wide range of different variables has been used in the previous empirical literature.

However, there is little consensus on which ones are postulated to be potential FDI determinants. As an example of this pattern, we have summarized in Table 2.1 the characteristics of seven recent studies on FDI determination, as well as a list of the variables they include in their specification. In total, we have found that they use 47 different covariates. Moreover, only a few of the total set of potential covariates (around a maximum of 10) is selected in each model, a fact that substantially increases the possibility of spurious correlations. A second striking fact is that these studies make also different choices concerning whether they include lags, take logarithms or make any other transformations of the variables. Finally, the studies also differ in the dependent variable: whereas some use FAS, others use FDI flows, or Mergers and acquisitions (M&A) or FDI stocks (Chiappini (2014)).[7]

The main reason for this lack of consensus on FDI determinants is that previous research has generally focused on regression models involving specific sets of variables determined by the researcher. By conditioning on a particular regression model specification, this practice ignores uncertainty regarding the model specification itself, which might have very serious consequences on inference.

The existence of many potential determinants and the heterogeneity of regression models chosen by different authors could make the researcher wonder what are the best variables and econometric specifications to explain the FDI determinants. Next, we summarize the most recent evidence and techniques applied on variable selection in the case of FDI determination.

[6]See, for example, Anderson and Wincoop (2003), Chaney (2008), Disdier and Head (2008), Head and Mayer (2013), and Head and Mayer (2014) for overviews of the trade gravity literature.

[7]In our case, as we will explain later, we take logarithms and have as dependent variable FDI stocks.

Table 2.1: FDI determinants proposed in selected empirical studies

	Carr et al. (2001)	Disdier and Mayer (2004)	Martí et al. (2017)	Chiappini (2014)	Bergstrand and Egger (2007)	Di Giovanni (2005)	Busse et al. (2010)
Data and specifications							
Dependent variable	FAS	Location choice	Location choice	FDI stocks	FAS	M&A	FDI flows
Variables logged	No	Yes	Yes	Yes	Yes	Yes	Yes
Panel data	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Two-way or one-way flows	Two-way	One-way	One-way	One-way	Two-way	Two-way	Two-way
Gravity measures							
Parent GDP					x	x	
Host GDP		x		x	x	x	x
Distance	x	x	x	x	x	x	
Other GDP - related terms							
Host GDP per capita		x	x	x			
GDP similarity					x		
GDP sum	x				x		
GDP difference	x						x
GDP per capita differences						x	
Host market potential			x				
Host GDP growth							x
Rest of the world GDP					x		
Country levels endowments							
Relative skilled-unskilled labour endowments (skill difference)	x				x		
Interaction GDP difference and skill difference	x						
Relative capital-labour endowments					x		
Host wages		x					
Host non-income HDI			x				
Agglomeration economies							
Host firms agglomeration		x	x				
Parent firms agglomeration			x				
Bilateral cultural and colonial linkages							
Common language					x	x	

	Carr et al. (2001)	Disdier and Mayer (2004)	Martí et al. (2017)	Chiappini (2014)	Bergstrand and Egger (2007)	Di Giovanni (2005)	Busse et al. (2010)
Multilateral trade openness							
Host trade costs	x						
Parent trade costs	x						
Host trade openness							x
Interaction host trade costs and skill differences	x						
Bilateral trade openness							
Bilateral transport costs					x		
Bilateral trade flows						x	
Regional Trade Agreement				x	x	x	x
Customs Union						x	
Common currency							x
Common Service Sector Agreement						x	
Host country FDI /Business costs							
Host FDI costs	x				x		
Host taxes				x			
Parent taxes						x	
Bilateral tax and investment agreements							
Tax Treaty						x	x
Bilateral Investment Treaty							x
Host country communications infrastructure							
Host telephone traffic						x	
Host internet users			x				
Host road density			x				
Host country financial infrastructure							
Host market capitalization						x	
Political environment and institutions							
Host corruption			x				
Host political rights		x					
Host institutional quality		x		x			x
Host liberalization economy		x					

	Carr et al. (2001)	Disdier and Mayer (2004)	Martí et al. (2017)	Chiappini (2014)	Bergstrand and Egger (2007)	Di Giovanni (2005)	Busse et al. (2010)
Macroeconomic and financial instability							
Host unemployment rate		x					
Host inflation rate			x	x			x
Natural resources							
Host ores and metal exports				x			
Exchange rate							
Exchange rate				x		x	
Volatility exchange rates		x					

Following a Frequentist approach, Chakrabarti (2001) used Extreme Bound Analysis (EBA) to determine which explanatory variables are robust and which are fragile FDI determinants to small changes in the conditioning information set. The dependent variable used is per capita FDI inflows. In a cross-section sample of 135 countries for 1994 he finds that market size, measured as GDP per capita, has a strong explanatory power to explain FDI in the host country.

A methodology that was proposed earlier, known as BMA, was found to be a better method to account for model uncertainty as part of the estimation procedure (see, for example Raftery, 1995). The BMA analysis has been increasingly applied in Economics one the first example being Fernández et al. (2001) in the context of growth models.[8] According to Berger and Sellke (1987), conventional sensitivity analyses overstate the significance and the width of confidence intervals when model uncertainty is not accounted for. If this is the case, whether a statistically significant FDI determinant is relevant when alternative specifications are considered remains ambiguous. The BMA methodology can be applied to examine the large set of variables that have been proposed as FDI determinants by alternative FDI theories. Another difficulty commonly found in this type of analysis is that even the most comprehensive FDI datasets contain large sections of missing data. This problem, as in the trade literature, happens when the researcher wants to include as many countries as possible. In our case, this problem does not apply, as we include only the countries with complete information. If the missing data are unevenly distributed, they may create a selection bias problem that can question the accuracy of the coefficient estimates. This problem is, notwithstanding, relevant in this literature and has been solved using different approaches[9].

Blonigen and Piger (2014) apply Bayesian statistical techniques to select the most relevant

[8]To mention a few examples, these are the cases, among others, of the analysis of the sacrifice ratio (Katayama et al., 2019), export market shares (Benkovskis et al., 2019), current account balances (Desbordes et al., 2018), the deterrent effect of capital punishment (Moral-Benito, 2015) or the nexus energy consumption-economic growth (Camarero et al., 2015).

[9]To address both model uncertainty and selection bias, Eicher et al. (2012) introduced the Heckit BMA, which extends the statistical foundations of BMA to include Heckman (1979) selection bias procedure. They use a sample of 46 countries (25 OECD countries) from 1988 to 2000, and FDI flows as the dependent variable. The results show only mixed support for horizontal or export platform FDI theories, whereas the evidence of VFDI was quite weak. Later, Jordan and Lenkoski (2018) use a Tobit BMA (TBMA) technique to improve the estimation of the inclusion probabilities of Eicher et al. (2012) and develop a full Bayesian model. Such method gives support for roughly the same determinants as the Heckit BMA when modeling the magnitude of FDI flows.

FDI determinants for a group of OECD countries, as well as for the world economy, in 2000. In contrast to Eicher et al. (2012), and Jordan and Lenkoski (2018), Blonigen and Piger (2014) use FDI stocks. They found that the variables with consistently high inclusion probabilities include traditional gravity variables such as cultural and distance factors, relative labour endowments and trade agreements.

Antonakakis and Tondl (2015) apply the same methodology to examine the determinants of OFDI stock from OECD investors in 129 developing countries over the period 1995-2008. Their results suggest that no single theory governs the decision of FDI from OECD regions to developing countries but a combination of theories. In particular, OECD investors tend to invest in countries with whom have established intensive trade relations and offer qualified labour force. Other potential determinants are low wages, attractive tax rates and resource abundance.

Pratiwi (2016) also applies Bayesian techniques to FDI inflows for 58 countries from Asia, Europe, Africa and Latin America between 2000 and 2014. The main findings are that, during the period, FDI inflows decreased in developed countries and increased in developing ones. Moreover, past FDI is a potential determinant for each group of countries, and human capital and inflation are only relevant for developing countries.

Finally, Odebunmi (2017) uses BMA techniques to determine the robust variables to explain Greenfield investment (GFI) and M&A on a sample of 36 developed and 84 developing countries. To this aim, he uses bilateral flows of both types of foreign investment. The study finds that the two FDI categories respond quite differently, with the robust determinants of GFI being nearly twice as many as those of M&A. The results are similar for both developed and developing countries, except that for the latter the market size of the host country matters in the case of GFI and very few variables are relevant for M&A, as this type of activity is dominated by developed countries.

In the present Chapter, we apply a robust probabilistic approach to select the explanatory variables from a large set of potential candidates. For that objective, we use the R-package BayesVarSel (García-Donato and Forte, 2015), and apply Bayesian Variable Selection techniques for linear regression models using Gibbs sampling.

2.3 Econometric methodology

2.3.1 Bayesian methods for model selection

We have seen in the previous Section that two important issues related to the study of FDI determinants are the large amount of potential explanatory variables and the heterogeneity of model specifications chosen by different researchers. The impact of these variables is predicted by the broad empirical literature, but their ultimate presence in the model response is unknown. This type of situation defines a particular model selection problem known as variable selection, formally introduced in this Section.

In model selection, the true statistical model is unknown and this uncertainty is explicitly considered. The Bayesian approach to model selection has a number of appealing theoretical properties described in Berger and Pericchi (2001). The final product of such approach is the posterior distribution over the model space; a probability mass function that assigns to each model its probability conditional on the data observed. The attractiveness of this function lies in its easiness for the evaluation of any question relevant to the analyst in probabilistic terms. Despite its appeal, the implementation of Bayesian variable selection presents some difficulties that are likely to preclude its broad use in economic researches. These obstacles are associated with the assignment of the prior distribution and the necessity of approximating the posterior distribution with a large number of potential models. These problems are addressed by using the R package BayesVarSel (García-Donato and Forte, 2015), which is a user-friendly interface for this methodology.

2.3.2 The variable selection problem

Concerning variable selection, each entertained model corresponds to a specific subset of a group of (e.g., k) initially considered potential explanatory covariates. Therefore, the model space $\mathcal{M}$ has 2^k potential models and each competing model M_j for $j = 0, \ldots, 2^k - 1$ relates the response variable to a subset of k_j covariates, such as:

$$y_{it} = \alpha_j + X_{j,it}\beta_j + \gamma_{j,i} + \epsilon_{j,it} \qquad \epsilon_{j,it} \sim \mathcal{N}_n(0, \sigma^2 I), \tag{2.3}$$

where $i = 1, ..., N$ is the number of countries; $t = 1, ...T$ is the number of periods of time; α_j is the constant term; y_{it} is the n dimensional vector of observations for the response variable, the Japanese OFDI stock in the host country; $X_{j,it}$ is the $n \ x \ k_j$ design matrix of FDI determinants; $\epsilon_{j,it}$ a white noise error with zero mean and constant variance; and $\gamma_{j,i}$ is a unobservable time-invariant country heterogeneity component. Such component may introduce a bias in the results. In order to remove it, we are going to apply fixed effects. Within the BMA methodology, as proposed by Moral-Benito (2013), it consists of subtracting the country mean for every observation using the within transformation. Considering the model $M_j (j = 1, \ldots, 2^k)$:

$$(y_{it} - \bar{y}_i) = \alpha_j + (X_{j,it} - \bar{X}_{j,i})\beta_j + (\gamma_{j,i} - \bar{\gamma}_{j,i}) + (\epsilon_{j,it} - \bar{\epsilon}_{j,i}) \tag{2.4}$$

$$\ddot{y}_{it} = \alpha_j + \ddot{X}_{j,it}\beta_j + \ddot{e}_{j,it} \qquad \ddot{e}_{j,it} \sim \mathcal{N}_n(0, \sigma^2 I). \tag{2.5}$$

where $\bar{X}_{j,i} = \frac{1}{T}\sum_{t=1}^{T} X_{j,it}$; $\bar{\epsilon}_{j,i} = \frac{1}{T}\sum_{t=1}^{T} \epsilon_{j,it}$; and α_j is the constant term. Moreover, $\ddot{y}_{it}$ is the n dimensional vector of observations for the response variable, the Japanese FDI stock in the host country; $\ddot{X}_{j,it}$ is the $n \ x \ k_j$ design matrix of host country FDI determinants; and $\ddot{e}_{j,it}$ a white noise error with zero mean and constant variance again, but this time in terms of mean deviations.

Assuming that one of the models in $\mathcal{M}$ is the true model, the posterior probability of any model is:

$$P(M_j^*|y) = \frac{m_j^*(y)P(M_j^*)}{\sum_j m_j(y)P(M_j)}, \tag{2.6}$$

where $P(M_j)$ is the prior probability of M_j and m_j is the integrated likelihood with respect to the prior distribution for the parameters π_j:

$$m_j(y) = \int f_j(y|\beta_j, \alpha_j, \sigma)\pi_j(\beta_j, \alpha_j, \sigma^2)d\beta_j d\alpha_j d\sigma^2, \tag{2.7}$$

also called the (prior) marginal likelihood.

An alternative expression for (2.6) is based on the Bayes factor:

$$P(M_j^*|y) = \frac{B_j^*(y)P(M_j^*)}{\sum_j B_j(y)P(M_j)}, \tag{2.8}$$

where B_j is the Bayes factor of M_j respect to a fixed model, say M_0, and hence, $B_j = m_j/m_0$ and $B_0 = 1$.

2.3.3 Prior specification

The two inputs that are needed to obtain the posterior distributions are π_j and $P(M_j)$: the 2^p prior distributions for the parameters within each model and the prior distributions over the model space, respectively.

The prior distributions π_j can be expressed as:

$$\pi_j(\beta_j, \alpha_j, \sigma^2) = \pi_j(\beta_j|\alpha_j, \sigma^2)\pi_j(\alpha_j|\sigma^2). \tag{2.9}$$

The vast majority of the literature has applied improper priors for the common parameters to all models (α_j, σ), and the Zellner's g priors (Zellner, 1986) for the specific parameters (β_j). In this Chapter, we implement the prior distribution for the parameters proposed by Bayarri et al. (2012), which fulfil different criteria that should be taken into account to drive a variable selection problem and provide a reliable theoretical result at relatively small computational cost. This prior, known as the Robust prior, is:

$$\pi_j^R(\alpha_j, \beta_j, \sigma) = \pi(\alpha_j, \sigma)x\pi_j^R(\beta_j|\alpha_j, \sigma) = \sigma^{-1} \times \int_0^\infty {}_{k_i}(\beta_i \mid 0, g\,\Sigma_i)\, p_i^R(g)\, dg, \tag{2.10}$$

where $\Sigma_i = Cov(\hat{\beta}_i) = \sigma^2\,(V_i^t V_i)^{-1}$ is the covariance of the maximum likelihood estimator of β_i with

$$V_i = (I_n - X_0(X_0^t X_0)^{-1} X_0^t)X_i, \quad X_0 = (1_n, y_{-1}), \tag{2.11}$$

In equation 2.10, the hyperparameter g determines the strength of the researcher's prior belief that the coefficients are zero. A small (large) value of g indicates that the researcher is very certain (uncertain) that the coefficients are zero. For a given value of g, it can be shown that the posterior mean of the slope parameter β_r for the candidate regressor x_r conditional on model M_j is

$$E(\beta_r|y, g, M_j) = \left(\frac{g}{1+g}\right)\hat{\beta}_r, \tag{2.12}$$

where $\hat{\beta}_r$ is the OLS estimator of β_r for model M_j.

The choice of a fixed value of g could critically affect posterior inference and predictive accuracy. According to Feldkircher and Zeugner (2009), a large value of g concentrates the posterior probability mass on few and parsimonious models, regardless of whether they have generated the data. This concentration is referred to as the "supermodel effect". It is overall problematic with very "noisy data", where a high g could attribute too much weight to results that are mainly driven by a particular realization of the error term, having considerable consequences for the robustness of BMA results. As for Liang et al. (2008), fixing g has undesirable consistency issues on selecting model. When the researcher chooses a very large g in order to be noninformative, the large spread of such prior has the unintended consequence of forcing the Bayes factor to favour the null, smallest model, regardless on the data. Such a phenomenon is noted in Bartlett (1957) and is often referred to as "Bartlett's paradox". Both studies highlight that flexible g-priors, those which allow to update prior beliefs according to data quality, adapt better to the information content in the data.

In the present Chapter, we apply a hyper prior for g as proposed by Bayarri et al. (2012) within the Robust prior:

$$p_j^R(g) = \frac{1}{2}\sqrt{\frac{1+n}{k_j+k_0}}\,(g+1)^{-3/2}, \;\; g > \frac{1+n}{k_j+k_0} - 1, \tag{2.13}$$

and zero otherwise. Above, k_0 denotes the number of fixed covariates, which in our case is $k_0 = 1$, the constant term.

With respect to the prior over the model space $\mathcal{M}$, it can be approximated as:

$$P(M_j|\theta) = \theta^{k_j}(1-\theta)^{k-k_j}, \tag{2.14}$$

where k_j is the number of covariates in M_j, and the hyperparameter $\theta \in (0, 1)$ has the interpretation of the common probability that a given variable is independently included.

Most of previous literature has chosen θ as fixed, $\theta = 1/2$, which assigns equal prior probability to each model ($P(M_j) = 1/2^k$); or random, $\theta \sim Unif(0, 1)$, giving equal probability to each possible number of covariates or model size (Scott and Berger, 2010). Forte et al. (2018) state that using a fixed value of θ performs poorly in controlling for multiplicity (the occurrence of spurious explanatory variables as a consequence of performing a large number of tests) and can lead to rather informative priors. According to Ley and Steel (2009), the use of a random θ increases the flexibility of the prior and reduces the dependence of posterior and predictive results (including model probabilities) on prior assumptions. They suggest the use of a binomial-beta prior over the model space, $\theta \sim Beta(1, b)$, that for $b = 1$ reduces to the uniform prior on θ. Therefore, in this Chapter we make use of the random $\theta \sim Unif(0, 1)$ for the prior distribution over the model space.

2.3.4 Summaries of the posterior distribution and model averaged inference

When k is moderate to large, posterior probabilities of individual models can be very small so that it would be very difficult to discriminate among the different models, since all of then would have very low probabilities. An interesting summary is the posterior inclusion probabilities (PIPs) of each covariate, defined as:

$$P(x_r|y) = \sum_{x_r \in M_j} P(M_j|y), i = 1, ..., k. \tag{2.15}$$

These should be interpreted as the probability of a variable of being included in the true model for explaining the response variable. According to Raftery (1995), evidence for a regressor with a PIP from 0.50 to 0.75 is called weak, from 0.75 to 0.95 positive, from 0.95 to 0.99 strong, and >0.99 very strong.

The posterior distribution easily allows for obtaining model averaged estimates of any quantity of interest Δ (assuming it has the same meaning across all models). Suppose $\hat{\Delta}$ is the estimate of Δ. Then, the model averaged estimate of Δ is

$$\hat{\Delta} = \sum_{M_j} \hat{\Delta} P(M_j|y). \tag{2.16}$$

Similarly, the entire posterior distribution of Δ would be:

$$P(\Delta|y) = \sum_{M_j} P(\Delta|M_j, y) P(M_j|y), \tag{2.17}$$

Consequently, if Δ refers to the regression coefficients (β_r):

$$P(\beta_r|Y) = \sum_{M_j} P(\beta_r|M_j, y) P(M_j|y). \tag{2.18}$$

In this case, the model averaged estimates should be used and interpreted with caution because the "same" parameter may have a different meaning in different models (Berger and Pericchi, 2001).

2.3.5 Sampling method for posterior estimation

Another important point within the Bayesian techniques is the number of models in $\mathcal{M}$ (2^k). If k is small (say, k in the twenties at most), exhaustive enumeration is possible but if k is larger, heuristic methods need to be implemented. According to García-Donato and Martínez-Beneito (2013), sampling methods with frequency-based estimators outperform searching methods with re-normalized estimators. The searching procedure of this last group could bias the estimation. To implement the described variable selection approach, we use the R package BayesVarSel. In particular, we apply the function GibbsBvs to obtain approximations to the PIP of the covariates, using a Markov Chain Monte Carlo (MCMC) technique, as proposed by George and McCulloch (1997).

2.4 Data and empirical results

2.4.1 Data

In our BMA analysis, we choose from 48 different variables that were available for the 27 FDI destinations and the period 1996-2017 those covariates that are found to have a relatively high inclusion probability. In the group of 48 potential variables we have included those that have been previously considered in the theoretical and/or empirical literature on the determinants of FDI (see Table 2.1), as well as others that may be proxies for them and that are available for the whole group of countries.

One potential disadvantage of using such a large number of potential explanatory variables in a group including heterogeneous countries is that the number of covariates with high inclusion probability increases. This problem is common to both Bayesian and Frequentist approaches, but becomes very relevant in this instance as our aim is to select and discriminate among potential FDI determinants. In order to identify more homogeneous groups we have analized, in addition to the complete group of 27 destination countries, also smaller groups including developed, emerging, EU and East Asian countries. In Table 2.2 we enumerate the countries included in the different groups considered in our analysis. Table 2.3 contains the candidate variables grouped by the different criteria (mostly countries' characteristics) commonly considered in the literature. We also describe how they have been defined, their source and report previous studies that have also used these countries' characteristics. As we estimate using fixed effects, time-invariant variables are not included in this Chapter[10]. Some variables are lagged one or two years in order to avoid possible endogeneity with the dependent variable[11] and high correlation with other covariates[12]. To ease the discussion of the empirical results, we will follow the same order in the next Section.

[10]For more information about fixed effects estimation in panel data, see Fernández-Val and Weidner (2016, 2018) and Weidner and Zylkin (2019).

[11]Japan's annual OFDI is part of the real GDP of the host country. Something similar happens with the sum of the host country's and Japan's real GDP. To avoid endogeneity, we lag both covariates one year.

[12]Japanese exports and imports are included in total Japanese trade, and at the same time, these three variables are contained in the real GDP of the host country, as well as in the sum of the host country's and Japan's real GDP. In this case, we lag total Japanese trade two years.

Table 2.2: Groups of countries

Groups of countries	Countries included	Number of countries
Whole group	Australia, Belgium, Brazil, Canada, China, France, Germany, India, Indonesia, Islamic Republic of Iran, Italy, Malaysia, Mexico, Netherlands, New Zealand, Philippines, Republic of Korea, Russian Federation, Saudi Arabia, South Africa, Spain, Sweden, Switzerland, Thailand, United Arab Emirates, United Kingdom and United States.	27
Developed countries	Australia, Belgium, Canada, France, Germany, Italy, Netherlands, New Zealand, Republic of Korea, Spain, Sweden, Switzerland, United Kingdom and United States.	14
Emerging countries	Brazil, China, India, Indonesia, Islamic Republic of Iran, Malaysia, Mexico, Philippines, Russian Federation, Saudi Arabia, South Africa, Thailand and United Arab Emirates	13
EU countries	Belgium, France, Germany, Italy, Netherlands, Spain, Sweden and United Kingdom.	8
East Asian countries	China, Indonesia, Malaysia, Philippines, Republic of Korea and Thailand.	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 Hong Kong, Luxembourg and Singapore.

Table 2.3: Variables

Variable	Definition	Source	Authors
Dependent variable			Blonigen and Piger (2014), Antonakakis and Tondl (2015).
FDI outward stock	FDI outward stock from Japan to the host country at current US dollars.	JETRO.	
Market size and population			Brainard (1997), Carr et al. (2001), Bergstrand and Egger (2007), Head and Mayer (2004), Martí et al. (2017), Chiappini (2014), Markusen et al. (1996),Markusen and Venables (1998, 2000) Markusen and Maskus (2002), Blonigen et al. (2003), Disdier and Mayer (2004) and Narciso (2010).
1. LogLagRealGDP	Logarithm of the lagged host country's real GDP at constant 2010 US dollars.	WDI from World Bank.	
2. LogRealGDPdiff	Logarithm of the absolute difference between the host country's and Japan's real GDP at constant 2010 US dollars.		
3. RealGDPgrowth	Averaged 5 years growth rate of the host country's real GDP.		
4. UrbanPopulation	Percentage of population of the host country living in urban areas according to national statistical offices.		
5.LifeExpectancy	Life Expectancy at birth of the host country, years.		
6. OldDependencyRatio	Ratio of older dependents of the host country, people older than 64, to the working-age population, those ages 15-64.		
Labour market			Carr et al. (2001) , Chiappini (2014), Markusen et al. (1996) and Markusen and Venables (1998, 2000),Markusen and Maskus (2002), Alfaro and Charlton (2009), Yeaple (2003b) and Blonigen et al. (2003),Markusen and Maskus (2002), Alfaro and Charlton (2009), Yeaple (2003b) and Blonigen et al. (2003).
7. EducLevel	Education level of the host country measured as the average education years of population.	UNDP.	
8. SkillLevel	Skill level of the host country measured as the percentage of population age 25 + with completed and incompleted secondary schooling.	Education statistics from World Bank.	
9. HCI	Human capital index of the host country, based on years of schooling and returns to education.	PWT 9.1.	
10. EducLeveldiff	Absolute difference between the host country's and Japan's education level.	UNDP.	
11. SkillLeveldiff	Absolute difference between the host country's and Japan's skill level.	Education statistics from World Bank.	
12. LogRealGDPdiff* EducLevdiff	Interaction between the logarithm of the absolute difference between the host country's and Japan's real GDP and the absolute difference between the host country's and Japan's education level.	Own elaboration.	

Variable	Definition	Source	Authors
13. LogRealGDPdiff* SkillLevdiff	Interaction between the logarithm of the absolute difference between the host country's and Japan's real GDP and the absolute difference between the host country's and Japan's skill level.	Own elaboration.	
14. LogPopulationDensity	Logarithm of the population density of the host country.	WDI from World Bank.	
Trade and international openness			Di Giovanni (2005), Bergstrand and Egger (2007), Brainard (1997), Camarero and Tamarit (2004), Camarero et al. (2018), Markusen and Venables (2000), Helpman and Krugman (1985) and Gygli et al. (2019).
15. LogJapExports	Logarithm of the Japan's exports to the host country at current US dollars.	DOTS from IMF.	
16. LogJapImports	Logarithm of the Japan's imports from the host country at current US dollars.		
17. Log2LagJapTrade	Logarithm of the two years lagged sum of the Japan's exports and imports with the host country.	.	
18. TradeOpenness	Total imports and exports of the host country divided by the total GDP at current US dollars.	WDI from World Bank.	
19. TradeFreedom	Trade freedom index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	The Heritage Foundation.	
20. RTA	Dummy variable which takes value 1 if Japan and the host country are in a regional trade agreement, whether bilateral or multilateral, at period *t*, 0 otherwise.	WTO.	
21. RTA*LogLagRealGDP	Interaction between the dummy variable RTA and the logarithm of the lagged host country's real GDP.	Own elaboration.	
22. KOFSoGIdf	KOF social globalization index de facto of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	Gygli et al. (2019)	
Investment openness			Neumayer and Spess (2005), Busse et al. (2010), Rose-Ackerman and Tobin (2005), Camarero et al. (2019) and Di Giovanni (2005).
23. InvestmentFreedom	Investment freedom index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	The Heritage Foundation.	
24. FinancialFreedom	Financial freedom index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).		
25. Chinn-ItoIndex	Index measuring a country's degree of capital account openness of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	Chinn and Ito (2006)	

Variable	Definition	Source	Authors
26. BIT	Dummy variable which takes value 1 if Japan and the host country are in a bilateral investment treaty at period t, 0 otherwise.	UNCTAD	
Institutional quality			
27. VoiceAccountability	Voice accountability index of the host country. It ranges from -2.5 (the lowest score) to 2.5 (the highest score).	WGI from World Bank.	Wei (2000), Chiappini (2014), Kinoshita and Campos (2003), Hyun (2006), Lui (1985), and Egger and Winner (2005).
28. PoliticalStability	Political stability and absence of violence index of the host country. It ranges from -2.5 (the lowest score) to 2.5 (the highest score).		
29. GovernmentEffectiveness	Government effectiveness index of the host country. It ranges from -2.5 (the lowest score) to 2.5 (the highest score).		
30. RegulatoryQuality	Regulatory quality index of the host country. It ranges from -2.5 (the lowest score) to 2.5 (the highest score).		
31. ControlCorruption	Control of corruption index of the host country. It ranges from -2.5 (the lowest score) to 2.5 (the highest score).		
32. RuleLaw	Rule of law index of the host country. It ranges from -2.5 (the lowest score) to 2.5 (the highest score).		
33. PropertyRights	Property rights index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	The Heritage Foundation.	
34. GovernmentIntegrity	Government integrity index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).		
Macroeconomic and financial stability			
35. Unemployment	Unemployment rate of the host country.	WDI from World Bank.	Martí et al. (2017) and Chiappini (2014).
36. InflationGDPDef	Inflation level of the host country measured by the annual growth rate of the GDP deflator.		
37. InflationCPI	Inflation level of the host country measured by the the annual percentage change of the Consumer Prices Index.		

Variable	Definition	Source	Authors
38. MonetaryFreedom	Monetary freedom index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	The Heritage Foundation.	
39. WUI	World Uncertainty index of the host country.	Ahir et al. (2018)	
Communications infrastructure			
40. Telephone	Fixed telephone subscriptions of the host country per 100 people.	WDI from World Bank.	Di Giovanni (2005) and Alfaro and Chen (2015).
41. Cellular	Mobile cellular subscriptions of the host country per 100 people.		
42. Internet	Individuals using the Internet in the host country per 100 people.		
Natural resources			
43. OilRents	Oil rents of the host country as a percentage of total GDP.	WDI from World Bank.	Dunning (1977), Dunning (1979), Chiappini (2014) and Khayat (2017).
44. GasRents	Gas rents of the host country as a percentage of total GDP.		
Government size			
45. FiscalFreedom	Fiscal freedom index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	The Heritage Foundation.	Di Giovanni (2005), Shah and Iqbal (2016), Salem Musibah (2017) and Othman et al. (2018).
46. GovernmentSpending	Government spending index of the host country. It ranges from 0 (the highest score) to 100 (the lowest score).		
Business Freedom			
47. BusinessFreedom	Business freedom index of the host country. It ranges from 0 (the lowest score) to 100 (the highest score).	The Heritage Foundation.	
Exchange rate			
48. NominalExchangeRate	Nominal exchange rate between Japan and the host country, measured as the value of a Japanese yen in foreign currency. 2010=100.	WDI from World Bank.	Froot and Stein (1991), Blonigen (1997), Benassy-Quere et al. (1999).

NOTES: JETRO=Japan External Trade Organization, WDI=World Development Indicators, UNDP=United Nations Development Programme, PWT 9.1=Penn World Table 9.1, DOTS=Direction of Trade Statistics, IMF=International Monetary Fund, WTO=World Trade Organization, UNCTAD=United Nations Conference on Trade and Development, WGI=World Governance Indicators.

2.4.2 Empirical results

The results for the different country-groups analyzed are presented in Table 2.4. The PIPs and the posterior means of the different groups and estimations are obtained from the best 100,000 models using the Gibbs sampling. This number of iterations guarantees PIPs convergence, as they stabilize long before, at around 20,000 iterations, which is the maximum that the R-function GibbsBvs allows to elaborate the plots (see Appendix 2.A, Figure 2.A.1). Following the same order as in Table 2.3, the variables are grouped according to country characteristics. We will consider that a covariate is potentially relevant when its PIP is higher than 0.5, as suggested by Raftery (1995), or is close to this threshold and is at least in one of the best 10 models. These cases are marked in bold. In addition to the Table, we have also included descriptive graphs of the PIPs in Appendix 2.B. It is important to highlight that the posterior means are averages of the coefficients of the best 100,000 models taking into account their posterior probabilities (see equation 2.18). However, they are still illustrative as they provide the mean effect of the covariate on Japanese OFDI stock. Finally, even if some interactions have high PIP, we only interpret them if both variables in such interaction are relevant individually.

The first group of variables that we consider includes **market size and population** measures. The *lagged host country's real GDP* is found to be a potential determinant of Japanese OFDI for the whole group, as well as for emerging and East Asian countries. Its posterior mean is positive, showing evidence in favour of market-seeking FDI or HFDI. Similar results, applied to different country groups were obtained, for example by Carr et al. (2001), Markusen and Maskus (2002), Blonigen et al. (2003), Bergstrand and Egger (2007) and Chiappini (2014) to name a few, some of them seminal papers in this literature. Additionally, *real GDP growth of the destination country* is a robust determinant for the East Asian countries group. A probable reason for this result is the rapid growth of China, the largest country in the area, and the ensuing attraction (and need) of foreign capital. *Urban population of the host country* has a PIP over 0.5 for developed, emerging and EU countries. However, its sign points in opposite directions for different country-groups: positive for developed and EU countries, consistent with HFDI, but negative for emerging countries. Indeed, market size in the latter is less relevant, and VFDI plays a major role. Concerning *life expectancy of the destination country* for the whole group, developed and emerging countries, its average coefficient is positive, as expected. Finally, the *old-dependency ratio of the host country* has been found to be a robust FDI determinant for East Asian countries. However, its posterior mean is positive, which could be considered unexpected. A possible explanation for this sign is that these economies are younger than the majority of developed countries, with low old-dependency ratios. According to Narciso (2010) these different ageing patterns may have a positive effect on capital flows to emerging markets, as in fact is the case of most East Asian countries.

As for the variables related to **labour market**, the *skill level of the host country* is a potential determinant of Japanese OFDI for the whole group. Its positive sign would mean that Japanese MNCs are attracted by countries with larger skilled labour endowments, strategy consistent with resource-seeking FDI (VFDI). Moreover, it could also be related with strategic asset-seeking FDI, where MNCs acquire human capital and skilled labour to access foreign pools of knowledge and technologies with the aim to augment their existing ownership advantages. We obtain more precise results when we consider smaller geographical areas. On the one hand, the *skill level difference of the host country* has a negative posterior mean for the EU countries, a result compatible with HFDI among countries with similar relative endowments, as pointed out by Markusen et al. (1996). Blonigen et al. (2003) found a similar result. On the other hand, the *human capital index (HCI) of the host country* reduces Japan's OFDI in Asian countries. This would imply that Japanese MNCs looked for locations with less skilled labour, in order to obtain cheaper workforce for their production processes. This result is consistent with resource-seeking FDI (VFDI) and compatible with strategies that Japanese manufacturing companies undertake in these countries to develop their GVCs networks, where production processes are fragmented according to relative (and cheaper) factor endowments.

Concerning the covariates related to **trade and investment openness**, all those that are found to be robust have a positive sign. This means that trade and FDI have been complements during the period considered, a pattern consistent with VFDI, and/or the positive effect of trade liberalization in investment strategies (both HFDI and VFDI), together with feedback effects between FDI liberalization and trade. This positive effect is described by Brainard (1997). For the Spanish case, Camarero and Tamarit (2004) also found complementarity between trade and FDI, as well as for Germany in Camarero et al. (2019) using also BMA. It is of special importance the case of the *RTA dummy* in the East Asian countries. The only countries of this group that have a trade agreement with Japan are those of the ASEAN region. The positive sign of this variable, together with the negative one of its interaction with the *lag of the real GDP of the host country*, and the results that we have obtained in the **labour market** measures, would imply that market size (HFDI) has lost in relevance in favour of VFDI. Therefore, this type of agreements have probably reinforced the GVCs networks of Japanese manufacturing firms with these countries.

The next group of variables is especially relevant for the purpose of this Chapter: the measures of **investment and financial openness**. These include the *investment and financial freedom indexes*, both from the Heritage Foundation; the *Chinn-Ito index*, that measures the degree of capital account openness and a dummy variable called *BIT* that represent the existence of a bilateral FDI treaty between the two countries. Concerning the *investment freedom index of the host country*, this is a robust determinant for Japanese OFDI in the developed countries. Its sign, positive, is as expected and could be compatible with both vertical and horizontal strategies of investment, as well as with the KK-Model. A second very relevant result is that the *financial freedom index of the destination country*, a measure of banking efficiency and independence of the financial sector from the government, is a potential determinant of Japan's OFDI for the whole group, as well as for emerging and East Asian countries. The incidence of the two financial crises in Asia and the lower depth of the financial markets in emerging economies explains that Japanese OFDI is positively influenced by the degree of development of the host country. Finally, the *Chinn-Ito index of the host country* is found to be another potentially robust determinant of Japanese OFDI. Its sign, as expected, is positive for the whole group and emerging countries, as a larger value in this index means a higher degree of capital account openness. However, it displays a negative effect for the East Asian countries. This result could seem counter-intuitive. However, there are several reasons that could explain this sign. According to Gochoco-Bautista et al. (2010), in the early 1990s, many Asian economies began to liberalize their capital accounts. It was recognized that capital restrictions were to be relaxed gradually and only after an economy had first undergone the necessary structural reforms to liberalize other markets and fulfill certain prerequisites such as well-developed financial markets, high-quality institutions, good governance, sound macroeconomic policies, and trade integration (Asian Development Bank and ASEAN, 2013). Policy makers in Asia were worried that unabated and large inflows could endanger financial stability by creating asset bubbles in the nontradeables sector, given shallow and underdeveloped domestic capital markets. These fears were validated when the Asian financial crisis hit in 1997. In fact, according to Wang (2007), a premature capital account liberalization was the direct cause of various financial crises in these countries. Consequently, most East Asian countries imposed tight capital controls during the Asian Crisis which started in 1997 and the Great Recession which arised in 2008. Indeed, coinciding with such periods, the *Chinn-Ito index* has experienced several falls in these countries. Currently, ASEAN countries maintain several classes of restrictions that may currently be providing legitimate safeguards against speculation and prevent the buildup of financial sector risk (Almekinders et al., 2015). Another reason for this result is that without adequate capital controls, capital inflows would cause the domestic currency to appreciate in real terms and make their countries' exports uncompetitive (Gochoco-Bautista et al., 2010). As a consequence, GVCs linkages of Japanese firms with East Asian countries would be weakened, reducing incentives for OFDI. Thus, OFDI from Japan is motivated by a moderate capital account openness of the East Asian countries with the aim to minimize macroeconomic and financial risks, given their underdeveloped financial markets, as well as strengthen the GVCs of Japanese companies. Therefore, the results for this group of variables confirm our hypothesis, that in order to attract Japanese OFDI (as well as OFDI from countries with highly developed financial markets) it is not enough having low labour costs or natural resources, but also a stable and deep financial sector.

Considering **institutional quality variables**, the results concerning the potential covariates for the whole group point in different directions, probably due to the high degree of heterogeneity of the largest group. However, when we focus on smaller groups of countries the outcome is less ambiguous: for developed and EU countries, *regulatory quality* and *property rights indexes of the host country* present a positive posterior mean, as expected. Higher quality and efficiency of institutions attracts FDI (see, for example, Wei (2000), Chiappini (2014), Kinoshita and Campos (2003), and Hyun (2006)). However, for emerging and East Asian countries the *control of corruption index at the destination country* has negative sign posterior mean. At first sight, this sign may seem unexpected, but according to Lui (1985) and Egger and Winner (2005), MNCs might be willing to accept paying bribes in order to speed up the bureaucratic processes to obtain the legal permissions for setting up a foreign plant. In this case, corruption acts as a helping hand, probably more common in transition and developing countries, where institutional quality is lower than in developed countries.

Regarding **macroeconomic and financial instability/stability**, the *inflation level of the host country* measured by the annual change of the CPI is a relevant OFDI determinant for the whole group and emerging countries. Its posterior mean is negative, as an increase in the inflation level could be indicative of higher macroeconomic risk. Moreover, the *monetary freedom index* is a potential FDI determinant as well, with negative sign for the emerging economies. This sign is capturing that these countries are more prone to suffer price instability and inflationary episodes, and price controls (lower monetary freedom) can be a tool for control these macroeconomic risks. In the same line, World Bank Group (2020) points out that in emerging and developing countries, price controls on goods are often imposed to serve social and economic objectives. They may be part of government efforts to protect vulnerable consumers, by addressing market failures or subsidizing the cost of essential goods. Thus, certain degree of price controls in emerging countries could attract Japanese OFDI.

As for the measures of **communications infrastructure**, *Telephone* is a robust covariate for the whole group, developed and EU countries. The negative sign of its posterior mean may be due to the progressive reduction in (obsolete) fixed phones with the simultaneous increase of mobile technology. On the other hand, *cellular* and *internet subscriptions of the host country* are relevant covariates in several country groups and have a positive posterior mean, an indicator of more developed communication infrastructure. Similar results were found by Di Giovanni (2005) and Alfaro and Chen (2015).

Concerning **natural resources**, the *gas rents of the host country* have a PIP higher than 0.5 for the whole group, as well as for developed and emerging countries. Its posterior mean is positive for developed countries, an effect consistent with resource seeking FDI (VFDI). On the other hand, it is negative for the whole group and for emerging countries, that may seem counter-intuitive. However, according to Khayat (2017), who studied the location determinants of FDI in Middle East North Afric (MENA) countries[13], abundant oil and gas

[13] These countries are Algeria, Bahrain, Djibouti, Egypt, Iran, Iraq, Israel, Jordan, Kuwait, Lebanon, Libya, Malta, Morocco, Oman, Qatar, Saudi Arabia, Syria, Tunisia, United Arab Emirates, Palestine, and Yemen.

resources could affect FDI negatively, due to government strategies of risk management across sectors and increased volatility in exchange rates. Therefore, a negative sign would not be unexpected if we take into account that in our group of emerging countries there are MENA countries with large oil and gas rents, such as Iran, Saudi Arabia and the United Arab Emirates.

Finally, **business freedom** of the host country is found to be a robust OFDI determinant with negative sign for both the whole group and emerging countries. This result is similar to the one obtained in the case of the institutional variables above.

In order to complete our analysis, we check the robustness of our results using Ordinary Least Squares (OLS) and Pseudo Poisson Maximum Likelihood (PPML) estimators in Appendices 2.C and 2.D, respectively. The findings obtained are similar.

Table 2.4: Empirical results

Variables	Whole group		Developed countries		Emerging countries		EU countries		East Asian countries	
	PIP	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**
Market size and population										
LogLagRealGDP	**0.644**	**0.469 (0.405)**	0.058	-0.004 (0.153)	**0.874**	**1.094 (0.543)**	0.318	-0.567 (0.943)	**1**	**1.428 (0.259)**
LogRealGDPdiff	0.059	0.000 (0.026)	0.079	-0.046 (0.24)	0.055	0.002 (0.041)	0.109	0.185 (0.663)	0.024	0.000 (0.020)
RealGDPgrowth	0.097	0.000 (0.001)	0.127	-0.001 (0.003)	0.060	0.000 (0.000)	0.078	0.000 (0.001)	**0.953**	**0.004 (0.002)**
UrbanPopulation	0.124	-0.001 (0.003)	**0.872**	**0.024 (0.012)**	**0.542**	**-0.009 (0.010)**	**0.755**	**0.030 (0.020)**	0.356	-0.006 (0.009)
LifeExpectancy	**0.998**	**0.050 (0.012)**	**0.940**	**0.078 (0.030)**	**0.571**	**0.019 (0.019)**	0.064	0.002 (0.014)	0.068	0.002 (0.015)
OldDependencyRatio	0.069	0.000 (0.002)	0.051	0.000 (0.003)	0.162	-0.007 (0.022)	0.052	0.000 (0.003)	**0.953**	**0.110 (0.042)**
Labour market										
EducLevel	0.244	-0.011 (0.023)	0.081	-0.003 (0.018)	0.099	-0.004 (0.018)	0.074	0.005 (0.027)	0.052	-0.002 (0.012)
SkillLevel	**0.656**	**0.004 (0.003)**	0.347	0.002 (0.003)	0.070	0.000 (0.002)	0.199	0.002 (0.004)	0.045	0.000 (0.002)
HCI	0.089	-0.010 (0.059)	0.062	0.013 (0.091)	0.091	-0.019 (0.094)	0.045	0.008 (0.110)	**0.710**	**-0.814 (0.611)**
EducLeveldiff	0.076	-0.003 (0.052)	0.266	-0.039 (0.280)	0.105	0.006 (0.104)	0.227	-0.318 (1.623)	0.037	0.001 (0.056)
SkillLeveldiff	0.094	0.005 (0.045)	0.419	-0.006 (0.071)	0.407	0.009 (0.061)	**0.706**	**-0.866 (0.709)**	0.049	0.001 (0.022)
LogRealGDPdiff*EducLevdiff	0.073	0.000 (0.004)	0.265	0.000 (0.022)	0.110	0.000 (0.008)	0.222	0.022 (0.130)	0.033	0.000 (0.004)
LogRealGDPdiff*SkillLevdiff	0.092	0.000 (0.004)	0.438	0.001 (0.006)	0.405	0.000 (0.005)	0.711	0.070 (0.057)	0.048	0.000 (0.002)
LogPopulationDensity	0.071	0.000 (0.088)	0.071	-0.059 (0.492)	0.141	0.079 (0.271)	0.166	-0.579 (1.504)	0.192	-0.416 (0.991)
Trade and international openness										
LogJapExports	**0.588**	**0.136 (0.135)**	0.042	0.001 (0.023)	0.123	0.019 (0.067)	0.039	0.002 (0.035)	0.128	0.026 (0.083)
LogJapImports	0.375	0.089 (0.132)	0.106	0.021 (0.076)	0.144	0.028 (0.086)	0.056	0.010 (0.055)	0.345	0.110 (0.166)
Log2LagJapTrade	**0.991**	**0.450 (0.123)**	**0.725**	**0.276 (0.200)**	0.312	0.090 (0.153)	0.037	0.000 (0.040)	0.232	0.061 (0.128)
TradeOpenness	**0.522**	**0.001 (0.001)**	0.222	0.001 (0.002)	**0.702**	**0.002 (0.002)**	0.075	0.000 (0.001)	0.038	0.000 (0.000)
TradeFreedom	**0.516**	**0.002 (0.002)**	**0.563**	**0.007 (0.008)**	0.062	0.000 (0.001)	**0.481**	**0.010 (0.012)**	0.026	0.000 (0.000)
RTA	0.250	0.375 (1.103)	0.048	-0.014 (0.356)	0.136	0.036 (0.377)			**0.520**	**1.228 (2.064)**
RTA*LogLagRealGDP	0.265	-0.034 (0.094)	0.049	0.001 (0.030)	0.144	-0.005 (0.033)			**0.471**	**-0.100 (0.179)**
KOFSoGIdf	0.099	0.000 (0.002)	0.071	0.000 (0.002)	0.362	0.005 (0.008)	0.048	0.000 (0.002)	0.038	0.000 (0.001)
Investment openness										
InvestmentFreedom	0.260	- 0.001 (0.001)	**0.717**	**0.004 (0.003)**	0.104	0.000 (0.001)	0.043	0.000 (0.001)	0.132	0.000 (0.001)
FinancialFreedom	**0.999**	**0.005 (0.001)**	0.048	0.000 (0.000)	**0.998**	**0.008 (0.002)**	0.048	0.000 (0.001)	**0.898**	**0.004 (0.002)**
Chinn-ItoIndex	**0.484**	**0.001 (0.001)**	0.136	0.000 (0.001)	**0.736**	**0.003 (0.002**	0.046	0.000 (0.001)	**0.655**	**-0.002 (0.002)**
BIT	0.146	-0.016 (0.045)	0.050	-0.001 (0.031)	0.074	-0.008 (0.048)			0.030	- 0.001 (0.013)

	Whole group		Developed countries		Emerging countries		EU countries		East Asian countries	
Variables	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**
Institutional quality										
VoiceAccountability	0.395	-0.053 (0.077)	0.042	0.001 (0.028)	0.208	-0.031 (0.074)	0.039	0.002 (0.042)	0.230	-0.027 (0.055)
PoliticalStability	0.070	0.000 (0.010)	0.039	0.000 (0.010)	0.065	0.001 (0.014)	0.082	0.007 (0.028)	0.031	0.000 (0.006)
GovernmentEffectiveness	0.071	-0.002 (0.018)	0.047	-0.002 (0.017)	0.087	-0.009 (0.040)	0.127	0.020 (0.061)	0.032	-0.001 (0.018)
RegulatoryQuality	**0.941**	**0.218 (0.087)**	**1**	**0.418 (0.073)**	0.065	0.001 (0.028)	**0.955**	**0.383 (0.132)**	0.060	-0.006 (0.026)
ControlCorruption	**1**	**-0.267 (0.058)**	0.039	0.001 (0.017)	**1**	**-0.344 (0.072)**	0.039	0.000 (0.021)	**0.570**	**-0.114 (0.108)**
RuleLaw	**0.501**	**0.098 (0.115)**	0.054	-0.004 (0.033)	0.095	0.010 (0.046)	0.056	-0.007 (0.042)	0.034	-0.001 (0.017)
PropertyRights	0.174	0.000 (0.001)	**0.990**	**0.008 (0.002)**	0.058	0.000 (0.000)	**0.807**	**0.008 (0.005)**	0.101	0.000 (0.001)
GovernmentIntegrity	0.270	-0.001 (0.001)	0.172	-0.001 (0.001)	0.080	0.000 (0.002)	0.169	-0.001 (0.001)	0.028	0.000 (0.000)
Macroeconomic and financial stability										
Unemployment	0.214	-0.002 (0.005)	0.259	-0.004 (0.009)	0.066	-0.001 (0.004)	0.116	-0.001 (0.004)	0.136	-0.004 (0.011)
InflationGDPDef	0.080	0.000 (0.001)	0.159	-0.003 (0.007)	0.089	0.000 (0.001)	0.038	0.000 (0.003)	0.028	0.000 (0.000)
InflationCPI	**0.972**	**-0.008 (0.003)**	0.201	-0.005 (0.011)	**0.914**	**-0.007 (0.003)**	0.051	-0.001 (0.004)	0.052	0.000 (0.001)
MonetaryFreedom	0.081	0.000 (0.000)	0.062	0.000 (0.001)	**0.593**	**-0.002 (0.002)**	0.040	0.000 (0.001)	0.171	-0.001 (0.002)
WUI	0.179	0.062 (0.162)	0.058	0.014 (0.086)	0.056	0.000 (0.074)	0.046	0.013 (0.097)	0.026	-0.003 (0.041)
Communications infrastructure										
Telephone	**1**	**-0.015 (0.002)**	**1**	**-0.013 (0.002)**	0.334	-0.003 (0.006)	**1**	**-0.020 (0.003)**	0.059	0.000 (0.001)
Cellular	0.395	0.003 (0.001)	0.173	0.000 (0.001)	**0.951**	**0.003 (0.001)**	0.149	0.000 (0.001)	0.286	0.001 (0.001)
Internet	**0.608**	**0.002 (0.001)**	0.078	0.000 (0.001)	0.103	0.000 (0.001)	**0.982**	**0.007 (0.003)**	0.039	0.000 (0.000)
Natural resources										
OilRents	0.152	-0.001 (0.003)	0.050	-0.001 (0.015)	0.063	0.000 (0.001)	0.209	-0.068 (0.150)	0.072	0.001 (0.005)
GasRents	**0.908**	**-0.068 (0.031)**	**0.534**	**0.064 (0.067)**	**1**	**-0.132 (0.026)**	0.035	0.000 (0.020)	0.031	0.000 (0.011)
Government Size										
FiscalFreedom	0.145	0.000 (0.001)	0.073	0.000 (0.001)	0.141	-0.001 (0.002)	0.118	-0.001 (0.002)	0.062	0.000 (0.002)
GovernmentSpending	0.079	0.000 (0.000)	0.127	0.000 (0.001)	0.070	0.000 (0.001)	0.062	0.000 (0.001)	0.026	0.000 (0.001)
Business Freedom										
BusinessFreedom	**0.780**	**-0.003 (0.002)**	0.111	0.000 (0.001)	**0.982**	**-0.007 (0.002)**	0.039	0.000 (0.000)	0.039	0.000 (0.000)
Exchange Rate										
NominalExchangeRate	0.154	0.000 (0.000)	0.046	0.000 (0.000)	0.144	0.000 (0.000)	0.036	0.000 (0.000)	0.180	0.000 (0.001)

NOTES: sd=standard deviation. The dummies RTA and BIT are not included in EU countries. It is because they are constant in such cases.

2.5 Conclusions

Japan has become one of the most important reference investors for many countries and MNCs for the last thirty years. Therefore, the analysis of the Japanese OFDI determinants is a matter of increasing academic and political interest.

In this Chapter, we select from a large set of 48 explanatory variables those that are robust determinants of Japanese OFDI in a sample of 27 host countries during the period 1996-2017. To the best of our knowledge, previous empirical studies on the role of location factors for Japanese foreign investment have generally focused on regression models involving specific sets of variables determined ex-ante by the researcher. This practice ignores uncertainty regarding the model specification itself, which can have dramatic consequences on inference. Due to the heterogeneity and variety of determinants that have been associated to FDI models, Bayesian statistical techniques, and in particular, BMA techniques are very suitable for this particular case. Our analysis discriminates between different country subgroups, looking for more homogeneous groups and more parsimonious models. More specifically, we analyze developed, emerging, EU and East Asian countries and provide the posterior mean obtained for the variables selected for each group. This allows us to discriminate among FDI theoretical approaches for the different groups of countries.

Concerning the whole group of countries, we select 18 variables out of the 48 potential covariates. The number of selected covariates decreases as the groups of countries become more homogeneous, pointing to relatively more parsimonious models: 9 variables for developed countries, 12 in the emerging countries group, and for the EU and East Asian countries 7 and 9, respectively. The main findings suggest, first, that Japanese OFDI can be explained by a wide variety of variables, including market size and population, labour market, trade, investment, institutions, macroeconomic factors, communications infrastructure, natural resources and business freedom measures. Second, for all the country-groups considered, Japan's OFDI is explained by both horizontal and vertical motives. However, in developed and EU countries, HFDI strategies prevail, while in emerging and East Asian countries VFDI motives associated to the development of GVCs and the segmentation of international production predominate. Third, the role played by the quality of institutions differs depending on the country group analysed. It attracts Japanese

OFDI in the first two groups, whereas it becomes a deterrent factor in the other two. Fourth, the presence of covariates related to investment openness, for all country groups, confirms our hypothesis on the relevance of financial development to maintain the level of Japanese investment abroad. This factor seems to be crucial in East Asian countries, where financial markets have not reached yet a desirable level of development. Under these circumstances, an excessive capital account liberalization could, instead of attracting, deterring FDI from Japan. Finally, another result common to all country groups is that, in the case of Japanese OFDI stocks, there is complementarity between trade and investment.

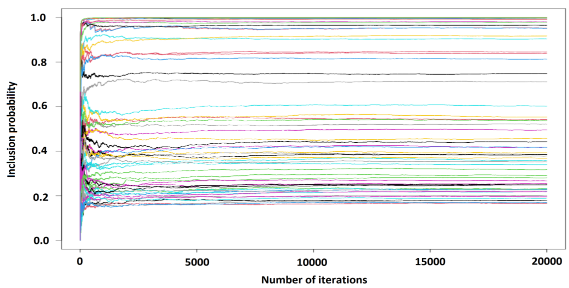
To sum up, the results point to two clearly different motives for Japan's OFDI: in developed countries, with similar income and resources endowment, horizontal strategies, directed to penetrate the foreign markets prevail, whereas in developing and neighbouring Asian countries, OFDI is related to vertical strategies.

Appendices

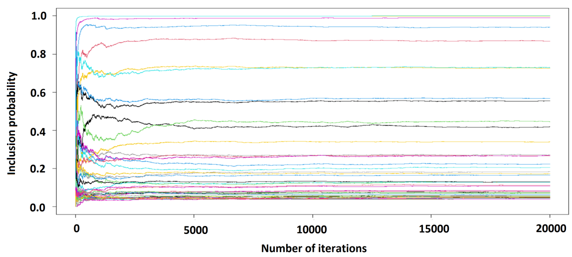
2.A Trace of posterior inclusion probabilities

The following trace plots are obtained from 20,000 iterations, the maximum that the R-function GibbsBvs allows to elaborate such plots. The PIPs are very close to converge with such number of iterations.

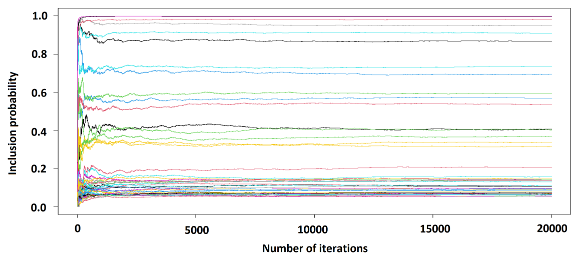
Figure 2.A.1: Trace estimation by groups of countries



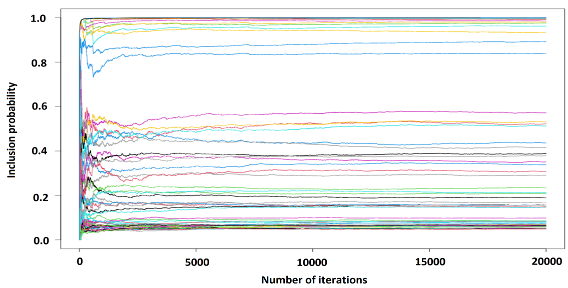
(a) Whole group



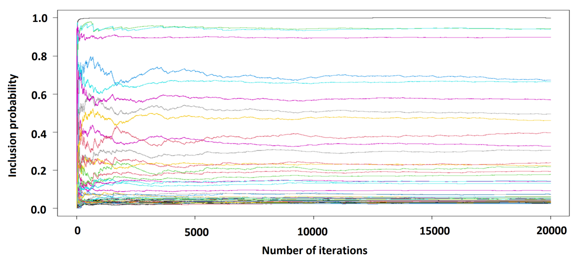
(b) Developed countries



(c) Emerging countries



(d) EU countries

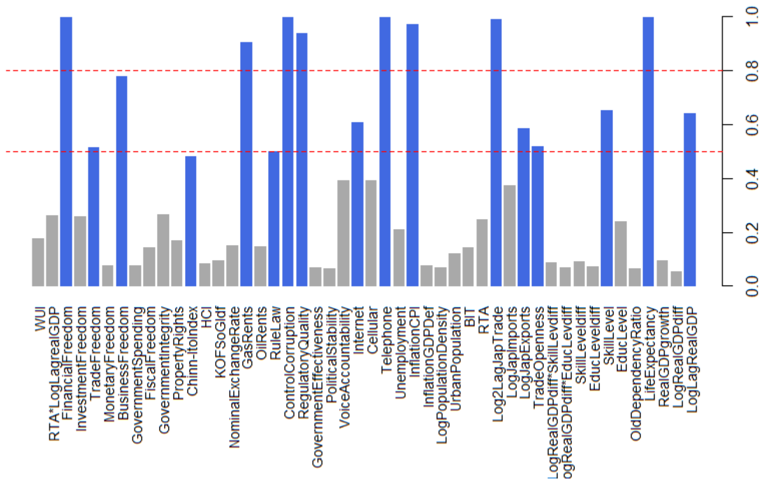


(e) East Asian countries

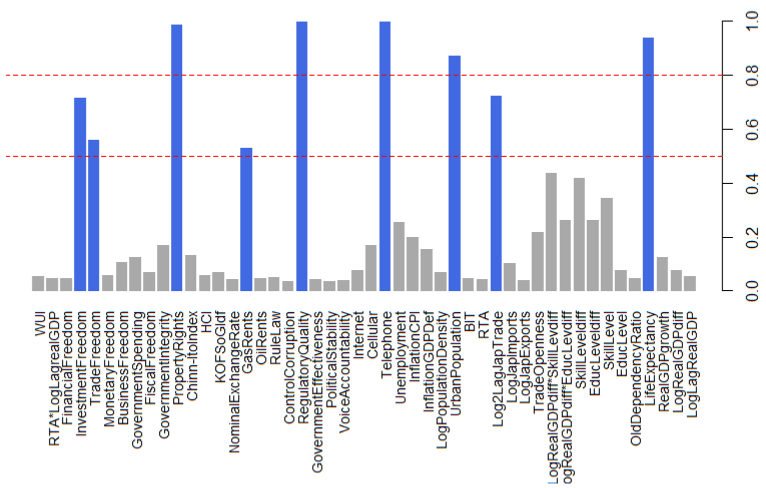
2.B Posterior inclusion probabilities

The next Figure shows the PIP of each variable by group of countries. The covariates considered robust, which are those whose PIP is higher than 0.5, are marked in blue.

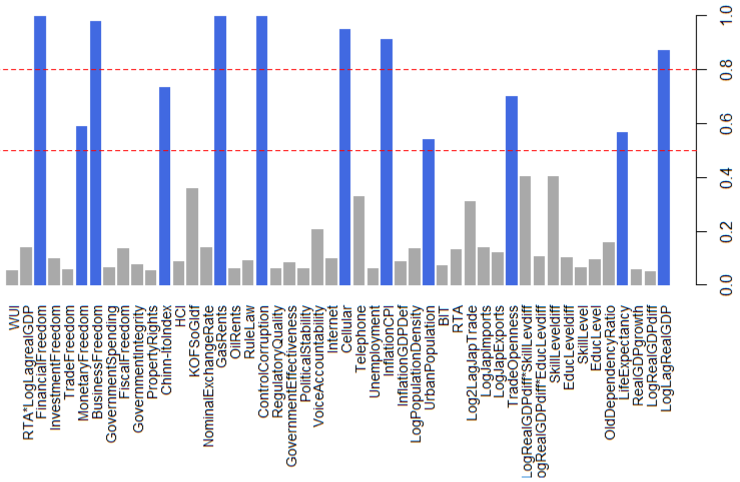
Figure 2.B.1: Posterior inclusion probabilities by groups of countries



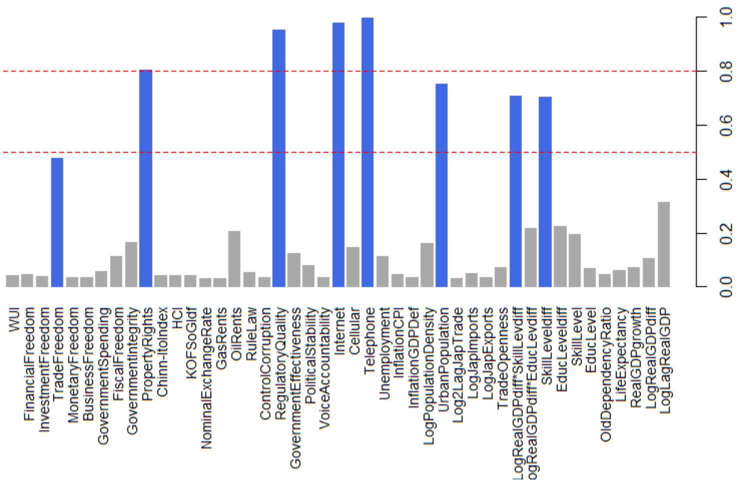
(a) Whole group



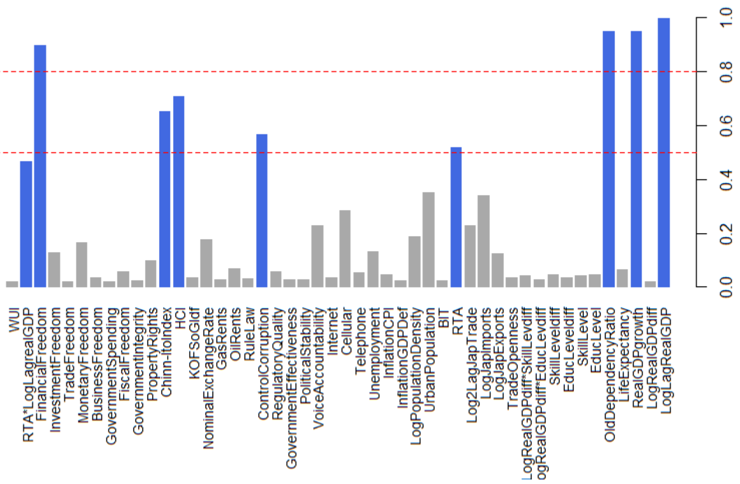
(b) Developed countries



(c) Emerging countries



(d) EU countries



(e) East Asian countries

2.C Robustness check: estimating the determinants of Japanese FDI using log-linear models

In this Appendix, we estimate the log-linear models for every group of countries studied in this Chapter 2. We start from the variables found to be robust in our BMA analysis. The results are presented in Table 2.C.1. We include country and year fixed effects to control for unobserved heterogeneity and multilateral resistance. All our specifications pass the Ramsey Regression Equation Specification Error Test (RESET) test, that we apply as a general misspecification test.

Although in some cases, the coefficients are slightly different from the posterior mean obtained in the BMA analysis. The reason for this is that the BMA analysis computes the mean from the best 100,000 models calculated by combining the 48 candidate variables. In our case, we just apply the OLS algorithm to the variables. In addition, we have re-scaled some variables from 0 to 100 for a more straightforward interpretation, as in the case of some labor and institutional indexes. Nonetheless, the main findings are similar. The results suggest that both horizontal and vertical strategies are present in all country groups. However, HFDI is more important in developed and EU countries, whereas VFDI prevails in emerging East Asian groups. Additionally, better institutional quality attracts Japanese OFDI for developed and emerging countries, whereas the opposite is true for the other two. Moreover, regarding investment openness, our variables included in this analysis confirm that OFDI from Japan is mainly attracted to countries with more developed financial markets. Finally, there is complementarity between trade and Japanese OFDI, the same we found in the BMA analysis.

Table 2.C.1: Linear estimations

Variables	**Whole group**	**Developed countries**	**Emerging countries**	**EU countries**	**East Asian countries**
LogLagRealGDP	0.567***		0.914***		0.821***
	(0.134)		(0.245)		(0.258)
RGDPgrowth					0.008***
					(0.002)
UrbanPopulation		0.035**	-0.038***	0.042***	
		(0.015)	(0.014)	(0.014)	
OldDependencyRatio					0.288***
					(0.033)
SkillLevel	-0.009**				
	(0.004)				
HCI					-0.132***
					(0.016)
TradeOpenness	0.006**			0.007***	
	(0.002)		(0.002)		
TradeFreedom				0.067*	
				(0.037)	
RTA					0.178**
					(0.086)
ChinnItoIndex	0.006**		0.007**		-0.003*
	(0.002)		(0.003)		(0.002)
InvestmentFreedom		0.007**			
		(0.004)			
ControlCorruption			-0.022*		-0.029***
			(0.011)		(0.005)
RegulatoryQuality	0.017**	0.048***		0.061***	
	(0.007)	(0.009)		(0.016)	
InflationCPI	-0.013**		-0.017***		
	(0.006)		(0.006)		
BusinessFreedom	-0.011***		-0.016***		
	(0.003)		(0.004)		
Telephone		-0.015***			
		(0.005)			
Internet				0.011**	
				(0.005)	
RESET test	0.104	0.207	0.925	0.606	0.398
N ° of observations	648	336	312	192	144

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. Robust standard errors are in parenthesis.

2.D Robustness check: estimating the determinants of Japanese FDI using Pseudo Poisson Maximum Likelihood models

In this Appendix, instead a log-linear approximation we use their multiplicative form for every country group. Recent contributions in trade and investment literature argue that when the gravity equation is applied, the OLS estimation can lead to biased results in the presence of heteroskedasticity. In this Section, for the sake of comparison with our Bayesian results, we apply the PPML as suggested by Silva and Tenreyro (2006). We start from the variables considered robust in our BMA analysis. The results are presented in Table 2.D.1. We include country and year fixed effects to control for unobserved heterogeneity and multilateral resistance. All our specifications pass the RESET test. However, the selected variables slightly differ from those chosen in Appendix 2.C. The reason is that some variables considered in the log-linear model are not significant in their multiplicative form or do not pass the specification test.

As explained in Appendix 2.C, in some cases, the coefficient of the variables can slightly differ from the posterior mean of the BMA analysis. However, we obtain similar findings. As in previous cases, both HFDI and VFDI are present in all country groups. However, HFDI has a more relevant role in developed countries, whereas VFDI prevails in the emerging, EU, and East Asian groups. In this analysis, no robust market size variable was significant or passed the RESET test for the EU countries. Furthermore, more institutional quality attracts Japanese OFDI in developed and EU countries, whereas the opposite is true in emerging and East Asian countries. Moreover, regarding investment openness, our variable included in this analysis confirms that OFDI from Japan goes to countries with more developed financial markets. Finally, we find complementarity between trade and Japanese OFDI.

Table 2.D.1: PPML estimations

Variables	Whole group	Developed countries	Emerging countries	EU countries	East Asian countries
LogLagRealGDP	0.585***		1.008***		0.410***
	(0.101)		(0.219)		(0.158)
RGDPgrowth					0.006***
					(0.002)
UrbanPopulation		0.023**	-0.027***		
		(0.010)	(0.010)		
LifeExpectancy		0.078**			
		(0.035)			
OldDependencyRatio					0.184***
					(0.026)
SkillLevel	-0.008**				
	(0.003)				
SkillLeveldiff				0.022***	
				(0.008)	
HCI					-0.110***
					(0.016)
TradeOpenness	0.008***		0.008***		
	(0.001)		(0.001)		
LogJapanExports		0.782***			
		(0.112)			
FinancialFreedom	0.004***		0.006**		
	(0.002)		(0.003)		
ControlCorruption	0.019***		-0.014*		-0.031***
	(0.005)		(0.008)		(0.005)
PropertyRights		0.012**		0.015**	
		(0.005)		(0.007)	
Telephone				-0.030***	
				(0.008)	
Internet	0.005**				
	(0.002)				
Cellular			0.006***		
			(0.001)		
RESET test	0.187	0.223	0.286	0.720	0.127
N ° of observations	648	336	312	192	144

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. Robust standard errors are in parenthesis.

Chapter 3

Is there a euro effect in the drivers of US FDI? New evidence using Bayesian model averaging techniques

3.1 Introduction and motivation

The economic impact of regional integration in Europe has been a topic widely addressed in the literature. The main focus has been on the effects on trade, but some studies have also given insights into the role of the deepening of the EU and, in particular, the creation of the EA, have had on FDI.

The increased intra-European capital mobility has been one of the expected benefits derived from the adoption of a single currency; this effect may be explained by the following reasons. First, the elimination of intra-area currency risks and the reduction of country-risk premia encouraged significant cross-border capital flows within the EA. Second, the first years of the single European currency coincided with an unprecedented growth of global capital flows. Rapid technological changes and the gradual opening and liberalization of markets have notably contributed to the increase in international direct investment. Third, the euro has also coincided with an important EU enlargement process to the East.

Most of the empirical literature so far has focused on the study of intra-European FDI and the measurement of a possible *EMU membership effect* at an aggregate level, mostly on the impact for the EA as a whole. The consensus emerging from this literature is that the euro has been pro-FDI, in particular as regards intra FDI[1]. Baldwin et al. (2008) and Neary (2009) suggest that the Single Market programme and the euro adoption should be positive for intra-EA VFDI due to the pro-trade effects of the Single Market integration and euro launching, but should discourage intra-EA HFDI, as the single currency and Single Market integration reduce trade costs. Empirically, the positive effect appears to dominate as shown inter alia by Flam and Nordstrom (2008), Brouwer et al. (2008), or De Sousa and Lochard (2011). Baldwin et al. (2008) also conclude that the euro stimulates VFDI based on the observation that the euro's pro-FDI effect was much larger in manufacturing than it was in services[2].

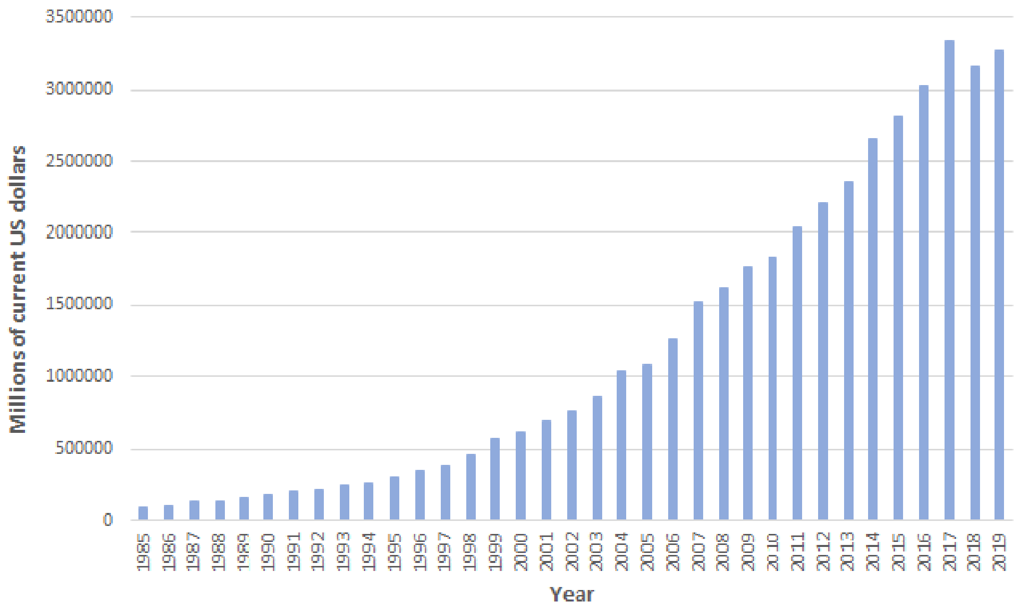
In this Chapter, we differ from most of the previous literature in that we analyze the

[1] As reported in Carril-Caccia and Pavlova (2018) the estimated increase in FDI due to the EU membership ranges between 28 and 83 percentage points, while the incremental effect of EA membership ranges between 21 and 44 percentage points. However, these studies consider different periods and different sets of countries, so they are not fully comparable. See, i.e. Baldwin et al. (2008), Neary (2009) and Stojkov and Warin (2018).

[2] See also Coeurdacier et al. (2018).

magnitude and determinants of FDI with a special focus on the *euro effect* from a third-country perspective, namely, the FDI coming from the US, the most prominent investor in the EU from a historical standpoint. We show the US OFDI stock in the EU in Figure 3.1. We can observe that American investment has progressively grown for the last 35 years. Moreover, this path has been more accentuated since the beginning of the XXI century. In 2019, the US OFDI stock in the EU was about 3,500 billion US dollars.

Figure 3.1: FDI outward stock from the United States in the EU



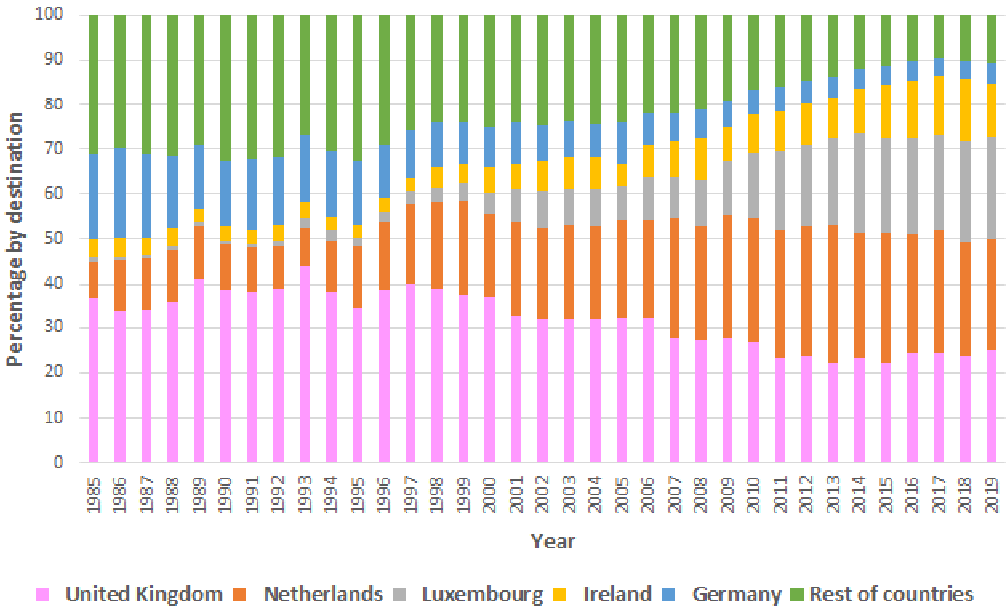
Source: Own elaboration. Data obtained from Bureau of Economic Analysis (BEA).

The analysis of the factors driving FDI into the EU from third countries, and especially from the US, although scarcely studied, is a major topical issue for several reasons. First, the EU is the main destination for FDI in the world: FDI stocks held by third country investors in the EU amounted to €6,295 billion at the end of 2017, providing Europeans with 16 million direct jobs (European Comission, 2019). Second, from an economic policy point of view, apart from the well-established advantages brought by FDI in terms of convergence and technological diffusion promoting growth and employment, it also represents a key source of external financing with clear macroeconomic consequences. As countries in the euro-area periphery are seeking to redress imbalances and reduce their liabilities in a period of low growth prospects, FDI is becoming increasingly important as a potential driver of growth. This is because it is a non-debt-creating liability, but also because it is typically more productive than internal investments.[3] Third, as the largest share of FDI into EU Member States is from EU firms (intra-EU), and this is also the component that has seen the greatest decline since the end of 2007, the analysis of inward FDI into the EU from third countries is gaining momentum. Finally, with the entry into force of the Lisbon Treaty in December 2009, the EU's exclusive competence over the common commercial policy has been extended to cover FDI as well now. The EU has one of the world's most open investment regimes, as acknowledged by the OECD in its IP/19/2088 investment restrictiveness index. In terms of countries of origin, the "traditional" main investors in the EU are still advanced economies such as the US, Switzerland, Norway, Canada, Australia and Japan. They remain well ahead and still control more than 80 percent of all foreign-owned assets. In 2016, US and Canadian investors accounted by far for the largest share of foreign investors in terms of assets controlled (61.8%). They started investing since the creation of the EU and have kept their acquisition rates constant over time.

Historically, the US and the EU (and its predecessors) have extensive trade and investment ties that have evolved since the Second World War as EU members have grown in parallel with the upsurge of global supply chains and increasing cross-border investment. According to Kim (2004) most of US FDI flows in Europe in the early 1960s were characterized as defensive import-substituting investments to supply local markets (HFDI). However, at the end of the 1980s, 85 percent of the market for US goods and services in the EU were supplied by the US affiliates, while exports from the US had just a residual role. As a result, the economic integration processes in Europe have turned the type of US FDI into "rationalizing" motive investments (VFDI) and offensive export substituting investments (HFDI). The former reduce the number of locations to supply all European markets and the latter are led by strategic asset seeking. In 2019, the largest destinations in the EU for US investment were the Netherlands ($810 billion), the UK ($830 billion), Luxembourg ($751 billion), Ireland ($398 billion). and Germany ($151 billion). As displayed in Figure 3.2, those destinations have traditionally been the main recipients of US OFDI in this region.

[3]See Helpman (2006).

Figure 3.2: FDI outward stock from the United States by European Union countries



Source: Own elaboration. Data obtained from BEA.

As regards the empirical literature on FDI stemming from countries outside the monetary union, Baldwin et al. (2008), Neary (2009) and Sondermann and Vansteenkiste (2019) argue that the greater integration of the Eurozone market might make it more attractive to have a production platform inside the Eurozone. Empirically, this is confirmed by Petroulas (2007) who finds also a pro-FDI euro effect from investor countries outside the monetary union; however, this effect was found to be smaller than for intra-EA FDI. Straathof et al. (2008), who analyze the internal market effect on trade and FDI using bilateral data of FDI stocks for 30 OECD countries from 1981 to 2005 in a gravity model find that EU countries attract 14% more FDI from EU-outsiders. More recently, two other additional factors may have interacted with the possible *euro effect* affecting inward FDI coming from third countries. First, the effects of the Great Recession. Indeed, the EU's weight in global inward FDI decreased after 2007, but has rebounded somewhat since 2015. On average, between 2000 and 2007, EU countries attracted 43.1% of the world's FDI, while in the period 2008-16 the EU attracted, on average, only a 26.7%. However, this drop in inward FDI into the EU owing to the crisis has been more marked in non-euro area EU countries and from 2015 the EU has been witnessing a surge in new investors from emerging economies, mainly China, Singapore and Brazil. In detriment of more classic investing countries, as the US, a second factor that may affect inward FDI from the US is the Brexit issue; although the impact of Brexit is uncertain, most studies have estimated an aggregate reduction in FDI into the UK of between 12% and 28% (See Campos, 2019; Campos et al., 2019)[4]. This FDI diversion from both, EU countries and the rest of the world, can be due to the future increasing cost of accessing the EU Single Market from the UK, making the country less attractive for foreign investors.

In this Chapter, we are interested in studying the determinants of US FDI in Europe and, in particular, the role of the euro and the process of monetary integration. But, in order to obtain robust statistical and economic results, we also consider the rest of the countries that receive American FDI around the world. In particular, our sample contains the stock of US OFDI in 56 countries from 1985 to 2017, which represents the 67.2% of total US FDI stock in 2017. We also consider EU and EA countries separately. Furthermore, to the best of our knowledge, no previous empirical study has analyzed whether and how the introduction of the euro has affected the US FDI patterns across different EA member groups, i.e. the locational choice between core and periphery of the EA. In our case, we distinguish between both groups not only in terms of geographical criteria, but also of 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. In the core we include Germany and its immediate neighbouring Eurozone countries whereas in the periphery are those EA countries which are farther from the centre, that is, those of Northern as well as the Southern Europe. Mostly in the latter, labour costs and GDP per capita are lower. Therefore, although both HFDI and VFDI motivations are possible in these two groups, we expect that in the core HFDI predominates, whereas in the periphery VFDI prevail.

Moreover, we divert from previous studies by introducing several contributions in this Chapter. First, to analyse the US OFDI determinants and the *euro membership effect*, instead of just focusing on a specific regression model and on an *ad hoc* gravity setting, we consider a wide set of 63 FDI potential determinants. Second, to select and assess the relative importance of the incumbent covariates overtime we apply BMA analysis. Bayesian inference

[4]See, also, Dhingra et al. (2016), Bruno et al. (2016) or Treasury (2016).

offers the tools to attach probabilities to the different possible models. Raftery (1995) showed that when there are many candidate independent variables, standard model selection criteria based on p-values can be misleading. The uncertainty surrounding FDI modelling makes the BMA methodology especially suited to discriminate among the large set of candidate regressors that has been posited as possible FDI determinants by different theories. Chakrabarti (2001) was the first to put forward this uncertainty in FDI studies using EBA. More recently, Blonigen and Piger (2014) and Eicher et al. (2012) use a BMA approach to account for model uncertainty in FDI. A third distinctive feature of our study is that we also introduce a deeper measure to review the effect of the common currency on US OFDI instead of using a "naive" euro dummy which simply takes the value 1 as of the euro adoption, and 0 otherwise. According to Sondermann and Vansteenkiste (2019), the launching of the euro was not a discrete event, but rather an on-going process which started several years prior to the introduction of the new currency and continued also thereafter. Consequently, we construct a variable euro that captures the whole process of monetary integration in Europe, that is, the different stages prior to the adoption of the common currency. Finally, to find out if the adoption of the euro has changed the drivers of US FDI, we use our dummy euro and its interaction with other variables (see Table 3.2).

The main findings suggest that many variables considered by the previous FDI literature are not found to be robust determinants using BMA techniques. Moreover, US OFDI is explained by both HFDI and VFDI motives in all country groups. However, HFDI strategies predominate in EA core countries, whereas VFDI prevails in the EA periphery. As for the euro effect, the launching of the common currency seems to have played an important role encouraging US FDI, being an important element in the integration of EA periphery to the core. In addition, our results indicate that the adoption of the euro has favoured VFDI to the detriment of market-seeking or HFDI.

The reminder of this Chapter is organized as follows: in Section 3.2 we briefly review the main theoretical approaches to FDI determination, with an emphasis in the formulated hypotheses and their differences; Section 3.3 presents a summary of the BMA methodology, while Section 3.4 describes our database and discusses the estimated results. Finally, Section 3.5 concludes.

3.2 The underlying literature

3.2.1 Types and decisions of foreign direct investment

The analysis of FDI determinants is complex because of the diversity of MNCs and different reasons for investing abroad. However, the literature has traditionally focused on two forms of FDI , namely, HFDI, motivated by market access, and VFDI, encouraged by comparative advantage.

In the theory of HFDI, a firm invests abroad by replicating a part of its activities or production processes in another country so as to avoid transportation costs, tariffs and other types of trade costs. This strategy is referred to as "market access motive" and was introduced by Markusen (1984) and Markusen and Venables (1998, 2000). In HFDI models, exports and FDI are substitutes, and the decision to serve a market via exports or setting up an affiliate company abroad constitutes a proximity-concentration trade-off, that is, to concentrate the production in a local firm and serve the foreign market via exports, or becoming close to the foreign market through a subsidiary firm. The key hypothesis concerning transportation cost is that FDI increases when transportation and trade costs are substantially high.

On the other hand, firms engage in VFDI when they fragment their production process across countries. The main reason for such disaggregation is the cost considerations arising from countries' factor cost difference. Firms are encouraged to fragment production and locate a production stage in a country where the factor used intensively in that stage is abundant. This strategy is known to as the "comparative advantage motive" and was introduced by Helpman (1984) and Helpman and Krugman (1985). The effect of trade and transportation costs is negative in VFDI, in contrast to HFDI, where such effect is positive.

More recent strands of the literature suggest other foreign investment strategies, alternatives to HFDI and VFDI, such as the KK model (Markusen et al., 1996; Carr et al., 2001; Markusen and Maskus, 2002). Overall, under the KK model, similarities in market size, factor endowments and transport costs were determinants of HFDI, while differences in relative factor endowments determined VFDI. The KK model has recently been extended to explain other forms of FDI such as export-platform FDI (Ekholm et al., 2007; Bergstrand and Egger, 2007) which is used to serve the neighboring markets of the host country. To sum up, while recent Eaton-Kortum (Ricardian) type models have been extended to motivate gravity equations for multinational production, theoretical foundations for FDI per se are limited primarily to Bergstrand and Egger (2007).[5]

The eclectic OLI paradigm has also a crucial importance in the literature of FDI decisions. This theory was proposed by John H Dunning in 1980[6], and until nowadays has remained the dominant analytical framework for accommodating a variety of operationally testable economic theories of the determinants of FDI and the foreign activities of MNCs. It maintains that FDI decisions of MNCs are determined by the interaction of three sets of interdependent variables: Ownership, location and internalization advantages. The eclectic paradigm reflects the economic and political features of the country or region of the investing firms and those of destination countries, as well as the industry and the characteristics of individual investing firms, including their objectives and strategies (Dunning, 2000). This contextual framework leads to four types of FDI: Market-seeking FDI or HFDI, resource-seeking FDI or VFDI, efficiency-seeking FDI and strategic asset-seeking FDI: Market-seeking motives try to satisfy a particular foreign market, or set of foreign markets; resource-seeking FDI is designed to gain access to natural resources, agricultural products or unskilled labor; efficiency-seeking FDI promotes a more efficient division of labor or specialization of an existing portfolio of foreign and domestic assets by MNCs; and strategic-asset seeking FDI protects or augments the existing ownership specific advantages of the investing firms and/or to reduce those of their competitors by acquiring specific technological competence or qualified human capital not available at home.

In order to discriminate between competing theoretical approaches of FDI determinants, the estimation of gravity equation has been successfully applied in the empirical literature. In this case, as in gravity models applied to trade flows, the gravity approach to FDI describes the volume of bilateral FDI between two countries as positively related to their economic sizes and negatively to the distance between them. During the last decade, some of the literature on FDI tried to generalize the use of the gravity approach to analyze FDI patterns (Brainard, 1997; Eaton and Tamura, 1994). Nonetheless, there was a lack of theoretical

[5] While Markusen and Maskus (2002) KK model is about FAS, Bergstrand and Egger (2007) is about both, FAS and proper FDI.

[6] See Dunning (1980).

foundation for the gravity equations for FDI. Since Bergstrand and Egger (2007) such a theoretical foundation does exist. They extend the 2x2x2 KK model in Markusen and Maskus (2002), by adding an extra factor and country, and derive a specification for the FDI gravity equation that explains its empirical fit to the data. This paper, together with the one by Head and Ries (2008), are considered the only two formal general equilibrium theories for FDI. Subsequently, more research followed and the theoretical justification of the gravity model for FDI is not longer questioned. Kleinert and Toubal (2010) illustrate how an aggregate FDI equation can be derived from different theoretical models. In particular, we adopt here the 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:

$$AS_{ij} = s_i(\tau D_{ij}^{\eta^1})^{(1-\sigma)(1-\in)} m_j \tag{3.1}$$

where AS_{ij} are FAS 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 3.1 can be log-linearized as

$$ln(AS_{ij}) = \alpha_1 + \zeta_1 ln(s_i) - \beta_1 ln(D_{ij}) + \xi_i ln(m_j) \tag{3.2}$$

This type of expression is the one commonly used in the gravity models for FDI as well. Next, we will see that most of the postulated covariates can be related either with some measurement of economic distance or with market size.

3.2.2 Choosing FDI determinants using Bayesian techniques: a short literature review

Most of the factors mentioned above are related to location determinants. Many empirical studies have adopted a gravity equation approach from the international trade literature and examined the patterns of FDI as a function of country characteristics such as market size, distance, factor endowment, transportation cost, tariffs, corporate taxes, natural resources, institutional quality and exchange rate among others[7]. Consequently, a wide range of different variables has been used in the literature.

However, there is little consensus on which ones are postulated to be potential FDI determinants. The main reason for this lack of consensus is that previous research has generally focused on regression models involving specific sets of variables determined by the researcher and the particular theoretical framework for FDI they chose to analyze. By conditioning on a particular regression model specification, this practice ignores uncertainty regarding the model specification itself, which might have dramatic consequences on inference. Particularly, inference regarding the effects of the covariates considered in a particular specification can depend critically on the rest of the included or even omitted variables. Next, we summarize the most recent evidence and techniques applied on variable selection in the case of FDI determination.

Following a Frequentist approach, Chakrabarti (2001) used EBA to determine which explanatory variables are "robust" and which are "fragile" FDI determinants to small changes in the conditioning information set. The dependent variable used is per capita FDI inflows. In a cross-section sample of 135 countries for 1994 he finds that market size, measured as GDP per capita, has a strong explanatory power to explain FDI in the host country.

A methodology that was proposed earlier, known as BMA, was found to be a better method to account for model uncertainty as part of the estimation procedure (see, for example Raftery, 1995). According to Berger and Sellke (1987), conventional sensitivity analyses overstate the significance and the width of confidence intervals when model uncertainty is not accounted for. If this is the case, whether a statistically significant FDI determinant is relevant when alternative specifications are considered remains ambiguous. The BMA methodology can be applied to examine the large set of variables that have been proposed as FDI determinants by alternative FDI theories.[8] A difficulty commonly found in this type of

[7]See, for example, Anderson and Wincoop (2003), Chaney (2008), Disdier and Head (2008), Head and Mayer (2014) for surveys of the trade gravity literature.

[8]Obviously, Bayesian statistical techniques have not only been applied to FDI, but also to other fields of economics. These are the cases of export market shares (Benkovskis et al., 2019), the current account balance (Desbordes et al., 2018), the relationship between energy consumption and economic growth (Camarero et al., 2015) and growth models (Fernández et al., 2001). In the present Chapter, we apply a robust probabilistic approach to select the explanatory variables from a large set of potential candidates. For that objective, we use the R-package BayesVarSel (García-Donato and Forte, 2015), and apply Bayesian Variable Selection techniques for linear regression models using Gibbs sampling.

analysis is that even the most comprehensive FDI datasets contain large sections of missing data, that happens when the researcher wants to include as many countries as possible. In our case, this problem does not apply, as we consider only the countries with complete information.[9]

More directly related to the present Chapter is the contribution of Blonigen and Piger (2014), that apply Bayesian statistical techniques to obtain the most relevant FDI determinants for a group of OECD countries, as well as for the world economy in 2000. In contrast to Eicher et al. (2012), and Jordan and Lenkoski (2018), Blonigen and Piger (2014) use both FDI flows and stocks. They found that the variables with consistently high inclusion probabilities include traditional gravity variables such as cultural and distance factors, relative labour endowments and trade agreements.

Antonakakis and Tondl (2015) apply the same methodology to examine the determinants of the OFDI stock from OECD investors to 129 developing countries over the period 1995-2008. Their results suggest that no single theory governs the decision of FDI from OECD regions to developing countries but a combination of theories. In particular, OECD investors tend to choose countries with whom they have established intensive trade relations and offer qualified labour force. Other potential determinants are low wages, attractive tax rates and resource abundance.

[9] If the missing data are unevenly distributed,they may create a selection bias problem that can question the accuracy of the coefficient estimates. This problem is, notwithstanding, relevant in this literature and has been solved using different approaches. For example, Eicher et al. (2012) who introduced Heckit BMA. They use a sample of 46 countries (25 OECD countries) from 1988 to 2000, and FDI flows as the dependent variable. The results show only mixed support for horizontal or export platform FDI theories, whereas the evidence of VFDI was quite weak. Jordan and Lenkoski (2018) use a TBMA technique to improve the estimation of the inclusion probabilities of Eicher et al. (2012) and develop a full Bayesian model. Such method gives support for roughly the same determinants as the Heckit BMA when modeling the magnitude of FDI flows.

3.3 Econometric methodology

3.3.1 Bayesian methods for model selection

As discussed above, two important challenges to the study of FDI determinants are, first, the large amount of potential explanatory variables and, second, the heterogeneity of model specifications proposed in the theoretical and empirical literature. Even if the potential effect of these variables on FDI is known and derived from the theory, their ultimate presence in the model is unknown. This type of situation defines a particular model selection problem known as variable selection, formally introduced in this Section.

In model selection, the true statistical model is unknown and this uncertainty is explicitly considered. The Bayesian approach to model selection has a number of appealing theoretical properties described in Berger and Pericchi (2001). The final product of such approach is the posterior distribution over the model space; a probability mass function that assigns to each model its probability conditional on the data observed. The attractiveness of this function lies in its easiness for the evaluation of any question relevant to the analyst in probabilistic terms. Despite its appeal, the implementation of Bayesian variable selection presents some difficulties. These obstacles are associated with the assignment of the prior distribution and the necessity of approximating the posterior distribution with a large number of potential models. The improvement in computing capacity and the implementation of the algorithms in widely used software have extended its academic use. In our case, we use the R package BayesVarSel (García-Donato and Forte, 2015), which solves the implementation problems in a user-friendly interface.

3.3.2 The variable selection problem

Concerning variable selection, each entertained model corresponds to a specific subset of a group of (e.g., k) initially considered potential explanatory covariates. Therefore, the model space $\mathcal{M}$ has 2^k potential models and each competing model M_j for $j = 0, \ldots, 2^k$ relates the response variable to a subset of k_j covariates, such as:

$$y_{it} = \alpha_j + X_{j,it}\beta_j + \gamma_{j,i} + \epsilon_{j,it} \quad \epsilon_{j,it} \sim \mathcal{N}_n(0, \sigma^2 I), \tag{3.3}$$

where $i = 1, ..., N$ is the number of countries; $t = 1, ...T$ is the number of periods of time; α_j is the constant term; y_{it} is the n dimensional vector of observations for the response variable, the US OFDI stock in the host country; $X_{j,it}$ is the n x k_j design matrix of FDI determinants; $\epsilon_{j,it}$ a white noise error with zero mean and constant variance; and $\gamma_{j,i}$ is an unobservable time-invariant country heterogeneity component. Such component may introduce a bias in the results. In order to remove it, we are going to apply fixed effects. Within the BMA methodology, as proposed by Moral-Benito (2013), it consists on subtracting the country mean for every observation using the within transformation. Considering the model $M_j (j = 1, \ldots, 2^k)$:

$$(y_{it} - \bar{y}_i) = \alpha_j + (X_{j,it} - \bar{X}_{j,i})\beta_j + (\gamma_{j,i} - \bar{\gamma}_{j,i}) + (\epsilon_{j,it} - \bar{\epsilon}_{j,i}). \tag{3.4}$$

$$\ddot{y}_{it} = \alpha_j + \ddot{X}_{j,it}\beta_j + \ddot{\epsilon}_{j,it} \qquad \ddot{\epsilon}_{j,it} \sim \mathcal{N}_n(0, \sigma^2 I). \tag{3.5}$$

Where $\bar{X}_{j,i} = \frac{1}{T}\sum_{t=1}^{T} X_{j,it}$; $\bar{\epsilon}_{j,i} = \frac{1}{T}\sum_{t=1}^{T} \epsilon_{j,it}$; and α_j is the constant term. Moreover, $\ddot{y}_{it}$ is the n dimensional vector of observations for the response variable, the US FDI stock in the host country; $\ddot{X}_{j,it}$ is the n x k_j design matrix of host country FDI determinants; and $\ddot{e}_{j,it}$ a white noise error with zero mean and constant variance again, but this time in terms of mean deviations.

Assuming that one of the models in $\mathcal{M}$ is the true model, the posterior probability of any model is:

$$P(M_j^*|y) = \frac{m_j^*(y)P(M_j^*)}{\sum_j m_j(y)P(M_j)}, \tag{3.6}$$

where $P(M_j)$ is the prior probability of M_j and m_j is the integrated likelihood with respect to the prior distribution for the parameters π_j:

$$m_j(y) = \int f_j(y|\beta_j, \alpha_j, \sigma)\pi_j(\beta_j, \alpha_j, \sigma^2)d\beta_j d\alpha_j d\sigma^2, \tag{3.7}$$

also called the (prior) marginal likelihood.

3.3.3 Prior specification

The two inputs that are needed to obtain the posterior distributions are π_j and $P(M_j)$: the 2^k prior distributions for the parameters within each model and the prior distributions over the model space, respectively.

The prior distributions π_j can be expressed as:

$$\pi_j(\beta_j, \alpha_j, \sigma^2) = \pi_j(\beta_j|\alpha_j, \sigma^2)\pi_j(\alpha_j|\sigma^2). \tag{3.8}$$

In the present Chapter, we implement the prior distribution for the parameters proposed by Bayarri et al. (2012), which fulfil different criteria that should be taken into account to drive a variable selection problem and provide a reliable theoretical result at relatively small computational cost. This prior, known as the Robust prior, is:

$$\pi_j^R(\alpha_j, \beta_j, \sigma) = \pi(\alpha_j, \sigma) x \pi_j^R(\beta_j|\alpha_j, \sigma) = \sigma^{-1} \times \int_0^\infty {}_{k_i}(\beta_i \mid 0, g\,\Sigma_i)\, p_i^R(g)\, dg, \tag{3.9}$$

where $\Sigma_i = Cov(\hat{\beta}_i) = \sigma^2\,(V_i^t V_i)^{-1}$ is the covariance of the maximum likelihood estimator of β_i with

$$V_i = (I_n - X_0(X_0^t X_0)^{-1} X_0^t) X_i, \quad X_0 = (1_n, y_{-1}), \tag{3.10}$$

In equation 3.9, the hyperparameter g determines the strength of the researcher's prior belief that the coefficients are zero. A small (large) value of g indicates that the researcher is very certain (uncertain) that the coefficients are zero. The choice of a fixed value of g could critically affect posterior inference and predictive accuracy. According to Liang et al. (2008) and Feldkircher and Zeugner (2009), posterior results depend substantially on the researcher's prior choice under a fixed g-prior, ignoring the true underlying data generating process. Both studies highlight that flexible g-priors, those which allow to update prior beliefs according to data quality, adapt better to the information content in the data.

In this Chapter, we apply the flexible-g prior proposed by Bayarri et al. (2012) within the Robust prior:

$$p_j^R(g) = \frac{1}{2}\sqrt{\frac{1+n}{k_j+k_0}}\,(g+1)^{-3/2}, \;\; g > \frac{1+n}{k_j+k_0} - 1, \tag{3.11}$$

Above, k_0 denotes the number of fixed covariates, which in our case is $k_0 = 1$, the constant term.

With respect the prior over the model space $\mathcal{M}$, it can be approximated as:

$$P(M_j|\theta) = \theta^{k_j}(1-\theta)^{k-k_j}, \tag{3.12}$$

where k_j is the number of covariates in M_j, and the hyperparameter $\theta \in (0, 1)$ has the interpretation of the common probability that a given variable is independently included.

Most of the previous literature has chosen θ as fixed, $\theta = 1/2$, which assigns equal prior probability to each model ($P(M_j) = 1/2^k$); or random, $\theta \sim Unif(0, 1)$, giving equal probability to each possible number of covariates or model size (Scott and Berger, 2010). According to Forte et al. (2018), using a fixed value of θ performs poorly in controlling for multiplicity (the occurrence of spurious explanatory variables as a consequence of performing a large number of tests). For these reasons, in the present Chapter we make use of random $\theta \sim Unif(0, 1)$ for the prior distribution over the model space.

3.3.4 Summaries of the posterior distribution and model averaged inference

When k is moderate to large, posterior probabilities of individual models can be very small. A useful summary is the PIPs of every covariate, defined as:

$$P(x_r|y) = \sum_{x_r \in M_j} P(M_j|y), i = 1, ..., k. \tag{3.13}$$

These should be interpreted as the importance of each variable for explaining the response variable. According to Raftery (1995), evidence for a regressor with a PIP from 0.50 to 0.75 is called weak, from 0.75 to 0.95 positive, from 0.95 to 0.99 strong, and >0.99 very strong.

The posterior distribution easily allows for obtaining model averaged estimates of any quantity of interest Δ (assuming it has the same meaning across all models). If Δ refers to the regression coefficients (β_r):

$$P(\beta_r|Y) = \sum_{M_j} P(\beta_r|M_j, y)P(M_j|y). \tag{3.14}$$

In this case, the model averaged estimates should be used and interpreted with caution because the "same" parameter may have a different meaning in different models (Berger and Pericchi (2001)).

3.3.5 Sampling method for posterior estimation

Another important question within the Bayesian techniques is the number of models in $\mathcal{M}$ (2^k). If k is small (say, k in the twenties at most), exhaustive enumeration is possible but if k is larger, heuristic methods need to be implemented. According to García-Donato and Martínez-Beneito (2013), sampling methods with frequency-based estimators outperform searching methods with renormalized estimators. The searching procedure of this last group could bias the estimation. Within the sampling methods with frequency-based estimators, highlights the Gibbs sampling of George and McCulloch (1997). This method is a MCMC technique which generates posterior samples by sweeping through each variable to sample from its conditional distribution with the remaining variables fixed to their current values. In this Chapter, we are going to apply this sampling method.

3.4 Data and empirical results

3.4.1 Data

In this Chapter, we analyze the potential determinants of US OFDI stock for the period 1985-2017, with special emphasis in the *euro effect*. To this aim, we have considered 63 different variables available for the 56 FDI destinations or host countries and the time range analysed in our sample. These variables have been selected in accordance to previous theoretical and/or empirical literature on the determinants of FDI. We also analyse whether these determinants differ when we consider all the host countries in the sample and when we focus on different groupings, namely the EU, EA and core and peripheral EA countries. As we estimate through fixed effects, time-invariant variables are not included [10]. Concerning the effect of the common currency, we create a dummy variable based on the methodology of Baier and Bergstrand (2007) in their Economic Integration Agreement (EIA) Database, taking different values following the process of monetary integration to the adoption of the euro. In particular, we distinguish three levels in the process of monetary integration in Europe: a value of 1 is given if the host country is outside the ERM but its currency is pegged to either the DMark/the ECU/or the Euro; 2 if its currency is pegged to the ECU or the euro via the ERM; 3 if its currency is the euro, and 0 otherwise. Moreover, we interact this variable with those classified in the groups "market size and population", "labour market", "trade and international openness" and "institutional quality". These groups of variables have been the most frequently used in previous FDI literature and suitable to assess whether there has been a change in the drivers of US FDI with the creation of the euro. In Table 3.1 we enumerate the countries included in the different groups considered in our analysis. Table 3.2 contains the candidate variables grouped by the different criteria (mostly countries' characteristics) commonly considered in the literature. We also describe how they have been defined, their source and report previous studies that have also used these countries' characteristics. To ease the discussion of the empirical results, we will follow the same ordering in the next Section.

[10] For more information about fixed effects estimation in panel data, see Fernández-Val and Weidner (2016), Fernández-Val and Weidner (2018) and Weidner and Zylkin (2019).

Table 3.1: 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, Hungary, India, Indonesia, Ireland, Israel, Italy, Jamaica, Japan, Kenya, Malaysia, Mexico, Morocco, Netherlands, New Zealand, Nicaragua, Norway, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Republic of Korea, Romania, Senegal, South Africa, Spain, Sri Lanka, Sweden, Switzerland, Thailand, Turkey, United Kingdom, and Uruguay	56
EU countries	Austria, Belgium, Cyprus, Denmark, Finland, France, Germany, Greece, Hungary, Ireland, Italy, Netherlands, Poland, Portugal, Romania, Spain, Sweden and United Kingdom.	18
EA countries	Austria, Belgium, Cyprus, Finland, France, Germany, Greece, Ireland, Italy, Netherlands, Portugal, Spain.	12
EA core countries	Austria, Belgium, France, Germany and Netherlands.	5
EA peripheral countries	Cyprus, Finland, Greece, Ireland, Italy, Portugal and Spain.	7

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 3.2: Variables

Variable	Definition	Source	Authors
Dependent variable			Blonigen and Piger (2014) and Antonakakis and Tondl (2015).
US outward FDI stock	Outward FDI stock from the United States to the host country at current U.S. dollars.	BEA	
Economic and monetary integration			Carril-Caccia and Pavlova (2018), Baldwin et al. (2008), Neary (2009), Stojkov and Warin (2018), Flam and Nordstrom (2008), Brouwer et al. (2008), De Sousa and Lochard (2011), Sondermann and Vansteenkiste (2019), Petroulas (2007), Straathof et al. (2008), Camarero et al. (2019) and Kox and Rojas-Romagosa (2019).
1. Euro	Variable which takes value 1 if the host country is outside the ERM with a currency pegged to D-Mark/ECU/Euro, 2 if its currency is pegged to the ECU/euro via the ERM, 3 if its currency is the euro, and 0 otherwise.	Own elaboration	
2. EconomicIntegration	Variable that measures the highest level of economic integration achieved by the host country with any other country in the world. It takes value 1 if the host country is in a Non Reciprocal Preferencial Trade Agreement with any other country in the world, 2 in the case of a Preferencial Trade Agreement, 3 for Free Trade Agreement, 4 for Custom Union, 5 for Common Market, 6 for Economic Union, and 0 otherwise. As the euro adoption is captured by the variable *Euro*, this variable only reaches up to 5 for EA countries.	EIA database elaborated by Baier and Bergstrand (2007)	
Market size and population			Brainard (1997), Carr et al. (2001), Bergstrand and Egger (2007), Head and Mayer (2004), Blonigen et al. (2007), Martí et al. (2017),Chiappini (2014), Markusen et al. (1996), Markusen and Venables (1998, 2000),Markusen and Maskus (2002), Blonigen et al. (2003), Disdier and Mayer (2004), Narciso (2010) and Coeurdacier et al. (2018).
3. LogRealGDP	Logarithm of the host country's real GDP at constant 2010 US dollars.	WDI from World Bank and WEO from IMF	
4. Euro*LogRealGDP	Interaction between the variable *Euro* and the logarithm of the host country's real GDP.	Own elaboration	
5. UrbanPopulation	Percentage of population of the host country living in urban areas according to national statistical offices.	WDI from World Bank	
6. Euro*UrbanPopulation	Interaction between the variable *Euro* and the urban population of the host country.	Own elaboration	
7. LogSumRealGDP	Logarithm of the host country's and US real GDP sum at constant 2010 US dollars.	WDI from World Bank and WEO from IMF	

Variable	Definition	Source	Authors
8. LogRealGDPdiff	Logarithm of the absolute difference between the host country's and US real GDP at constant 2010 US dollars.	WDI from World Bank and WEO from IMF	
9. RealGDPgrowth	Averaged 5 years growth rate of the host country's real GDP.		
10. LogRealMarketPotential	Logarithm of the sum of the host country's neighbours real GDP of the host country weighted by distance between host and neighbouring capital cities.		
11. LogSpatialLagUSFDI	Logarithm of the sum of US FDI in the host country neighbours weighted by distance between host and neighbouring capital cities.	BEA	
12.LifeExpectancy	Life Expectancy at birth of the host country, years.	WDI from World Bank	
13. OldDependencyRatio	Ratio of older dependents, people older than 64, to the working-age population, those ages 15-64 of the host country		
Labor market 14. SkillLevel	Skill level of the host country measured as the percentage of population age 25 + with completed and incompleted secondary schooling.	Education statistics from World Bank and UNDP	Carr et al. (2001) , Chiappini (2014), Markusen et al. (1996),Markusen and Venables (1998, 2000) Markusen and Maskus (2002), Alfaro and Charlton (2009), Yeaple (2003b), Blonigen et al. (2003) and Billington (1999).
15. Euro*SkillLevel	Interaction between the variable *Euro* and the skill level of the host country.	Own elaboration	
16. HCI	Human capital index of the host country, based on years of schooling and returns to education.	PWT 9.1	
17.Euro*HCI	Interaction between the variable *Euro* and the HCI of the host country.	Own elaboration	
18. LogPopulationDensity	Logarithm of the population density of the host country.	WDI from World Bank	
19. Euro*LogPopulationDensity	Interaction between the variable *Euro* and the logarithm of the population density of the host country.	Own elaboration	
20. EducLevel	Education level of the host country measured as the average education years of population.	Education statistics from World Bank and UNDP	
21. SkillLeveldiff	Absolute difference between the host country's and US skill level.	Own elaboration	

Variable	Definition	Source	Authors
2. EducLeveldiff	Absolute difference between the host country's and US education level.	Own elaboration	
23.LogRealGDPdiff*SkillLevdiff	Interaction between the logarithm of the absolute difference between the host country's and US real GDP and the absolute difference between the host country's and US skill level.		
24.LogRealGDPdiff*EducLevdiff	Interaction between the logarithm of the absolute difference between the host country's and US real GDP and the absolute difference between the host country's and US education level.		
25. LabourCompensation	Share of labour compensation in GDP of the host country at current national prices.	PWT 9.1	
26. TFP	Total factor productivity of the host country at constant national prices (2011=1)		
Trade and international openness			Di Giovanni (2005), Bergstrand and Egger (2007), Brainard (1997), Camarero and Tamarit (2004), Camarero et al. (2018), Markusen (1984), Markusen and Venables (1998, 2000), Helpman (1984), Helpman and Krugman (1985), Blonigen (2001) and Kox and Rojas-Romagosa (2019).
27. TradeOpenness	Total imports and exports of the host country divided by total GDP at current US dollars.	WDI from World Bank	
28. Euro*TradeOpenness	Interaction between the variable *Euro* and the trade openness of the host country.	Own elaboration	
29. MeanTariffRate	Mean tariff rate of the host country imposed to product imports	Fraser Institute	
30. Euro*MeanTariffRate	Interaction between the *euro* dummy and the mean tariff rate of the host country	Own elaboration.	
31. FTA	Dummy variable which takes value 1 if the US and the host country are in a free trade agreement, whether bilateral or multilateral, at period t, 0 otherwise	WTO	
32. DepthFTA	Variable which measures the depth of the FTAs between the US and the host country. It ranges from 1 (the lowest depth) to 7 (the highest depth)	DESTA database elaborated by Dür et al. (2014)	
33. RevenueTradeTaxes	Revenue from trade taxes (% of trade sector) of the host country. It measures the amount of of tax on international trade as a share of exports and imports.	Fraser Institute	
34. KOFSoGIdf	KOF de facto social globalization index of the host country.	Gygli et al. (2019)	

Variable	Definition	Source	Authors
Investment openness			
35. Chinn-ItoIndex	Index measuring the degree of capital account openness of the host country. It ranges from 0 to 1, being a higher score a higher degree of capital account openness.	Chinn and Ito (2006)	Neumayer and Spess (2005), Busse et al. (2010), Rose-Ackerman and Tobin (2005), Camarero et al. (2019) and Di Giovanni (2005).
36. BlackMarketExchangeRate	Index measuring the absence of a black-market exchange rate in the host country. It ranges from 0 to 10, being a higher score a lower existence of a black-market exchange rate. Countries with a rating of 10 do not have a black-market exchange rate, that is, their domestic currency is fully convertible without restrictions.	Fraser Institute	
37. BIT	Dummy variable which takes value 1 if the US and the host country are in a bilateral investment treaty at period t, 0 otherwise.	UNCTAD	
Institutional quality			
38. Corruption	Index measuring the absence of corruption in the host country. It ranges from 0 to 6, being a higher score a lower level of corruption.	ICRG	Wei (2000), Chiappini (2014), Kinoshita and Campos (2003), Hyun (2006), Lui (1985), Egger and Winner (2005) and Ghazalian and Amponsem (2019).
39. Euro*Corruption	Interaction between the variable *Euro* and the corruption level of the host country.	Own elaboration	
40. DemocraticAccountability	Index measuring how responsive government is to its people in the host country. It ranges from 0 to 6, being a higher score a higher level of democratic accountability.	ICRG	
41.Euro*Democratic Accountability	Interaction between the variable *Euro* and the democratic accountability level of the host country.	Own elaboration	
42. LawOrder	Index measuring the strength and impartiality of the legal system of the host country. It ranges from 0 to 6, being a higher score a higher level of law and order.	ICRG	
43. BureaucracyQuality	Index measuring the institutional strength and quality of the bureaucracy of the host country. It ranges from 0 to 4, being a higher score a higher level of bureaucracy quality.		

Variable	Definition	Source	Authors
44. ProtectionPropertyRights	Index measuring the level of protection of property rights of the host country.It ranges from 0 to 10, being a higher score a higher level of protection of property rights.	Fraser Institute	
45. IntegrityLegalSystem	Index measuring the level of integrity of the legal system of the host country. It ranges from 0 to 10, being a higher score a higher level of protection of property rights.		
46. CivilLiberties	Index measuring the level of civil liberties of the host country. It ranges from 1 to 7, being a higher score a lower level of civil liberties.	Freedom House	
47. PoliticalRights	Index measuring the level of political rights of the host country. It ranges from 1 to 7, being a higher score a lower level of political rights.		
Government size			
48. GovernmentConsumption	General government consumption spending of the host country as a percentage of total consumption.	Fraser Institute	Wei (2000), Di Giovanni (2005), Shah and Iqbal (2016), Salem Musibah (2017), Othman et al. (2018) and Ghazalian and Amponsem (2019).
49. GovernmentInvestment	General government investment of the host country as a share of total investment.		
50. TopMarginalIncomeTaxRate	Marginal income tax rates of the host country.		
51. StateOwnershipAssets	Index measuring the degree to which the state owns and controls capital (including land) in the industrial, agricultural, and service sectors of the host country. It ranges from 0 to 10, being a higher score a lower level of state ownership.		
Bank and credit regulation			
52. OwnershipBanks	Index measuring the percentage of bank deposits held in privately owned banks in the host country. It ranges from 0 to 10, being a higher score a higher share of privately held deposits.	Fraser Institute	Ghazalian and Amponsem (2019)
53. PrivateSectorCredit	Index measuring the extent of government borrowing relative to private-sector borrowing in the host country. It ranges from 0 to 10, being a higher score a lower government borrowing.		
54. InterestRateControls	Index measuring the level of interest rate controls in the host country. It ranges from 0 to 10, being a higher score a lower level of interest rate controls.		

Variable	Definition	Source	Authors
Monetary conditions			
55. InflationCPI	Inflation level of the host country measured by the the annual percentage change of the Consumer Prices Index.	WDI from World Bank and WEO from IMF	Chiappini (2014), Buckley et al. (2007) and Ghazalian and Amponsem (2019).
56. MoneyGrowth	Money growth of the host country measured by the average annual growth of the money supply in the last five years minus average annual growth of real GDP in the last ten years.	Fraser Institute	
57.ForeignCurrencyBank Accounts	Index measuring the freedom to own foreign currency bank accounts in the host country. It ranges from 0 to 10, being a higher score a higher level of freedom.		
Communications infrastructure			
58. Telephone	Fixed telephone subscriptions of the host country per 100 people.	WDI from World Bank	Di Giovanni (2005) and Alfaro and Chen (2015).
59. Cellular	Mobile cellular subscriptions of the host country per 100 people.		
60. Internet	Individuals using the Internet in the host country per 100 people.		
Natural resources			
61. OilRents	Oil rents of the host country as a percentage of total GDP.	WDI from World Bank	Dunning (1977), Dunning (1979), Chiappini (2014) and Khayat (2017).
62. GasRents	Gas rents of the host country as a percentage of total GDP.		
Exchange rate			
63. NominalExchangeRate	Nominal exchange rate between the US and the host country, measured as the value of a US dollar in foreign currency. 2010=100.	WDI from World Bank	Froot and Stein (1991), Blonigen (1997) and Benassy-Quere et al. (1999).

NOTES: BEA=Bureau of Economic Analysis, EIA= Economic Integration Agreement, WDI=World Development Indicators, WEO=World Economic Outlook , IMF=International Monetary Fund, UNDP=United Nations Development Programme, PWT 9.1=Penn World Table 9.1, WTO=World Trade Organization, DESTA= Design of Trade Agreements, UNCTAD=United Nations Conference on Trade and Development and ICRG=International Country Risk Guide.

3.4.2 Empirical results

The results for the different country-groups analyzed are presented in Table 3.3. The PIPs and the posterior means of the different groups and estimations have been obtained using the Gibbs sampling from the best 100,000 models. This number of iterations guarantees PIPs convergence, as they stabilize long before, at around 20,000 iterations, which is the maximum that the R-function GibbsBvs allows in the plots (see Appendix 3.A, Figure 3.A.1). Following the same order as in Table 3.2, the variables are grouped according to country characteristics. We will consider that a covariate is potentially relevant when its PIP is higher than 0.5, as suggested by Raftery (1995), or is close to this threshold and is at least in one of the best 10 models. These cases are marked in bold in the Table 3.3. In addition, we have also included descriptive graphs of the PIPs in the Appendix 3.B. It is important to highlight that the posterior means cannot be considered parameters, as they are averages of the coefficients of the best 100,000 models taking into account their posterior probabilities (see equation 3.14). However, they are still illustrative as they provide the mean effect of each covariate on US OFDI stock. Finally, even if some interactions have high PIP, we only interpret them if both variables in such interaction are relevant individually.

As the main focus of this Chapter is to study the role of the euro on US OFDI, the first group of variables that we discuss are those under the heading **economic and monetary integration**. Our variable *euro* is a relevant determinant and has a positive posterior mean for the whole group, as well as for EU and EA countries groups. Moreover, we obtain interesting results when we divide our EA group into core and peripheral countries. For the core countries, the euro is not selected, probably because (with the exception of Austria that joined the EU and the ERM in 1995) all of them were old members of the system since 1979 and even before that[11] and their currencies have remained stable during the whole period considered. Instead, we find that what really has affected US OFDI in these countries is being members of the EU, as the variable *economic integration* is the one relevant for this group[12]. On the other hand, the adoption of the common currency is a potential determinant with a positive posterior mean for the EA peripheral countries. This result, together with the irrelevance of the *euro* for the core countries, implies that participating in

[11]Germany, the Netherlands, France and Belgium not only founded the ERM in 1979 but were also members of the European Snake since 1972.

[12]This dummy captures the different levels of integration, from trade agreements to a common market.

the process of monetary integration and stabilizing exchange rates has attracted FDI from the US into the peripheral countries. Therefore, there are two phases of American FDI into the European continent, more recent for the periphery, whereas earlier stages of economic integration drove US MNCs towards the core. Indeed, the dummy *economic integration*, with the exception of the whole group, is a robust US OFDI determinant for the rest of groups, that is, for EU countries.

The second group consist of **market size and population** measures. At first sight, it is remarkable that for the whole group we obtain many variables with high PIP.[13] When we study more homogeneous and small groups, the number of potential covariates notably decreases.

Concerning the selected variables, the *real GDP of the host country* is relevant for all the groups, with a posterior mean positive and between 0.6 and 2.9. The *sum of host and US real GDP* also appears in the larger group and the EU countries, with a positive sign as well and around 1.5, consistent in both cases with market-seeking FDI or HFDI. Similar results where found by Carr et al. (2001), Markusen and Maskus (2002), Blonigen et al. (2003), Bergstrand and Egger (2007) and Chiappini (2014) among others. The *urban population of the host country* is also relevant for the whole group, core countries and periphery.[14] Regarding the interactions with the euro included in this group, the joint effect with the *real GDP of the host country* is a potential OFDI determinant for all the groups with the exception of the core and a negative mean effect. On the other hand, the interaction *euro-urban population of the host* is only relevant for the large group, with a positive sign.

Three covariates (the *difference between US and host real GDP*, *real GDP growth* and *real market potential*) are only relevant in the larger group. The positive sign of the first might capture the relative importance of small countries as FDI destinations in comparison with other large countries considered in this group, such as Japan and China. Indeed, once we consider more homogeneous groups, where only European countries are included, this variable is

[13]This is, by far, the largest group of countries we analyze (a total of 56), and even if we have removed the unobservable time-invariant country heterogeneity from our estimation (see Subsection 3.3.2), they remain very diverse. A large number of countries increases the power of the BMA analysis, being able to detect very small size effects, and then, a large number of variables can be considered relevant.

[14]Its posterior mean is positive for the core (HFDI) and negative for the other two groups, that would imply resource seeking FDI or VFDI.

not longer relevant. Similarly, the real GDP growth of the host country is only a potential FDI determinant for the whole group with a negative sign. Concerning the third variable, *real market potential*, we have calculated it following Blonigen et al. (2007) to capture spatial interdependence in FDI location decisions. We find a negative sign for the whole group. This effect is unexpected, but may represent a substitutability pattern between FDI in the host country and neighbouring regions, as an increase in their GDP reduces FDI in the host country. A related variable, the *spatial lag of US FDI*[15] has a positive posterior mean for the whole group. In this case, the variable is relevant for the EU and the core as well, the latter with a negative sign. Comparing *market potential* and *spatial lag* the results seem contradictory for the larger group. However, this situation changes when we study the rest of the groups. The absence of the covariate *market potential* and the relevance and positive sign of the *spatial lag US FDI* for EU countries point at the importance of agglomeration forces and of having suppliers in neighbouring regions, strategy consistent with vertical specialization. On the other hand, the negative posterior mean of this last variable for the core countries means that US MNCs evaluate all neighbouring markets, which in this case are mostly EA peripheral countries, to find the one that is the lowest-cost provider of the activity, motivation in line with VFDI. Lastly, the non relevance of any of these two variables for EA countries,including the periphery, would imply HFDI. Finally, the *old dependency ratio of the host country* is a robust determinant for the EA countries. Its positive posterior mean could indicate that advanced economies have more developed credit markets and a wider social security coverage (Coeurdacier et al., 2018).

As for the **labour market** variables[16], the *skill level*, *HCI* and *labour compensation of the host country* display a negative posterior mean. Moreover, except for the whole group, the *population density* of the host country has a positive sign[17]. Therefore, US MNCs have been looking for unskilled, cheap and abundant labour probably with the progressive fragmentation of their production processes, strategy consistent with VFDI. This motivation is reinforced when we analyze labour endowment dissimilarities. *Education* and the *difference*

[15]Defined as the sum of US FDI in the host's neighboring countries wieighted by the distances (see Table 3.2 for more details).

[16]See Table 3.2 for the complete list, definition and sources of candidates.

[17]The reason explaining the negative sign of *population density* is that it could attract a higher concentration of firms looking for abundant and cheaper labour. Consequently, the competition effect could offset the positive spillovers arising from a common pool of resources, deterring the entry of new firms. For more information about competition forces and FDI location, see Crozet et al. (2004).

in skill level between the US and the host country are, as well, robust FDI determinants with a positive sign for the whole and EU groups. These groups of countries contain the largest proportion of emerging and developing countries[18], whose labour endowments in terms of education and skill levels are notably lower in comparison with the US. These results are compatible with the KK model of Carr et al. (2001). Concerning the *euro effect*, its interaction with population density it is found to be relevant for all the groups with the exception of the core countries, with a positive sign. In addition, its interaction with the skill level of the host country is also a potential FDI determinant for EA countries. Its posterior mean is positive. Therefore, with the introduction of the euro, US MNCs have been looking for skilled and abundant workforce in EA countries. Because abundant labour endowment represents lower labour costs, this result would still be consistent with VFDI strategies. As for the US MNCs shift from unskilled to skilled labour demand, there are several papers that can explain this change. According to Noorbakhsh et al. (2001), the importance of human capital has increased as MNCs need local skills together with complementary factors of production or business related services such as the access to local finance. Furthermore, Machin (2001) and McIntosh (2002) agree on that the increasing importance of technology in the production of goods and services has shifted the demand requirements of employers to hire more qualified, replacing many low-skilled jobs. This trend has deepened during the last two decades, especially if we take into account that the percentage of population with at least some secondary education has notably increased for EA countries during this period. Moreover, beyond labour cost considerations, skilled workers can also be a VFDI attractiveness. Alfaro and Charlton (2009) found that most VFDI is North-North, where many subsidiaries that supply goods to their parents are located in sectors in which both the input and final good are in the same industry. This is known as intra-industry VFDI. Intra-industry firms are generally located in high-skill countries and sectors that produce also high-skill inputs involving products that are at stages close to the parent firm's final stage of production. In contrast to inter-industry VFDI, this type of FDI is much harder to explain with the standard theories of VFDI, which emphasize factor cost differences as the primary motivation for fragmentation. Another possible explanation for this positive joint effect of the euro and the skill level of the host country is that US MNCs might be

[18]In the whole group an important proportion of countries are from Central and Latin America, East Asia, East Europe and Africa. Moreover, the EU group contains the available Central and Eastern European countries.

interested in acquiring skilled labour to access foreign pools of knowledge and technologies with the aim of augmenting their existing ownership advantages, a strategy consistent with asset-seeking FDI (Dunning, 2000). Concerning the *total factor productivity* of the host country, this covariate is relevant for the whole and EU groups. Its sign, as expected, is positive in the former, but negative in the latter. A possible reason for this finding is that Romania, whose US FDI stock is small in comparison with the Western EU countries, has high productivity levels, and therefore, could act as an outlier. Lastly, the fact that no labour variable is a potential US FDI determinant for EA core countries, could be indicative that VFDI loses relevance in favour of HFDI in these countries.

Regarding **trade and openness** measures, the different posterior means of the relevant covariates in this group does not allow us to opt for a particular US FDI strategy[19]. However, once we study the *euro effect*, its interaction with trade openness of the host country is relevant for the whole group and its posterior mean is positive. Moreover, the joint effect of the common currency and the mean tariff rate of the host country is negative and relevant for the EA and its periphery. All this taken together would mean that the process of monetary integration has encouraged VFDI strategies. As for worldwide openness, the *KOF social globalization index* has a positive sign for the whole group, as expected.

The next group consist of **investment openness** variables. In those cases where the *Chinn-Ito index* of the host country and *BIT* (bilateral investment agreements) are relevant, their sign is positive, as expected. The same occurs with the variable *black market exchange rate*, an index measuring the absence of a black market exchange rate (where a value of 10 means full convertibility, see Table 3.2).

Concerning **institutional quality**, we include several indexes from the ICRG and the Fraser Institute in order to measure the host country quality and efficiency of its institutions[20]. To ease the interpretation of the results, they have been defined so that a higher score is

[19] On the one hand, the positive sign of trade openness of the host country for the whole group and EA core countries, as well as the negative sign of *revenue from trade taxes* for the whole group, would imply that FDI and trade have been complements during the period considered (consistent with VFDI). Similar results were found by Helpman (1984), Helpman and Krugman (1985), Brainard (1997) and Camarero and Tamarit (2004). On the other hand, the mean tariff rate of the host country for the EA group and its periphery, and that one of the revenue from trade taxes for EU countries, would indicate a substitution pattern between trade and FDI and, thus, HFDI (Markusen, 1984; Markusen and Venables, 1998, 2000; Blonigen, 2001).

[20] These variables are *corruption*, *democratic accountability*, *law and order*, *bureaucracy quality*, *protection of property rights*, and *integrity of the legal system*.

associated with better institutions (see Table 3.2). Moreover, we also add the *civil liberties* and *political rights indexes* from the Freedom House. In this case, a larger score means a lower level of freedom. As for the results, the potential covariates for the whole group point into different directions, probably due to the high degree of heterogeneity of the largest group. Law and order and civil liberties are robust US OFDI determinants with a positive and negative posterior mean, respectively. These effects are as expected, because higher quality and efficiency of institutions attracts FDI[21]. On the other hand, the protection of property rights in the destination country has a negative sign. At first sight, this sign may seem unexpected, but according to Lui (1985) and Egger and Winner (2005), MNCs might be willing to accept paying bribes in order to speed up the bureaucratic processes. In this case, corruption acts as a "helping hand". As for the other country-groups, the *corruption index* in the EU countries and *democratic accountability* in the EA periphery have a negative sign. Some individual countries' inclusion in the groups may explain this result. Concerning the *euro effect*, its interaction with the *corruption index* is a robust determinant for EU countries. Its mean effect is positive. Consequently, among EU countries, the introduction of the common currency has played an important role attracting US FDI to these countries with better institutions.

Concerning the covariates labeled **government size**, *government investment* and the *top marginal income tax* of the host country present a negative sign. On the other hand, the mean effect of *government consumption* is positive and relevant for EA countries. Both signs are potentially possible: an increase in the government size implies lower fiscal freedom and high-taxation policy. Such situations could deter the entrance of FDI since high taxation would decrease returns on private investment (De Haan et al., 2006; Justesen, 2008; Cebula, 2011; Miller and Kim, 2016). Nevertheless, higher taxes could also attract FDI, because they could be indicative of significant spending on infrastructure, transportation systems and public investment (Justesen, 2008).

Related with the previous measures, in this Chapter we have also included variables which represents **banking and credit regulation**. *Bank ownership* and *interest rate controls* (larger values imply lower level of interest rate controls) are potential US OFDI determinants for the whole group. Its sign, as expected, is positive, as restrictive regulations tend to generate

[21] See, for example, (Wei, 2000; Chiappini, 2014; Kinoshita and Campos, 2003; Hyun, 2006).

additional production and transaction costs, imposing burdens on private investment. Similar results were found by Ghazalian and Amponsem (2019).

Regarding **monetary conditions**, the *level of inflation* measured by the CPI, as well as the *money growth* of the host country are relevant FDI determinants for the EU group. Their mean effect is negative, because volatile and unpredictable inflation discourages FDI. Moreover, high rates of inflation may also lead to domestic currency depreciation, which at the same time reduces the real value of earnings in local currency for market-seeking inward (HFDI) investing firms. VFDI could also be negatively affected by inflation, as an increase in the prices of locally sourced inputs makes the exporter country harder to maintain a cost advantage in foreign markets (Buckley et al. (2007)). Chiappini (2014) obtained similar results.

Concerning the variables included in **communications infrastructure**, except for *Cellular* in the whole group, the largest and most heterogeneous group, the rest of the measures with a PIP higher than 0.5 have a positive sign, as expected. Larger values imply more developed communications infrastructure. Similar results were found by Di Giovanni (2005) and Alfaro and Chen (2015).

Finally, the nominal **exchange rate** of the host country is a relevant covariate for EA countries as well as for the core. According to Benassy-Quere et al. (1999), an appreciation of the local currency increases FDI inflows due to the higher purchasing power of local consumers, but reduces them through lower competitiveness (higher labor costs) if FDI aims at producing for re-exporting. Moreover, a depreciation in the real exchange rate of the recipient country increases FDI through reduced cost of capital (Froot and Stein, 1991). In our case, an increase of the variable implies an appreciation of the US dollar (a depreciation of the host country currency) and the obtained the negative sign could be explained by US MNCs investing abroad to serve local markets (market-seeking FDI or HFDI) in the EA core countries.

Comparing the groups of countries, some additional insights can be gained. Concerning the larger group, the euro effect is very relevant, but most of the potential determinants are related to the traditional gravity variables, such as the size and population of the countries, density, etc. In addition, skills and labor productivity attract American FDI as well as different measures of openness, both in trade and investment. The institutions are relevant, especially those related to law and order as well as the banking system and credit. For the group of EU countries, that includes new and old members, as well as the UK, the euro effect remains very relevant, as well as the gravity variables (size) and the spatial lag and labor market variables. However, trade variables and institutions are not so important, probably because this group of countries already shares economic institutions via the EU. Taxes and tariffs are robust determinants in contrast to the whole group. Within the EU, if we restrict the group to euro countries, the two variables related to integration are again relevant, possibly once the UK is not in the group. Openness, market size and and labor-market determinants are also chosen, but the institutional variables are omitted, probably because euro and integration capture these effects. However it remains important to find out whether the US has different reasons to invest in the core of the EA and in the periphery. Once we divide the group, in the core the euro effect disappears, but economic integration remains; no labor market variable is relevant, whereas GDP and urban population have high inclusion probabilities. Trade openness and communications infrastructure, as well as the nominal exchange rate are the last relevant variables. In the periphery, the two integration variables have high probabilities attached and maintains GDP its interaction with the euro and urban population. However, no openness measure is relevant nor the exchange rate. Only tariffs and its interaction as well as democratic accountability (with a negative sign). Therefore, European integration has provided exchange rate and institutional stability, that has benefited especially to the most recent and peripheral members, gaining from the reputation of the older EU members. Europe is a very important market for US MNCs, but also VFDI is still relevant, as labor costs are still relatively low in some EA countries and the labor force is skilled and productive.

In order to complete our analysis, we check the robustness of our results using OLS and PPML estimators in Appendices 3.C and 3.D, respectively. The findings obtained are similar.

Table 3.3: Empirical results

	Whole group		EU countries		EA countries		EA core countries		EA peripheral hspace2.5mmcountries	
Variables	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**
Economic and monetary integration										
Euro	**0.907**	**0.659 (0.326)**	**0.578**	**0.501 (0.503)**	**0.997**	**2.190 (0.420)**	0.012	0.000 (0.026)	**0.992**	**2.020 (0.430)**
EconomicIntegration	0.165	0.000 (0.004)	**0.998**	**0.095 (0.022)**	**1**	**0.152 (0.024)**	**0.994**	**0.138 (0.026)**	**0.999**	**0.141 (0.026)**
Market size and population										
LogRealGDP	**1**	**0.610 (0.189)**	**1**	**2.014 (0.446)**	**1**	**1.795 (0.301)**	**0.990**	**2.969 (0.578)**	**0.786**	**1.299 (0.770)**
Euro*LogRealGDP	**0.982**	**-0.091 (0.031)**	**0.986**	**-0.085 (0.042)**	**0.997**	**-0.210 (0.038)**	0.012	0.000 (0.002)	**0.997**	**-0.188 (0.033)**
UrbanPopulation	**0.848**	**-0.005 (0.003)**	0.145	0.001 (0.003)	0.367	0.003 (0.005)	**0.997**	**0.027 (0.004)**	**0.915**	**-0.026 (0.011)**
Euro*UrbanPopulation	**0.918**	**0.003 (0.001)**	0.048	0.000 (0.000)	0.051	0.000 (0.000)	0.016	0.000 (0.000)	0.166	0.001 (0.003)
LogSumRealGDP	**0.975**	**1.303 (0.464)**	**0.608**	**1.545 (1.569)**	0.157	0.187 (0.525)	0.017	0.023 (0.326)	0.172	0.571 (1.820)
LogRealGDPdiff	**0.998**	**1.568 (0.423)**	0.187	-0.030 (1.173)	0.122	0.119 (0.424)	0.015	0.002 (0.189)	0.121	-0.320 (1.438)
RealGDPgrowth	**0.841**	**-0.001 (0.001)**	0.055	0.000 (0.000)	0.049	0.000 (0.000)	0.017	0.000 (0.001)	0.315	0.001 (0.002)
LogRealMarketPotential	**1**	**-0.540 (0.102)**	0.285	-0.119 (0.220)	0.035	0.000 (0.030)	0.011	-0.001 (0.097)	0.028	0.003 (0.033)
LogSpatialLagUSFDI	**1**	**0.092 (0.010)**	**1**	**0.239 (0.028)**	0.164	-0.020 (0.055)	**0.993**	**-0.439 (0.086)**	0.199	0.035 (0.079)
LifeExpectancy	0.255	0.001 (0.003)	0.065	-0.001 (0.007)	0.399	-0.019 (0.027)	0.018	0.000 (0.005)	0.050	0.000 (0.008)
OldDependencyRatio	0.395	-0.003 (0.004)	0.056	0.000 (0.002)	**1**	**0.045 (0.010)**	0.059	0.001 (0.005)	0.062	0.000 (0.003)
Labour market										
SkillLevel	0.178	0.000 (0.001)	0.074	0.000 (0.001)	**0.806**	**-0.010 (0.006)**	0.127	-0.001 (0.002)	0.043	0.000 (0.002)
Euro*SkillLevel	0.713	-0.001 (0.001)	0.655	-0.001 (0.001)	**0.776**	**0.003 (0.002)**	0.030	0.000 (0.000)	0.034	0.000 (0.000)
HCI	0.184	0.007 (0.044)	**0.998**	**-1.061 (0.261)**	**0.987**	**-1.290 (0.357)**	0.017	0.008 (0.100)	0.043	0.009 (0.131)
Euro*HCI	0.441	-0.041 (0.060)	0.102	0.004 (0.030)	0.257	0.022 (0.055)	0.015	0.001 (0.009)	0.066	-0.008 (0.052)
LogPopulationDensity	**1**	**-1.676 (0.300)**	**0.792**	**1.832 (1.160)**	**1**	**6.125 (0.751)**	0.049	-0.129 (0.697)	**1**	**6.264 (1.460)**
Euro*LogPopulationDensity	**0.992**	**0.142 (0.042)**	**1**	**0.213 (0.041)**	**0.996**	**0.195 (0.043)**	0.012	0.000 (0.011)	**0.994**	**0.223 (0.061)**
EducLevel	0.204	0.005 (0.020)	0.087	-0.001 (0.016)	0.071	0.002 (0.013)	0.030	0.001 (0.010)	0.025	0.000 (0.007)
SkillLeveldiff	0.178	0.023 (0.074)	**0.475**	**0.166 (0.196)**	0.063	0.000 (0.007)	0.091	0.000 (0.004)	0.066	-0.004 (0.034)
EducLeveldiff	**0.946**	**2.471 (0.831)**	0.177	0.267 (1.038)	0.129	-0.052 (0.380)	0.027	-0.005 (0.123)	0.025	-0.003 (0.095)
LogRealGDPdiff*SkillLeveldiff	0.240	-0.002 (0.006)	0.472	-0.013 (0.015)	0.063	0.000 (0.001)	0.084	0.000 (0.000)	0.060	0.000 (0.003)
LogRealGDPdiff*EducLeveldiff	**0.945**	**-0.189 (0.064)**	0.178	-0.021 (0.080)	0.123	0.003 (0.029)	0.028	0.000 (0.010)	0.025	0.000 (0.007)
LabourCompensation	0.371	0.096 (0.162)	0.270	-0.206 (0.387)	**0.946**	**-1.171 (0.437)**	0.164	-0.246 (0.622)	0.036	-0.011 (0.106)
TFP	**1**	**0.510 (0.119)**	**0.491**	**-0.290 (0.335)**	0.093	-0.028 (0.113)	0.016	-0.002 (0.065)	0.027	0.004 (0.063)

	Whole group		EU countries		EA countries		EA core countries		EA peripheral hspace2.5mmcountries	
Variables	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**
Trade and international openness										
TradeOpenness	**0.502**	**0.001 (0.001)**	0.054	0.000 (0.000)	0.039	0.000 (0.000)	**0.913**	**0.005 (0.002)**	0.228	-0.001 (0.002)
Euro*TradeOpenness	**1**	**0.002 (0.000)**	0.067	0.000 (0.000)	0.055	0.000 (0.000)	0.026	0.000 (0.000)	0.367	0.001 (0.001)
MeanTariffRate	0.352	0.001 (0.001)	0.193	0.002 (0.005)	**1**	**0.107 (0.011)**	0.037	-0.001 (0.010)	**1**	**0.123 (0.014)**
Euro*MeanTariffRate	0.172	0.000 (0.001)	0.119	0.001 (0.002)	**1**	**-0.037 (0.004)**	0.018	0.000 (0.003)	**1**	**-0.041 (0.006)**
FTA	0.454	0.030 (0.058)								
DepthFTA	0.380	0.002 (0.008)								
RevenueTradeTaxes	**1**	**-0.037 (0.005)**	**0.676**	**0.034 (0.027)**	0.308	-0.014 (0.024)	0.010	0.000 (0.004)	0.030	0.000 (0.005)
KOFSoGIdf	**1**	**0.012 (0.002)**	0.051	0.000 (0.001)	0.040	0.000 (0.001)	0.012	0.000 (0.001)	0.035	0.000 (0.001)
Investment openness										
Chinn-ItoIndex	**0.542**	**0.033 (0.037)**	0.164	-0.021 (0.055)	0.042	0.001 (0.017)	0.037	0.004 (0.025)	0.071	0.011 (0.047)
BlackMarketExchangeRate	0.249	-0.001 (0.003)	**0.909**	**0.054 (0.025)**	**0.998**	**0.106 (0.023)**	0.121	0.025 (0.074)	0.392	0.023 (0.031)
BIT	**0.752**	**0.048 (0.037)**	0.115	0.022 (0.076)						
Institutional quality										
Corruption	0.198	-0.001 (0.005)	**0.786**	**-0.077 (0.050)**	0.120	-0.007 (0.023)	0.010	0.000 (0.004)	0.057	0.000 (0.010)
Euro*Corruption	0.598	0.008 (0.008)	**0.730**	**0.028 (0.020)**	0.167	0.003 (0.010)	0.019	0.000 (0.002)	0.144	0.002 (0.007)
DemocraticAccountability	0.226	0.002 (0.005)	0.066	-0.001 (0.008)	0.188	-0.007 (0.017)	0.015	0.000 (0.003)	**0.797**	**-0.056 (0.034)**
Euro*DemocraticAccountability	0.273	-0.004 (0.009)	0.169	-0.003 (0.010)	0.050	0.000 (0.003)	0.009	0.000 (0.001)	0.077	0.002 (0.007)
LawOrder	**0.554**	**0.013 (0.014)**	0.180	0.007 (0.016)	0.040	0.000 (0.005)	0.009	0.000 (0.002)	0.024	0.000 (0.003)
BureaucracyQuality	0.247	0.003 (0.009)	0.059	0.001 (0.013)	0.232	0.018 (0.037)	0.044	0.003 (0.018)	0.184	0.018 (0.041)
ProtectionPropertyRights	**0.995**	**-0.023 (0.006)**	0.043	0.000 (0.003)	0.057	-0.001 (0.003)	0.012	0.000 (0.003)	0.039	0.000 (0.004)
IntegrityLegalSystem	0.366	-0.004 (0.006)	0.441	0.013 (0.016)	0.065	0.001 (0.005)	0.010	0.000 (0.003)	0.023	0.000 (0.002)
CivilLiberties	0.391	-0.006 (0.010)	0.452	0.026 (0.033)	0.054	0.001 (0.007)	0.012	0.000 (0.003)	0.028	-0.001 (0.006)
PoliticalRights	**0.542**	**-0.008 (0.010)**	0.065	-0.002 (0.013)	0.041	0.001 (0.012)			0.056	-0.004 (0.019)
Government Size										
GovernmentConsumption	0.172	0.000 (0.001)	0.178	-0.001 (0.003)	**0.678**	**0.008 (0.006)**	0.030	0.000 (0.001)	0.064	0.001 (0.003)
GovernmentInvestment	**0.964**	**-0.002 (0.001)**	0.104	0.000 (0.001)	0.049	0.000 (0.000)	0.017	0.000 (0.001)	0.035	0.000 (0.001)
TopMarginalIncomeTaxRate	**1**	**-0.006 (0.001)**	**0.995**	**-0.007 (0.002)**	**0.973**	**-0.007 (0.002)**	0.013	0.000 (0.000)	0.1524	-0.001 (0.003)
StateOwnershipAssets	0.293	0.003 (0.006)	0.049	0.000 (0.004)	0.040	0.000 (0.003)	0.014	0.000 (0.003)	0.131	0.005 (0.014)

	Whole group		EU countries		EA countries		EA core countries		EA peripheral countries	
Variables	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**	**PIP**	**Posterior mean (sd)**
Banking and credit regulations										
OwnershipBanks	**0.999**	**0.015 (0.004)**	0.123	0.001 (0.004)	0.069	-0.001 (0.003)	0.026	0.000 (0.003)	0.026	0.000 (0.002)
PrivateSectorCredit	0.312	-0.002 (0.003)	0.053	0.000 (0.002)	0.063	0.000 (0.002)	0.010	0.000 (0.001)	0.032	0.000 (0.002)
InterestRateControls	**0.810**	**0.009 (0.006)**	0.046	0.000 (0.003)	0.069	-0.001 (0.006)	0.015	0.001 (0.009)	0.071	-0.002 (0.008)
Monetary conditions										
InflationCPI	0.234	0.000 (0.000)	**1**	**-0.003 (0.000)**	0.036	0.000 (0.001)	0.296	-0.005 (0.010)	0.033	0.000 (0.001)
MoneyGrowth	0.337	0.000 (0.000)	**1**	**-0.008 (0.002)**	0.040	0.000 (0.001)	0.038	0.000 (0.002)	0.028	0.000 (0.001)
ForeignCurrencyBankAccounts	0.217	0.000 (0.001)	0.197	-0.002 (0.004)	0.042	0.000 (0.001)	0.255	0.004 (0.008)	0.022	0.000 (0.001)
Communications infrastructure										
Telephone	0.417	-0.001 (0.001)	0.289	-0.001 (0.002)	0.057	0.000 (0.000)	0.015	0.000 (0.000)	0.022	0.000 (0.000)
Cellular	**0.994**	**-0.001 (0.000)**	0.066	0.000 (0.000)	0.060	0.000 (0.000)	**0.985**	**0.002 (0.001)**	0.026	0.000 (0.000)
Internet	**0.525**	**0.001 (0.001)**	**0.673**	**0.003 (0.002)**	0.050	0.000 (0.000)	0.016	0.000 (0.000)	0.043	0.000 (0.001)
Natural resources										
OilRents	0.417	-0.003 (0.005)	0.146	-0.011 (0.033)	0.051	-0.018 (0.134)	0.010	0.002 (0.040)	0.029	0.002 (0.108)
GasRents	0.219	-0.003 (0.010)	0.042	-0.001 (0.016)	0.237	0.033 (0.068)	0.011	0.000 (0.006)	0.020	-0.004 (0.066)
Exchange Rate										
NominalExchangeRate	0.282	0.000 (0.000)	0.048	0.000 (0.000)	**1**	**-0.002 (0.000)**	**1**	**-0.003 (0.000)**	0.038	0.000 (0.000)

NOTES: sd=standard deviation. FTA, DepthFTA, BIT and PoliticalRights are not included in some groups. This is because they are constant in such cases.

3.5 Conclusions

In the present Chapter we analyse the determinants of the US OFDI stock of using a large sample of 56 host countries (that represent over 67% of total American FDI) during the period 1985-2017. In particular, to capture the role of the euro, we compare the most relevant covariates obtained for the whole group of countries with the sub-groups of EU and EA countries, and within this last group, to what we call its core and periphery. Although this variable selection exercise is relevant by itself, we also provide the posterior mean obtained for the variables selected in each group. Tentatively, this allows us to discriminate among FDI locational theoretical approaches and assess how the euro has affected the determinants of US FDI for each group of countries.

This Chapter shows that many variables chosen in the previous FDI literature are not necessarily robust determinants. According to our BMA analysis, at most, only around the 50% of the potential covariates, 30 out of 63, are relevant for the whole group, our largest and most heterogeneous country group. Moreover, as expected, the results point to more parsimonious models when more homogeneous sub-groups are analyzed. For EU countries, 19 variables are robust US FDI determinants, 17 in the EA group, and for core and peripheral countries 7 and 10, respectively. Our main findings suggest that US FDI is explained by both HFDI and VFDI motives in all country groups. However, HFDI strategies predominate in EA core countries, whereas VFDI prevails in the EA periphery.

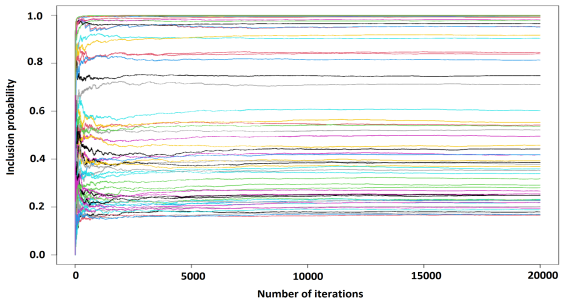
As for the *euro effect*, the adoption of the common currency has played an important role encouraging US FDI not only when we analyse the whole group, but also EU and EA countries, and within this last group, the peripheral ones. Concerning the role of the euro in the EA periphery, the common currency has encouraged US FDI towards those destinations, mostly attracted by relatively skilled labor force and lower costs. Therefore, joining the euro has been an important element in the convergence process of EA peripheral countries to the core, as these peripheral countries have become important investment destinations for US MNCs. In addition, we also find that the interaction of our variable euro with other relevant measures play a role to explain the concentration of US FDI in Europe. Our results indicate that market size has been losing relevance, thereby suggesting that the single currency may have been to the detriment of HFDI. This is because the euro has mainly favoured VFDI strategies, as we can derived from our results on labour and trade measures. Finally, we can also conclude that the adoption of the common currency has encouraged US OFDI to that countries that have higher quality of institutions.

Appendices

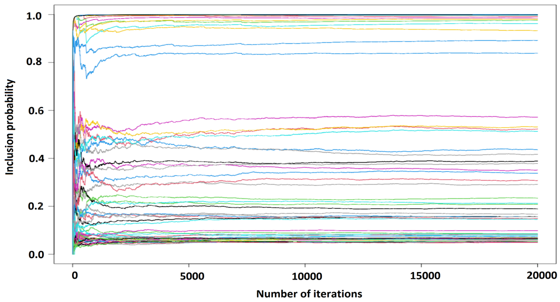
3.A Trace of posterior inclusion probabilities

The following trace plots are obtained from 20,000 iterations, the maximum that the R-function GibbsBvs allows to elaborate such plots. The PIPs are very close to converge with such number of iterations.

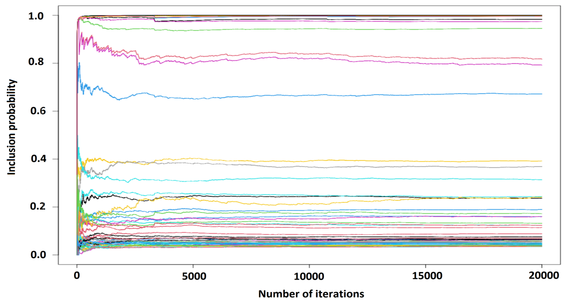
Figure 3.A.1: Trace estimation by groups of countries



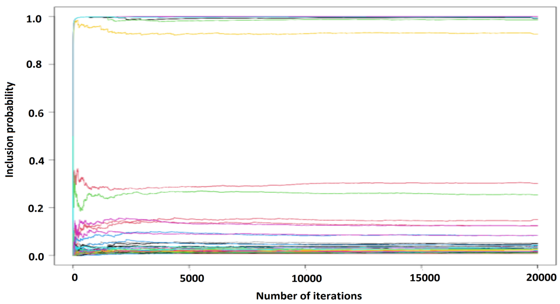
(a) Whole group



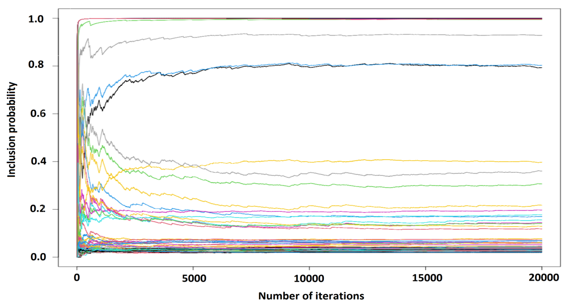
(b) EU countries



(c) EA countries



(d) EA core countries

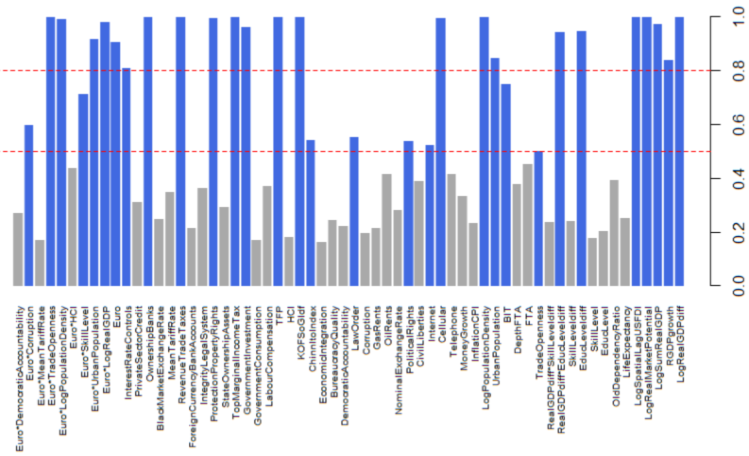


(e) EA peripheral countries

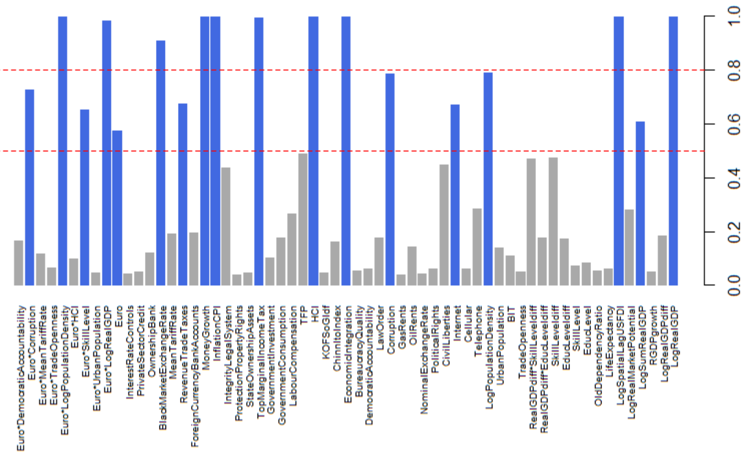
3.B Posterior inclusion probabilities

The next Figure shows the PIP of each variable by group of countries. The covariates considered robust, which are those whose PIP is higher than 0.5, are marked in blue.

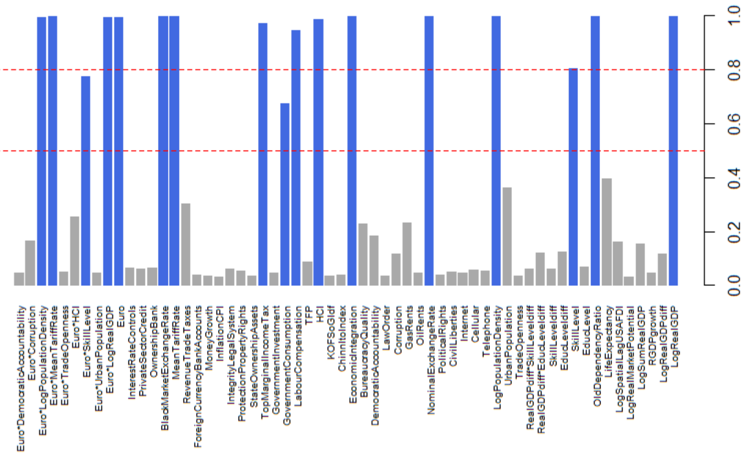
Figure 3.B.1: Posterior inclusion probabilities by groups of countries



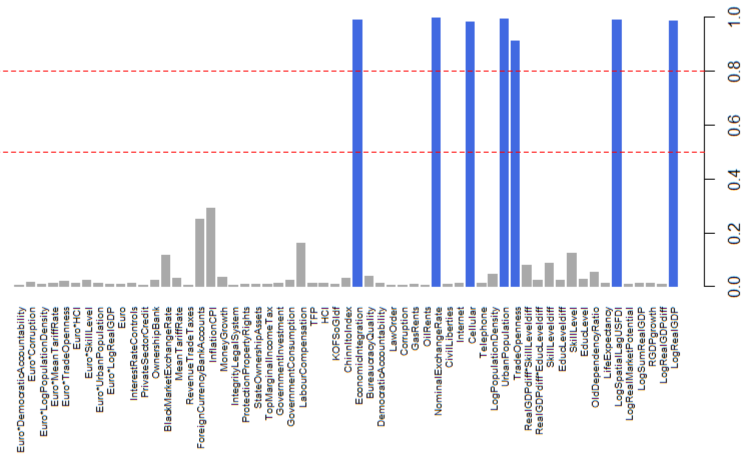
(a) Whole group



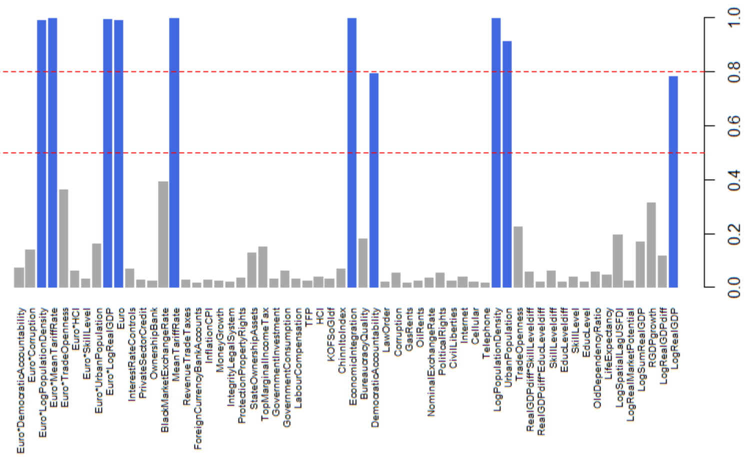
(b) EU countries



(c) EA countries



(d) EA core countries



(e) EA peripheral countries

3.C Robustness check: estimating the determinants of US FDI using log-linear models

In this Appendix, we estimate the log-linear models for each of the country groups studied in this Chapter. Our point of departure are the variables considered robust in our BMA analysis. Some exceptions are the covariates *Euro* and *Euro*LogRealGDP* in the EA core countries, and *SkillLevel* and *Euro*SkillLevel* in the Eurozone core and the periphery. However, they were robust determinants in the whole Eurozone group. We include such variables in these two subgroups to study if there is any difference between the core and the peripheral countries concerning the euro's effect. We estimate two regressions for each group of countries, one without interactions with our variable Euro (columns 1,3,5,7 and 9), in order to assess the sole effect of the Euro and the other with interactions (columns 2,4,6,8 and 10) to know if the common currency has changed the determinants of US FDI. The results are presented in Table 3.C.1. We include country and year fixed effects to control for unobserved heterogeneity and multilateral resistance. All our specifications pass the RESET specification test.

In some cases, the coefficients that we obtain slightly differ from the posterior mean of the BMA analysis. The reason for this is that the BMA analysis computes the mean from the best 100,000 models calculated by combining the 63 candidate variables. In our case, we just apply the OLS algorithm to the variables. Moreover, we have re-scaled some variables from 0 to 100 for a more straightforward interpretation. Nonetheless, the main findings are similar. We confirm the evidence of simultaneous HFDI and VFDI in all country groups. However, horizontal strategies are more relevant in the EA core countries, whereas VFDI prevails in the periphery. Furthermore, our variable euro suggests that US OFDI has increased in the countries that have adopted the euro or taken part in the ERM. Concerning the interaction of the common currency with other robust determinants, except for the EA core, market size has lost relevance, suggesting that the euro has discouraged HFDI. In addition, regarding labor market variables, US MCNs have looked for abundant and skilled workforce, a strategy compatible with VFDI. As for trade measures, trade costs deter the entrance of US OFDI, an effect that also indicates VFDI. Finally, the adoption of the common currency has also encouraged US OFDI in countries with more institutional quality.

Table 3.C.1: Linear estimations

Variables	Whole group		EU countries		EA countries		EA core countries		EA peripheral countries	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Euro	0.076*	4.677***	0.065*	2.410***	0.240**	4.916***	0.136**	-2.428*	0.363***	5.667***
	(0.041)	(0.451)	(0.037)	(0.416)	(0.107)	(1.447)	(0.052)	(1.248)	(0.120)	(0.956)
LogRealGDP	1.180***	1.179***	1.965***	2.122***	1.538***	1.995***	3.174***	2.675***	1.334***	0.988***
	(0.104)	(0.103)	(0.194)	(0.165)	(0.258)	(0.246)	(0.670)	(0.613)	(0.221)	(0.222)
Euro*LogRealGDP		-0.214***		-0.144***		-0.203***		0.077*		-0.204***
		(0.018)		(0.016)		(0.051)		(0.045)		(0.038)
LogSpatialLag			0.096***	0.125***			-0.515***	-0.549***		
			(0.036)	(0.033)			(0.082)	(0.083)		
UrbanPopulation							0.050***	0.040***		
							(0.005)	(0.007)		
SkillLevel					-0.016***	-0.034***	-0.006**	-0.031***	-0.007**	-0.014*
					(0.003)	(0.006)	(0.003)	(0.010)	(0.003)	(0.008)
Euro*SkillLevel						0.010***		0.009**		0.006***
						(0.002)		(0.004)		(0.002)
LogPopulationDensity	-2.319***	-2.911***	3.149***	1.357**	4.135***	3.158***			6.813***	8.573***
	(0.278)	(0.262)	(0.623)	(0.552)	(1.148)	(1.055)			(1.105)	(1.058)
Euro*LogPopulationDensity		0.170***		0.253***		0.157***				0.163***
		(0.022)		(0.028)		(0.037)				(0.035)
HCI					-0.101***	-0.059***				
					(0.025)	(0.019)				
TradeOpenness	0.008***	0.007***					0.022***	0.023***		
	(0.001)	(0.001)					(0.002)	(0.002)		

Variables	**Whole group**		**EU countries**		**EA countries**		**EA core countries**		**EA peripheral countries**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Euro*TradeOpenness		0.003***								
		(0.001)								
MeanTariffRate					-0.035	0.156**			0.010	0.245***
					(0.049)	(0.078)			(0.047)	(0.054)
Euro*MeanTariff						-0.075*				-0.149***
						(0.045)				(0.033)
Corruption			-0.006***	-0.012***						
			(0.002)	(0.003)						
Euro*Corruption				0.004***						
				(0.001)						
PropertyRights	0.014**	0.009**								
	(0.005)	(0.004)								
ChinnItoIndex	0.004***	0.003***								
	(0.001)	(0.001)								
BlackMarket			0.040***	0.033***	0.006	0.010*				
			(0.004)	(0.004)	(0.005)	(0.005)				
TopMarginal	-0.014***	-0.014***	-0.018***	-0.014***						
	(0.002)	(0.002)	(0.004)	(0.004)						
MoneyGrowth			-0.029***	-0.025***						
			(0.007)	(0.008)						
Internet	0.004***	0.002**	0.024***	0.022***						
	(0.001)	(0.001)	(0.003)	(0.003)						
RESET test	0.190	0.128	0.482	0.150	0.115	0.563	0.230	0.141	0.303	0.106
N ° of observations	1950	1950	620	620	420	420	175	175	245	245

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. Robust standard errors are in parenthesis.

3.D Robustness check: estimating the determinants of US FDI using Pseudo Poisson Maximum Likelihood models

This appendix reports the results of using a their multiplicative model applied to for each country group studied in this chapter. Recent contributions in trade and investment literature argue that the OLS estimation of the gravity equation can produce biased results in the presence of heteroskedasticity. In this Section, for the sake of comparison with our Bayesian techniques, we apply the PPML estimator of Silva and Tenreyro (2006). We use the variables selected in the BMA analysis. Some exceptions are *Euro*, *Euro*LogRealGDP* in the EA core, *UrbanPopulation* in the EA group, and *SkillLevel* and *Euro*SkillLevel* in the core and the periphery. However, they were robust determinants in at least one of these groups. We include these covariates for the sake of comparison. We estimate two regressions by group of countries, one without interactions with our variable *Euro* (columns 1,3,5,7 and 9), in order to assess the sole effect of the euro and the other with interactions (columns 2,4,6,8 and 10) to assess whether the common currency has changed the determinants of US FDI. The results are presented in Table 3.D.1. We include country and year fixed effects to control for unobserved heterogeneity and multilateral resistance. All our specifications pass the RESET test. The selected variables slightly differ from those chosen in Appendix 3.C. The reason is that some variables considered in the log-linear model are not significant in their multiplicative form or do not pass the misspecification test.

As already explained in Appendix 3.C, in some cases, the parameters obtained with this methodology can slightly differ from the posterior mean of the BMA analysis. However, our findings are similar. We confirm the dual strategy of the US in all country-groups. However, HFDI strategies are more important in the EA core and VFDI prevails in the periphery. Furthermore, the euro effect is clearly significant with the exception of the EU group, probably due to the presence of the UK, which is outside the Eurozone. As for the interaction of the common currency with other robust determinants, except for the EA core, the market size has lost relevance. In addition, concerning labor market measures, with the introduction of the euro, US MNCs have looked for cheaper and/or unskilled labor in the periphery, a strategy consistent with VFDI. However, in the case of the EA core, countries with higher-skilled labor endowments have attracted more US FDI (what is called intra-industry VFDI). Moreover, the common currency has also motivated US OFDI to those countries with better institutions. Finally, as for trade covariates, we do not find a significant euro effect.

Table 3.D.1: PPML estimations

Variables	**Whole group**		**EU countries**		**EA countries**		**EA core countries**		**EA peripheral countries**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Euro	0.106**	1.714*	-0.063**	1.361*	0.204**	3.089***	0.201***	-3.276***	0.128**	4.411***
	(0.042)	(0.953)	(0.031)	(0.811)	(0.099)	(0.858)	(0.069)	(1.201	(0.059)	(0.651)
LogRealGDP	1.412***	1.502***	2.041***	1.913***	1.901***	2.152***	3.283***	2.120***	2.943***	3.148***
	(0.092)	(0.085)	(0.216)	(0.193)	(0.215)	(0.191)	(0.520)	(0.556)	(0.190)	(0.183)
Euro*LogRealGDP		-0.134***		-0.060**		-0.122***		0.091**		-0.134***
		(0.038)		(0.029)		(0.031)		(0.041)		(0.025)
LogSpatialLag	0.101***	0.116***	-0.274***	-0.283***			-0.427***	-0.531***		
	(0.026)	(0.026)	(0.069)	(0.067)			(0.073)	(0.076)		
UrbanPopulation					0.106***	0.105***	0.055***	0.040***	-0.059***	-0.142***
					(0.006)	(0.006)	(0.006)	(0.007)	(0.017)	(0.025)
SkillLevel					0.002	-0.012**	-0.004	-0.054***	-0.006	0.023**
					(0.003)	(0.006)	(0.003)	(0.107)	(0.005)	(0.010)
Euro*SkillLevel						0.007***		0.017***		-0.012***
						(0.002)		(0.003)		(0.004)
LogPopulationDensity	-1.171***	-1.339***			2.597***	2.298***				
	(0.253)	(0.245)			(0.675)	(0.665)				
Euro*LogPopulationDensity		0.401***								
		(0.056)								
SkillLeveldiff			0.026***	0.028***						
			(0.003)	(0.003)						
TradeOpenness							0.019***	0.019***		
							(0.001)	(0.001)		

Variables	**Whole group**		**EU countries**		**EA countries**		**EA core countries**		**EA peripheral countries**	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
KOFSoGIdf	-0.033***	-0.032***								
	(0.004)	(0.004)								
Corruption			-0.007***	-0.013***						
			(0.002)	(0.003)						
Euro*Corruption				0.004***						
				(0.001)						
DemocraticAccountability									-0.005	-0.011***
									(0.003)	(0.004)
BlackMarket			0.033***	0.035***						
			(0.008)	(0.008)						
TopMarginal	-0.007***	-0.006**			-0.021***	-0.024***				
	(0.003)	(0.003)			(0.005)	(0.005)				
OwnershipBank	-0.006***	-0.005***								
	(0.001)	(0.001)								
Cellular	-0.004***	-0.005***								
	(0.001)	(0.001)								
RESET test	0.997	0.597	0.356	0.578	0.891	0.933	0.624	0.570	0.254	0.192
N ° of observations	1950	1950	620	620	420	420	175	175	245	245

NOTES: ***, ** and * denote significance at levels 1%, 5% and 10%, respectively. Robust standard errors are in parenthesis.

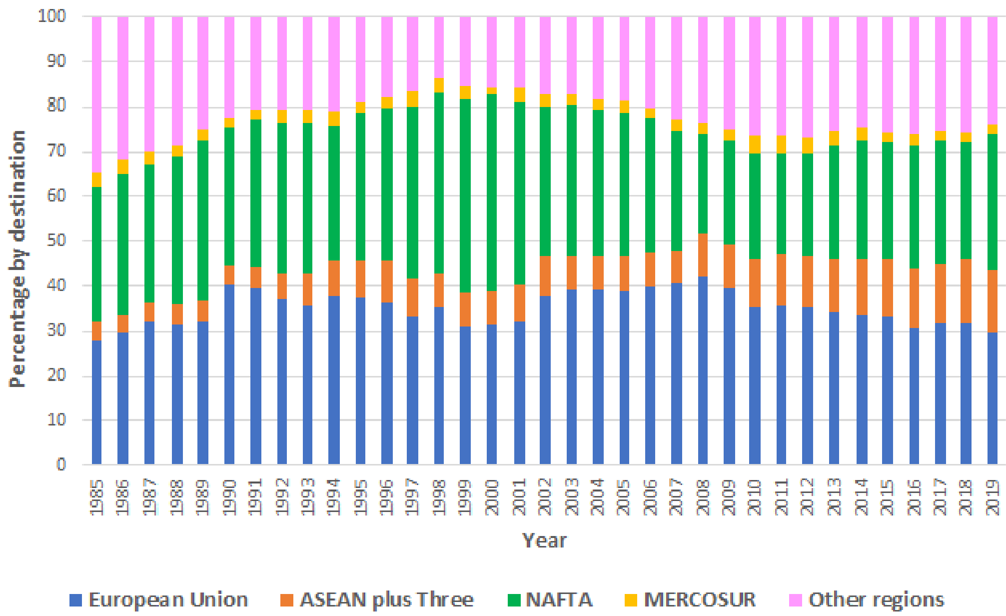
Chapter 4

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

4.1 Introduction and motivation

Historically, the EU has been one of the primary recipients of FDI. Figure 4.1 presents the overall inward FDI stock by destination region for the period 1985-2019. 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 ASEAN and Japan, China, and the Republic of Korea (ASEAN plus Three), and Mercado Común del Sur (MERCOSUR).

Figure 4.1: World stock of inward FDI by destination region



Source: Own elaboration. Data obtained from UNCTAD.

The EU has followed a progressive economic integration process, from a customs union in the sixties up to a currency union in 1999, with clear and distinct consequences on the patterns and reasons for FDI. To translate the said integration process into an empirical approximation, we should take into account the fact that the number of country members differs over time, giving rise to different groupings with heterogeneous behavior; moreover, the variables may present changes related to external events as well as to the EU institutional changes. This calls for new econometric approaches capable of accounting for these issues.

In this Chapter 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 in a panel 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, 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 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 the economic relationships.

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 OFDI. The EU had its origins in the 1957 Treaty of Rome, which founded the European Economic Community (EEC), that is a customs union since 1968. A step forward was taken in 1985 with a White Paper on the Internal Market that set the road map to eliminate physical, technical, and fiscal non-tariff barriers and the establishment of the Single Market in 1993.

Indeed, the Single Market was a second landmark that boosted FDI from both EU and non-EU members[1]. However, uncovering the reasons that attract FDI to the EU is a difficult task. Aristotelous and Fountas (1996) find that firms outside the EU invest in the union to avoid trade barriers and take advantage of a larger market size. This strategy is known as HFDI. On the other hand, internal FDI increased with the creation of the Single Market, due to the significant differences in labour costs and relatively short supply chains. Therefore, production is fragmented across countries and located in those where the factor used intensively is abundant. This motivation, known as VFDI is especially relevant in the new

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

Central and Eastern member states (Bevan and Estrin, 2004)[2]. Similar results were obtained by Dauti (2016), who found evidence in favour of VFDI for a group of 10 EU New Member States[3]. Moreover, both HFDI and VFDI strategies may coexist[4] within the EU, as pointed out by Dorakh (2020).

Nonetheless, the highest level of economic integration was achieved with the creation of the EA, the EMU established in 1999. The introduction of the common currency implied a substantial deepening in the degree of economic integration among the member states that adopted the euro. Most empirical literature has identified a positive euro effect on FDI from both countries inside and outside the EA[5]. Baldwin et al. (2008), and Neary (2009) suggest that the euro adoption should encourage intra-EA VFDI, due to the pro-trade effects of the Single Market and the euro launching, but should discourage intra-EA HFDI, as the common currency and the Single Market reduce trade costs. Regarding FDI stemming from countries outside the monetary union, Baldwin et al. (2008), Neary (2009) and Sondermann and Vansteenkiste (2019) argue that the monetary union might make more attractive to have a production platform inside the Eurozone.

More recently, the EU and, especially the EA, has been affected by the irruption of the economic crisis in 2008. A financial downturn harms international capital mobility (Clowes and Bilan, 2014) and, consequently, FDI is directly affected. Indeed, Ucal et al. (2010) show that before the crisis, FDI inflows registered a maximum, and afterward, there was a dramatic decrease. Moreover, Poulsen and Hufbauer (2011), who compared this recession with previous crises, found that whereas the decrease in outflows from developed countries was similar to other economic downturns, the recovery was much slower than in the past. This trend is shown in Figure 4.2, where both inward FDI stocks and inflows in the EU from the rest of the world fell significantly in 2008, and afterwards recovered their previous levels.

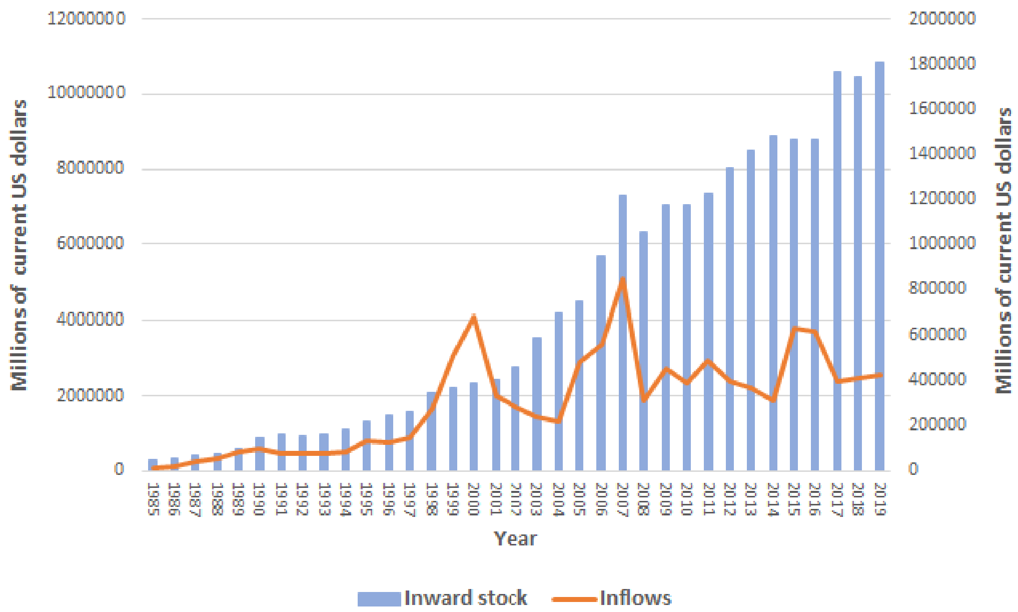
[2]The expansion and complexity of the production fragmentation across border via GVCs has led Yeaple (2003a) to coin the FDI generated by these mixed motives as "complex FDI" and more recently Baldwin and Okubo (2014) have developed the concepts of "horizontal-ness" and "vertical-ness" to systematically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

[3]These countries are Bulgaria, Romania, Slovenia, the Slovak Republic, the Czech Republic, Hungary, Poland, Latvia, Lithuania and Estonia.

[4]See the KK model of (Carr et al., 2001).

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

Figure 4.2: Inward FDI in the European Union

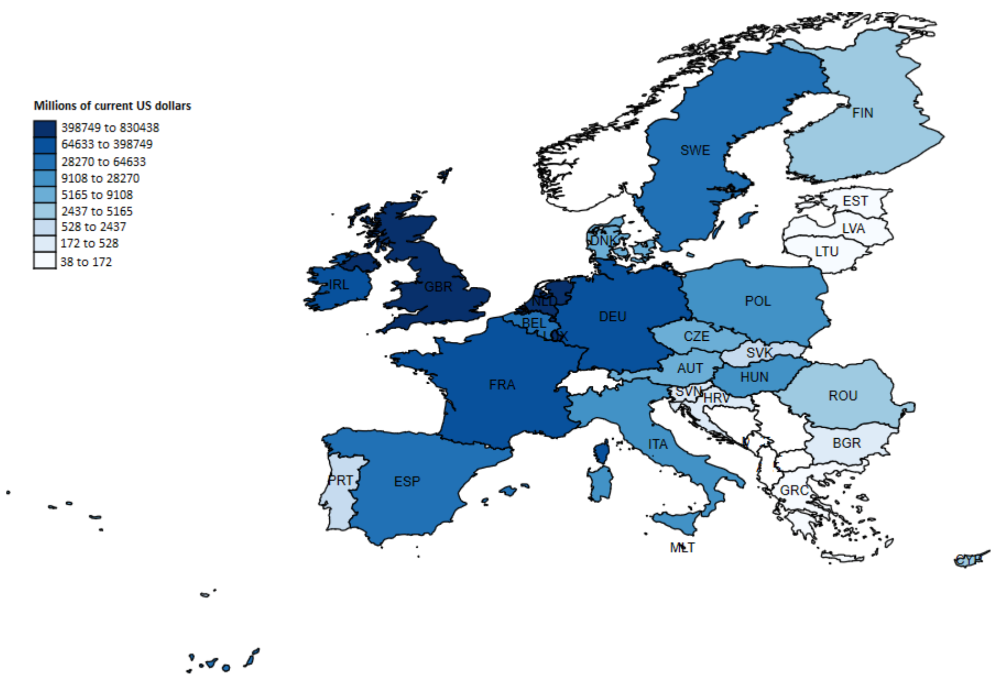


Source: Own elaboration. Data obtained from UNCTAD.

In this Chapter, we analyze the long-run determinants of OFDI stock with a particular focus on the EA from a third-country perspective, namely, the FDI originating in the US, the most prominent investor in the EU (European Comission, 2019). Historically, the US and the EU (and its predecessors) have had extensive trade and investment relationships since World War II. According to Kim (2004), by the early 1960s, most US FDI flows in Europe were characterized as defensive import-substituting investments to serve local markets, a strategy consistent with HFDI. However, since the 1980s, due to the improvement in technology that reduced production costs and stimulated the dispersion of production and service networks, and the progressive economic integration in Europe, US FDI has turned into rationalization investments, motivation related to export platform FDI and VFDI, and offensive export substituting investments, more oriented towards HFDI. Therefore, the persistent trade and investment links between the two regions and the evolution of US OFDI in these countries make it especially relevant to know the long-run determinants of US OFDI in the EU, and particularly, in the EA.

Moreover, for comparison, we also study a large group of countries from different continents that receive American FDI. In particular, our sample contains the stock of US OFDI in 54 countries from 1985 to 2019, which represents over the 70% of the total US OFDI stock in 2019. Furthermore, we consider EU and EA countries separately. Additionally, within the EA, we distinguish between the core and the periphery. This division, in the same way that in the previous Chapter, is based not only on geographical criteria but also on economic similarities. In the core, 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. These differences are also evident in the spatial distribution of US OFDI in the EU in 2019 in the map of Figure 4.3. The main recipients of US FDI are those in the core of the EU: the 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.

Figure 4.3: US OFDI stock distribution in the EU in 2019



Source: Own elaboration. Data obtained from BEA.

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. (2019, 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[6]. Precisely, the salient feature of our econometric approach in this Chapter 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 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 DCCE due to Chudik and Pesaran (2015) with the Pesaran et al. (1999) PMG 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 Chapter 3 to select the incumbent drivers of our empirical model, drawing on their BMA analysis.

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

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 Chapter is organized as follows: in Section 4.2 we briefly review the econometric methodology adopted as well as its rationale and previous empirical literature following this approach; Section 4.3 describes the theoretical model, as well as the data and the specification of the empirical model; Section 4.4 presents a summary of the econometric methodology and our empirical results, and finally, Section 4.5 concludes.

4.2 A brief review of the related empirical literature

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

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 more 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 Generalized Least Squares (GLS) estimators in models[7].

While early panel literature assumed that errors were cross-sectionally independent and the 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 applied 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

[7]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.

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 (MG) estimator, 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[8].

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) proposed tests 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 cross 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 [9] when the source of correlation is related to the distance between the units.[10] 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[11]. However, Pesaran (2006) demonstrates that this procedure is inconsistent if the unobserved factors and the regressors are correlated. Alternatively, he proposes the Common Correlated Effects (CCE) estimator. It consists of filtering the individual-specific regressors utilizing

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

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

[10] 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 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.

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

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 Chapter, as we estimate Dynamic Error Correction Models (DECM) with the PMG estimator of Pesaran et al. (1999), augmented by the cross-section averages and their lags, the so-called DCCEPMG estimator. This estimator is applied because it is robust to endogeneity, slope heterogeneity and correlations in residual terms (Chudik and Pesaran, 2015; Ditzen, 2018)

Chudik and Pesaran (2014) points out, the presence of correlation across units in panels also 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 CSD 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 used 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 DECM, 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 OFDI 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[12]. Finally, we estimate heterogeneous coefficient models using CCE in a dynamic panel using the DCCEPMG estimator.

4.2.2 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 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

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

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 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 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[13] 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 Chapter we aim to fill this methodological gap using state of the art econometrics for large long memory panels.

4.3 Theoretical approach, data and empirical model

The purpose of this Chapter is to analyze the long-run determinants of US OFDI, with a focus on European countries, as the US and the EU are the two largest hosts and recipients of

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

FDI. For this aim, we use stock data[14] 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 this Section, we describe the theoretical approach and data that we apply, as well as the empirical model implemented in this Chapter.

In order to choose between competing theoretical approaches of FDI determination, the estimation of a gravity equation has been the most successful tool. 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:

$$AS_{i,j} = s_i(\tau D_{i,j}^{\eta^1})^{(1-\sigma)(1-\in)} m_j \tag{4.1}$$

where AS_{ij} are FAS 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 4.1 can be log-linearized as

$$ln(AS_{i,j}) = \alpha_1 + \zeta_1 ln(s_i) - \beta_1 ln(D_{i,j}) + \xi_i ln(m_j) \tag{4.2}$$

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 the BMA analysis of the previous Chapter. 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.

[14] 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.

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 4.1, and the chosen variables[15] for each of them are marked in red. A detailed description of the selected covariates is available in Table 4.2. 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 4.3. 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. The variables chosen slightly differ depending on the group of countries analyzed, as the results of the BMA analysis in the previous Chapter 3 detected different robust determinants for each country group[16]. Therefore, our empirical model can be written as:

$$lusofdi_{i,t} = \theta_0 + \theta_1 x_{i,t} + \epsilon_{i,t} \tag{4.3}$$

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.

[15]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.

[16]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 4.1.

Table 4.1: Variables selected as robust determinants of US FDI. Results of the BMA analysis in Chapter 3

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 bold. [a]In Chapter 3 we do not find any 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 4.2: 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 4.3: 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.

4.4 Econometric methodology and results

4.4.1 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 this issue into account. To begin, we apply the Pesaran (2004) test.

Pesaran (2004) cross dependence test

Consider the following panel data model

$$y_{i,t} = \alpha_i + \beta_i' x_{i,t} + u_{i,t} \tag{4.4}$$

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, $u_{i,t} \sim \left(0, \sigma^2_{iu}\right)$ 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[17].

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 size distortions for N large and T small.

$$CD = \sqrt{\frac{2T}{N(N-1)}} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{i,j} \right) \tag{4.5}$$

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, $Cov(u_{i,t}, u_{j,t}) = 0, \;$ 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 4.4. 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.

Chudik and 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:

$$CD = \sqrt{\frac{TN(N-1)}{2}} \hat{\bar{p}}_N \tag{4.6}$$

[17]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.

where

$$\hat{\bar{p}}_N = \frac{2}{N(N-1)} \left(\sum_{i=1}^{N-1} \sum_{j=i+1}^{N} \hat{p}_{i,j} \right) \tag{4.7}$$

is the the average pairwise error correlation coefficient.

The results are presented in the second part of Table 4.4, where the null hypothesis of weak CSD is clearly rejected at 1% level of significance.

Table 4.4: Tests for cross-section dependence

			$lusofdi_t$	$lgdp_t$	$lpod_t$	tfp_t	$labc_t$	$trdo_t$	$rtrd_t$	$mtrt_t$
Pesaran	P	0	17.10***	43.08***	9.18***	25.82***	10.23***	60.56***	21.76***	41.38***
(2004) test		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 cross-section dependence 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.

Therefore, after applying the two tests, we can conclude that there is CSD in our panel. Consequently, we control for it in our 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.

4.4.2 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 Subsection, and allowing for CSD.

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

$$y_{i,t} = (1-\phi_i)\mu_i + \phi_i y_{i,t-1} + u_{i,t}, \tag{4.8}$$

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 (4.8) as

$$\Delta y_{i,t} = \alpha_i + \beta_i y_{i,t-1} + \gamma_i f_t + \varepsilon_{i,t} \tag{4.9}$$

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

$$H_0 : \beta_i = 0 \text{ for all } i \tag{4.10}$$

against the possibly heterogeneous alternatives,

$$H_1 : \beta_i < 0, i = 1, 2, ..., N_1, \beta_i = 0, i = N_1 + 1, N_1 + 2, ..., N \tag{4.11}$$

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 (4.10) 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:

$$\Delta y_{i,t} = a_i + b_i y_{i,t-1} + c_i \bar{y}_{t-1} + d_i \Delta \bar{y}_t + \epsilon_{i,t} \tag{4.12}$$

Subsequently, the individual CADF statistics are used to develop 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 4.5. 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 the *logarithm of US OFDI* or *lusofdi* with no lags at 5%.

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 (BIC) proposed by in Bai and Ng (2002).

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

$$X_{i,t} = D_{i,t} + F_t' \pi_i + e_{i,t} \tag{4.13}$$

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 (4.13), 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:

$$H_0 : \rho_i = 1 \;\; \forall i = 1, ..., N \tag{4.14}$$

against the alternative:

$$H_1 : |\rho_i| < 1 \;\; \text{for some} \;\; i. \tag{4.15}$$

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 4.5. 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.

Table 4.5: 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		Pm^*	0.059	1.036	-0.900	0.611	0.213	-0.332	0.112	-0.848
Silvestre (2009) test		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.

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.

4.4.3 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:

$$y_{i,t} = D_{i,t} + x'_{i,t}\delta_{i,t} + u_{i,t} \tag{4.16}$$

$$u_{i,t} = F_t'\pi_i + e_{i,t} \tag{4.17}$$

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

$$D_{i,t} = \alpha_i + \phi_i t + \sum_{j=1}^{m_i} \eta_{i,j} DU_{i,j,t} + \sum_{j=1}^{m_i} \gamma_{i,j} DT_{i,j,t} \tag{4.18}$$

where $DU_{i,j,t} = 1$ and $DT_{i,j,t} = (t - T_{i,j}^b$ for $t > T_{i,j}^b$ and 0 otherwise, with $T_{i,j}^b = \lambda_{i,j}^b T$ denoting the timing of the jth break, $j = 1, ..., m_i$, for the ith unit, $i = 1, ..., N$, $\lambda_{i,j}^b \in \wedge$, $\wedge$ being a closed subset of (0,1). Note also that the cointegrating vector in equation (4.16) is specified as a function of time so that

$$\delta_{i,t} = \delta_{i,j} \ \ \text{for} T_{i,j-1}^c < t \leq T_{i,j}^c \tag{4.19}$$

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

The combination of the specifications given by equations (4.18) and (4.19) 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[18]. 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:

$$Z_j^* = inf(Z_j(\lambda)), j = c, \tau, \gamma \tag{4.20}$$

[18] 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.

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 selected models will be the ones applied in our empirical estimation. It is important to bear in mind that the variables used 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 4.6. The Z_j^* statistic is in the third column, the fourth column presents the time of the break, and the Akaike (AIC) and the BIC Information Criterion 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 2004 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.

Table 4.6: 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.

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.

4.4.4 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 purpuse 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:

$$y_{i,t} = \alpha_i + \beta' x_{i,t} + \varepsilon_{i,t}, \tag{4.21}$$

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

$$H_0 : \beta_i = \beta \ \text{ for all } \ i, \tag{4.22}$$

against the alternative

$$H_1 : \beta_i \neq \beta_j \ \text{ for a non-zero fraction of pairwise slopes for } i \neq j \tag{4.23}$$

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 4.7. 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.

Table 4.7: 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.

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.

4.4.5 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 the effect differs.

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

$$y_{i,t} = \alpha_i + \sum_{j=1}^{p} \lambda_{i,j} y_{i,t-j} + \sum_{j=0}^{q} \beta_{i,j} x_{i,t-j} + \varepsilon_{i,t} \tag{4.24}$$

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 4.4.3. Thus, equation (4.24) can be written as:

$$y_{i,t} = \beta_{0,i} D_{i,t} + \sum_{j=1}^{p} \lambda_{i,j} y_{i,t-j} + \sum_{j=0}^{q} \beta_{i,j} x_{i,t-j} + \sum_{l=0}^{pT=2} \delta'_{i,l} \bar{z}_{t-l} + \varepsilon_{i,t} \tag{4.25}$$

where $D_{i,t}$ is the deterministic component in equation (4.18), 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 (4.25) is transformed into an Error Correction Model (ECM):

$$\Delta y_{i,t} = \phi_i [\sum_{j=1}^{p} y_{i,t-j} - \theta_{0,i} D_{i,t} - \theta_{1,i} x_{i,t}] + \sum_{j=1}^{q} \beta_{i,j} \Delta^j x_{i,t} + \sum_{l=0}^{pT} \delta'_{i,l} \bar{z}_{t-l} + \varepsilon_{i,t} \tag{4.26}$$

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

$$\theta_{0,i} = \frac{\beta_{0,i}}{1 - \sum_{j=1}^{p} \lambda_{i,j}}, \quad \theta_{1,i} = \frac{\sum_{j=0}^{q} \beta_{i,j}}{1 - \sum_{j=1}^{p} \lambda_{i,j}} \tag{4.27}$$

and the ECM parameter is:

$$\phi_i = -\left(1 - \sum_{j=1}^{p} \lambda_{i,j}\right) \tag{4.28}$$

In Table 4.8 we present a summary of the empirical results obtained in the present Chapter. 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[19]. In the next three columns, we present the coefficient homogeneity restrictions,

[19] The list of variables and abreviations can be found in Table 4.2.

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 the 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[20].

As mentioned previously, the selection of the variables is based on the BMA analysis of Chapter 3, where a large set of potential covariates was considered (as described in Table 4.1). 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 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 OFDI, the interpretation is that American FDI is attracted by some variables with similar intensity, and this can be related to important

[20]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 LR tests usually reject the hypothesis of equal error variances and/or slopes (short-run or long-run) at conventional significance levels.

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 *trade 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.

Table 4.8: 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

Once we have enumerated the long-run variables that are estimated to be 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 4.9, 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 ECM 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 GVCs. Sondermann and Vansteenkiste (2019) obtained similar results concerning the impact of the euro on the drivers of FDI inflows.

A second group of variables is the one containing those variables 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 4.9, *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[21]. 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 MNCs have been giving preeminence to the more 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

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

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[22]. 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 the whole sample[23]. Finally, for the Eurozone countries (third column in Table 4.9), increases in the mean tariff rate ($mtrt_t$) imply more US FDI, intended at jumping the barriers.

In the center of Table 4.9 we have included the value of the 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 significant 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 4.9 includes the estimated short-run coefficients for all the

[22] 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.

[23] 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.

country groups. All of them are heterogeneous across groups. The ARDL order is shown in the last column of Table 4.8. 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 group, 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 feature is consistent with the KK 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.

Table 4.9: 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 lusofdi$_t$	**Model 5**	**Model 6**	**Model 6**	**Model 5a**	**Model 5b**	**Model 3**
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.

4.5 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 Chapter, we analyze the long-run determinants of US OFDI, from 1985 to 2019, in a large group of 54 countries from all the continents, representing over 70% of the total US OFDI stock in 2019. In our case, 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 Chapter 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 the Chapter 3 using BMA analysis.

The complexity of the international economic linkages makes studying the factors that attract FDI to a particular area particularly 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 attrack 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.

Chapter 5

Conclusions

FDI has significantly increased over the last three decades in a context of growing trade and investment liberalization. Within this landscape, the establishment of multilateral and regional FTAs has gained importance, leading to a more integrated world. However, this integration process has not evolved evenly since most investment flows and capital movements are mainly concentrated in three economic blocs: North America, East Asia, and Europe.

Against this background, the leading investors have traditionally been the US, Japan, and the EU. These economies have dominated the world economy until the end of the 20th century, and although other countries have emerged in the international panorama, they continue to have an undoubted relevance. Therefore, the analysis of the driving patterns of OFDI for these three economies is a crucial topic. In this Dissertation, we analyze the cases of Japan and the US as investors and the EU as one of the leading destination regions.

Researchers have typically used the gravity equation to study FDI determinants in the empirical analysis. Due to the wide variety of FDI theories developed in the literature, many different variables have been used in previous works. However, there is no consensus about the potential FDI determinants. Additionally, the increasing availability of panels with large N and T has rendered traditional panel methods somewhat obsolete and calls for new approaches to obtain unbiased and efficient estimators when working with large data panels.

The aim of this Doctoral Dissertation has been to study the determinants of Japanese and US OFDI, dealing with the problem of model uncertainty and applying an efficient estimator suitable for large long-memory panels.

In particular, in Chapter 2, we have analyzed the main determinants of Japanese OFDI. Our analysis starts with a group of 27 countries that we later split into developed and emerging countries. Finally, we focus on more integrated areas, such as the EU and East Asia. To this aim, instead of using a predetermined set of variables, we apply a BMA approach developed by García-Donato and Forte (2015) to identify the most robust covariates.

The next two Chapters focus on the case of the US. Chapter 3 also identifies the most robust determinants of American OFDI, emphasizing the effect of European integration on investment decisions. The EU has been one of the leading destinations of US OFDI, and our maintained hypothesis is that the process of economic integration, which culminated with the creation of a monetary union, has played a crucial role. Therefore, we are interested in assessing whether the euro has changed the drivers of OFDI originating in the US or whether the drivers are different in the EA. In this case, we initially analyze a group of 56 countries to subsequently restrict the analysis to the EU. Finally, we focus on the EA, and within this group, we distinguish between core and peripheral countries. As in Chapter 2, we use the BMA approach of García-Donato and Forte (2015) to select the variables.

Finally, in Chapter 4, our objective is to find the most important long-run determinants of US OFDI, primarily focusing on the EA. Instead of using PPML, the long-lasting investment links that the US and the EU have maintained make it plausible to look for a cointegration relation between FDI and some characteristics of EU countries as hosts. Moreover, as the time-series dimension is large, potential structural breaks may affect the long-run parameters related to the process mentioned above of economic integration. Therefore, we apply a dynamic econometric approach that permits us to include these changes and accounts for CSD. Moreover, we are also interested in searching for similarities across country groups in the long run. Therefore, we use a DCCEPMG estimator in the form of error correction representation. First, we estimate the model for all the (54) countries available, and subsequently, we study smaller and more homogeneous groups, as is the case of the EU, Eurozone, EA core, and periphery. We start from the variables found robust in the previous Chapter.

The Chapters of this Doctoral Dissertation contribute in several respects to previous literature. First, our study uses FDI stock data instead of flows. In a long-run approach, like the one we adopt, stocks of FDI are not subject to the volatility of flows and are influenced by long-term factors instead of short-term or cyclical events. Second, to the best of our knowledge, the specific cases we explore have not been analyzed previously. Lastly, we apply an econometric approach suitable for panel data, where both N and T have a similar and relatively large dimension. Moreover, we add to the DCCEPMG estimator the possibility of common structural breaks endogenously detected. We also allow for CSD and test for slope homogeneity. As far as we know, no previous work has adopted this methodology to analyze the long-run determinants of foreign investment coming from the US.

In what follows, we describe the main findings of this Dissertation. Chapters 2 and 3 deal with the variable selection problem by applying a BMA analysis. The overall results indicate, in both cases, that not all the potential FDI determinants mentioned in the literature are robust. Only around the 50% of the analyzed variables can be considered robust in the larger group, whereas this percentage significantly decreases when considering smaller and more homogeneous groups. In line with the seminal paper of Blonigen and Piger (2014), we show evidence in favor of more parsimonious models in comparison with previous FDI literature.

Nonetheless, these robust variables are related to very different characteristics of the host country: GDP and population, labor costs, trade, investment conditions, institutions, macroeconomic factors, and communication infrastructure, among others. Thus, investment decisions are complex and composed of factors and circumstances that go beyond the mere consideration of market size or labor endowments.

In addition, this complexity also extends to the type of strategies that MNCs undertake in the destination countries. Our findings suggest that there is no single motivation for investing abroad, and both HFDI and VFDI strategies coexist in all country groups analyzed in Chapters 2 and 3. These results are consistent with the recent theories formulated in the empirical literature, as is the case of the knowledge capital model of Markusen and Maskus (2002), where both HFDI and VFDI are present simultaneously. However, HFDI strategies are predominant in those groups mainly composed of countries with an important market size, such as developed and EU countries in Chapter 2 and EA core countries in Chapter 3. On the other hand, VFDI motivations are more relevant in those groups where labor costs are lower. The latter is the case of emerging and ASEAN countries in the second Chapter and EA peripheral countries in the third one.

Moreover, additional insights can be drawn from the results obtained from the BMA analysis. In the case of Japan, the degree of financial development of the host countries is relevant, especially for East Asian countries. During the period studied, 1996-2017, two financial crises (the 1997 Asian crisis and the 2008 global downturn) occurred. According to our findings, a higher degree of financial development attracts Japanese FDI, an especially relevant factor in East Asian countries (that were not profound during the sample period).

Therefore, large FDI inflows to this region could dramatically endanger the financial stability of these countries, with disastrous effects on foreign investors. Thus, instead of attracting FDI, capital account liberalization could deter investment from Japan.

In the case of the US, our results suggest that the adoption of the euro has encouraged US OFDI. Moreover, the common currency has been an essential element in the convergence process of the EA peripheral countries to the core, as these countries have become important investment destinations for US FDI. Furthermore, due to the common currency, HFDI strategies have lost relevance in favor of VFDI motivations. This result is consistent with the pro-trade effects of the euro and the growing participation of the Eurozone in GVCs. Finally, we can also conclude that the euro has driven US OFDI to countries with more institutional quality.

Lastly, in Chapter 4, we estimate a model for the long-run determinants of US OFDI using the DCCEPMG estimator. We find a cointegration or long-run relationship between OFDI stocks and country characteristics of the host economies. The size of the country, labor costs and/or skills, as well as the degree of openness are the most relevant factors in the long run. In addition, the estimated relationships have been affected by institutional developments or by deep economic crises. More specifically, this is the case of the introduction of the euro and the 2004 EU enlargement or external events, such as the 2008 financial crisis.

In the same vein as in the other two Chapters, both HFDI and VFDI strategies coexist in each country group. However, VFDI strategies are predominant in smaller and more homogeneous groups, in this case, Eurozone countries. At the same time, the results point towards a higher degree of homogeneity among the long-run determinants of US OFDI for these groups. A plausible explanation for this pattern could be the growing economic interdependence across countries not only in Europe but also in the rest of the world.

In addition, these shifts are also indicative of changes in US OFDI strategies. We should mention the case of the entire group of countries, where trade openness had a positive and homogeneous coefficient before the 2008 financial crisis and changed to a negative heterogeneous one afterward. The implication is that the reason for FDI moves from vertical to horizontal. Similarly, in the EU countries, revenue trade taxes changes has a positive sign after the euro. Lastly, the negative impact of labor compensation of the host country is reduced once the break takes place. Therefore, after the 2004 EU enlargement, US MNCs have looked for more skilled workers, a strategy consistent with intra-industry VFDI in the Eurozone.

The research carried out in this Dissertation presents some limitations that give rise to potential lines of future research. In the three main Chapters of this Thesis, we have focused on log-linear models. However, recent contributions in trade and investment literature point out that when the gravity equation is applied, the standard practice of interpreting the parameters of log-linearized models estimated by OLS as elasticities can be highly misleading in the presence of heteroskedasticity. Consequently, some argue that gravity models should be estimated in their multiplicative form. Therefore, the development in the future of techniques that allow solving the variable selection problem in multiplicative models would be an interesting line to follow.

Labor mobility or migrations constitute a second potential extension of this Dissertation. Although the characteristics and the models that explain labor movement differ from those of capital, variable selection is also a common problem associated with empirical applications. Looking for the reasons some countries attract significant flows of migrants, and the effects of migration in both the origin and destination countries are relevant problems from an academic, social, or political point of view.

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