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

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ABSTRACT

In this paper we analyse the determinants of Japanese outward FDI stock for the period 1996–2017. This period is especially relevant as it covers a process of increasing economic globalization and two financial crises. To this aim, we consider a large set of candidate variables based on the theory as well as on previous empirical analysis. Our sample includes a total of 27 host countries. We select the covariates using a data-driven methodology, the Bayesian Model Averaging (BMA) analysis. Moreover, we also analyse whether these determinants change depending on the degree of development (emerging vs developed) or the geographical areas (EU vs East Asia) of the countries considered. We find that Japan's FDI can be explained by a wide variety of variables, that include not only the typical gravitational ones but also institutional and macroeconomic variables, including those that measure financial development. Moreover, Japanese FDI can be explained by both horizontal and vertical FDI motives in the groups of countries analysed. However, in developed, and more precisely, EU countries, horizontal FDI strategies are predominant, whereas for East Asian and emerging countries, there is more evidence in favour of vertical FDI.

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 outward foreign direct investment (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

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[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.

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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 outward FDI (Desbordes and Wei, 2017). In the specific case of Japan, Klein et al. (2002) find that the links between multinational companies (MNCs) and troubled banks at home help explain the decline of Japanese OFDI in the US in the 1990s.

In this paper we analyse 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 GATT/WTO multilateral framework as well as increasing number of Free Trade Agreements (FTA) 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 (GR), 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 United States, China and the European Union. Concretely, it was the sixth largest world investor in 2018[3] in terms of OFDI stock, after the United States, the Netherlands, China, Hong Kong and the United Kingdom.

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 Fig. 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 U.S. dollars, and in 2018 around seven times more, that is, close to 1700 billion U.S. dollars.

Concerning its geographical distribution, as we can observe in Fig. 2, at the end of the 1990s the United States 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 European Union (EU) have gained a remarkable importance as host country regions, and nowadays, together with the United States, are the main recipients of Japanese OFDI.

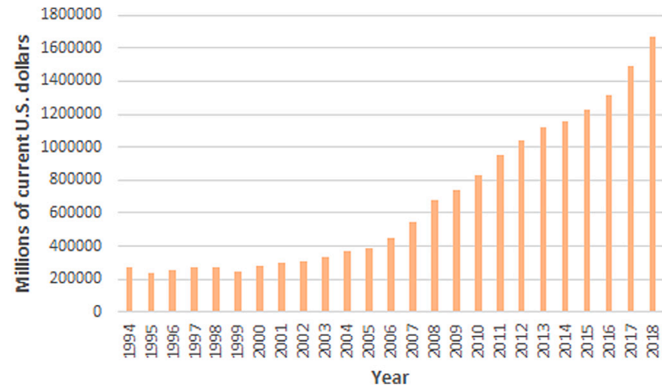

Fig. 1. Japan's FDI outward stock for the last twenty–five years.
Source: Own elaboration. Data obtained from United Nations Conference on Trade and Development statistics (https://unctad.org/en/Pages/statistics.aspx).

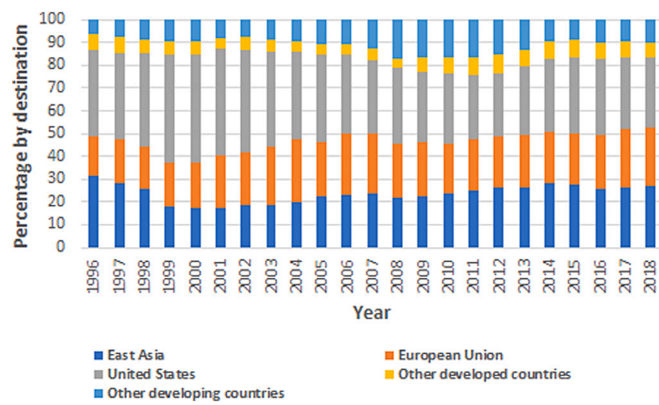

Fig. 2. Japan's OFDI stock by host region for the period 1996–2018.
Source: Own elaboration. Data obtained from Japan External Trade Organization statistics (https://www.jetro.go.jp/en/reports/statistics/).

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 labour-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 Global Value Chains (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",[4] and production of low-value and intermediate-value goods were concentrated on China and the ASEAN region.[5] The main destinations of Japanese OFDI in the East Asia region have

[2] See Alfaro et al. (2010), Kinda (2010) or Desbordes and Wei (2017).
[3] See UNCTAD statistics (https://unctad.org/en/Pages/statistics.aspx).
[4] These countries are South Korea, Hong Kong, Taiwan and Singapore.
[5] These countries are Brunei, Cambodia, Indonesia, Laos, Malaysia, Myanmar, Philippines, Singapore, Thailand and Vietnam.

traditionally been China, Singapore, Thailand, the Republic of Korea and Hong Kong.[6]

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. The EU countries which have received the largest amount of Japanese OFDI have been the United Kingdom (UK), the Netherlands, Germany and France.[7]

On 1 February 2019 the European Union 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 United States, 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 United States, far behind the United Kingdom 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 employed 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 research, we select from a large set of 48 candidates those variables most likely to be determinants of OFDI from Japan implementing Bayesian Model Averaging (BMA) techniques. To this aim, we study Japanese OFDI stock in a sample of 27 countries during the period 1996–2017. We also analyse 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, horizontal FDI (HFDI) strategies are predominant, whereas for East Asian and emerging countries, there is more evidence in favour of vertical FDI (VFDI).

The rest of the paper is organized as follows. Section 2 includes a review of the theoretical and empirical literature on the location determinants of FDI. Section 3 presents the econometric methodology, Section 4 describes our database and discusses the estimated results, whereas the final section concludes.

2. The underlying literature

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 OLI[8] 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 labour; efficiency-seeking FDI promotes a more efficient division of labour 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

[6] See JETRO statistics (https://www.jetro.go.jp/en/reports/statistics/).

[7] See JETRO statistics (https://www.jetro.go.jp/en/reports/statistics/).

[8] Ownership, Location and Internalization.

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 model (Markusen et al., 1996; Carr et al., 2001; Markusen and Maskus, 2002). Overall, under the knowledge-capital model, similarities in market size, factor endowments and transport costs were determinants of HFDI, while differences in relative factor endowments determined VFDI. The knowledge-capital 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 neighbouring 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).[9]

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 analyse 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 knowledge-capital 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:

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

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

Eq. (1) can be log-linearized as

$$ln(AS_{ij}) = \alpha_1 + \zeta_1 ln(s_i) - \beta_1 ln(D_{ij}) + \xi_i ln(m_j) \tag{2}$$

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. 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.[10] Consequently, a wide range of different variables has been employed 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 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 foreign affiliate sales (FAS), others use FDI flows, or Mergers and Acquisitions (M&A) or FDI stocks Chiappini (2014).[11]

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.

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 employed 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 Economicsone the first example being Fernández et al. (2001) in the context of growth models.[12] According to Berger and Sellke (1987), conventional sensitivity

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

[10] 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.

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

[12] 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).

Table 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	Sales	Location choice	Location choice	FDI stocks	Sales	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	
Multilateral trade openness							
Host trade costs	x						
Parent trade costs	x						
Host trade openness							x
Interaction host trade costs and skill differences	x						

(*continued on next page*)

Table 1 (*continued*).

	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)
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					
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					

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.[13]

Blonigen and Piger (2014) apply Bayesian statistical techniques to select 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 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) employ the same methodology to examine the determinants of the outward FDI 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) employs BMA techniques to determine the robust variables to explain Greenfield Investment (GFI) and Mergers and Acquisitions on a sample of 36 developed and 84 developing countries. To this aim, he employs 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 research, 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.

[13] 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 vertical FDI was quite weak. Later, Jordan and Lenkoski (2018) use a Tobit Bayesian Model Averaging (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 modelling the magnitude of FDI flows.

3. Econometric methodology

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.

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:

$$y_{it} = \alpha_j + X_{j,it}\beta_j + \gamma_{j,i} + \epsilon_{j,it} \qquad \epsilon_{j,it} \sim \mathcal{N}_n(0, \sigma^2 c I), \tag{3}$$

where $i = 1, \ldots, N$ is the number of countries; $t = 1, \ldots, T$ 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 employ 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 $(j = 1, \ldots, 2^k)$:

$$(y_{it} - \bar{y}_i) = \alpha_j + (X_{j,it} - \bar{X}_{j,i})\beta_j + (\gamma_{j,i} - \bar{\gamma}_{j,i}) + (\epsilon_{j,it} - \bar{\epsilon}_{j,i}) \tag{4}$$

$$\ddot{y}_{it} = \alpha_j + \ddot{X}_{j,it}\beta_j + \ddot{\epsilon}_{j,it} \qquad \ddot{\epsilon}_{j,it} \sim \mathcal{N}_n(0, \sigma^2 I). \tag{5}$$

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 $\ddot{\epsilon}_{j,it}$ 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:

$$P(M_j^* | y) = \frac{m_j^*(y) P(M_j^*)}{\sum_j m_j(y) P(M_j)}, \tag{6}$$

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:

$$m_j(y) = \int f_j(y | \beta_j, \alpha_j, \sigma) \pi_j(\beta_j, \alpha_j, \sigma^2) d\beta_j d\alpha_j d\sigma^2, \tag{7}$$

also called the (prior) marginal likelihood.

An alternative expression for (6) is based on the Bayes factor:

$$P(M_j^*|y) = \frac{B_j^*(y)P(M_j^*)}{\sum_j B_j(y)P(M_j)}, \tag{8}$$

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 $B_0 = 1$.

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:

$$\pi_j(\beta_j, \alpha_j, \sigma^2) = \pi_j(\beta_j|\alpha_j, \sigma^2)\pi_j(\alpha_j|\sigma^2). \tag{9}$$

The vast majority of the literature has employed 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 our work, 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:

$$\pi_j^R(\alpha_j, \beta_j, \sigma) = \pi(\alpha_j, \sigma)x\pi_j^R(\beta_j|\alpha_j, \sigma) = \sigma^{-1} \times \int_0^\infty {}_{k_i}(\beta_i \mid 0, g\,\Sigma_i)\, p_i^R(g)\, dg, \tag{10}$$

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

$$V_i = (I_n - X_0(X_0^t X_0)^{-1} X_0^t)X_i, \quad X_0 = (1_n, y_{-1}), \tag{11}$$

In Eq. (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

$$E(\beta_r|y, g, M_j) = \left(\frac{g}{1+g}\right)\hat{\beta}_r, \tag{12}$$

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 our research, we employ a hyper prior for g as proposed by Bayarri et al. (2012) within the Robust prior:

$$p_j^R(g) = \frac{1}{2}\sqrt{\frac{1+n}{k_j+k_0}}(g+1)^{-3/2}, \quad g > \frac{1+n}{k_j+k_0} - 1, \tag{13}$$

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:

$$P(M_j|\theta) = \theta^{k_j}(1-\theta)^{k-k_j}, \tag{14}$$

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 our research we make use of the random $\theta \sim Unif(0, 1)$ for the prior distribution over the model space.

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:

$$P(x_r|y) = \sum_{x_r \in M_j} P(M_j|y), i = 1, \ldots, k. \tag{15}$$

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 posterior inclusion probability 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

$$\hat{\Delta} = \sum_{M_j} \hat{\Delta} P(M_j|y). \tag{16}$$

Similarly, the entire posterior distribution of Δ would be:

$$P(\Delta|y) = \sum_{M_j} P(\Delta|M_j, y)P(M_j|y), \tag{17}$$

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

$$P(\beta_r|Y) = \sum_{M_j} P(\beta_r|M_j, y)P(M_j|y). \tag{18}$$

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).

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.

Table 2
Samples of countries.

Sample of countries	Countries included	Number of countries
Whole sample	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

NOTE: We exclude from our sample the micro-states where Japanese MNCs invest 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 favourable corporate tax conditions of the host country (see Blanchard and Acalin, 2016). These are the cases of Hong Kong, Luxembourg and Singapore.

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 posterior inclusion probability of the covariates, using a Markov Chain Monte Carlo (MCMC) technique, as proposed by George and McCulloch (1997).

4. Data and empirical results

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 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 sample 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 analysed, in addition to the complete group of 27 destination countries, also smaller samples including developed, emerging, EU and East Asian countries. In Table 2 we enumerate the countries included in the different groups considered in our analysis. Table 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 our study.[14] Some variables are lagged one or two years in order to avoid possible endogeneity with the dependent variable[15] and high correlation with other covariates.[16] To ease the discussion of the empirical results, we will follow the same order in the next section.

4.2. Empirical results

The results for the different country-groups analysed are presented in Table 4. The posterior inclusion probabilities and the posterior means of the different samples 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 A, Figs. 3–7). Following the same order as in Table 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 posterior inclusion probabilities in Appendix 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 Eq. (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 **GDP and population measures**. The lagged host country's real GDP is found to be a potential determinant of Japanese OFDI for the whole sample, 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 sample, 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.

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

[15] 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.

[16] 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 3
Variables.

Variable	Definition	Source	Authors
Dependent variable			
FDI outward stock	FDI outward stock from Japan to the host country at current U.S. dollars.	Japan External Trade Organization.	Blonigen and Piger (2014), Antonakakis and Tondl (2015).
GDP and population			
1. LogLagRealGDP	Logarithm of the lagged host country's real GDP at constant 2010 US dollars.	World Development Indicators from World Bank.	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).
2. LogRealGDPdiff	Logarithm of the absolute difference between the host country's and Japan's real GDP at constant 2010 US dollars.	World Development Indicators from World Bank.	
3. RealGDPgrowth	Averaged 5 years growth rate of the host country's real GDP.	World Development Indicators from World Bank.	
4. UrbanPopulation	Percentage of population of the host country living in urban areas according to national statistical offices.	World Development Indicators from World Bank.	
5. LifeExpectancy	Life Expectancy at birth of the host country, years.	World Development Indicators from World Bank.	
6. OldDependencyRatio	Ratio of older dependents of the host country, people older than 64, to the working-age population, those ages 15–64.	World Development Indicators from World Bank.	
Labour endowment			
7. EducLevel	Education level of the host country measured as the average education years of population.	United Nations Development Program.	Carr et al. (2001), Chiappini (2014), Markusen et al. (1996), Markusen and Venables (1998), Markusen and Venables (2000), Markusen and Maskus (2002), Alfaro and Charlton (2009), Yeaple (2003) and Blonigen et al. (2003).
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.	Penn World Table 9.1.	
10. EducLeveldiff	Absolute difference between the host country's and Japan's education level.	United Nations Development Program.	
11. SkillLeveldiff	Absolute difference between the host country's and Japan's skill level.	Education statistics from World Bank.	Markusen and Maskus (2002), Alfaro and Charlton (2009), Yeaple (2003) and Blonigen et al. (2003).
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.	
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.	World Development Indicators from World Bank.	
Trade and worldwide openness			
15. LogJapExports	Logarithm of the Japan's exports to the host country at current US dollars.	Direction Of Trade Statistics from International Monetary Fund.	

(continued on next page)

Table 3 (*continued*).

Variable	Definition	Source	Authors
16. LogJapImports	Logarithm of the Japan's imports from the host country at current US dollars.	Direction Of Trade Statistics from International Monetary Fund.	
17. Log2LagJapTrade	Logarithm of the two years lagged sum of the Japan's exports and imports with the host country.	Direction Of Trade Statistics from International Monetary Fund.	
18. TradeOpenness	Total imports and exports of the host country divided by the total GDP at current US dollars.	World Development Indicators 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.	World Trade Organization.	
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			
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).	The Heritage Foundation.	
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)	Neumayer and Spess (2005), Busse et al. (2010), Rose-Ackerman and Tobin (2005), Camarero et al. (2019) and Di Giovanni (2005).
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.	United Nations Development Program.	
Institutions			
27. VoiceAccountability	Voice accountability index of the host country. It ranges from −2.5 (the lowest score) to 2.5 (the highest score).	World Governance Indicators from World Bank.	
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).	World Governance Indicators from World Bank.	
29. GovernmentEffectiveness	Government effectiveness index of the host country. It ranges from −2.5 (the lowest score) to 2.5 (the highest score).	World Governance Indicators from World Bank.	
30. RegulatoryQuality	Regulatory quality index of the host country. It ranges from −2.5 (the lowest score) to 2.5 (the highest score).	World Governance Indicators from World Bank.	Wei (2000), Chiappini (2014), Kinoshita and Campos (2003), Hyun (2006), Lui (1985), and Egger and Winner (2005).
31. ControlCorruption	Control of corruption index of the host country. It ranges from −2.5 (the lowest score) to 2.5 (the highest score).	World Governance Indicators from World Bank.	

(continued on next page)

Table 3 (*continued*).

Variable	Definition	Source	Authors
32. RuleLaw	Rule of law index of the host country. It ranges from −2.5 (the lowest score) to 2.5 (the highest score).	World Governance Indicators from World Bank.	
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).	The Heritage Foundation.	
Macroeconomic and financial instability/stability			
35. Unemployment	Unemployment rate of the host country.	World Development Indicators from World Bank.	
36. InflationGDPDef	Inflation level of the host country measured by the annual growth rate of the GDP deflator.	World Development Indicators from World Bank.	
37. InflationCPI	Inflation level of the host country measured by the annual percentage change of the Consumer Prices Index.	World Development Indicators from World Bank.	Martí et al. (2017) and Chiappini (2014).
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.	World Development Indicators from World Bank.	
41. Cellular	Mobile cellular subscriptions of the host country per 100 people.	World Development Indicators from World Bank.	Di Giovanni (2005) and Alfaro and Chen (2015).
42. Internet	Individuals using the Internet in the host country per 100 people.	World Development Indicators from World Bank.	
Natural resources			
43. OilRents	Oil rents of the host country as a percentage of total GDP.	World Development Indicators 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.	World Development Indicators from World Bank.	
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).	The Heritage Foundation.	
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.	World Development Indicators from World Bank.	Froot and Stein (1991), Blonigen (1997), Benassy-Quere et al. (1999).

Table 4
Empirical results.

Variables	Whole sample		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)
GDP 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 endowment										
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 worldwide 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)
Institutions										
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 instability/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)

(*continued on next page*)

Table 4 (*continued*).

Variables	Whole sample		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)
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.

As for the variables related to **labour endowment**, the skill level of the host country is a potential determinant of Japanese OFDI for the whole sample. 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 multinational companies 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 worldwide 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 endowment 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 purposes of this research: 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 sample, 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 sample 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 fulfil 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 variables**, the results concerning the potential covariates for the whole sample 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), multinational firms 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 sample 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 sample, 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 sample, 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 MENA countries,[17] abundant oil and gas 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 sample 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 sample and emerging countries. This result is similar to the one obtained in the case of the institutional variables above.

5. Conclusions

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

In this work, 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, Bayesian Model Averaging (BMA) techniques are very suitable for this particular case. Our analysis discriminates between different country group subsamples, looking for more homogeneous groups and more parsimonious models. More specifically, we analyse 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 sample, 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 GDP and population, labour endowment, 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.

[17] 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.

Appendix A. Trace of posterior inclusion probabilities

The following trace plots are obtained from 20000 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.

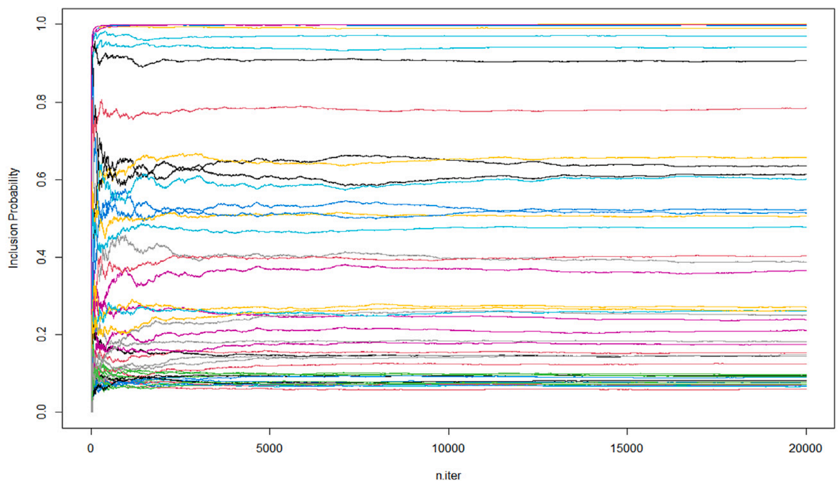

Fig. 3. Whole sample trace estimation.

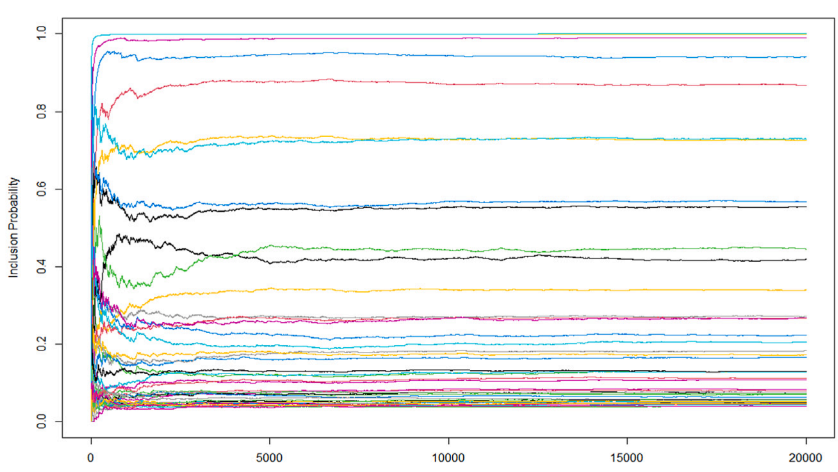

Fig. 4. Developed countries trace estimation.

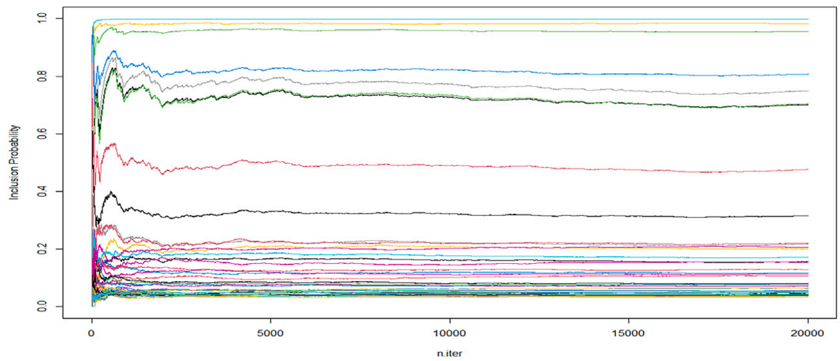

Fig. 5. EU countries trace estimation.

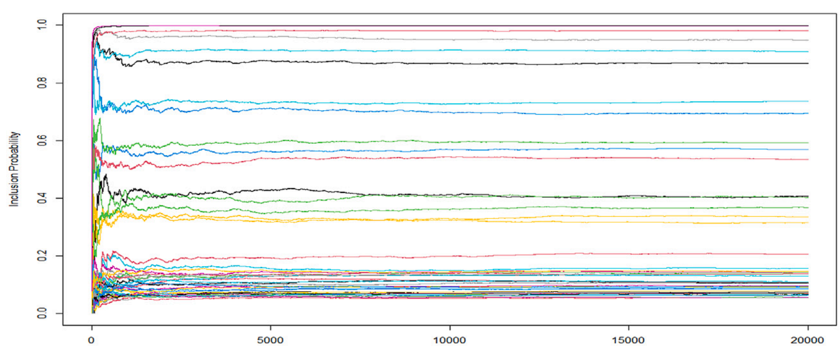

Fig. 6. Developing countries trace estimation.

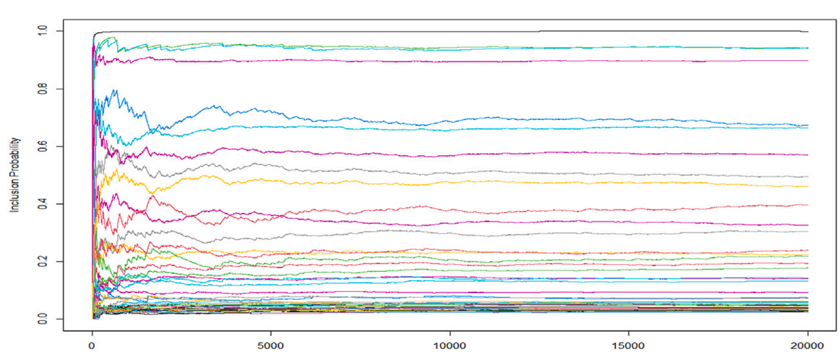

Fig. 7. East Asian countries trace estimation.

Appendix B. Posterior inclusion probabilities

See Figs. 8–12.

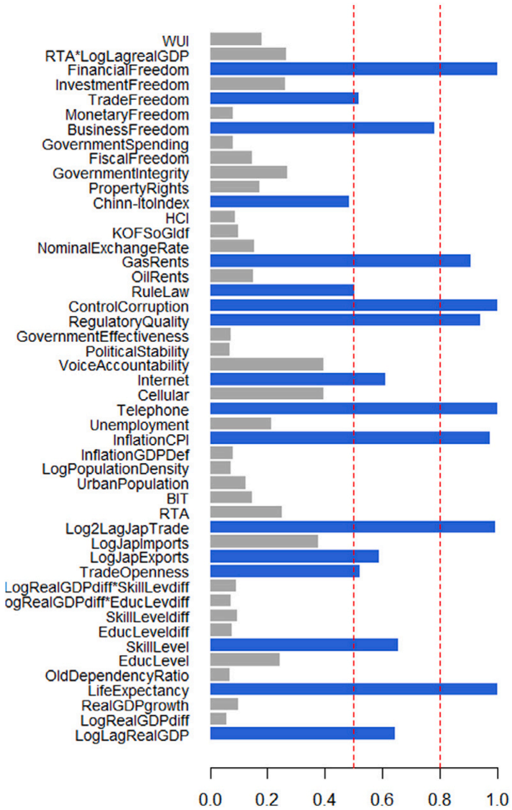

Fig. 8. PIPs for whole sample.

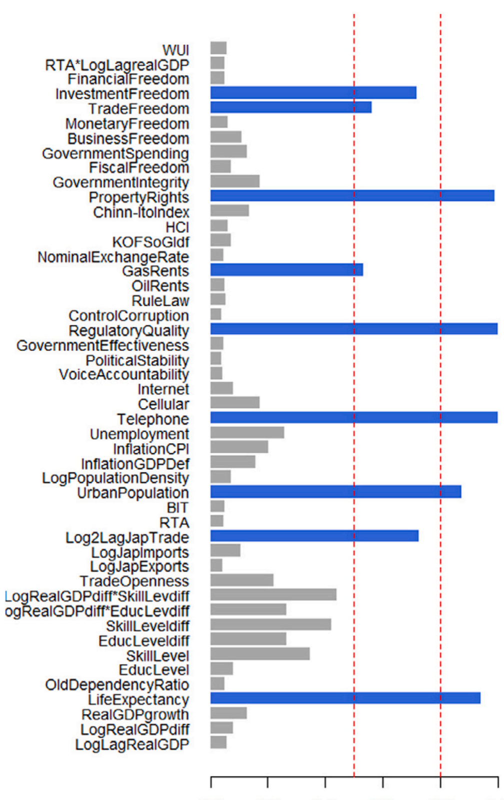

Fig. 9. PIPs for developed countries.

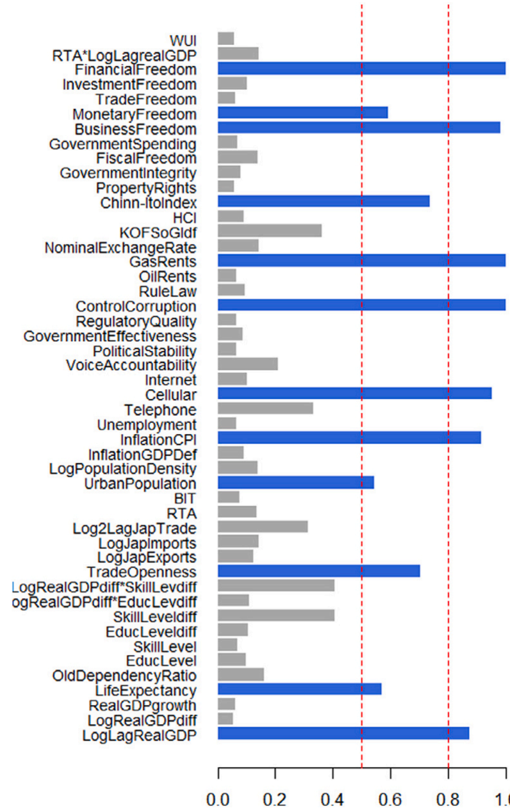

Fig. 10. PIPs for emerging countries.

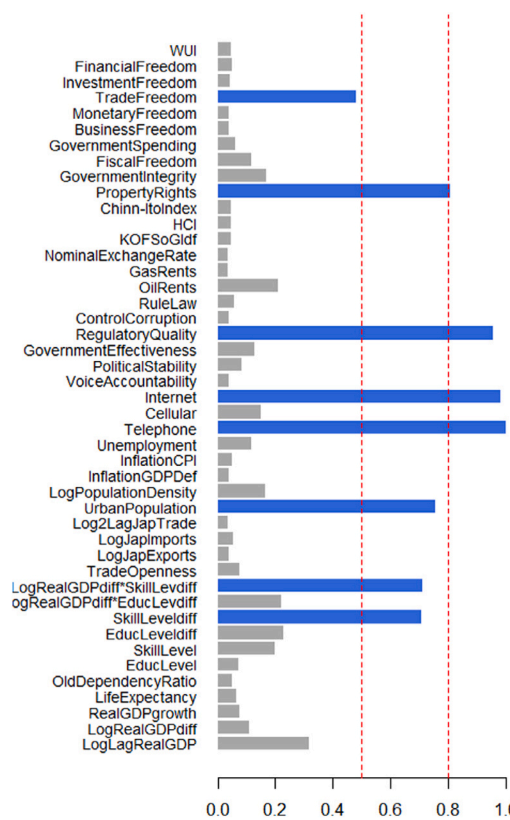

Fig. 11. PIPs for EU countries.

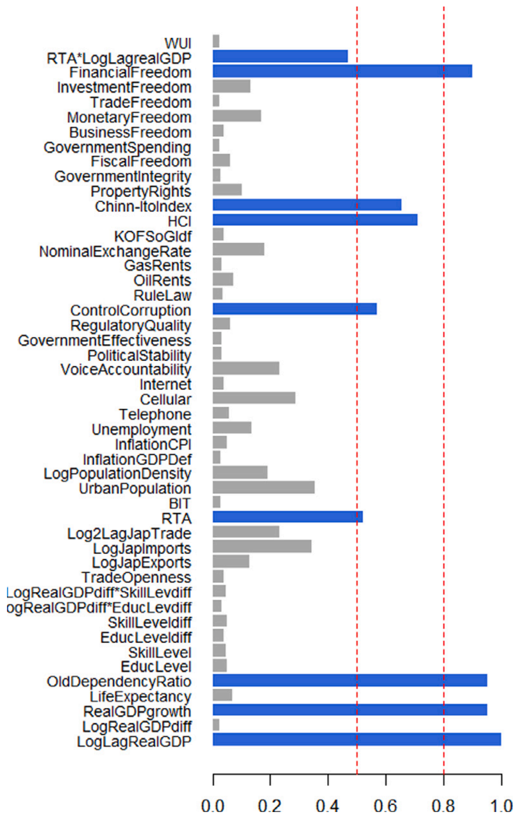

Fig. 12. PIPs for East Asian countries.

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