A Model of Corruption and Foreign Direct Investment *à la* John Dunning

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Abstract

We model the relationship between foreign direct investment (FDI) and the level of corruption in multinational firms' (MCNs') home and host countries. There are two effects of corruption. The first is that host-country corruption reduces FDI by increasing foreign firms' costs. The second effect, based on John Dunning's theory that an MNC's skills reflect its home-country environment, leads MNCs to invest more in countries with corruption levels similar to those of their home country. MNCs develop skills for dealing with home-country corruption, and these skills become a competitive advantage in host countries with similar corruption levels. We test the model using bilateral FDI flows and find that both effects are economically significant.

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Keywords: Corruption, Foreign Directing Investment, competitive advantage

I. Introduction

In 1998, El Salvador privatized its telecom sector through the sale of the national telephone company to France Telecom. After a five-year period of erratic profits and some losses, France Telecom sold a controlling interest in its Salvadoran affiliate to a Mexican company, which quickly succeeded in improving the telecom's financial performance. What can explain the success of the Mexican owner in improving the affiliate's performance so markedly? A Salvadoran telecom manager told one of the authors of this paper, "… the Mexicans understood how to get things done in El Salvador, and they were uninhibited and ruthless in comparison to the French." This vignette reflects a broader phenomenon, the tendency of multinational corporations (MNCs) from relatively corrupt countries to become successful investors in host countries that have similarly high levels of corruption.[1]

Perhaps the most often cited example of this phenomenon is China, whose outward foreign direct investment (FDI) is heavily slanted toward host countries that have weak market institutions and high levels of state involvement in the economy (Buckley *et al*., 2007; Kolstad and Wiig, 2012). In the data set used in this paper, we find that China, with a Corruption Perception Index of 3.4 on a scale of 1 to 10 where 1 is the most corrupt, has positive FDI flows to a total of 144 host countries. Forty of these host countries have a corruption index of 3, 39 countries have corruption index of 2 and 18 have a corruption index of 4. Thus 67% of the host countries in which Chinese firms invest have corruption levels similar to, or worse than, that of China. The most frequent explanation for this choice of host countries is that Chinese firms, by

[1]For example, Cuervo-Cazurra (2006) and Cuervo-Cazurra and Genc (2008) find that MNCs from developing countries invest more frequently in "least-developed" countries where corruption is high.

virtue of the institutions they encounter in their home country, develop skills in dealing with "complex patron-client relationships and personal and institutional favours in relatively opaque and difficult business environments'' (Yeung and Liu, 2008:71) and in dealing with exploitative government bureaucracies and regulations in the host countries.

While the ability of MNCs to undertake successful foreign direct investments can be explained by many factors, in this paper we explore one specific channel that reflects the insight of the Salvadoran manager that the skills for dealing with corruption are a competitive advantage of MNCs investing in corrupt economies. If the MNC's home country has weak market and legal institutions and thus high levels of corruption, the MNC will develop skills and governance structures that enable it to cope with such an environment. Conversely, firms from countries with good market institutions will develop different competitive skills and organizational structures that reflect their home-country environment. Once these skills and organizational features are developed in the home country, its MNCs are also able to exploit them abroad in host countries with similar levels of corruption and institutions. This idea is based on the work of John Dunning (1998), who argued that MNCs invest in host countries that offer the economic and institutional environment that allows the MNCs' competitive advantages to be efficiently utilized, and these competitive advantages reflect the MNCs' home-country environment.

Our model of the effects of corruption on MNC's investment decisions retains the widely accepted view that host-country corruption influences MNCs' foreign investment decisions by creating economic environments that are either favorable or unfavorable to rational economic activity. The contribution of this paper is to introduce a second channel through which corruption influences MNCs' foreign investment decisions. Rather than viewing corruption only as an environmental factor that either facilitates or hinders firms' activities, we construct a model where a home country's institutions have an important impact on the skills and organization of home-based MNCs, and where these skills, in turn, influence MNCs' choices of host countries in which to invest as well as the amount that they invest.

We test the model using data on bilateral FDI flows between 49 home countries and 167 host countries for the period 2005-2009. Our results confirm that both corruption levels and differences in corruption levels between home and host countries influence the likelihood and size of bilateral FDI flows. Our most conservative estimates show that average FDI inflows fall by 9% when the CPI of the host country worsens by one unit, and bilateral FDI flows will be 6% smaller for each additional CPI unit difference between the home and host country.

In the next section of this paper, we present a brief literature survey to place our contribution in the context of the research on MNCs' FDI decisions. We also discuss the economic intuition for our model and then formally develop it and draw out its implications. Section III is devoted to the empirical test of the model, including data description, methodology, empirical results and a number of robustness checks. Section IV concludes.

II. A General Model of Corruption and MNCs' Competitive Advantage

A. Literature Review and Economic Intuition of the Model

Most studies on the relationship between corruption and FDI find that high levels of corruption in host countries make them less attractive for foreign investors and thus reduce their FDI inflows.[2] MNCs investing in corrupt host countries encounter an environment where they face dangers of predation by both the government and by private agents, a lack of protection for their property, including intellectual property, and costly contracting and transactions with other

[2] See Al-Sadig (2009), Wei (2000) and Javorcik and Wei (2009).

economic agents. Such an environment imposes costs on firms that reduce their productivity and ability to innovate. As a result, foreign investors are less likely to invest in such countries. High levels of corruption in home countries have more ambiguous effects. Some observers (e.g., Di Guardo et al. 2016) argue that firms in corrupt countries seek to escape such unfavourable business environments by investing in host countries that have better institutions; others (Barnard (2014) suggest that home-country corruption reduces FDI outflows because firms that operate in corrupt home countries are less likely to invest in the technology and skills needed to succeed in less corrupt ones.

There is also recent evidence that MNCs from countries with a given level of corruption favor investments in host countries with similar levels of corruption.[3] The so-called cultural distance between countries, usually measured by the difference between their respective levels of corruption, acts as a barrier to FDI. Brada et al. (2012) and Qian and Sandoval-Hernandez (2016) have investigated the role of cultural distance and shown that such differences in home-host country corruption levels do have an appreciable effect on bilateral FDI within the framework of some version of the gravity equation.[4] Indirect evidence of these effects can be also deduced from Harding and Javorcik's (2010) findings that investment promotion leads to higher US FDI flows to countries in which red tape and information asymmetries are severe. If these investment

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[3] See, for example, Buckley *et al*. (2007), Cuervo-Cazurra (2006), Cuervo-Cazurra and Genc (2008), Habib and Zurawicki (2002).

[4] This effect of cultural distance on FDI is sometimes attributed to information asymmetries and dates back to Adam Smith's (Smith 1976 p. 454) early observations with respect to capital mobility discussed by Gordon and Bovenberg (1996). The greater the cultural distance between the home and the host country, the less able is the foreign investor to gain accurate knowledge of the host country's institutions, local customs, and laws, resulting in less efficient use of the investor's resources. The negative effects of cultural distance or differences in levels of corruption on international portfolio capital flows are examined by Portes *et al*. (2001), Portes and Rey (2005), Gelos and Wei (2005) and Jain et al. (2017).

promotions reduce the effects of information asymmetry and red tape, then the increase in US FDI outflows reflects the compensation for the large cultural distance.

This paper advances the understanding of the role of home-host country differences in corruption on FDI both from the standpoint of theory and of empirics. On the theoretical side, we set out an explicit model of how cultural distance influences FDI. Previous work provides largely intuitive and verbal explanations of why cultural distance reduces FDI flows.[5] In this paper, we propose a model where both, the level of host-country corruption and home-host country differences in corruption, influence the volume and direction of FDI. We solve for bilateral FDI in a multi-country setting where countries are identical except in their levels of corruption. Using this model we then make predictions about the pattern of bilateral FDI that we test in our empirical work. Our contribution on the empirical side is that we test the predictions of the model using data on bilateral FDI flows between 49 home countries and 167 host countries over a period of five years, yielding over 30,000 observations. This is considerably larger than the rather restricted sample of six transition economy home countries and 84 host countries used by Brada et al. (2012) as well as the 45 home and host countries used by Qian and Sandoval-Hernandez (2016). This larger sample size not only improves the precision of our estimates, but its panel nature enables us to test for non-linearity, to investigate a variety of fixed effects and to account for selection bias.

In our model we propose a more precise explanation for greater FDI between countries with similar levels of corruption or institutional quality that is based on the work of John

[5] Brada *et al*. (2012) do sketch a theory of how cultural distance influences FDI, but their model relies on random differences in home and host countries' firms' ability to cope with corruption. While this yields a similar conclusion to our model regarding the likelihood of FDI between countries with different levels of corruption, the theory developed in this paper also makes explicit predictions about the volume of bilateral FDI, and it does not rely on a stochastic *deus ex machina* to drive its results.

Dunning (1998). Dunning argued that MNCs develop competitive competencies and governance structures that reflect specific aspects of their home-country environments such as resource endowments, factor prices, levels of development and intensity of domestic competition. Host-countries that offer similar environments, which complement the MNC's core competitive advantages, will be attractive candidates for FDI. We propose that MNCs also develop competencies in dealing with their home country's level of corruption or institutional quality. Firms in corrupt countries will learn how to deal with an environment characterized by predation, uncertainties in the security of transactions and ambiguous property rights. Conversely, they are less likely to develop firm-specific advantages such as proprietary technologies, brand names, etc. because these are largely unprotected in their home countries. Skills in coping with corruption and weak home-country institutions should be transferable to other countries where the firm decides to invest, but the value or transferability of the skill will depend on the level of corruption in the host country. If both home and host country have similar levels of corruption, the skills learned in the home country can provide valuable competitive advantages in the host country, but if the host country has a very different corruption level, then the skills learned in the home country will yield small or no competitive advantages abroad. Similarly, firms in home countries with low levels of corruption will have less experience and ability in dealing with a corrupt environment in host countries.[6]

[6] For evidence that skills in dealing with institutional weaknesses developed by MNCs in their home country carry over to their ability to operate in similar environments in potential host countries see Hillman and Hitt (1999), McWilliams, et al., (2002) and Henisz, (2003). The closely related idea that counties' comparative advantage may be shaped by domestic institutions is well developed in the literature. See, for example, Belloc (2006) and Levchenko (2007). Moreover, Athanasouli and Goujard, (2015) and Mironov (2015) demonstrate the advantages that managers used to corrupt environments have over managers from less corrupt countries when an MNC's foreign affiliate is located in a country characterized by high levels of corruption. MNCs may also learn skills for coping with corruption by doing business in corrupt host countries rather than in their home country, but we view such learning to be of secondary importance.

Thus there are two ways in which corruption influences MNCs' foreign investment decisions. One is what we call the corruption environment effect (CEE), which reflects the effects of host-country corruption levels on the productivity or economic efficiency that firms can achieve given the institutional quality of the host country. The second effect is what we call the skill-matching effect (SME), which is the effect on MNCs' FDI decisions of similarities between home- and host-country levels of corruption. In this paper, we propose a model that incorporates these two ways in which corruption influences MNCs' investment decisions. The model predicts that MNCs' foreign investment will be greater to host countries with lower levels of corruption, and that MNCs' foreign investment will be greater the more similar are home and host countries in their levels of corruption. Moreover, differences in corruption levels will influence both the likelihood of investment between any two countries taking place and the volume of FDI that takes place.

B. Model of Corruption and Foreign Direct Investment

To focus on the role played by differences in cross-country corruption levels, our model makes simplifying assumptions that make home and host country corruption levels the only country-level determinants of MNCs' investment decisions. Specifically, we assume that all countries are identical in terms of size, available production technologies, consumer preferences, endowments, etc. The ten stylized countries in our model are assumed to differ only in the level of corruption that prevails throughout their economy. Each country falls within one of ten corruption categories where a value of 1 signifies that a nation is most corrupt and 10 signifies the one that is least corrupt.[7] Additionally, we treat the skills and experience in coping with corruption as a public good so that their transfer and employment in another country does not diminish the amount available for use by the MNC elsewhere.[8]

Each country has a group of MNCs that are identified with that nation such as *American* multinationals or *French* multinationals, etc. Additionally, consumers in each country view the output of their national group of MNCs as similar, but not identical, to the outputs of the other nine foreign multinational groups operating in their country. That is, in each nation, the preferences of consumers are assumed to be as in Armington (1969) in that the product produced domestically by the domestic firms and those produced by foreign affiliates of the MNCs from the other nine nations fall within the same broad product group, say manufacturing, but consumers treat each product as a different variety or product segment. Thus each nation has a unique corruption rating and product variety. As a result, in what follows, we use a nation's corruption rating to identify both the nation and its product variety. Specifically, subscripts i and j refer to nation i and nation j respectively or to product varieties i and j where i denotes home countries and j host countries. The context will clarify the particular usage.

We now turn to the formal model, beginning with demand side conditions in each host country. Assume that consumers in host country j spend β_{ij} percent of their total budget (Y_j) on product variety i within the MNC product group. Also assume that the sum of these shares is less

[7] The categorization is motivated by Transparency International's Corruption Perceptions Index that ranks nations such a scale that is used in the empirical part of this paper.

[8] This assumption simplifies the model, but it is not critical. Note that if there are costs to transferring such coping skills internationally, then the negative effect of differences in home-host corruption on FDI would be greater. Such costs could be modeled as iceberg trading costs are in models of international trade, although, in this case, it is the amount of capital transferred that would be "melted" by cultural distance. Moreover, we do address investment costs in our robustness tests.

than one: $\sum \beta_{ij} < 1$. If we ignore products outside the broad MNC product group and adopt Cobb-Douglas preferences, we can then write the utility function for consumers in country *j* as

$$U_j = \prod_{i=1}^{10} X_{ij}^{\beta ij}$$

where X_{ij} is the amount of variety *i* consumed by consumers in host country *j*. This specification yields simple product demand functions so that the amount of each variety demanded, D_{ij} is given by:

$$D_{ij} = \beta_{ij} Y_j \left(\frac{1}{P_{ij}}\right) \qquad i = 1, \dots, 10 \qquad Eq. 1$$

where P_{ij} is the price of variety i in host country *j*. In the ensuing analysis we assume that the β_{ij} are identical across the varieties and the same for all ten countries.[9]

The production side of the model assumes that all firms within this "manufacturing" product segment populated by the ten groups of multinationals share the same Cobb-Douglas production technology where the output of variety *i* by a MNC from country *i* in host country *j* is given by:

$$Q_{ij} = A_j K_{ij}^{\alpha k} L_{ij}^{\alpha l} \qquad i = 1, \dots, 10$$

where αk and αl are, respectively, the capital and labor factor shares, K_{ij} and L_{ij} are the capital and labor inputs used by MNCs from country i in country *j*, and A_j is total factor productivity. This production function yields a tractable conditional factor demand function for capital. Letting w_j and r_j represent, respectively, the wage and rental rate for capital in country *j*, the solution to the standard cost minimization problem yields the following demand for capital by MNCs from country *i* in country *j*:

[9] These assumptions greatly simplify the analysis, but they are not essential for the qualitative results that follow later.

$$K_{ij} = \left[\frac{w_j\,\alpha k}{r_j\,\alpha l}\right]^{\alpha l/(\alpha l+\,\alpha k)} \left[\frac{Q_{ij}}{A_j}\right]^{1/(\alpha l+\,\alpha k)}$$

Assuming $\alpha k + \alpha l = 1$, simplifies this expression to:

$$K_{ij} = \left[\frac{w_j \alpha k}{r_j \alpha l}\right]^{\alpha l} \left[\frac{Q_i}{A_j}\right] \qquad Eq. 2$$

These expressions, known as conditional input demand equations, indicate each investing firm's optimal or desired capital stock in country *j*.

We now turn to the treatment of corruption and its impact on investment. We can proceed in one of two ways. One is to treat corruption as a tax on the sale of a final good. This would be appropriate in those cases where corruption is facilitated by the physical presence of each unit so that the additional costs per unit are in turn transferred to consumers in terms of higher prices. An alternative approach is to treat corruption as causing a reduction in total factor productivity (*A*). Here, productivity declines as producers divert time, energy, and resources to addressing the demands placed on them by a corrupt environment and, as a result, they produce less output from a given level of inputs. Both approaches lead to identical results in our framework, and thus, without loss of generality, we treat the effects of corruption akin to the imposition of a tax on the final good.[10]

In the analysis that follows, we assume that two broad influences impact the magnitude of the corruption tax that a multinational from country *i* faces when operating its affiliate in country j. This tax, denoted as τ_{ij}, will reflect the skill matching effect and the corruption environment effect. We model each effect as follows.

[10] In this formulation we follow Wei (2000), who also views corruption as imposing a tax on the foreign investor and estimates the tax-equivalent of a host country's level of corruption.

The skill-matching effect depends on two factors. First, it depends directly on $|Ci - Cj|$, the absolute value of the difference in corruption levels between the home country, the location where the multinational gained its experience in addressing corruption, and the host nation.[11] The more similar the home and host countries' corruption ratings, the lower is the value of $|Ci - Cj|$ and hence the lower the implicit tax rate on foreign MNCs. Alternatively, the more dissimilar the respective ratings, the higher the value of $|Ci - Cj|$ and the higher the tax. Second, in terms of the skill-matching effect, we also consider the breadth or span of applicability of the skills learned in one setting to a different setting. The corruption-tax level may be low if the host and source nation have similar corruption level, but how close must the host country's corruption level be to the source nation's level? To capture the transferability of the skills learned in the home-country setting to the host country, we introduce the parameter δ. If the skills learned coping with the home-country level of corruption are specific to a given level of corruption, then δ has a low value, say 1, meaning that skills learned in a nation with corruption level 3 may not be very applicable in a nation with a corruption classification only one level higher (corruption level 4) or lower (corruption level 2). If the skills are easily transferable and relevant across a broader range of corruption environments, so that δ has a higher value, say 5, then skills learned in a country with one level of corruption will, to a lesser extent, also be applicable in host nations with a corruption classification that is somewhat different from that of the home country. In the extreme, skills learned in a home country could be so highly applicable in any host nation that the corruption tax becomes irrelevant, in which case δ = 10. To capture the importance of the span of applicability of skills gained coping with corruption, we scale $|Ci - Cj|$ by (10 – δ)

[11] Using the absolute value rather than the difference assumes symmetry for this effect.

where δ is assumed to range from 1 to 10. Putting these two elements together, the skill-matching (SME) component of the corruption tax is:

$$SME_{ij} = 1 + (\tfrac{1}{\lambda})(10 - \delta)\,|C_i - C_j| \qquad Eq.\ 3$$

where λ is a scalar used to parameterize the corruption tax rate.[12]

The corruption environment (CEE) component is straightforward to model. All else the same, a host nation with a higher level of corruption will impose greater costs on firms than one with less corruption.[13] Thus,

$$CEE_{ij} = (\tfrac{1}{\emptyset})(10 - C_j) \qquad Eq.\ 4$$

where ϕ is a scalar that determines the maximum tax rate. For instance, if $\phi = 20$, the maximum tax rate is to 45%, which occurs when $C_i = 1$. Combining the SME and CEE effects, we have

$$\tau_{ij} = 1 + \left(\tfrac{1}{\emptyset}\right)(10 - C_j) + (\tfrac{1}{\lambda})(10 - \delta)\,|C_i - C_j| \quad \text{if } i \neq j \qquad Eq.\ 5$$

$$\tau_{ij} = 1 + \left(\tfrac{1}{\emptyset}\right)(10 - C_j) \quad \text{if } i = j \qquad Eq.\ 6$$

Equation 6 reflects the fact that the skill matching effect does not apply to the home country MNC group when it invests in the home country economy, but the corruption environment effect (CEE) does apply to those firms as well. Also, note that when the least corrupt country is also the host country, then $\tau_{10,10} = 1$.

The final set of assumptions pertains to the market conditions under which the various firms operate. We abstract from general equilibrium effects so that the home and multinational firms are price takers in the host countries' product and factor markets. This means that all firms

[12] Since the tax is multiplicative, if either δ = 10 or $C_i = C_j$, then SME = 1 meaning there is no SME effect.

[13] So as not to complicate the model unnecessarily, we ignore the effect of home country corruption on FDI flows, although we include it in our empirical tests.

take factor prices, the wage rate w for labor and the rental rate r for capital, as set exogenously. It also means that all firms are price takers in their respective product market and that they set price equal to marginal cost. In light of the earlier assumptions regarding the similarity of the technology, all firms have the same unit cost. Using duality results and defining c as marginal cost, the competitive pricing conditions (i.e., price equals unit cost) for the host and other MNC groups may be expressed as:

$$P_{ij} = \left[\frac{w_j}{\alpha l}\right]^{\alpha l} \left[\frac{r_j}{\alpha k}\right]^{\alpha k} \left[\frac{1}{A_j}\right] \tau_{ij} = \boldsymbol{c}\, \tau_{ij} \qquad \textit{Eq. 7}$$

for the output of the multinational firms. Foreign firms will encounter a higher implicit tax due to the SME effect, which will raise their costs and thus the price of their products in the host country, and this will reduce host-country demand for their product. As we noted earlier, corruption could also be modeled as reducing the efficiency of multinationals, which would be captured by a reduction in A. This also would lead to a higher price, which confirms our earlier comment regarding the equivalence of the two approaches to modeling the effects of corruption.

We are now able to derive an expression that indicates how the desired level of investment in a particular country is impacted by the degree of corruption in the host country. We begin by substituting Equation 7, the price equation, into the set of product demand equations identified as Equation 1. Doing so allows us to determine the values of the Q_{ij}'s or industry outputs for the home firms and each of the foreign firms. These values are in turn substituted into the conditional factor demands given by Equation 2 to obtain, K_{ij}^{*}, the desired stocks of capital of home-country firms and multinational firms as:

$$K_{ij}^* = \left(\frac{1}{\tau_{ij}}\right) \left(\frac{\beta Y_j}{r_j}\right) \left[\frac{\alpha k}{\alpha l}\right]^{\alpha l} / \left(\left[\frac{\alpha l}{\alpha k}\right]^{\alpha k} + \left[\frac{\alpha k}{\alpha l}\right]^{\alpha l} \right) = \boldsymbol{c} \left(\frac{1}{\tau_{ij}}\right) \qquad Eq.\ 8$$

It is evident that K_{ij}^* are functions of corruption levels across countries as captured by the τ_{ij} term. Higher levels of τ_{ij}, whether due to higher levels of corruption and thus greater CEE effects or to greater SME effects resulting for greater differences in home-host corruption levels, reduce the amount of foreign investment that MNCs desire to undertake. Note that since all MNCs in a given country are identical, their FDI decisions will also be the same, and thus aggregate FDI flows reflect firm-level FDI decisions. Thus, our model can be tested using aggregate rather than firm-level FDI flows.

Several conclusions flow from Equation 8. If there is no corruption in any of the countries, τ_{ij} = 1, and the desired capital stock for both home and host nation multinationals in each country is the same given our assumptions of identical endowments, tastes and technology. This means that each country's MNCs would invest in all other countries and that they would have the same size of production facility and charge the same price in all countries, including in their home country. With inter-country differences in corruption levels, the CEE effect will result in smaller desired capital stocks for both foreign and home-country firms in more corrupt countries. The skill matching effect implies that the optimal capital stock, K_{ij}^*, desired in host country j is highest for its own country multinational since there is no skill matching tax on domestic firms (compare Equations 5 and 6). MNCs from other countries will have smaller desired capital stocks, with MNCs from countries that differ the most from the host country in their corruption level having the smallest ones.

Figure 1 shows the influence of the corruption environment and skill-matching effects on desired levels of investment as predicted by simulations of our model. The figure shows the optimal capital stock K_{ij}^* desired by host country j from home country i as for all possible country corruption levels. Results are presented as percentage of $K_{10,10}^*$, i.e. the optimal capital stock desired by the least corrupt host country from its own country multinational. The highest levels of desired capital for each host country come from their own country MNCs (as depicted by the peaks in each line). However the optimal level of capital desired by each host country is higher as we move to the right, that is toward lower levels of host-country corruption. This means that MNCs from less corrupt countries will desire larger affiliates in less corrupt countries than they would in more corrupt countries even if the differences in corruption level were of the same absolute value. The model thus reflects the general negative effect of corruption on economic activity since even host-country MNCs in corrupt countries have a lower desired level of investment in their own nation than they would in the absence of corruption.

An unresolved issue for an empirical test of this model is that it predicts that the MNCs of every home country will invest in all potential host countries. But the predicted investment in some hosts may be a very small relative to the size of the parent company's capital stock in its home country, implying that foreign affiliates could be quite small. However, there is a large literature on the way in which MNCs chose to serve foreign markets that suggests the existence of a minimum efficient size for affiliates, and, if the host country does not provide a market large enough to meet the production of such an affiliate, then licensing or selling of technology, franchising and exports will replace FDI as the more profitable way of serving this market.[14] Like the concept of minimum efficient scale (Scherer *et al*. 1975), there may be a minimum investment threshold that the desired capital stock must satisfy before an MNC decides to enter a host nation's market through FDI.

[14] Helpman et al., (2004) and Pyo (2010).

To sum up, our model predicts that, *ceteris paribus*, differences in the corruption level between home and host countries reduce the desired volume of bilateral FDI, and, if there is a minimum viable size for foreign affiliates, bilateral investment between such pairs of countries may not take place. Moreover, countries with either very high or very low levels of corruption may also expect to receive or undertake fewer investment projects in total. Finally, MNCs from less corrupt countries will undertake larger FDI projects than do MNCs from more corrupt ones.

III. Testing the Model

In this section, we test the predictions of our model regarding corruption and MNCs' investment decisions. Our tests are based on bilateral foreign direct investment flows obtained from the UNCTAD FDI database for the period 2005-2009. We focus on flows rather than stocks of FDI for several reasons. First, because MNCs will dynamically adjust their optimal level of capital stock in host countries in response to changes in host-country environments, FDI flows will capture these dynamic effects on MNCs' desired level of capital stock. Second, while bilateral FDI flows are quite volatile over time, FDI stocks change only slowly. Hence, stocks of FDI as a dependent variable exhibit relatively little variation over time, reducing the value of the panel nature of the data. Finally, we note that the studies of the relationship between FDI and corruption mentioned above all utilize FDI flows as well, so, by also focussing our work on flows, we maintain comparability with previous studies.

A. The Knowledge-Capital Model of the Multinational Enterprise

The model developed in Section II assumes that all countries are identical except for their levels of corruption. In our empirical work, we embed the theoretical insights of that model into a broader empirical model of bilateral FDI based on the gravity equation with additional covariates that capture important drivers of FDI, sometimes referred to as the knowledge-capital model of the multinational enterprise (Carr et al., 2001). This model focuses on differences in country sizes, location, incomes, endowments, etc., that are traditionally seen as the drivers of FDI. It distinguishes between vertical MNCs, which engage in trade between the parent firm and foreign affiliates established abroad in order to access low-priced non-tradable or hard-to-trade inputs (Helpman, 1984). Horizontal MNCs, on the other hand, save on trade costs by serving markets through host-country affiliates rather than through international trade (Markusen, 1984).[15]

The model's variables include: (1) absolute and relative country size, (2) transportation and trade costs, and (3) differences in factor endowments.[16] Larger countries attract greater FDI flows since the access to larger markets creates opportunities to achieve scale and scope economies. Also, MNCs find larger host countries more profitable because the costs of undertaking FDI are to some extent fixed. Furthermore, larger economies are more likely to have a greater variety of specialized factors of production and resources attractive to foreign investors. We follow Egger and Winner (2006) and use the following variables to control for relative country size:

$$\sum GDP_{ij} = GDP_i + GDP_j$$

$$\Delta GDP_{ij} = 1 - \left(GDP_i / \sum GDP_{ij}\right)^2 - \left(GDP_j / \sum GDP_{ij}\right)^2$$

where GDP_i and GDP_j are the GDPs of the home and host countries respectively.

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[15] The role of hybrid or ''complex'' MNEs, which are neither purely horizontal nor purely vertical, has been emphasized by Ekholm *et al.* (2007), Grossman *et al.* (2006), and Yeaple (2003) and has been to some extent incorporated into the Carr et al. (2001) model.

[16] Applications of the model often include additional variables such as tax policies and political risk that are specific to the FDI process, and we consider these in our robustness tests.

The second set of drivers of FDI are home- and host-country transportation and trade costs. The role of distance as a measure of transportation and trade cost between countries in gravity equations of FDI is ambiguous. FDI overcomes high transportation costs for low-value bulky goods or for non-tradables and thus distance promotes FDI, but proximity also has a positive effect on FDI because it implies similar tastes and consumption patterns, promoting FDI that to serve host-country needs. Adjacency of the home and host countries is also an important stimulus to FDI. To account for these two effects, we use both distance and adjacency as separate explanatory variables so that:

$Distance_{ij}$= distance between the capitals of countries *i* and *j*

$Adjacent_{ij}$ = 1 if countries *i* and *j* are adjacent, 0 otherwise

We use a host country's imports as percentage of its GDP as a measure of host-country trade costs such as tariffs, and we call this variable $Trade\ Cost_j$. For home-country trade costs we use the home country's external balance of goods and services as a percentage of GDP and refer to this variable as $Trade\ Cost_i$. Higher trade costs in the host country should encourage FDI since foreign firms will prefer to serve the market through affiliates rather than through foreign trade. Higher trade costs in the home country suggest high barriers to imports of finished goods, making resource-seeking FDI more attractive.

International factor endowment differences are also an important motive for FDI (Helpman 1984; Markusen and Maskus 2002). We use the United Nations Human Development Index (HDI) to capture skill endowments.[17] The HDI is a comprehensive measure of

[17] The Human Development Index is published by the United Nation Development Programme in their Human Development Reports.

development that aggregates country-level achievements in education, life expectancy and income levels. We define skill endowment differences based on the HDI as follows:

$$Skill\ Difference_{ij} = HDI_i - HDI_j.$$

Finally, our theoretical model does not directly predict the effect of home country corruption on optimal capital stock, since the skill matching effect only measures differences in host- and home-country corruption levels. In order to disentangle skill-matching effects from home-country corruption effects, we include the home-country corruption as a control variable: $Corruption\ home = (10 - Home\ country\ CPI)$.

B. Data

Our sample of countries, reported in Table 1, includes FDI flows for 49 home countries and 167 host countries.[18] The explanatory variables described above come from the World Bank's *World Development Indicators* CD-ROM. As in many of the related studies of FDI mentioned above, our home and host country corruption measure is the Transparency International Corruption Perceptions Index (CPI).[19] The bilateral investment flows, measured in billions of US$, are taken from the UNCTAD FDI database, and we employ data for 2005-2009. The home countries encompass a broad variety of country sizes, locations, levels of development and corruption levels. The host countries make up a large fraction of all countries. The bilateral distances are obtained from the French Research Center in International Economics' (CEPII) Geodist data set.

[18] Data sets used to study MNCs decisions at the firm level often incorporate only a few countries, resulting in low variation in corruption levels. See, for example, Javorcik and Wei (2009).

[19] Cuervo-Cazurra (2006) and Wei (2000) find that substituting other measures of corruption for the CPI does not change their conclusions regarding the effect of corruption on FDI.

Descriptive statistics of the FDI flows in our sample are presented in Table 2. Positive FDI flows represent 20.58% of our sample, negative flows are 6.63% and 72.80% are zero. There is significant time variation in FDI flows. The size of positive flows peaks in 2007 and 2008, with the average bilateral investment flow close to 2 billion US dollars (US$), although the spread, as is to be expected, quite large. Negative investment flows, meaning either divestitures or a decline in the value of foreign affiliates, accounts for a small part of our observations and the dollar value of these flows is also small relative to the positive investment flows. In Table 3 we present descriptive statistics of the corruption index by year and host or home country. There is only a small difference between the average level of corruption of home and host countries. Home countries have a higher average corruption index, meaning that they are less corrupt than are the host countries, but, as Table 3 shows, both home- and host-country samples encompass a broad range of corruption levels, and a more detailed examination of the data shows that differences in corruption levels between pairs of home and host countries vary over the sample period.

C. Estimation

In order to estimate the model and test its implications, we use both a non-linear specification to reflect the theoretical model and linear specifications to account for issues that frequently arise in studies of FDI.

Non-linear specification

According to our theoretical model, the relation between the desired capital stock of a MNC and the SME and CEE effects is given by the following equation:

$$K_{ij}^{*} = c\left(\frac{1}{\tau_{ij}}\right) \qquad \textit{Eq. 8}$$

where: $\tau_{ij} = SME_{ij} + CEE_{ij}$, and

$$SME_{ij} = 1 + \left(\frac{1}{\lambda}\right)(10 - \delta)\left|C_i - C_j\right|$$

$$CEE_{ij} = \left(\frac{1}{\emptyset}\right)\left(10 - C_j\right).$$

We reparametrize our model to obtain identification. For the CEE effects, as explained in Section II, the parameter $\emptyset$ measures the effects of the corruption environment. We define the parameter $\gamma_{CEE} = \frac{1}{\emptyset}$ to capture these effects. For the SME, the parameter $\frac{1}{\lambda}$ captures the effects of skill matching on the desired stock of capital, and δ captures the level of transferability of these skills across countries. It is impossible to disentangle these two effects because a direct measure that captures the level of transferability is not available. Thus our empirical model combines both effects in the parameter $\gamma_{SME} = \left(\frac{1}{\lambda}\right)(10 - \delta)$.[20]

Our final specification is as follows:

$$FDI_{ij} = c\left(\frac{1}{1+\gamma_{CEE}(10-C_j)+\gamma_{SME}\left|C_i-C_j\right|}\right) + \beta X_{ij} + \alpha + \varepsilon_{ij} \qquad \textit{Eq. 9}$$

where, FDI_{ij}, the dependent variable, is the observed positive FDI outflow from home country *i* to host country *j* measured in billions of US$, and X_{ij} are control variables described above. Our data is a panel, but we omit time subscripts to reduce notation.[21] We expect that the coefficients c, γ_{CEE} and γ_{SME} will be positive and significant, confirming negative CEE and SME effects on capital flows.[22]

[20] Our estimated coefficient can be also interpreted as the pure SME effect if $\delta = 9$, which represents the lower bound for the SME effect. The SME effects assuming other values of δ can be calculated by dividing γ_{SME} by $(10 - \delta)$

[21] Our estimation is based on pooled panel regressions. However in the robustness section below we use the panel nature of our data to control for possible omitted variable bias due to country fixed effects.

[22] Other non-linear specifications have been proposed in the literature (Brada et al., 2012 and Jain et al., 2017). Our use of a non-linear model is based on the theoretical model developed in this paper.

We estimate our model using non-linear least squares with robust standard errors, and report the results in Table 4, column 1. The estimated coefficients c, γ_{CEE} and γ_{SME} are positive and significant. This confirms the prediction of our model that the corruption environment of the host country (CEE) and differences in corruption levels of home and host countries (SME) both affect FDI negatively. The parameter estimates for the control variables are also significant and in accord with theoretical expectations. Home-country corruption is also significant, suggesting that it also has an important negative effect on bilateral FDI flows.

A disadvantage of the non-linear model is that the magnitude of the effect of CEE and SME on specific FDI flows cannot be directly observed from the estimated parameters. Marginal effects would have to be calculated for every host-country corruption level and for every home-host difference in corruption to obtain these economic effects.[23]

Linear specification

The advantage of the non-linear specification is that it links the theoretical result with the available data directly. However, it has limitations in dealing with econometric issues often observed in empirical work on FDI. One such issue is the fact that many bilateral investment flows are zero because there are no investment flows between countries in a given year, creating a censoring problem. In order to deal with this and also with negative FDI flows we estimate a linear specification of the model as follows:

$$FDI_{ij} = \alpha + \beta X_{ij} + \lambda_{CEE}(10 - C_j) + \lambda_{SME}|Ci - Cj| + \varepsilon_{ij} \qquad \textit{Eq. 10}$$

This differs from the non-linear model in that the corruption effects CEE and SME affect FDI linearly.[24] The advantage of the linear model is that we can account for a number of

[23] We estimate and analyse these effects in section D.

[24] Notice that the total effect of host-country corruption on FDI still is non-linear in this linear specification.

estimation issues such as sample censoring, sample selection, and fixed effects that we discuss in our robustness test section below. In addition, the linear results can be more easily compared with previous estimates of the effects of corruption on FDI. The disadvantage of the linear model is that the estimates cannot be linked directly to the parameters of the theoretical model. Nevertheless, the implications of a negative relation between CEE and SME and FDI flows can still be tested using the linear specification by examining the significance and sign of the coefficients of λ_{CEE} and λ_{SME}. If our theoretical model is correct, we expect negative and significant signs for λ_{CEE} and λ_{SME}.

We use two estimation methods. First, we estimate Equation 10 using OLS with all positive, negative and zero FDI observations. Second, we use a Tobit estimation where the censoring is at 0.[25] Results using the two estimation techniques are reported in columns 2 and 3 of Table 4. The parameter estimates for the basic knowledge-capital model are significant, in accord with theoretical expectations and very similar in magnitude to the parameters of the non-linear specification. Moreover, the addition of the corruption variables does not change the parameter estimates much, which suggests that the corruption variables do not serve as proxies for some of the traditional variables. The corruption environment effect (CEE) coefficients are negative and significant for both OLS and Tobit. This negative coefficient means that more corrupt countries receive smaller FDI inflows as our theory predicts.

The coefficient for the skill matching effect (SME) is also negative, meaning that the greater the difference in corruption levels between the home and host countries, the smaller bilateral FDI will be. Note that the coefficients for CEE and SME are similar in magnitude. This

[25] We refer to our Tobit estimation as a linear specification since the CEE and SME linearly influence FDI flows. Thus our model is linear in parameters.

means that the effect on FDI of the skill-matching component of the "corruption tax" is comparable to the effect of the general corruption environment variable in its effect because a one point improvement in the corruption level has about the same effect on FDI as a one point change in the difference in corruption levels between a pair of countries.

Our theory also predicts that differences in corruption influence not only MNCs' FDI volumes, but also the probability of selecting a host country for FDI. We test this hypothesis using a Probit estimation where FDI = 1 if a bilateral FDI flow is positive and 0 otherwise. The results are reported in Table 5. The estimates of the marginal effects of the corruption variables are all significant. An increase in the difference between home and host country CPIs has a negative effect on the probability of FDI taking place between the two countries that is comparable to the effect of an increase in the corruption level of the host country. Thus, both in terms of its effect on the volume of FDI flows and on their direction, the SME effect plays a significant role in determining the pattern of FDI.

D. Economic Significance of Corruption

In this section we evaluate the economic significance of the skill-matching and corruption environment effects. We start with the non-linear model as given by Equation 9. In order to understand the economic effects of CEE and SME on FDI, we need to calculate marginal effects. Given the non-linear nature of the model these effects are not constant as they would be in a linear model. Specifically, to measure the pure CEE, we start by assuming that there are no SME effects ($\lambda_{SME} = 0$), and thus the marginal effects from Equation 9 can be calculated as follows:

$$\frac{\delta FDI_{ij}}{\delta C_i} = -c\,\gamma_{CEE}\left(\frac{1}{1+\gamma_{CEE}(10-C_j)}\right)^2 \qquad \textit{Eq. 11}$$

Similarly we calculate marginal effects for SME by assuming no CEE effects ($\lambda_{CEE} = 0$), as follows:

$$\frac{\delta FDI_{ij}}{\delta(C_i - C_j)} = \begin{cases} -c\,\gamma_{SME}\left(\frac{1}{1+\gamma_{SME}|C_i - C_j|}\right)^2, if\ \ |C_i - C_j| > 0 \\ c\,\gamma_{SME}\left(\frac{1}{1+\gamma_{SME}|C_i - C_j|}\right)^2, if\ \ |C_i - C_j| < 0 \\ not\ defined,\ if\ \ |C_i - C_j| = 0 \end{cases} \qquad Eq.\ 12$$

Thus, for a home country with corruption level 5 ($C_j = 5$) investing in a host country with corruption level 6 ($C_i = 6$), an increase in the host country's corruption level will have a negative effect on FDI. However if the same home country is investing in a host country with corruption level 3 ($C_i = 3$), an increase in the host-country corruption level will increase FDI.

In Table 6 we report the marginal effects calculated using Equations 11 and 12. The CEE effects change depending on the host-country corruption level. The largest effects are observed for countries with low corruption levels (high CPI). For example, for a very honest country (CPI=10), a unit increase in the level of corruption (i.e. to CPI=9) results in a reduction of FDI inflows of 655.90 million US$ a year. The impact for highly corrupt countries is smaller. For example, for a corrupt country with CPI=2, a unit increase in corruption to CPI=1 will result in a reduction of 62.41million US$ in FDI inflows. On average, a one unit increase in corruption implies a reduction of 205.87 million US$ of FDI flows. Since the average positive FDI flow in our sample is 940.52 million US$, this implies that investment inflows decline by an average of 21.89% for each unit decrease in the host country CPI.

The SME marginal effects differ depending on the difference in corruption levels between home and host countries. Thus, in Table 6, we present estimation results for all possible corruption differences (i.e. 0 to 9). For a home-host country pair with a difference in corruption of 1 CPI unit, an increase in this difference by one unit can reduce FDI flows by as much as

355.74 million US$ per year. The SME marginal effects decrease as the difference in countries' CPI increases, with an expected reduction on FDI flows of 57.10 million US$ for a home-host country pair with 9 CPI units of difference. On average, an increase of one unit of corruption differences between a given home-host country pair implies a reduction of 150.77 million US$ a year, which represents a 16.03% reduction in FDI for the average home-host country pair. The regression coefficient $\gamma_{SME} = \left(\frac{1}{\lambda}\right)(10 - \delta)$ captures the effects of skill matching, $\frac{1}{\lambda}$, and also the level of transferability of these skills across countries, δ. Thus, the estimated SME effects in Table 6 can be interpreted as the pure SME effects if $\delta = 9$. This can be interpreted as the lower limit of the pure skill matching effect.

For comparison, we also analyze the economic significance of corruption under our linear OLS specification of Equation 10. According to this specification (Table 4), an increase of one unit in a host country's corruption implies an average decrease of 90 million US$ of yearly bilateral FDI flows through the CEE effect. This implies that MNCs reduce their investment flows on average by 9.5% for each unit decrease in the host country's CPI due to the higher cost of doing business in more corrupt economies.[26] Similarly, an increase of one unit in the difference between the CPIs of the home and host countries causes, through the SME effect, an average reduction of 60 million US$ in yearly bilateral FDI flows. This implies that, ceteris paribus, multinational corporations invest less in countries with dissimilar corruption levels, reducing their investments on average by 6.5% for each additional unit of corruption difference.

The Tobit estimation produces larger effects for both CEE and SME that are similar to those of the non-linear model. In the Tobit estimation (Table 4), a decrease of one unit in a host

[26] This estimate is of the same order of magnitude as the estimates of the corruption tax on foreign investors obtained by Wei (2000).

country's CPI implies an average decrease of 210 million US$ of yearly bilateral FDI flows through the CEE effect, a 22.33% reduction in average FDI flows. The SME effects imply that, for an increase of one unit in the difference between the CPIs of the home and host countries, the average FDI yearly flows decrease by 150 million US$, which represents a 15.95% reduction in average FDI flows.

To summarize, our most conservative estimates, based on the OLS model, predict an average reduction of 9.5% in FDI flows caused by an increase of one unit of corruption in the host country; and a 6.5% decrease in FDI for an increase in corruption differences between the home and host country. Other estimates place the reduction in the neighborhood of 20%.

E. Robustness Checks

In this subsection we address additional estimation issues to evaluate the robustness of our results. Given the large number of zero FDI flows, our results may be driven by sample selection bias. Suppose that the propensity of a home-country firm to invest in a given host country is determined by the variables in Equation 10. If this propensity reaches a given threshold value, we will observe FDI flows between these two countries. However, if this propensity is low we will observe zero FDI flows. In order to deal with this potential problem, we use the Heckman (1979) selection model. We model the FDI decision as a two-stage process. In the first stage the investor selects the host countries in which to invest. Then, in the second stage, she determines the amount to be invested. The first stage of the Heckman model is as follows:

$$FDI_{ij}^{*} = \alpha + \beta X_{ij} + \lambda_{CEE}\left(10 - C_j\right) + \lambda_{SME}\left|Ci - Cj\right| + \varepsilon_{ij} \qquad \textit{Eq. 13}$$

$$FDIprobit_{ij}^{*}=1 \; if \; FDI_{ij}^{*} \geq \kappa$$

$$FDIprobit_{ij}^{*}=0 \; if \; FDI_{ij}^{*} \leq \kappa$$

where FDI_{ij}^{*} is a non-observable variable that measures the incentives for MNCs in country i to undertake FDI in country j. MNCs in country i will invest in country j only if the factor endowments, trade and transport costs, country size, etc., and the levels of corruption in the two countries make the investment sufficiently advantageous. If the propensity to invest is larger than the threshold value, then we will observe FDI from country i to country j. $FDIprobit_{ij}^{*}$ is a dummy variable equal to 1 if country j receives FDI from country i and 0 otherwise. The variables X_{ij} and the corruption variables are defined as before, and ε_{ij} is the random error. We estimate the parameters of Equation 13 using Probit.

In the second stage we estimate the effect of corruption on the volume of bilateral FDI flows by controlling for sample selection. Specifically, we use a specification similar to Equation 10 although we add a selectivity regressor obtained from the first stage, yielding the following specification:

$$FDI_{ij} = \alpha + \beta X_{ij} + \lambda_{CEE}(10 - C_j) + \lambda_{SME}|Ci - Cj| + \lambda_{Mills} Mills_{ij} + \varepsilon_{ij} \qquad \textit{Eq. 14}$$

where FDI_{ij}, the dependent variable, is the observed positive FDI outflow from home country i to host country j measured in millions of US$. We include the variable $Mills_{ij}$, the selectivity regressor that controls for possible sample selection in our data. The selectivity regressor corresponds to the Inverse Mill's ratio of the fitted values of the first stage (Equation 13).[27]

[27] The independent variables included in the first stage regression (Equation 13) are not exactly the same as the ones included as explanatory variables in Equation 14. The use of exactly the same variables would lead to multicollinearity problems. Thus, we use a different measure of factor endowment differences for Equation 14. Following Egger and Winner (2006) we control for factor endowment differences using the absolute value of the differences between home and host countries per capita GDPs.

Results of these estimations are reported in Table 7. Once again, the coefficient for the SME is negative and significant in both models, meaning that both the likelihood and amount of FDI between two countries is negatively influenced by the differences in their corruption levels. The CEE as measured by the host-country corruption level coefficients is negative; less corrupt hosts are more likely to receive FDI and the inflows will be larger, while more honest home countries are more likely to undertake FDI, and, when they do, their investments are larger. In the first stage model, the coefficients for SME and CEE are of the same magnitude and same sign, which shows that the skill matching and general corruption environment effects both play a more or less equal role in determining the location of FDI. However, in the second stage model (labeled VOLUME in Table 7), the CEE effects are over five times as large as the SME effects, indicating that, once the decision to invest in a country is made, the size of the investment is much more sensitive to host-country corruption than to differences in home and host corruption levels. Comparing the results in Tables 4 and 7, the effect CEE and SME effects are larger in magnitude in Table 7 and, thus, our OLS estimates are still the most conservative ones.

Next, we consider the possibility of omitted-variables bias. If important country-specific variables are omitted from our regression and are correlated with corruption levels, our estimation results will be biased. Fortunately, our data is a panel and controlling for omitted variables can be done by including country fixed effects. Results controlling for home-country fixed effects are presented in Table 8, for the OLS, and Tobit Models (Equation 10) and the Heckman model of Equation 14.[28] Our results are robust to all specifications. Also note that, since inter-country distances are invariant over time, our estimates can be interpreted as

[28] We do not control for fixed effects in the Probit model since the dependent variable is not continuous. However the Probit model is the first stage of the Heckman selection model. We report Heckman model results controlling for fixed effects.

controlling for home-host country fixed effects as well, thus further insulating the results from missing variable bias.

Finally, we analyze the effect of including a different set of control variables. These include alternative specifications of the explanatory variables and the inclusion of additional variables proposed in the literature. First, in Table 9, columns 1 and 2, we follow Carr *et al*. (2001) and incorporate interaction terms in order to capture possible non-linear relations between variables that measure differences in endowments and trade barriers (column 1) and also include investment costs in the host country (column 2). We control for investment cost ($Investment\ Cost_j$) using the Fraser Institute's Economic Freedom of the World Index (EFWI). This index measures the extent to which the policies and institutions of a country minimize government regulation on business.

Third, Perez et al. (2012) find that host countries that are money-laundering centers tend to attract higher levels of FDI. Because money laundering activities may be related to home- and host-country corruption levels, failure to control for these effects could bias our results. We use the measure of money laundering compiled by Perez et al. (2012), $Money_j$, which is set to one if the host country is considered a money laundering center (Table 9, column 3).[29] The coefficient for $Money_j$ is positive and significant, meaning that countries that allow or facilitate money laundering do receive more FDI, but our results for CEE and SME remain negative and significant.

FDI can be also be motivated by similarities between home and host country economic environments, especially similarities in wealth and infrastructure. Cuervo-Cazurra and Genc

[29] In unreported results we also include interaction terms between the money laundering proxy and other control variables. Results are similar and available upon request.

(2008) address this issue, emphasizing possible advantages an MNE from a poor home country can gain from investing in a poor host country by using its experience serving low-income populations. Likewise, MNEs from home countries with inefficient markets or poor business infrastructure can have competitive advantages in countries with similar business environments. In order to control for these possible effects, we use countries' unemployment as a measure of the level of efficiency with which a country's markets function, and the number of internet connections for every 1000 habitants as a measure of the development of a country's infrastructure. Using these proxies we compute the absolute value of the differences between home and host countries and add them to our model as $Unemployment_{ij}$ and $Internet_{ij}$ (Table 9 column 4). The coefficient of differences in unemployment is negative and significant, confirming that similarities in market efficiency increase FDI flows; however differences in infrastructure do not have a significant effect. The last column of Table 9 reports the results for a model that includes all the variables in the previous columns and also controls for country fixed effects. Our main results are robust to these changes in specifications. The magnitudes of the SME and CEE effects are even larger than the basic linear OLS specification reported in Table 4, and thus our OLS results remain the most conservative ones.

Finally we note that Qian and Sandoval-Hernandez (2016) and Jain et al. (2017) suggest that the SME effect may not be either symmetrical or linear as in our formulation of the SME effect. Using our sample of countries and specifications we are not able to verify such asymmetry in many of the specifications that we use, and further research in needed to better understand the nature of the SME effect suggested by Dunning's work.

IV. Conclusions

In this paper we have developed and tested a theory of the influence of home- and host-country corruption on MNCs investment decisions. Our theory argues that corruption, or, more broadly, institutional quality has two effects on FDI decisions of MNCs. One effect works through the environment of the host country, which influences the costs to foreign MNCs of doing business in that environment. The second effect posits that corruption or institutional quality also shapes the abilities and skills of the firms to which that environment is home. Thus, corruption determines the organization and skills of the firms in the home country, and these skills may be useful in a similar foreign environment. Our results show that host-country corruption has a negative effect on the volume and likelihood of FDI inflows, and that these effects are, in economic terms, quite large. Our most conservative estimates show an average reduction of 9% in FDI flows for one unit deterioration in the host-country corruption level and the effects may be as large as 20%. Corruption also influences the skills that a firm acquires in its home-country environment; firms from corrupt countries will become adept at dealing with corruption while firms from less corrupt countries will be less adept. Thus, firms from a corrupt home country are able to transfer these skills to their affiliates in other corrupt countries, and this effect steers FDI toward countries with similar levels of corruption. We estimate that average FDI flows are reduced by at least 6% when the difference between home and host country corruption increases by one unit although, again, the effect may be larger. Given the magnitude of these effects, it is clear that reducing corruption can be an important way for host countries to increase inflows of FDI.

REFERENCES

Al-Sadig, A. (2009). The effects of corruption on FDI inflows. Cato J., 29, 267.

Armington, P. S. (1969). A theory of demand for products distinguished by place of production. *IMF Staff Papers*, 16(1), 159-178.

Athanasouli, D., & Goujard, A. (2015). Corruption and management practices: Firm level evidence. *Journal of Comparative Economics*, 43(4), 1014-1034.

Barnard, H. (2014). Migrating EMNCs and the theory of the multinational. In A. Cuervo-Cazurra and R. Ramamurthi, (Eds.) *Understanding multinationals from emerging markets*, 195-223. Cambridge University Press, Cambridge, UK.

Belloc, M. (2006). Institutions and international trade: A reconsideration of comparative advantage. *Journal of Economic Surveys*, 20(1): 3–27.

Branstetter, L., & Saggi, K. (2011). Intellectual property rights, foreign direct investment and industrial development. *The Economic Journal*, 121(555), 1161-1191.

Brada, J. C., Drabek, Z., & Perez, M. F. (2012). The effect of home-country and host-country corruption on foreign direct investment. *Review of Development Economics*, 16(4): 640-663.

Buckley, P. J., Clegg, L. J., Cross, A. R., Liu, X., Voss, H., and Zheng, P. (2007). The determinants of Chinese outward foreign direct investment. *Journal of International Business Studies,* 38: 499-518.

Carr, D.L., J.R. Markusen, & K.E. Maskus (2001). Estimating the knowledge-capital model of the multinational enterprise. *American Economic Review*, 91(3): 693-708.

Cuervo-Cazurra, A. (2006). Who cares about corruption? *Journal of International Business Studies,* 37(6):807-822.

Cuervo-Cazurra, A., & Genc, M. (2008). Transforming Disadvantages into Advantages: Developing-Country MNEs in the Least Developed Countries. *Journal of International Business Studies* 39: 957-979.

Di Guardo, M. C., Marrocu, E., & Paci, R. (2016). The effect of local corruption on ownership strategy in cross-border mergers and acquisitions. *Journal of Business Research*, 69(10), 4225-4241.

Dunning, J. H. (1998). Location and the multinational enterprise: A neglected factor? *Journal of International Business Studies* 29(1): 45-66.

Egger, P., & Winner, H. (2006). How corruption influences foreign direct investment: A panel data study. *Economic Development and Cultural Change*, 54(2), 459-486.

Ekholm, K., Forslid, R., & Markusen, J. R. (2007). Export-platform foreign direct investment. *Journal of the European Economic Association*, 5(4), 776-795.

Gelos, R. G., & Wei, S. J. (2005). Transparency and international portfolio holdings. The *Journal of Finance*, 60(6), 2987-3020.

Gordon, R., and Bovenberg, L. (1996). Why is capital so mobile internationally? Possible explanations and implications for capital income taxation. *American Economic Review* 86 (5), 1057–1075.

Grossman, G. M., Helpman, E., & Szeidl, A. (2006). Optimal integration strategies for the multinational firm. *Journal of International Economics*, 70(1), 216-238.

Habib, M., & Zurawicki, L. (2002). Corruption and foreign direct investment. *Journal of International Business Studies*, 33(2), 291-307.

Harding, T., & Javorcik, B. S. (2011). Roll out the red carpet and they will come: Investment promotion and FDI inflows. *The Economic Journal*, 121(557), 1445-1476.

Heckman, J. (1979). Sample selection bias as a specification error. *Econometrica* 47, 153–162.

Helpman, E. (1984). A Simple Theory of International Trade with Multinational Corporations, *Journal of Political Economy,* 92(3): 451-71.

Helpman, E. Melitz, M. J. & Yeaple, S. R. (2004). Export versus FDI with Heterogeneous Firms. *American Economic Review,* 94(1): 300-316.

Henisz, W. J. (2003). The power of the Buckley and Casson thesis: the ability to manage institutional idiosyncrasies. *Journal of International Business Studies*, 34(2), 173-184.

Hillman, A. J., & Hitt, M. A. (1999). Corporate political strategy formulation: A model of approach, participation, and strategy decisions. *Academy of Management Review*, 24(4), 825-842.

Jain, P.K., Kuvvet, E., and Pagano M.S. (2017). Corruption's Impact on Foreign Portfolio Investment. *International Business Review*,26(1):23-35.

Javorcik, B. S., & Wei, S. J. (2009). Corruption and cross-border investment in emerging markets: Firm-level evidence. *Journal of International Money and Finance*, 28(4), 605-624.

Kolstad, I., & Wiig, A. (2012). What determines Chinese outward FDI?. *Journal of World Business*, 47(1), 26-34.

Levchenko, A. A. (2007). Institutional quality and international trade. *Review of Economic Studies*, 74(3): 791–819.

Markusen, J. R. (1984). Multinationals, multi-plant economies, and the gains from trade. *Journal of International Economics*, 16(3-4), 205-226.

Markusen, J. R., & K. E. Maskus, (2002). Discriminating among alternative theories of the multinational enterprise. *Review of International Economics,* 10(4): 694-707.

McWilliams, A., Fleet, D.D., & Cory, K.D. (2002). Raising rivals' costs through political strategy: an extension of resource-based theory. *Journal of Management Studies*, 39(5): 707-724.

Mironov, M. (2015). Should one hire a corrupt CEO in a corrupt country? *Journal of Financial Economics*, 117:29-42.

Perez, M. F., Brada, J.C. & Drabek, Z. (2012). Illicit money flows as motives for FDI. *Journal of Comparative Economics*, 40(1)108-126.

Portes, R., Rey, H., (2005). The determinants of cross-border equity flows. *Journal of International Economics* 65 (2): 269–296.

Portes, R., Rey, H., Oh, Y., (2001). Information and capital flows: the determinants of transactions in financial assets. *European Economic Review* 45 (4–6): 783–796.

Pyo, M. C. (2010). Why firms provide goods to foreign markets using a combination of entry modes: Foreign direct investment and export. *Seoul Journal of Business*, 16(2), 67.

Qian, X., & Sandoval-Hernandez, J. (2016). Corruption distance and foreign direct investment. *Emerging Markets Finance and Trade*, 52(2), 400-419.

Scherer, F.M., Beckenstein A., Kaufer E., & Murphy, R. D. (1975). *The economics of multi-plant operation: an international comparisons study*. Harvard University Press, Cambridge, MA.

Smith, A. (1976). *An inquiry into the nature and causes of the wealth of nations, Vol. 1*, Oxford: Claredon Press.

Wei, S.J. (2000). How taxing is corruption on international investors? *Review of Economics and Statistics,* 82 (1), 1–11.

Yeaple, S. R. (2003). The complex integration strategies of multinationals and cross country dependencies in the structure of foreign direct investment. *Journal of International Economics*, 60(2): 293-314.

Yeung, H. W., & Liu, W. (2008). Globalizing China: The rise of mainland firms in the global economy. *Eurasian Geography and Economics*, 49(1): 57–86.

Table 1
List of Home and Host Countries

Home Countries (49): Australia, Austria, Belgium, Bulgaria, Belarus, Brazil, Canada, Switzerland, Chile, China, Cyprus, Czech, Republic, Germany, Denmark, Spain, Finland, France, United Kingdom, Greece, Croatia, Hungary, Ireland, Iceland, Israel, Italy, Japan, Lithuania, Latvia, Macedonia, Malaysia, Netherlands, Norway, New Zealand, Oman, Poland, Korea Republic of, Portugal, Romania, Russian Federation, Sweden, Thailand, Turkey, United States.

Host countries (167):

Afghanistan	Costa Rica	Indonesia	Namibia	South Africa
Albania	Croatia	Iran, Islamic Rep.	Nepal	Spain
Algeria	Cuba	Ireland	Netherlands	Sri Lanka
Angola	Cyprus	Israel	New Zealand	Sudan
Argentina	Czech Rep.	Italy	Nicaragua	Suriname
Armenia	Côte d'Ivoire	Jamaica	Niger	Swaziland
Australia	Denmark	Japan	Nigeria	Sweden
Austria	Djibouti	Jordan	Norway	Switzerland
Bahrain	Dominica	Kazakhstan	Oman	Syrian Arab Republic
Bangladesh	Dominican Rep.	Kenya	Pakistan	São Tomé and Princ.
Barbados	Ecuador	Kuwait	Palau	Tajikistan
Belarus	Egypt	Kyrgyzstan	Panama	Thailand
Belgium	El Salvador	Lao People's D.R.	Papua New Guinea	Togo
Belize	Equatorial Guinea	Latvia	Paraguay	Tonga
Benin	Estonia	Lebanon	Peru	Trinidad and Tobago
Bolivia	Ethiopia	Lesotho	Philippines	Tunisia
Bosnia and Herz.	Fiji	Liberia	Poland	Turkey
Botswana	Finland	Libya	Portugal	Turkmenistan
Brazil	France	Lithuania	Qatar	Uganda
Brunei Darussalam	Gabon	Luxembourg	Romania	Ukraine
Bulgaria	Gambia	Macedonia, FYR	Russian Federation	United Arab Emirates
Burkina Faso	Georgia	Madagascar	Rwanda	United Kingdom
Burundi	Germany	Malawi	Saint Kitts and Nevis	Unit. Rep. of Tanzania
Cambodia	Ghana	Malaysia	Saint Lucia	United States
Cameroon	Greece	Maldives	Saint Vinc. & Grenadines	Uruguay
Canada	Guatemala	Mali	Samoa	Uzbekistan
Central Afric. Rep.	Guinea	Malta	Saudi Arabia	Venezuela
Chad	Guyana	Mauritania	Senegal	Vietnam
Chile	Haiti	Mauritius	Seychelles	Yemen
China	Honduras	Mexico	Sierra Leone	Zambia
Colombia	Hong Kong	Moldova, Rep. of	Singapore	Zimbabwe
Comoros	Hungary	Mongolia	Slovakia	
Congo, D.R.	Iceland	Morocco	Slovenia	
Congo	India	Mozambique	Solomon Islands	

Table 2
FDI Descriptive Statistics

FDI in US million dollars.

Positive FDI Net Flows

Year	Observations	Average	Std. Dev.	Min	Max
2005	1368	800.567	4,932.819	0.000	130,765.400
2006	1390	780.986	2,939.207	0.000	44,599.010
2007	1491	1,171.411	5,148.907	0.000	109,097.000
2008	1390	1,157.029	4,472.900	0.001	58,256.120
2009	1236	752.840	2,800.976	0.002	42,974.000

Negative FDI Net Flows

Year	Observations	Average	Std. Dev.	Min	Max
2005	500	-472.139	2,172.313	-28,935.370	-0.000
2006	394	-306.876	1,554.924	-26,000.620	-0.000
2007	420	-345.678	1,509.095	-22,450.240	-0.000
2008	413	-331,076	1,547.091	-21,064.200	-0.000
2009	487	-403.373	1,561.671	-23,147.780	-0.000

FDI Sample Composition

	Observations	Percentage	Average
Negative FDI flows	2,214	6.63	-377.299
Zero FDI flows	24,321	72.80	0
Positive FDI flows	6,875	20.58	940.524
Total	33,410	100	168.535

Table 3
Corruption Statistics

Transparency International Corruption Perception Index (CPI)

Home Country CPI

Year	Observations	Mean	Std. Dev.	Min	Max
2005	6,803	6.20	2.35	2.40	9.70
2006	6,510	6.20	2.34	2.10	9.60
2007	6,552	6.23	2.19	2.10	9.40
2008	6,665	6.19	2.08	2.00	9.30
2009	6,880	6.16	2.11	2.20	9.40
All	33,410	6.19	2.22	2.00	9.70

Host Country CPI

Year	Observations	Mean	Std. Dev.	Min	Max
2005	6,215	4.14	2.19	1.70	9.70
2006	6,006	4.15	2.17	1.90	9.60
2007	6,384	4.06	2.12	1.70	9.40
2008	6,536	4.10	2.10	1.50	9.30
2009	6,708	4.14	2.15	1.30	9.40
All	31,849	4.12	2.15	1.30	9.70

Table 4
Corruption environment and the skill-matching effects and FDI

We report estimation results of the CEE and SME on FDI. The non-linear model in column (1) is as follows:

$$FDI_{j,i} = c\left(\frac{1}{1+\gamma_{CEE}(10-C_j)+\gamma_{SME}\,|C_i-C_j|}\right)+\beta X_{ij}+\alpha+\varepsilon_{ij}$$

The OLS (2) and Tobit (3) models are estimated based on: $FDI_{ij} = \alpha + \beta X_{ij} + \lambda_{CEE}(10 - C_i) + \lambda_{SME}|Ci - Cj| + \varepsilon_{ij}$. All control variables X_{ij} are described in the text. C_i and C_j are the home and host country CPI indexes. FDI is measured in billion USS$. t-statistics are in parenthesis. Tobit coefficients are marginal effects. Standard errors are robust to heteroskedasticity. *, **, *** indicate significance at the at the 10%, 5%, and 1% levels.

	(1) Non-linear	(2) OLS		(3) TOBIT	
Variables	Controls, CEE, and SME	Controls only	Controls, CEE, and SME	Controls only	Controls, CEE, and SME
c	2.34***				
	(7.32)				
γ_{CEE}	0.28***				
	(3.11)				
γ_{SME}	0.23***				
	(2.98)				
λ_{CEE}			-0.09***		-0.21***
			(7.76)		(7.34)
λ_{SME}			-0.06***		-0.15***
			(-4.60)		(-6.26)
$Skill\ Endowment_{ij}$	0.27***	-0.46***	0.34***	-6.24***	-3.91***
	3.02	(-9.79)	(5.77)	(-10.55)	(-8.33)
$Adjacent_{ij}$	1.28***	1.31***	1.30***	3.24***	3.23***
	(16.95)	(6.29)	(6.27)	(10.92)	(10.64)
$Distance_{ij}$	-0.02***	-0.02***	-0.02***	-0.21***	-0.20***
	(-8.65)	(-9.66)	(-9.28)	(-10.09)	(-9.98)
$\sum GDP_{ij}$	0.13***	0.14***	0.13***	0.58***	0.56***
	(29.54)	(9.65)	(9.38)	(11.36)	(11.27)
ΔGDP_{ij}	0.02	0.06**	0.02	1.02***	0.85***
	(0.80)	(2.46)	(0.95)	(8.27)	(7.57)
$Trade\ Cost_j$	1.01*	1.87***	1.02*	7.50***	4.83***
	(2.16)	(3.27)	(1.70)	(4.96)	(3.27)
$Trade\ Cost_i$	-0.32	-0.34	-0.08	23.71***	22.81***
	(-0.23)	(-0.38)	(-0.08)	(5.65)	(5.45)
$Corruption\ home$	-0.03***	-0.04***	-0.05***	-0.33***	-0.32***
	(4.94)	(-9.10)	(4.95)	(-12.05)	(11.94)
Observations	31,849	33,410	31,849	33,410	31,849
Adjusted R-squared	0.06	0.05	0.06	0.102	0.107

Table 5
Corruption environment and the skill-matching effects and FDI, Probit Model

We report estimation results of the CEE and SME on the location of FDI, based on a Probit model, as follows:

$$Pr(FDIprobit_{ij} = 1) = \Phi(\alpha + \beta X_{ij} + \lambda_{CEE}(10 - C_j) + \lambda_{SME}|Ci - Cj|)$$

All control variables X_{ij} are described in the text. C_i and C_j are the home and host country CPI indexes. We report estimated marginal effects and corresponding t-statistics in parenthesis. We use robust standard errors . *, **, *** indicate significance at the 10%, 5%, and 1% levels.

Variables	Controls only	Controls, CEE, and SME
λ_{CEE}		-0.01***
		(3.99)
λ_{SME}		-0.01***
		(-4.20)
$Skill\ Endowment_{ij}$	-0.39***	-0.35***
	(-27.03)	(-17.72)
$Adjacent_{ij}$	0.25***	0.26***
	(14.77)	(14.66)
$Distance_{ij}$	-0.01***	-0.01***
	(-24.99)	(-23.07)
$\sum GDP_{ij}$	0.04***	0.04***
	(35.04)	(33.19)
ΔGDP_{ij}	0.08***	0.07***
	(18.78)	(16.58)
$Trade\ Cost_j$	0.28***	0.24***
	(3.34)	(2.63)
$Trade\ Cost_i$	1.64***	1.59***
	(6.72)	(6.19)
$Corruption\ home$	-0.02***	-0.02***
	(-16.05)	(14.30)
Observations	33,410	31,849
Pseudo R-squared	0.102	0.107

Table 6
Economic Implications of SME and CEE

We report estimates of FDI flows motivated by the corruption environment effect (CEE) and the skill matching effect (SME) as predicted by our non-lineal model in Table 4, column 1. For the CEE we report the average reductions in FDI flows motivated by a unit increase in corruption (i.e. a unit decrease in CPI). Results are reported for host countries with different levels of CPI. For the SME we report the average reductions in FDI flows motivated by a unit increase in the difference in the level of corruption of home and host countries. Results are reported for home-home countries pairs with different levels of corruption differences. All numbers are in million US dollars. We also report the average percentage reduction as proportion of the average level of positive FDI flows.

CEE		SME	
Host CPI	FDI reduction	Corruption Differences	FDI reduction
1	-52.88	0	0
2	-62.41	1	-355.74
3	-74.78	2	-252.49
4	-91.22	3	-188.44
5	-113.75	4	-146.00
6	-145.78	5	-116.43
7	-193.53	6	-95.01
8	-269.23	7	-79.01
9	-399.90	8	-66.73
10	-655.20	9	-57.10
Average	-205.87	Average	-150.77
% average	-21.89%	% average	-16.03%

Table 7
Estimation using the Heckman selection model

We report regression coefficients for the Heckman (1979) selection model regressions. Volume represents results of the second stage regression controlling for possible sample selection. Location includes results of the first stage Probit model. We also report corresponding z-statistics in parenthesis immediately after. Standard errors are robust to heteroskedasticity. *, **, *** indicate significance at the 10%, 5%, and 1% levels

	Controls only		Controls, CEE and SME	
VARIABLES	Volume	Location	Volume	Location
λ_{CEE}			-0.56***	-0.02***
			(14.74)	(3.97)
λ_{SME}			-0.09**	-0.02***
			(-2.09)	(-4.23)
$Skill\ Endowment_{ij}$	-30.50***	-1.58***	-28.10***	-1.35***
	(-10.08)	(-27.72)	(-7.10)	(-17.42)
$Adjacent_{ij}$	1.69***	0.77***	4.00***	0.78***
	(7.20)	(15.46)	(12.16)	(15.43)
$Distance_{ij}$	-0.13***	-0.05***	-0.29***	-0.05***
	(-7.31)	(-25.99)	(-13.39)	(-23.94)
$\sum GDP_{ij}$	0.34***	0.15***	0.70***	0.15***
	(11.60)	(47.70)	(16.65)	(45.57)
ΔGDP_{ij}	0.50***	0.32***	0.95***	0.29***
	(4.62)	(20.35)	(7.22)	(17.90)
$Trade\ Cost_j$	11.50***	1.13***	39.69***	6.18***
	(6.48)	(3.42)	(3.21)	(2.65)
$Trade\ Cost_i$	24.92***	6.60***	0.04***	0.01***
	(3.22)	(6.04)	(4.59)	(5.58)
$Corruption\ home$	-0.27***	-0.07***	-0.36***	-0.07***
	(-10.25)	(-15.99)	(11.33)	(14.36)
Observations	33,410	33,410	31,849	31,849

Table 8
Regression controlling for Country fixed effects

We report regression coefficients for the linear OLS and Tobit models (Table 4) and the Heckman model (Table 8) controlling for home country unobservable fixed effects. All models include control variables and also the measures of the corruption environment and the skill-matching effects. We also report corresponding t-statistics in parenthesis immediately after. Standard errors are robust to heteroskedasticity. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

Variables	OLS	Tobit	Heckman Volume
λ_{CEE}	-0.08***	-0.14***	-0.53***
	(6.98)	(5.32)	(13.17)
λ_{SME}	-0.06***	-0.15***	-6.18***
	(-4.48)	(-5.45)	(-2.13)
$Skill\ Endowment_{ij}$	0.32***	-4.53***	-27.67***
	(4.63)	(-8.52)	(-6.82)
$Adjacent_{ij}$	1.32***	3.02***	4.14***
	(6.41)	(10.04)	(11.69)
$Distance_{ij}$	-0.02***	-0.22***	-0.31***
	(-8.46)	(-9.66)	(-12.39)
$\sum GDP_{ij}$	0.25***	0.29***	0.69***
	(6.26)	(6.10)	(13.82)
ΔGDP_{ij}	-0.11***	2.64***	1.76***
	(-3.00)	(8.63)	(8.57)
$Trade\ Cost_j$	1.62***	11.68***	11.68***
	(2.69)	(6.87)	(5.26)
$Trade\ Cost_i$	-2.55	-88.58***	11.84***
	(-1.50)	(-5.60)	(0.26)
$Corruption\ home$	-0.04	-0.06	-0.23
	(-0.90)	(-0.43)	(-1.21)
Observations	31,849	31,849	31,849
Adjusted R-squared	0.07		
Pseudo R-squared		0.166	

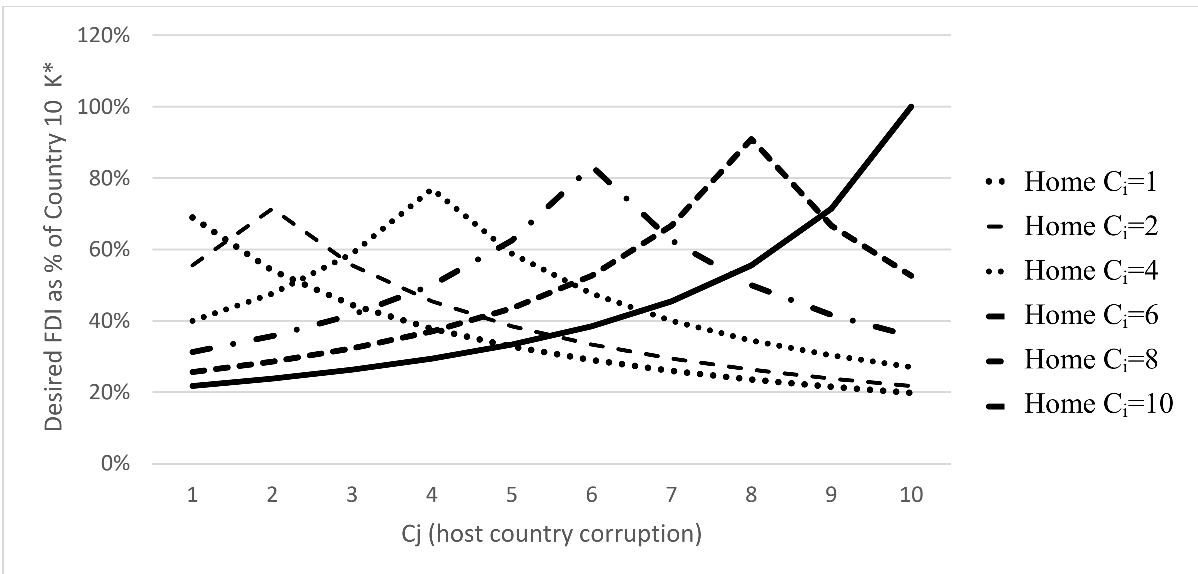
Table 9
Additional Robustness test

We report Tobit marginal effects coefficients for the model in Table 4, including several additional control variables as described in the text. t-statistics are in parenthesis and standard errors are robust to heteroskedasticity. *, **, *** indicate significance at the 10%, 5%, and 1% levels.

VARIABLES	(1)	(2)	(3)	(4)	(5)
λ_{CEE}	-0.27***	-0.28***	-0.23***	-0.28***	-0.24***
	(7.89)	(6.51)	(7.59)	(5.87)	(-5.30)
λ_{SME}	-0.06**	-0.02	-0.17***	-0.14***	-0.06*
	(-2.21)	(-0.75)	(-6.74)	(-4.93)	(-1.79)
$Skill\ Endowment\ (SK_{ij})$	-0.02	1.15**	-3.38***	-2.33***	0.37
	(-0.06)	(2.38)	(-7.69)	(-4.57)	(0.44)
$Adjacent_{ij}$	3.20***	3.21***	3.10***	3.25***	3.03***
	(10.66)	(10.61)	(10.47)	(10.13)	(9.42)
$Distance_{ij}$	-0.20***	-0.19***	-0.21***	-0.22***	-0.23***
	(-9.89)	(-9.82)	(-10.05)	(-9.58)	(-9.27)
$\sum GDP_{ij}$	0.72***	0.73***	0.52***	0.58***	0.38***
	(11.42)	(11.42)	(11.15)	(11.26)	(6.65)
ΔGDP_{ij}	0.81***	0.75***	0.43***	0.51***	2.15***
	(7.28)	(7.02)	(4.65)	(5.23)	(7.73)
$Trade\ Cost_j$	10.24***	11.31***	3.73***	4.40***	13.88***
	(6.19)	(6.09)	(2.64)	(2.64)	(7.15)
$Trade\ Cost_i$	17.11***	15.65***	16.29***	5.14	-89.15***
	(4.11)	(3.72)	(4.04)	(1.05)	(-5.05)
$Corruption\ home$	-0.22***	-0.20***	-0.30***	-0.32***	0.31*
	(9.34)	(8.47)	(11.68)	(10.89)	(1.70)
$(GDP_i - GDP_j) * SK_{ij}$	-0.96***	-0.97***			-0.95***
	(-8.49)	(-8.27)			(-4.57)
$Trade\ Cost_j * SK_{ij}$	-0.11***	-0.21***			-131.43***
	(-4.66)	(-5.88)			(-2.83)
$Investment\ Cost_j$		0.00			
		(0.22)			
$Money_j$			1.27***		0.74***
			(9.86)		(6.36)
$Unemployment_{ij}$				-0.05***	-0.02***
				(-5.46)	(-2.63)
$Internet_{ij}$				-0.00	-0.00
				(-0.87)	(-0.24)
Observations	31,849	30,026	31,849	19,540	19,540
Pseudo R-squared	0.112	0.110	0.111	0.0803	0.135

Figure 1
Desired Capital Stock K_{ij}^*

The figure shows the desired capital stock K_{ij}^* in host country j from home country i, as function of countries corruption classification. K_{ij}^* is measured as % of capital stock desired by least corrupt country (i.e. with corruption index 10) from its own country multinational ($K_{10.10}^*$).



Note: δ= 2, λ= 180.