Corruption and Multinational Investment:
Micro-foundations and Empirical evidence

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Abstract

How multinational corporations' (MNCs) investment decisions are affected by countries' corruption levels? In this paper, we develop a model to study the interaction between multinational corporations (MNCs) and the level of corruption in their home and host countries. The model predicts that host country corruption tend to reduce the likelihood and size of multinational investments. Moreover, our model also shows that, ceteris paribus, MNCs have incentives to invest in countries with similar levels of corruption as their home country. MNCs develop skills for dealing with corruption, and these skills become a valuable competitive advantage as they can be used in other nations with similar corruption levels. We empirically test the model's predictions using data on foreign direct investment from 49 home countries to 167 host countries for the period 2005-2009.

I. Introduction

How corruption influences multinational corporations' (MNCs) decisions to invest in a foreign country? In general, countries corruption level is viewed as deterrent for multinational capital, since corruption is viewed as an additional cost of doing business for foreign investors.[1] However, the empirical evidence on the relation of corruption and foreign direct investment (FDI) is mixed.[2]

We argue that the relation between corruption and MNCs foreign investment is more complex that a simple linear negative relation in which more corrupt countries receive less investment. While more corrupt environments may reduce MNCs' incentives to invest, ceteris paribus, differences in the corruption level between home and host countries also can reduce these incentives. MNCs in more corrupt environments may have developed a specific set of "skills" that can be transferable to other countries with similar level of corruption. If both home and host country have similar levels of corruption, the skills learned in the home country can provide valuable competitive advantages. In this paper, we propose a model that incorporates these two channels in which corruption influences MNCs investment decisions; we refer to these two channels as the corruption environment effect, and the skill-matching effect. Our model predicts that the combined effects of corruption environment and skill-matching lead to a nonlinear relation between corruption and MNCs investment.

We empirically test our model using data on Foreign Direct Investment (FDI) between 49 home countries and 167 host countries for the period 2005-2009, with corruption levels ranging from

[1] See Al-Sadig (2009) for a review of some of this extensive literature.

[2] For example, Hinnes (1995) and Javorcik and Wein (2009) find a negative effect of corruption on foreign direct investment, but Henisz (2000) a finds not significant or positive effect.

1.30 to 9.70.[3] Our results confirm that both corruption levels and differences in corruption levels between home and host countries influence the likelihood and size of FDI flows between any two countries. Low levels of corruption in host countries lead to larger and more frequent FDI outflows while low levels of corruption in host countries also have a positive effect on the frequency and size of FDI inflows. Differences in home and host country levels of corruption also affect the likelihood and size of bilateral FDI. The larger the differences in national corruption levels, the less likely and smaller are is the FDI between the countries, a result that is consistent with our model.

Our model is motivated on the theoretical and empirical literature on MNCs decisions, FDI and corruption. The first effect, the economic environment effect, follows from studies that examine the influence of corruption on the cross-country pattern of FDI (Wheeler and Mody, 1992; Hines, 1995; Wei, 2000). In corrupt countries, firms face dangers of predation by both the government and by private agents, a lack of protection for their property, including intellectual property, and an environment where contracting and exchange with other economic agents is both costly and subject to considerable risk. Such an environment imposes costs on firms and thus productivity and innovation suffer. As a result, foreign investors are less likely to invest in such countries. On the other hand, firms from countries with good institutions, where corruption and predation are controlled, will be more attractive to foreign investors and have firms better equipped and more inclined to undertake investments.

[3] Data sets often used for MNCs decisions, at the firm level just incorporate few countries, thus very low variation in corruption levels

This economic environment effect can also be understood as an information asymmetry effect. The negative effects of information asymmetry on capital flows have largely documented in the literature (Portes et al., 2001; Portes and Rey, 2005; Gelos and Wei, 2005). If information asymmetry constitutes an obstacle for capital flows across countries[4], then high levels of corruption are likely to exacerbate this information asymmetry problem, thus host countries with higher level of corruption, may receive less foreign investment from MNCs.

The idea behind the skill-matching effect is linked to Adam Smith[5] early observations with respect to capital mobility discussed by Gordon and Bovenberg (1996). Foreigners lack of knowledge of the country economic prospects, institutions, local customs and laws may lead to a less efficient use of resources, thus may discourage foreign investment. Therefore, capital flows are more likely to occur among countries with similar institutions, laws an economics prospects. However, as explained by Dunning (1998), MNCs' location in a given home country forces them to develop skills to be successful in the local environment and these skills acquired at home can become a source of competitive advantage abroad. This basic principle can be applicable to the skills to deal with corruption. Firms in corrupt countries will learn how to best deal with an environment characterized by predation, uncertainties in the security of transactions and ambiguous property rights. Conversely, they are less likely to seek to develop firm-specific advantages such as proprietary technologies, brand names, etc. since these will be largely unprotected in their home countries. Such skills may be transferable to other countries where the

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[4] Examples of empirical test on the negative effects of information asymmetries on capital flows are Portes et al., 2001; Portes and Rey, 2005; Gelos and Wei, 2005.

[5] See Adam Smith (1976 p. 454)

firm undertakes 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, the home country skills will yield smaller competitive advantages. Firms in countries with low levels of corruption will have little experience and ability in dealing with a corrupt environment, but they will seek to develop firm-specific assets such as proprietary technology, brand names, etc. as the means for competing with other firms in their home country.

The skill-based effect is related with the literature on the influence of the home country environment often discussed in the context of MNC-host government relations (Luo, 2006; Buckley *et al.,* 2007; Cuervo-Cuzarra and Genc, 2008).[6] Dealing with a corrupt and bribe-seeking government in its home country provides the MNC with both the skills for, and lack of aversion to, negotiating with or even bribing officials in host countries in which they may be considering investments. Firms from less corrupt countries will lack these skills, and thus are less likely to find potential investments in corrupt economies attractive. This is borne out by studies by Sima-Eichler (2006) and Cuervo-Cazzura (2006), who find that home countries that impose sanctions on their MNCs that engage in bribery abroad experience a reduction of FDI to corrupt countries.[7] Cuervo-Cazurra (2006) also finds that investors from corrupt home countries have relatively higher levels of FDI in corrupt host countries. Cuervo-Cuzarra and Genc (2008)

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[6] Thus Luo (2006) writes that "relationships with (host country) governments are critical" (p. 747) because "political or governmental corruption is often the main origin or cause of widespread corruption in the whole society" (p. 750).

[7] These home countries have signed the OECD Convention on Combating Bribery of Foreign Public Officials or are subject to the US Foreign Corrupt Practices Act.

emphasize that MNCs from such corrupt countries often lack the firm-specific competitive advantages such as technology, brand name, organizational skills, etc. that characterize firms from less corrupt economies. The lack of these advantages reflects the fact that corrupt home countries are often also less-developed countries.

In the next section of this paper, we present our theoretical model of corruption and MNCs investment. 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. General Model of Corruption and MNCs' Competitive Advantage

In this section we develop a model that shows how firms' skills in dealing with home country corruption are competitive advantages when they undertake investments in similarly corrupt host countries; but may be disadvantages when they invest in other host countries with very different levels of corruption. We refer to this effect as the skill-matching effect. We also consider the influence that a host nation's corruption environment has on the incentives of MNCs investment independent of the skill-matching effect.

The skill-matching effect, in our model is based on Dunning's (1998) well-established theory that an MNC's location in a given home country forces it to develop skills that enable it to be successful in the local environment and that these skills acquired at home can become a source of competitive advantage abroad. Dunning's (1998) argument suggests that firms that operate in corrupt home-country environments are likely to succeed if they develop skills and assets appropriate to that environment, meaning skills in dealing with an environment that provides little in the way of legal protection for firm-specific assets such as technology, brand names, etc. Instead, firms in these environments benefit from developing firm-specific skills for dealing with corrupt environments and from investments in their relations with politicians, but they will find investments in firm-specific advantages in technology, branding, etc. to be of little competitive value.

Similarly, firms in countries characterized by low levels of corruption will find making investments in bribing politicians, stealing rivals' technology, etc., of little competitive value while investments in technology, brand name, etc., that confer competitive advantages in a non-corrupt environment will have a higher payoff. It follows then that firms from countries that are intermediate in the corrupt-non-corrupt ranking scale will find it advantageous to invest in both types of assets. Consequently, MNCs from corrupt home countries will find it difficult to invest in host countries with low levels of corruption because competition in those countries is based on the possession of firm-specific advantages in technology, brand names, etc. Firms from low-corruption countries will find that the firm-specific advantages they have developed in their home countries will be less useful in competing with rivals in corrupt countries. If all firms are identical except in the degree to which they are skilled in dealing with corruption, investment will only be possible if firms in the home or source country have developed skills for dealing with corruption to more or less the same degree, as have firms in the host country. There is clear evidence that such skills developed in the home (source) country then carry over to their ability to operate in similar environments in potential host countries (Hillman and Hitt, 1999; McWilliams, et al., 2002; Henisz, 2003).

To sharpen the focus on the role played by differences in cross-country corruption levels, our model makes number of simplifying assumptions that make home and host country corruption levels the only determinant of the pattern of bilateral FDI. Specifically, we assume that all nations are identical in terms of size, available production technologies, consumer preferences, endowments, etc. They are assumed to differ only in the level of corruption that prevails throughout the entire economy. Consequently, countries are distinguished by a value between 1 and 10 where a value of 1 signifies that a nation is most corrupt and a value of 10 signifies one that is least corrupt. To simplify the analysis, we assume that an equal number of the world's nations fall within each of the ten corruption categories.[8] Additionally, we treat the skills, experience or knowledge in coping with corruption as like a public good: its transfer and employment in another nation does not diminish the amount available for use elsewhere.

Each nation serves as the home base for a group of MNCs that produce at home and abroad. Each of these groups is identified or referenced by their home country as in terms of *American* multinationals or *French* multinationals, etc. Moreover, from the perspective of consumers, the output of country 1's MNCs is similar to, but also different from, the outputs of the other nine multinational groups operating in the host country. That is, in each host country, consumer preferences are Armington-like in that the product produced domestically by the home nation's multinationals and those produced by firms with parents 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. Ignoring products outside this broad grouping, we adopt Cobb-Douglas preferences, where consumers spend a fixed share, β_i, of their budget (Y) on each of the ten goods:

$$U = \prod_{i=1}^{10} X_i^{\beta i}$$

where $\sum \beta_i < 1$. The advantage of this particular specification is that it yields simple product demand functions:

$$D_i = \beta_i Y \left(\frac{1}{P_i}\right) \qquad i = 1, \ldots, 10 \qquad Eq. 1$$

[8] The ranking is motivated by Transparency International's Corruption Perception index that ranks nations in a similar way.

where P_i s the price of good i. Again, for simplicity, in the ensuing analysis we assume that the β_i are identical and thus drop the subscript.

The production side of the model is also stylized. By assumption, all firms within this 'manufacturing' product segment populated by these ten groups of multinationals share the same Cobb-Douglas production technology:

$$Qi = A\, K_i^{\alpha k} L_i^{\alpha l} \qquad i = 1, \ldots, 10$$

where αk and αl are, respectively, the capital and labor factor shares. The advantage of this production function is that it yields a tractable conditional factor demand function for capital. Letting w and r represent, respectively, the wage and rental rate on capital, the solution to the standard cost minimization problem yields the following demand for capital:

$$Ki = \left[\frac{w\, \alpha k}{r\, \alpha l}\right]^{\alpha l / (\alpha l + \alpha k)} \left[\frac{Qi}{A}\right]^{1/(\alpha l + \alpha k)}$$

which simplifies to

$$Ki = \left[\frac{w\, \alpha k}{r\, \alpha l}\right]^{\alpha l} \left[\frac{Qi}{A}\right] \qquad i = 1, \ldots 10 \qquad Eq. 2$$

if $\alpha k + \alpha l = 1$. These expressions, known as conditional input demand equations, indicate each investing firm's optimal or desired capital stock.

Having described the production and demand side of the model, 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 accurate, for instance, 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.[9]

In the analysis that follows below, we assume that two broad influences impact the magnitude of the corruption tax that a multinational from country j faces when operating its affiliate in country i. This tax, denoted as τij, will reflect the skill-matching identified by Dunning's (1998) and the corruption environment effect. We model each effect as follows.

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. The more similar the source and receiving nation's corruption ratings, the lower the value of $|Ci - Cj|$ and hence the lower the tax. Alternatively, the more dissimilar the respective ratings, the higher the value of $|Ci - Cj|$ and the higher the tax. Again, this specification reflects the hypothesis that multinationals are more successful in overcoming corruption in their new production location if they originate from a nation characterized by a similar level of corruption.

[9] 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.

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 those in a different setting. In other words, the corruption-tax level may be low if the host and source nation have a 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 a specific level of corruption are unique to that environment, that is, 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 applicable in a nation with a corruption classification only one level higher (corruption level 4) or lower (corruption level 2). On the other hand, if the skills are more transferable across a broader range of corruption environments, so that δ has a higher value, say 5, then skills learned in a nation with one level of corruption may be at least partially applicable in a host nation with a corruption classification that is somewhat different from that of the home country. In the extreme, skills learned in a host country could be so highly applicable in any 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) where δ is assumed to range from 1 to 10. Putting these two elements together, the skill-matching (SM) component of the corruption tax is

$$SM = 1 + (\tfrac{1}{\lambda})(10 - \delta)\,|Ci - Cj|$$

where λ is a scalar used to limit the maximum corruption "tax" rate. Specifically, as in our numerical examples below, if we set λ = 180, then the maximum "tax" rate is 45%, which occurs when δ = 1 and $|Ci - Cj|$ = 9.

The corruption environment (CE) component is straightforward to model. Clearly, all else the same, a host nation with a higher level of corruption should be impose greater costs on firms than one with less corruption. Thus,

$$CE = (\frac{1}{\emptyset})(10 - C_i)$$

where ϕ is a scalar also used to set the maximum tax rate. For instance, if ϕ = 20, the maximum tax rate is limited to 45%, which occurs when C_i = 1. Combining SM and CE, we have

$$\tau ij = 1 + \left(\frac{1}{\emptyset}\right)(10 - C_i) + (\frac{1}{\lambda})(10 - \delta)\,|Ci - Cj|$$

The final set of assumptions pertains to the market conditions under which the various firms operate. Essentially, we abstract from general equilibrium effects. First, the home and multinational firms are price takers in the host-nation product and factor markets. This means that all firms 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 of these firms share the same unit cost. Again, the analysis gains little from moving to a general equilibrium setting. The competitive pricing conditions are

$$P_{h,i} = \left[\frac{w}{\alpha l}\right]^{\alpha l} \left[\frac{r}{\alpha k}\right]^{\alpha k} \left[\frac{1}{A}\right] = c \qquad \text{Eq. 3a}$$

for the home product and

$$P_{m,j} = \left[\frac{w}{\alpha l}\right]^{\alpha l} \left[\frac{r}{\alpha k}\right]^{\alpha k} \left[\frac{1}{A}\right] \quad \tau ij \; = \boldsymbol{c}\,\tau ij \qquad \text{Eq. 3b}$$

for the output of the multinational firms. Parenthetically, note that corruption potentially rises the multinational firms' product price in the host country and this reduces host-country demand for the product. As we noted earlier, corruption could reduce the production 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 similarity 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 Equations 3a and 3b, the price equations, into the set of product demand equations identified as Equation 1. Doing so allows us to determine the values of the Q_i's or industry outputs for the home firms and each of the multinational sectors. These values are in turn substituted into the conditional factor demands as given by Equation 2 to obtain, K*, the desired stocks of home-country firm's and multinational firms' capital:

$$K_i^* = \left(\frac{1}{\tau ij}\right) \left(\frac{\beta Y}{r}\right) \left[\frac{\alpha k}{\alpha l}\right]^{\alpha l} / \left(\left[\frac{\alpha l}{\alpha k}\right]^{\alpha k} + \left[\frac{\alpha k}{\alpha l}\right]^{\alpha l} \right) = \boldsymbol{c} \left(\frac{1}{\tau ij}\right)$$

It is evident that the K*s are functions of corruption levels across countries as captured by the τij term. Note that in the absence of corruption, τij = 1, and the desired capital stock for both source and host nation multinationals be the same and would reflect traditional considerations such as factor prices, technology and demand.

Note that if the only channel through which corruption influences the optimal capital stock is through skill matching, then the optimal capital stock K_i^* in county i is highest for the host country multinational since τij = 1. If we divide the desired level of the capital stock for a multinational from home country j by that for the host country multinational, we obtain an indicator of the extent of foreign firms' desired investment relative to the corresponding level for the host country multinational. Table 1, Panel A and B show the results from this calculation for δ = 2 and δ = 8, respectively. The calculations reported in the Tables are also illustrated in Figures 1a and 1b. Two patterns are immediately evident. First, excepting the two end values of corruption, 1 and 10, each row has an inverted-U shape in both Tables. The largest desired size of affiliates in the host country occurs when the source-country corruption level is closest to the corruption level of the host nation. The second pattern is that the higher δ, that is, the greater the span or range over which skills coping with corruption are applicable, the higher the MNC investment in any given country. For instance, the second entry in row 1 of Table 1 Panel A indicates that MNCs from source country 2 only desire a capital stock that is 71% of the host country's investors, whereas in row 1 of Table 1b, these multinationals desire 91% of the host country investors' capital stock. If MNCs' skills at dealing with corruption are applicable over a broader range of host-country environments, as in Table 1b, corruption in the host country has a less dampening effect on the desired stock of investment. Thus, in Table 1 Panel B all the percentages are higher than those in Table 1 Panel A. These patterns are also clearly visible in Figures 1a and 1b.

Figure 2 adds the general corruption environment effect to the skill-matching effect. The results in this Figure should be compared to those in Figure 1. The lines for each host nation still have peaks, but the peaks occur at higher and higher levels as we move rightward. This means that MNCs from less corrupt countries will desire larger affiliates in other less corrupt countries than they would in more corrupt countries even if the differences in corruption level are 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 each home country will invest in all potential host countries. Although the predicted investment in some hosts may be a very small fraction of the size of the parent company's home country's desired capital stock in its home country, thus foreign affiliates will be very small relative to the parent firm. However, there is a large literature on the way in which MNCs chose to serve foreign markets, either through FDI or through exports (see Pyo, 2010). This literature suggests that there is a minimum 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 means of serving this market and no FDI will take place. 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. The effect of this assumption on the model's predicted bilateral FDI is shown in the last row of Table Panel A. If we assume that the required minimum desired capital stock in any host country is 33 percent of the host nation's optimal investment, then the last row shows how many MNCs choose to enter a particular nation's host market through FDI. In cases where MNCs face large differences in corruption levels between home and host countries will choose not to undertake bilateral FDI reducing the total number of investors in countries that are the most and least corrupt while nations with a moderate amount of corruption tend to attract a larger number of investors.

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 be less likely to take place altogether. Moreover, countries with either very high or very low levels of corruption may also expect to receive or undertake fewer investment projects in total, but less corrupt countries will undertake larger FDI projects than do more corrupt ones.

III. Empirical Test

In this section we focus on empirically testing the predictions of our model for corruption and MNCs investment decisions. Our tests are based on foreign direct investment flows data, from UNCTAD FDI database, for the period 2005-2009. We choose country FDI data for our test, since the testable predictions of our model require a sample that has sufficient variability of corruption levels. Our sample includes FDI data for 49 home countries and 167 host countries, with corruption levels ranging from 1.30 to 9.70 (see Table 4). Data sets often used for MNCs decisions, at the firm level just incorporate few countries, thus very low variation in corruption levels.

The model developed in Section II was sufficient to demonstrate the effects of inter-country differences in corruption on MNCs investment decisions. However, the model assumes that all countries are the same, in the sense of country size, endowments, level of development, location, etc. In our empirical work, we embed the theoretical insights of our model into a broader empirical model of MNCs investment, the so-called Knowledge-Capital Model of the Multinational Enterprise, or KK model, in order to account for the effects of these other drivers of FDI as well.

A. The Knowledge-Capital Model of the Multinational Enterprise

Theoretical models of trade and multinational firms distinguish between two types of multinational corporations (MNCs). Vertical MNCs engage in trade and seek to exploit international factor price differentials. They locate their headquarters in the skilled labor-abundant home country and engage in unskilled labor-intensive production in an unskilled labor-abundant host. This reflects the firm's desire to locate operations in foreign countries in order to obtain access to low-priced non-tradable or hard-to-trade inputs (Helpman, 1984; Helpman and Krugman, 1985). Horizontal MNCs seek to save on trade costs by serving markets locally rather than trading. This results in higher fixed investment costs than those incurred by exporting national firms (Markusen, 1984; Markusen and Venables, 2000).

The recent literature consider both, vertical and horizontal motivations in the ''knowledge-capital'' (KK) model of MNCs (Carr et al., 2001; Markusen, 2002). Depending on factor endowments, as well as on trade and investment impediments, the equilibrium configuration of horizontal and vertical MNCs and of national firms is endogenously determined.[10]

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[10] The role of hybrid or ''complex'' MNEs, which are neither purely horizontal nor purely vertical, has been emphasized by Ekholm et al. (2003), Grossman et al. (2003), Yeaple (2003) and Egger et al. (2004).

The econometric specification of the KK model proposed by Carr, et al. (2001), combines "horizontal" and "vertical" motivations for FDI. The model includes variables related with absolute and relative country size, bilateral trade costs, relative factor endowment and investment cost differences as key drivers of FDI. Specifications of the KK model often include additional variables such as tax policies and political risk that are specific to the FDI process and we consider some of these in our robustness tests.[11]

According to the knowledge-capital model (KK), the main drivers of FDI are: (1) absolute and relative country size, (2) transportation costs (distance) as well as foreign plant set-up costs, and (3) relative factor endowment differences. The larger the home and the host countries' GDPs, the more probable it is that there should be FDI flows from country *i* to country *j* because a large host-country domestic market creates opportunities for capturing economies of scale and scope that promote the exploitation of firm-specific competitive advantages based on R&D, branding and the finer subdivision of production. A larger host-country GDP attracts FDI because the costs of undertaking FDI are to some extent fixed, and thus investors will find larger host countries more profitable if they wish to expand sales at the least cost. Large economies are also likely to have a greater variety of specialized factors of production and resources that the foreign investor will find attractive. Following Egger and Winner (2006) we use the following variables to control for relative country size:

$$SUM_{ij} = GDP_i + GDP_j$$
$$GDP2_{ij} = 1 - (GDP_i / SUM_{ij})^2 - (GDP_i / SUM_{ij})^2$$

[11] Blonigen (2005) provides an argument for including such additional variables in the gravity equation specification as well as a discussion of the gravity equation's shortcomings.

where GDP_i and GDP_j are the GDPs of the home and host countries in billions of 1995 US$ respectively.

The role of distance between countries is ambiguous. On one hand, FDI is used to overcome high transportation costs for low-value bulky goods or for non-tradable services, and, in this case, distance between the home and host countries has a positive effect on FDI. On the other hand, proximity also has a positive effect on FDI because proximity implies similar tastes and consumption patterns, promoting FDI that will increase sales in the host country. The literature on FDI suggests that not only is proximity a driver of FDI, but that adjacency of the home and host countries is also a particularly important stimulus to FDI. Consequently, in our model we use both distance and adjacency as separate explanatory variables so that:

$DIST_{i,j}$ = distance between the capitals of countries i and j

$ADJ_{i,j}$ = 1 if countries i and j are adjacent, 0 otherwise

The existence of international factor endowment differences is also an important motive for FDI (Helpman 1984; Markusen and Maskus 2002). As a measure of differences in skill endowments we use the differences between home and host countries values in the Human Development Index (HDI). The HDI has been published since 1990 by the United Nations Development Programme in their *Human Development Reports*. The HDI aims to provide a broader characterization of "development" by aggregating country-level attainments in life expectancy and education as well as income levels. Our measure of skill endowment differences, based on the HDI, is defined as follows:

$$SK_{ij} = HDI_i - HDI_j$$

The second set of drivers of FDI according to the KK model is home- and host-country trade costs. We use a host country's imports as percentage of GDP of the host country as a measure of host- country trade costs such as tariffs, and we call this variable $TChost_j$. For home-country trade costs we use the home-country external balance of goods and services and refer to this variable as $TChom_i$. Higher trade costs in the host country should stimulate FDI, as foreign firms will seek to serve the market through affiliates rather than through trade. Higher trade costs in the home country will make resource-seeking FDI less attractive for home country firms because they will find it more difficult to import components, parts and finished goods from foreign affiliates into the home country.

Our benchmark model will incorporate the all the KK variables described above. In order to test the empirical implications of our general model of corruption and MNCs competitive advantage as described in Section II, we will incorporate measures of corruption to the KK model.

B. Data

The explanatory variables described above come from the World Bank's *World Development Indicators* CD-ROM. Like many of the studies cited of bilateral FDI mentioned above, our home and host country corruption measure is the Transparency International corruption perception index (CPI).[12] The bilateral investment flows, measured in US $, are taken from the UNCTAD FDI database, and we employed data for 2005-2009. There are 43 home

[12] Cuervo-Cazurra (2006), Smarzynska and Wei (2002) 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.

countries (see Table 2) and 167 host countries. The home countries encompass a broad variety of country sizes, locations, levels of development and corruption levels. The host countries include a large proportion of existing countries. The bilateral distances are obtained from the French Research Center in International Economics' (CEPII) Geodist data set.

Descriptive statistics of the FDI flows in our sample are presented in Table 3. Positive FDI flows represent 20.58% of our sample, negative flows are 6.63% of all observations, and, thus, 72.80% of observations consists of zero FDI flows. There is significant time variation in FDI flows. Positive flows peak in average size in 2007and 2008, with the average bilateral investment flow close to 2 billion dollars, although the spread, as is to b expected is quite large. Positive flows drop to 752 million dollars in 2009 largely due to the global financial crisis. Negative investment flows, meaning either divestitures or a decline in the value of foreign affiliates account for a small part of our observations and the dollar value of these flows is small relative to the positive investment flows. In Table 4 we present descriptive statistics of the corruption index by year and host or home country. The average index is stable over time for both host and home countries. There is a difference between the average level of corruption of home and host countries. Home countries have a higher average corruption index, i.e., they are less corrupt than are the host countries. Nevertheless, Table 4 also shows that both home- and host-country samples encompass countries with a broad range of corruption levels.

C. Estimation

The theoretical results on section II imply that the skill-matching effect and the corruption environment effect have a negative relation with desired levels of multinational firms' capital. Following our theoretical model, we define the skill-matching and corruption environment variables as follows:

$$SM = 1 + (\frac{1}{\lambda})(10 - \delta)\,|Ci - Cj| = |Ci - Cj|$$

$$CE = (\frac{1}{\emptyset})(10 - C_i) = 10 - C_i$$

The variables C_i and C_j are home and host countries' CPI indexes. The parameters λ and $\emptyset$ are simply scalars defined to limit the values of the parameters in the simulations of the theoretical model, thus can be omitted without loss of generality. Similar case is the number 1, in the *SM* equation. The parameter δ is defined as the 'breadth' or span of applicability of the skills learned in one country to those in a different country. Thus it is possible that δ is different for any pair of countries. We assume that δ is constant in our empirical exercise, since reliable identification of this parameter will require a longer panel. Our results of the effect of *SM* on FDI, should be interpreted the effects for an average δ.

In order to control for possible effects of corruption of the home country we also include in our estimation a control variable for the corruption level of the home country: $Home\ corr = 10 - C_j$. Including the KK-model of MNCs and the corruption effects, the optimal level of FDI flows can approximated by the following equation:

$$FDI = \alpha + \beta KK_{ij} + \lambda_1 SM + \lambda_2 CE + \lambda_3 Home\_corr + \varepsilon_{it} \qquad \text{Eq (4)}$$

Where KK variables include: $SK_{ij}, ADY_{ij}, DISTL_{ij}, SUM_{ij}, GDP2_{ij}, TChost_{ij}, \mathrm{TChome}_{ij}$; as described before. According to our model, less corrupt countries will attract larger FDI flows. But, more important, we expect to observe larger FDI flows for countries with similar corruption levels, and the coefficient of the variable SM captures this effect.

Estimating the KK model of bilateral FDI flows presents some econometric issues. One such issue is the fact that many bilateral investment flows are zero because there are no investment flows between many countries in a given year and there are also negative flows, for example in cases where foreign affiliates are sold off to host-country investors. To better accommodate the nature of our FDI data and to test for the robustness of our results, we use three different estimation methods. We estimate the KK model using OLS with all FDI flows, including all positive, negative and zero FDI observations; using a Probit estimation where FDI= 1 if a bilateral FDI flow is positive and 0 otherwise; and a Tobit estimation, where the censoring is at 0. Estimation results using OLS, Probit and Tobit models are reported in Table 5.

The parameter estimates for the KK model are significant and in accord with theoretical expectations. While, for all three models, the inclusion of the corruption variables does not change the KK parameter estimates much, the Corruption Environment effect (CE) coefficients are negative and significant across the three estimation methods. Thus this negative coefficient means that more corrupt countries receive smaller FDI inflows[13], as our model predicts.

Also, the coefficient for the skill matching effect SM is negative, meaning that the greater the difference in corruption levels, the less likely or smaller FDI will be. Note that the

[13] or in the case of Probit are less likely to receive a greater number of FDI inflows

coefficients for CE and SM are similar in magnitude. This 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. Finally, the coefficient of the home-country corruption index is also negative and significant, which may imply that less-corrupt home countries have larger MNCs, and thus more incentives to have larger foreign affiliates. Results using the Probit or Tobit models are qualitativley similar to the OLS results.

D. Robustness

In this subsection we address additional estimation concerns to evaluate the robustness of our results. First we consider possible sample selection bias. Given the large number of zero FDI flows, we recognize that 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 4. 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. Thus, we model the FDI flows as a two-stage process. First, in what we call the Location Choice Model, the investor selects the host countries in which to invest. Then, using what we call the FDI Outflows Model, she determines the amount to be invested. The first stage of the Heckman model is as follows:

$$FDI^{*} = \alpha + \beta KK_{ij} + \lambda_1 SM + \lambda_2 CE + \lambda_2 Home\_corr + \varepsilon_{ij} \qquad \text{Eq. 5}$$

$$FDIpro_{ij} = 1 \; if \; FDIpro_{ij}^{*} \geq C$$

$$FDIpro_{ij} = 0 \; if \; FDIproL_{ij}^{*} < C$$

where FDI_{ij}^{*} is a non-observable variable that measures the incentives for investors in country *i* to undertake FDI in country *j*. Investors in country *i* will invest in country *j* only if the endowments, distance, the level of economic development, 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 C, ($FDIpro_{ij}^{*} \geq C$), then we will observe FDI from county *i* to country *j*. $FDIpro_{ij}$ is a dummy variable equal to 1 if country *j* receives FDI from country *i* and 0 otherwise. The variables of KK_{ij} represent characteristics of countries *i* and *j* as specified by the KK model, the corruption variables are as before, and ε_{ij} is the random error. We estimate the parameters of the LC Model using Probit.

In the second stage we model the effect of corruption on the volume of bilateral FDI flows. Specifically, we propose a FDI Outflows Model, or OM model, which is specified in a way similar to the model in Eq. (4), we add a selectivity repressor obtained from stage 1, the estimation of the LC model, yielding the following specification:

$$FDI = \alpha + \beta KK_{ij} + \lambda\lambda_1 SM + \lambda_2 CE + \lambda_3 Home\_corr + \lambda_4 Mills_{ij} + \varepsilon_{ij} \qquad \text{Eq. 6}$$

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\$. We include in our model specification a selectivity regressor denoted by $Mills_{ij}$. We include this selectivity regressor in order to control for possible sample selection in our data in the sense of Heckman (1979). The selectivity regressor corresponds to the Inverse Mill's ratio of the fitted values of the location choice model (Eq. 5), where:[14]

$$Mills_{ij} = \frac{\phi\left(\alpha + \beta KK_{ij} + \lambda_1 SM + \lambda_2 CE + \lambda_3 Home\_corr\right)}{\Phi\left(\alpha + \beta KK_{ij} + \lambda_1 SM + \lambda_2 CE + \lambda_3 Home\_corr\right)}$$

and ϕ and Φ are the standard normal probability and cumulative density functions respectively.

Results of these estimations are reported in Table 6. Once again, the coefficient for the difference in corruption levels 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 host-country and the home-country corruption level coefficients are both negative as above; 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 location choice model, the coefficients for differences in home-host corruption and host-country corruption are of the same magnitude and same sign,

[14] The independent variables included in the location choice model (Eq. 5) are not exactly the same as the ones included as explanatory variables in Eq. 6. The use of exactly the same variables would lead to multicollinearity problems. Thus, we use a different measure of factor endowment differences SK for Eq. 6. 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:

$$SK_{ij} = abs\left(\frac{GDP_i}{POP_i} - \frac{GDP_j}{POP_j}\right)$$

which shows that the skill matching and general corruption environment in the host country effects play an equal role in determining the location of FDI. However, in the FDI Outflows Model (labeled VOLUME in Table 6), the host corruption coefficient is over 5 times as large as the corruption differences coefficient, indicating that the size of investments, once the decision to invest in a country is made, is much more sensitive to host-country corruption than to differences in home and host corruption levels. Comparing the Probit results for location in Tables 5 and 6 suggests that correcting for selection bias has a significant effect on the parameter estimates.

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 7, for the OLS, and Tobit Models (Eq. 4) and the Heckman model of Eq. 6.[15] Results are robust to all specifications.

Finally, we analyze the effect of including alternative specifications of the KK model variables and the inclusion of other nontraditional variables in the regression. First (Table 8, columns 1 and), 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), in the KK model the cost of investing in the host country. As a proxy for investment cost we use

[15] We do not control for fixed effects in the Probit model since the dependent variable is not continues, however Probit model is the first stage of the Heckman selection model. WE report Heckman model results controlling for fixed effects.

the Economic Freedom of the Word Index (EFWI), developed by the Fraser Institute and we refer to this measure as $ICHost_j$. According to the Fraser Institute, the EFWI measures the degree to which the policies and institutions of countries are supportive of economic freedom by summarizing countries' information from five broad areas: (1) size of government, (2) legal structure and security of property rights, (3) access to sound money, (4) freedom to trade internationally and (5) regulation of credit, labor, and business. Third, Perez et al. (2011) find that an important non-traditional driver of FDI is money laundering, and 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 may bias our results. We use the measure of money laundering used by Perez et al. (2011), and we estimate results for two different specifications that control for money laundering, (Table 8 columns 3 and 4).[16] In each specification, the coefficient for the variable *Money,* which is set to one if the host country is considered a money laundering center, is positive and significant, meaning that countries that allow or facilitate money laundering do receive more FDI.

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 (2008) address this issue emphasizing possible advantages an MNE from a poor home country can have for investing in a poor host country, because such MNEs have experience in meeting

[16] They define a country as a money laundering center if it is listed as a "jurisdiction of primary concern" in the *International Narcotics Control Strategy Report* of the US Bureau for International Narcotics and Law Enforcement Affairs.

the needs of low income populations. Similarly, an MNE that has more experience working in a home country with inefficient markets or poor business infrastructure will have more success investing in a similar business environment. Based on this intuition we include unemployment (UNEMP) as measure of the efficiency with which a host country's markets function, and the number of internet connections for every 1000 habitants (INTER) as a measure of the host's infrastructure. We compute the absolute value of the differences between home and host countries and add them to our model (Table 8 column 5). The unemployment variable is negative and significant, meaning that countries with less efficient markets receive less FDI. The last column of Table 8 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.

IV. Conclusions

In this paper we have developed and tested a model of the influence of home and host-country corruption on FDI. Our results show that host-country corruption has a negative effect on the volume and likelihood of FDI inflows. 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 host country are able to transfer these skills to their affiliates in other corrupt countries, thus steering FDI toward countries with similar levels of corruption. Our empirical results corroborate the model predictions. Additionally, home-country corruption also seems to reduce the likelihood and volume of outward FDI.

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Table 1

Corruption and FDI model predictions

We report the predicted FDI in the host country as percentage of total host country investment. WE only consider the the Skill matching effect. In Panel A, we consider δ=2, and in Panel B δ=8. Other model parameter values: are λ = 20, ϕ = 20. WE also report the number of MNCs investing the host nation, #MNCs.

Panel A: Skill-Matching Effect Only (**δ=2**)

Host Country Corruption Ranking	Home Country Corruption Ranking: 1	2	3	4	5	6	7	8	9	10
1	100%	71%	56%	45%	38%	33%	29%	26%	24%	22%
2	71%	100%	71%	56%	45%	38%	33%	29%	26%	24%
3	56%	71%	100%	71%	56%	45%	38%	33%	29%	26%
4	45%	56%	71%	100%	71%	56%	45%	38%	33%	29%
5	38%	45%	56%	71%	100%	71%	56%	45%	38%	33%
6	33%	38%	45%	56%	71%	100%	71%	56%	45%	38%
7	29%	33%	38%	45%	56%	71%	100%	71%	56%	45%
8	26%	29%	33%	38%	45%	56%	71%	100%	71%	56%
9	24%	26%	29%	33%	38%	45%	56%	71%	100%	71%
10	22%	24%	26%	29%	33%	38%	45%	56%	71%	100%
#MNCs	6	7	8	9	10	9	8	8	7	6

Panel B: Skill-Matching Effect Only (**δ=8**)

Host Country Corruption Ranking	Home Country Corruption Ranking: 1	2	3	4	5	6	7	8	9	10
1	100%	91%	83%	77%	71%	67%	63%	59%	56%	53%
2	91%	100%	91%	83%	77%	71%	67%	63%	59%	56%
3	83%	91%	100%	91%	83%	77%	71%	67%	63%	59%
4	77%	83%	91%	100%	91%	83%	77%	71%	67%	63%
5	71%	77%	83%	91%	100%	91%	83%	77%	71%	67%
6	67%	71%	77%	83%	91%	100%	91%	83%	77%	71%
7	63%	67%	71%	77%	83%	91%	100%	91%	83%	77%
8	59%	63%	67%	71%	77%	83%	91%	100%	91%	83%
9	56%	59%	63%	67%	71%	77%	83%	91%	100%	91%
10	53%	56%	59%	63%	67%	71%	77%	83%	91%	100%
#MNCs	6	7	8	9	10	9	8	8	7	6

Table 2
Home and Host Countries
We report the list of all home and host countries used in our empirical tests

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, TFYR	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 3
FDI Descriptive statistics
We report descriptive statistics of the FDI data used in the empirical test in US million dollars

Positive FDI Net Flows (in million US dollars)

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 (in million US dollars)

Year	Observations	Average	Std. Dev.	Min	Max
2005	446	-35.434	75.114	-435.263	-0.000
2006	360	-44.798	96.801	-493.012	-0.000
2007	374	-39.037	84.045	-514.907	-0.000
2008	368	-50.504	100.348	-513.187	-0.000
2009	423	-49.874	91.880	-459.823	-0.000

FDI sample composition

	Observations	Percentage
Negative FDI flows	2,214	6.63
Zero FDI flows	24,321	72.80
Positive FDI flows	6,875	20.58
Total	33,410	100

Table 4
Corruption Statistics
We report descriptive statistics of the Transparency International corruption perception index (CPI) used in our empirical tests.

Home Country Corruption Index

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 Corruption Index

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 5
Empirical test of the corruption environment and the skill-matching effects
We report regression coefficients for ordinary least squares regressions (OLS), and marginal effects from Probit and Tobit regressions of the model in equation 4. All variables are described in the text. KKK represents the model using only the Knowledge Capital (KKK) model variables, and KKK+CORR include also 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

	OLS		PROBIT		TOBIT	
VARIABLES	KKK	KKK+CORR	KKK	KKK+CORR	KKK	KKK+CORR
SK	-0.29***	0.34***	-0.32***	-0.35***	-4.79***	-3.91***
	(-7.15)	(5.77)	(-24.03)	(-17.72)	(-9.70)	(-8.33)
ADY	1.29***	1.30***	0.23***	0.26***	3.02***	3.23***
	(6.20)	(6.27)	(14.03)	(14.66)	(10.42)	(10.64)
DIST	-0.02***	-0.02***	-0.01***	-0.01***	-0.22***	-0.20***
	(-9.52)	(-9.28)	(-25.02)	(-23.07)	(-10.27)	(-9.98)
SUM	0.14***	0.13***	0.04***	0.04***	0.61***	0.56***
	(9.87)	(9.38)	(36.77)	(33.19)	(11.57)	(11.27)
GDP2	0.08***	0.02	0.08***	0.07***	1.14***	0.85***
	(3.07)	(0.95)	(20.28)	(16.58)	(8.83)	(7.57)
TChost	2.11***	1.02*	0.37***	0.24***	9.09***	4.83***
	(3.67)	(1.70)	(4.36)	(2.63)	(5.82)	(3.27)
TChome	2.91***	-0.08	2.96***	1.59***	48.16***	22.81***
	(3.01)	(-0.08)	(13.04)	(6.19)	(9.62)	(5.45)
Skill matching SM		-0.06***		-0.01***		-0.15***
		(-4.60)		(-4.20)		(-6.26)
Corrup. Environment		-0.09***		-0.01***		-0.21***
		(7.76)		(3.99)		(7.34)
Corruption home		-0.05***		-0.02***		-0.32***
		(4.95)		(14.30)		(11.94)
Constant	0.02	-0.46***			-4.40***	-6.44***
	(0.44)	(-8.15)			(-9.72)	(-10.14)
Observations	33,410	31,849	33,410	31,849	33,410	31,849
Adjusted R-squared	0.05	0.06				
Pseudo R-squared			0.182	0.186	0.102	0.107

Table 6
Estimation using the Heckman selection model

We report regression coefficients for 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. KKK represents the model using only the Knowledge Capital (KKK) model variables, and KKK+CORR include also 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

	KKK		KKK+CORR	
VARIABLES	VOLUME	LOCATION	VOLUME	LOCATION
SK	-21.92***	-1.27***	-28.10***	-1.35***
	(-7.54)	(-24.06)	(-7.10)	(-17.42)
ADY	2.03***	0.72***	4.00***	0.78***
	(8.21)	(14.45)	(12.16)	(15.43)
DIST	-0.18***	-0.05***	-0.29***	-0.05***
	(-9.74)	(-26.43)	(-13.39)	(-23.94)
SUM	0.46***	0.16***	0.70***	0.15***
	(13.60)	(50.33)	(16.65)	(45.57)
GDP2	0.82***	0.34***	0.95***	0.29***
	(6.96)	(21.85)	(7.22)	(17.90)
TChost	13.17***	1.47***	39.69***	6.18***
	(7.16)	(4.48)	(3.21)	(2.65)
TChome	48.26***	11.80***	0.04***	0.01***
	(6.05)	(11.48)	(4.59)	(5.58)
Skill matching SM			-0.09**	-0.02***
			(-2.09)	(-4.23)
Corrup. Environment			-0.56***	-0.02***
			(14.74)	(3.97)
Corruption home			-0.36***	-0.07***
			(11.33)	(14.36)
Constant	-1.72***	-0.83***	-10.27***	-1.23***
	(-3.46)	(-27.16)	(-12.60)	(-28.21)
Observations	33,410	33,410	31,849	31,849

Table 7

Regression controlling for Country fixed effects

We report regression coefficients for the models reported in Table 5, including country dummy variables to control for home country unobservable fixed effects. All model include Knowledge Capital (KKK) model variables, also 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
SK	0.32***	-4.53***	-27.67***
	(4.63)	(-8.52)	(-6.82)
ADY	1.32***	3.02***	4.14***
	(6.41)	(10.04)	(11.69)
DIST	-0.02***	-0.22***	-0.31***
	(-8.46)	(-9.66)	(-12.39)
SUM	0.25***	0.29***	0.69***
	(6.26)	(6.10)	(13.82)
GDP2	-0.11***	2.64***	1.76***
	(-3.00)	(8.63)	(8.57)
TChost	1.62***	11.68***	11.68***
	(2.69)	(6.87)	(5.26)
TChome	-2.55	-88.58***	11.84***
	(-1.50)	(-5.60)	(0.26)
Skill matching SM	-0.06***	-0.15***	-6.18***
	(-4.48)	(-5.45)	(-2.13)
Corrup. Environment	-0.08***	-0.14***	-0.53***
	(6.98)	(5.32)	(13.17)
Corruption home	-0.04	-0.06	-0.23
	(-0.90)	(-0.43)	(-1.21)
Constant	-0.04	-1.84	-6.66***
	(-0.29)	(-1.46)	(-3.91)
Observations	31,849	31,849	31,849
Adjusted R-squared	0.07		
Pseudo R-squared		0.166	

Table 8
Additional Robustness test

We report Tobit marginal effects coefficients for the model in equation 5, including several additional control variables as described in the text. All model include Knowledge Capital (KKK) model variables, also measures of the corruption environment and the skill-matching effects. Several versions of the KKK model are reported 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	KKK2 + CORR	KKK3 + CORR	KKK1+ CORR+MON 1	KKK1+ CORR+MON 2	KKK1 + CORR+UNE MP+INTER	KKK1+ CORR + ALL+ FIXED
SK	-0.02	1.15**	-3.38***	-3.15***	-2.33***	0.42
	(-0.06)	(2.38)	(-7.69)	(-7.37)	(-4.57)	(0.50)
ADY	3.20***	3.21***	3.10***	3.16***	3.25***	3.23***
	(10.66)	(10.61)	(10.47)	(7.98)	(10.13)	(7.40)
DIST	-0.20***	-0.19***	-0.21***	-0.19***	-0.22***	-0.19***
	(-9.89)	(-9.82)	(-10.05)	(-9.31)	(-9.58)	(-8.37)
SUM	0.72***	0.73***	0.52***	0.53***	0.58***	0.26***
	(11.42)	(11.42)	(11.15)	(9.95)	(11.26)	(3.27)
GDP2	0.81***	0.75***	0.43***	1.16***	0.51***	2.59***
	(7.28)	(7.02)	(4.65)	(7.88)	(5.23)	(8.78)
TChost	10.24***	11.31***	3.73***	0.71	4.40***	13.81***
	(6.19)	(6.09)	(2.64)	(0.36)	(2.64)	(4.22)
TChome	17.11***	15.65***	16.29***	34.23***	5.14	-92.19***
	(4.11)	(3.72)	(4.04)	(5.87)	(1.05)	(-5.20)
Skill matching SM	-0.06**	-0.02	-0.17***	-0.16***	-0.14***	-0.07**
	(-2.21)	(-0.75)	(-6.74)	(-6.85)	(-4.93)	(-2.12)
Corrup. Environment	-0.27***	-0.28***	-0.23***	-0.22***	-0.28***	-0.22***
	(7.89)	(6.51)	(7.59)	(7.23)	(5.87)	(4.52)
Corruption home	-0.22***	-0.20***	-0.30***	-0.30***	-0.32***	-0.31*
	(9.34)	(8.47)	(11.68)	(11.61)	(10.89)	(-1.70)
(GDPi-GDPj)*SK	-0.96***	-0.97***				-0.88***
	(-8.49)	(-8.27)				(-4.63)
TChost*SK^2	-0.11***	-0.21***				-0.13***
	(-4.66)	(-5.88)				(-2.83)
Money						1.14***
						(3.23)
Money*SK				-3.08		3.63
				(-0.77)		(0.73)
Money*ADY				-0.19		-0.48
				(-0.36)		(-0.79)
Money*DIST				-0.05***		-0.06***
				(-2.97)		(-3.33)

Money*SUM				0.02		0.14**
				(0.43)		(2.55)
Money *GDP2				-1.23***		-0.57***
				(-7.84)		(-3.76)
Money*TChost				3.82		0.51
				(1.37)		(0.14)
Money *TChome				-30.43***		4.39
				(-3.16)		(0.36)
Unemployment					-0.05***	-0.02**
					(-5.46)	(-2.30)
Internet					-0.00	0.00
					(-0.87)	(0.07)
Money			1.27***	2.23***		
			(9.86)	(6.29)		
IChost		0.00				
		(0.22)				
Constant	-6.99***	-7.16***	-6.43***	-6.72***	-6.16***	0.39
	(-10.21)	(-9.58)	(-10.12)	(-9.56)	(-9.76)	(0.23)
Observations	31,849	30,026	31,849	31,849	19,540	19,540
Pseudo R-squared	0.112	0.110	0.111	0.113	0.0803	0.135

Figure 1a

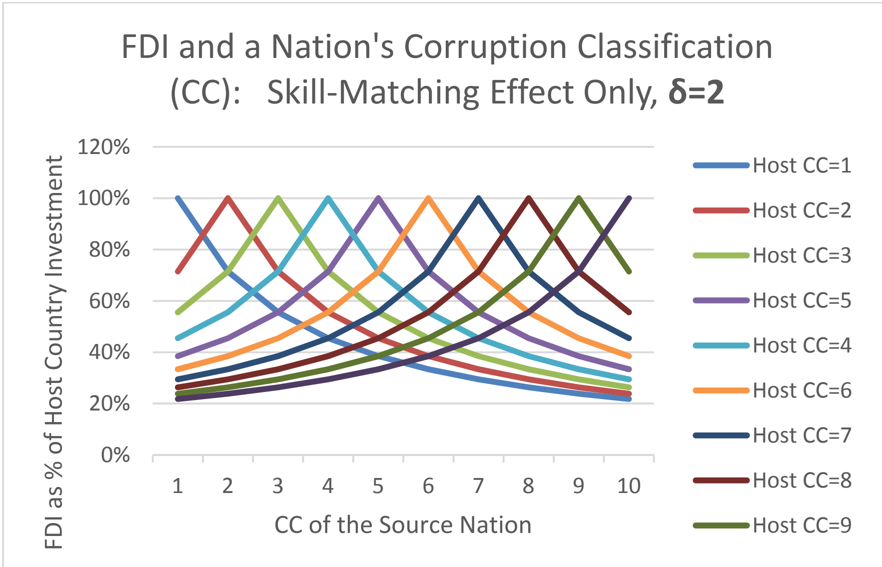


Figure 1b

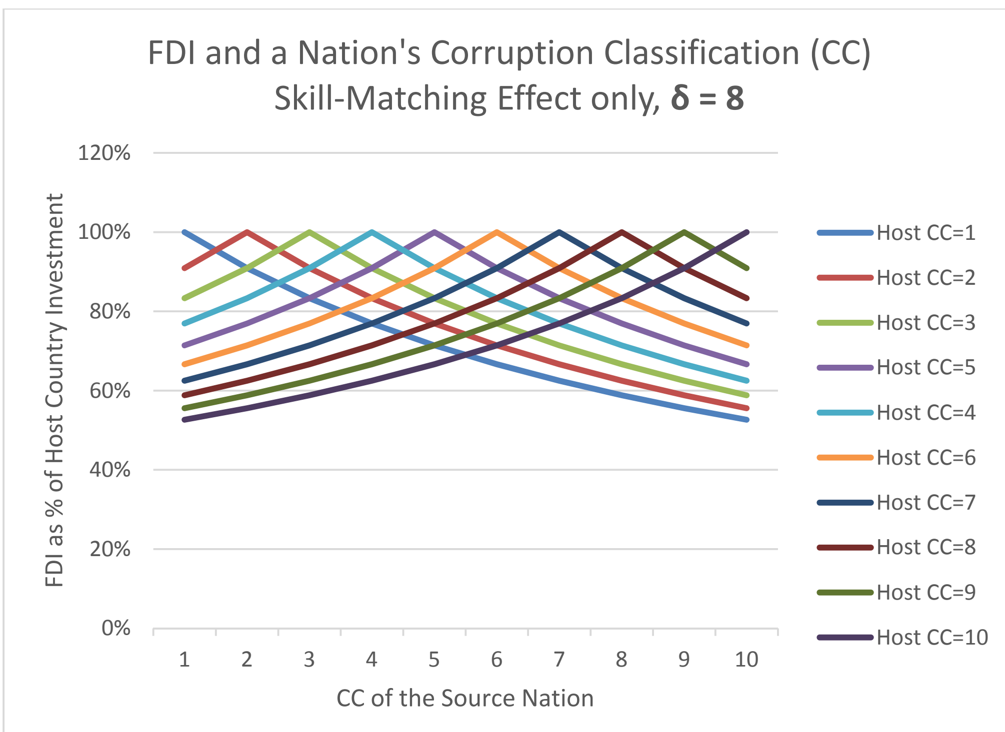
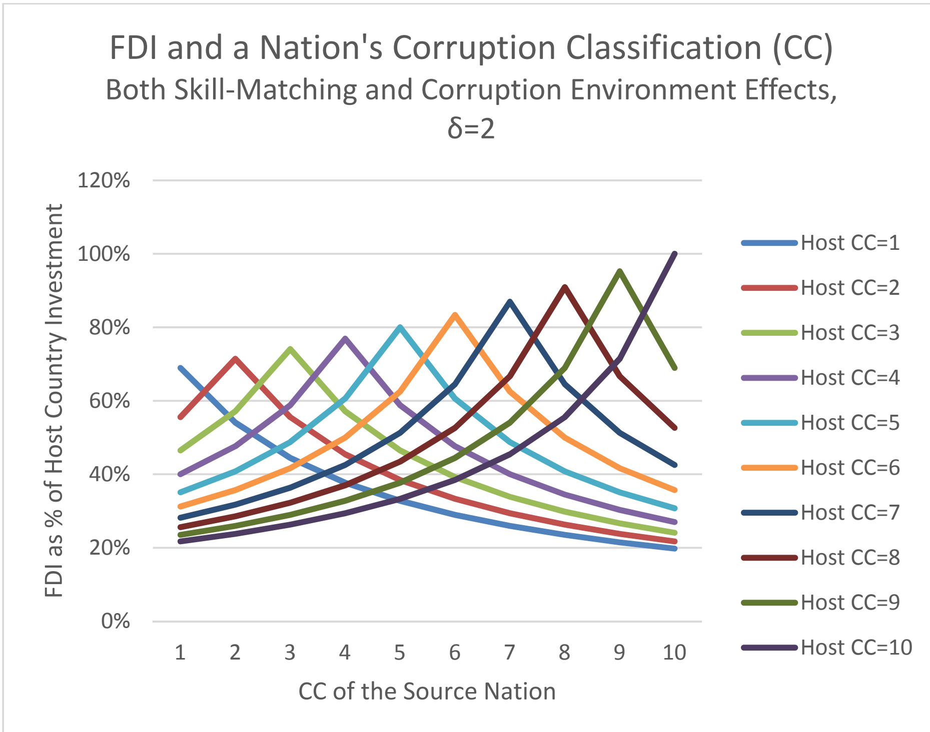


Figure 2


FDI and a Nation's Corruption Classification (CC)
Both Skill-Matching and Corruption Environment Effects, δ=2
FDI as % of Host Country Investment
120%
100%
80%
60%
40%
20%
0%
1
2
3
4
5
6
7
8
9
10
CC of the Source Nation
Host CC=1
Host CC=2
Host CC=3
Host CC=4
Host CC=5
Host CC=6
Host CC=7
Host CC=8
Host CC=9
Host CC=10