TRADING UP OR TRADING DOWN?

HOW CORRUPTION DISTANCE AFFECTS CROSSBORDER R&D INVESTMENTS

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ABSTRACT

Prior research has demonstrated that corruption has largely negative effects on incoming international investments. Less clear is to what extent these negative effects are a product not of a host country's absolute level of corruption, but of the relative distance to the home country's degree of corruption. We propose a framework of trading up, down and laterally between countries of different levels of corruption. We define the Directional Corruption Distance (DCD) as the arithmetic difference between two countries' corruption levels. Avoiding distorted Foreign Direct Investment (FDI) measures, we analyze the change in Research & Development Stock (RDS) representing more than 10,000 R&D centers of 500 technology-intensive MNCs taken from the Fortune 1000 list. In support of earlier research with FDI as a dependent variable, we observe that countries have a marginal tendency to prefer countries of respectively lower corruption as destinations (Trading Up Hypothesis), despite the market attraction of large but relatively corrupt FDI recipients such as China and India. Firms from high-corruption countries do not exhibit a significant tendency in either direction but appear to be open towards investments in other high-corruption countries (Familiarity Hypothesis). We also find that countries with relatively low levels of patents per capita prefer to trade up, regardless of their degree of corruption. While the level of tertiary sector contribution to GDP does not play a role for high-corruption countries, a lower level abolishes the trading-up effect for low-corruption countries (Comfort Hypothesis). We also find support for Intellectual Property (IP) and Service Sector sensitivity hypotheses. These findings connect the emerging literature on corruption in international business to the more established literature on international innovation and FDI.

INTRODUCTION

The espoused view of international business theory is that corruption is a non-value-adding cost associated with doing business, and as such detrimental to inbound foreign direct investment (FDI). If a country is corrupt—a condition which is mainly self-imposed—then it is likely to receive less FDI from other countries (e.g., Mauro, 1998; Wei, 2000; Cuervo-Cazurra, 2016).

The verdict on corruption, however, is not as clear at it seems, and some research indicates even an investment-conducive effect (e.g., Egger & Winner, 2005). Countries such as China and India have relatively high degrees of corruption, but also receive significant amounts of FDI. One argument is that firms are able to mitigate negative effects of corruption through a mix of managerial and strategic means (Buckley et al., 2018; Rabbiosi & Santagelo, 2019). This line of reasoning works less well for investments in R&D (research and development), as its intermediate products (such as knowledge and intellectual property) are easily copied in environments characterized by poor governance, market intransparency, and weak rule of law, i.e., conditions associated with corruption (Cuervo-Cazurra, 2008). Yet, many countries with high levels of corruption also receive substantial R&D-related FDI (Motohashi, 2015).

Our study explores whether it is relative rather than absolute corruption that matters, i.e. whether the source of investment (the home country) perceives the destination (the host country) to be corrupt. Building on Habib & Zurawicki (2002), who showed that greater perceived corruption distance reduces FDI exchange between two countries, and Qian & Sandoval-Hernandez (2016), who found that corruption distance has asymmetric effects on FDI, we use directional corruption distance in our analysis.

We focus on international R&D, a discipline within the international business literature which so far has received little attention in the context of corruption research, even though host-country corruption seems to affect incoming R&D FDI differently from general FDI (Javorcik & Wei, 2009), and even though global R&D increasingly flows toward and originates from countries with higher perceived corruption levels (e.g., Di Minin et al., 2012). We use a database of more than ten thousand crossborder R&D investments among the top 15 R&D emanating and receiving countries. Proposing a framework that identifies the direction of crossborder R&D investments as either "trading up" (investing in a less corrupt country), "trading down" (investing in a more corrupt country), and "trading lateral" (investing in a country with similar corruption), we find support for trading up for firms from countries with low IP stock and trading lateral for firms from relatively corrupt countries, and we find partial support for general trading up for firms from countries with a strong service sector, and trading lateral for firms from relatively uncorrupt countries. Not surprisingly, we do not find support for trading down after controlling for market size, economic growth and other context conditions.

This study makes a contribution to the expanding literature on international business and corruption by investigating not only whether the relative corruption distance between home and host country affects crossborder investments, but also whether the origin of this investment matters. In particular, by focusing on international R&D and corruption, it closes a gap in a literature that so far has considered only host country conditions for international R&D. In the following sections we briefly review the literature leading up to the trading up/down framework, propose and test six hypotheses, and discuss the results in the context of international business literature. By using directional corruption distance on a unique dataset of crossborder R&D locations, we are able to offer a more nuanced interpretation of the effect of corruption on the sources and destinations of global R&D investment flows.

THEORY DEVELOPMENT

Literature Review

The study of international investment in other countries is one of the main pursuits within the field of international business research. Among several others, two substreams of research have emerged: the internationalization of R&D and innovation (e.g., Behrmann & Fischer, 1979; Cheng & Bolon, 1993), and the role of corruption in international business (e.g., Wei, 2000; Habib & Zurawicki, 2002). The first substream comprises the motivations, models, and challenges of internationalizing a company's R&D investments and, thus, a company's future means of differentiation. OLI theory is an essential piece in this research stream, as it has shown how location-specific factors such as labor costs and export ratios can exert influence on companies' decisions to internationalize central business processes pertaining to R&D (Dunning, 1988). Reasons to internationalize have been intensely investigated for decades, as Dachs (2017) demonstrated in a comprehensive review of the pertinent literature, with e.g. Le Bas and Sierra (2002) providing insight on the home country perspective of R&D location decision making. International R&D was a marginal phenomenon both in industry and management research until the 1990s (Cheng & Bolon, 1993), until widespread adoption of modern information and communication technologies (Howells, 1995) and a general expansion of global business in the 1990s led to stronger interest in global R&D research (Niosi, 1999). The global rise of China and other developing economies drew attention to R&D investment toward, in and from emerging markets (e.g., Govindarajan and Ramamurti, 2011; Awate et al., 2015). Important research themes were focused on location drivers (von Zedtwitz, 2004) and challenges in such markets (Gassmann and Han, 2004). Corruption and institutional quality were recognized as barriers for inbound R&D investments in developing economies (Wei, 2000; Cuervo-Cazurra, 2006).

The second relevant substream of research deals with the influence of corruption on the internationalization of firms. Research on corruption in an international business context dates back almost as far as research on international R&D. Shleifer & Vishny (1993), Mauro (1995) and Hines (1995) were among the first to report on the negative (albeit sometimes inconclusive) impact of corruption on international trade. Wei (2000), Habib & Zurawicki (2002) and later Cuervo-Cazurra (2006, 2008) established the field within the discipline of international business research, further legitimizing more focused research such as country-level attractiveness for FDI given certain types of corruption (e.g., Rodriguez et al., 2005). Research on the home country corruption's effect on FDI is still limited mostly to aspects such as its level of development, the institutional and political system, or economic size and degree of economic openness (Cuervo-Cazurra et al., 2018). The effect of corruption on FDI is ambiguous: It functions sometimes as "sand" (e.g. Wei, 2000) and sometimes as "grease" (e.g., Egger & Winner, 2005), while better conceptualization are being developed (e.g., Bahoo et al., 2020). Paunov (2016) showed that larger firms seem to be less affected by corruption than small firms, perhaps—as recent work by Buckley et al. (2018), Rabbiosi & Santangelo (2019) and Sartor & Beamish (2020) suggests—because multinationals have more diverse and capable resources to mitigate host-country corruption effects.

While corruption research in the international context has made significant strides forward, research on the effects of corruption on crossborder R&D investments has been limited. Much of the research on corruption and host-country investments suggests negative or at least ambivalent consequences for R&D (Gan & Xu, 2019; Wen et al., 2020). But under certain conditions, bribery supports local innovation in developing countries (Krammer, 2019), and patent-based research by Aghion et al. (2005a) found a non-linear relationship between corruption and innovation in certain countries. Smarzynska & Wei (2000) provided evidence that corruption affected FDI by technology-intensive companies especially strong, and Javorcik & Wei (2009) showed that R&D-intensive MNCs favor sole ownership investments in corrupt countries. MNCs are fine-tuning R&D strategies for countries with weak intellectual property regimes (e.g., Keupp et al., 2012). Yet, research on the specific impact that corruption may have on crossborder R&D has been sparse. Overall, the extent to which corruption affects foreign R&D in host countries is generally assumed to be negative (i.e., more corruption is worse for foreign R&D), but the extent to which corruption distance affects crossborder R&D is poorly understood.

Main Hypotheses Development

We formulate our hypotheses in parallel to the extant literature detailing the effects of corruption on FDI. A potential host country is exposed to an investment-repellent effect if firms avoid investing in it because it has relatively higher corruption than their home countries (Cuervo-Cazurra, 2006). Conversely, if firms prefer investing in host countries, e.g., because of lower corruption, higher business transparency and greater governance integrity, we speak of an investment-conducive effect. As Lall (1978) pointed out, institutional stability counts as one of the main determinants of a host country's attractiveness to FDI, and Mauro (1995) found that higher corruption countries are also generally less developed. According to Rodrik, Subramanian and Trebbi (2004), the disadvantage of institutional instability is more prevalent in less developed than in developed countries, which leads to a higher cost of capital in the host country, negatively affecting the profitability of investments, and thereby acting as a deterrent to FDI (De Mello, 1997).

While general FDI seeks to acquire strategic resources (Habib & Zurawicki, 2002; Rodriguez, Uhlenbruck, & Eden, 2005), crossborder R&D tends to be capability-seeking (Doz, Santos, & Williamson, 2001; Dunning, 1988). Even when R&D is primarily aimed at local product and market development, the results tend to be knowledge-intensive goods, which firms seek to guard and protect as sources of future competitive advantage. If corruption acts as an impediment to FDI inflows (Mauro, 1998; Wei, 2000), then we would expect less crossborder R&D from less corrupt to more corrupt countries, and more crossborder R&D from more corrupt to less corrupt countries. As a result, international R&D toward corrupt countries should be subjected to higher institutional difficulties and uncertainties than international R&D toward less corrupt countries. Outbound R&D is therefore expected to avoid environments characterized by uncertain appropriability rights, institutional intransparency, unreliability of public governance, and personal gains-seeking profiteering: characteristics associated with corrupt countries. Moreover, we would expect the magnitude of the investment-conducive resp. -repellent effect to coincide with the absolute corruption distance between the two countries. This suggests that a positive corruption distance coincides with a larger stock of crossborder R&D from home to host country, and that the corruption distance between two countries is positively correlated with the amount of crossborder R&D between these countries.

Trading Up Hypothesis ***H1a****: Firms from more corrupt countries are more likely to invest in less corrupt countries.*

However, research has shown that corruption may also present an investment-conducive effect (Egger & Winner, 2005; Henisz, 2000; Huntington, 1968; Leff, 1989; Wheeler & Mody, 1992). There is, after all, ample empirical evidence of international R&D investments in relatively corrupt countries (Ervits, 2018). Krammer (2019) showed how bribery can help firms to introduce new products in corrupt markets. Host countries sometimes offer attractive tax credits and subsidies specifically for R&D investments, which may serve as an indirect venue for corruption. A more direct benefit may stem from influence over governance of R&D compliance and oversight, e.g., to do certain types of R&D in the host country that would not be permitted in a less corrupt country. This could lead firms to move R&D to host countries that are more relaxed about regulations and more interested in harnessing certain externalities and spillovers from the R&D-focused investments. Under certain conditions, corrupt countries may therefore be attractive to crossborder R&D investments. Thus, we also propose a hypothesis that is diametrically opposed to our first hypothesis:

Trading Down Hypothesis ***H1b****: Firms from less corrupt countries are more likely to invest in more corrupt countries.*

The level of corruption of the home country of FDI, especially relative to the destination country, has received less attention in FDI research, partially because the importance of the host country's level of corruption appeared to be dominant, and partially because the developed and thus relatively incorrupt home countries accounted for the majority of FDI. However, with increasing wealth of countries across the spectrum of corruption levels, and thus their ability and inclination to invest abroad, the level of corruption in the home country could very well have greater significance. For instance, Brada et al. (2012) hypothesized that the direction and volume of FDI is affected more by the level of corruption of the home country than the host country, but their analysis was based on only six small Eastern European countries and therefore is difficult to generalize. Still, this line of research suggests that the level of corruption in a home country could matter for the extent and direction of foreign investment. The differing motives for firms from developed and less developed countries to invest in each other accentuates the importance of the home country perspective in the analysis of FDI. This leads us to assume that countries with extreme corruption scores—very high or very low—behave differently with respect to the level of corruption in host countries.

Given the IP protection available in low-corruption host countries, we would expect home countries with low levels of corruption to prefer investing in host countries with similar properties and equally low exposure to corruption. De Mello (1997) summarized two major disincentives within developing countries that act as deterrents to FDI: technology transfer, i.e. the need for a foreign investing company to share their knowledge with local firms, and equity requirements, e.g. the need for the investment to be held also by locals. The well-researched topic of FDI-induced technology or innovation spillovers (Kokko, 1994) describes the danger of losing competitiveness through unwanted transfer of important R&D and technology. Yan & Grey (1994) detailed the difficulties of equity requirements by analyzing China's policy to require foreign firms to form joint ventures with local businesses upon their market entry and thereby placing some extent of control into the hands of others. Firms from less corrupt countries are thus deterred to invest in more corrupt countries, hence would find investing R&D into countries with similarly low corruption more comforting and more appealing.

A similar argument can be made for firms from more corrupt countries. Even though less corrupt countries may be attractive for FDI (e.g., Mauro, 1998), equally high corrupt countries are also attractive because they offer a similar economic and institutional context, minimizing switching and learning costs, and limit the competitiveness of investors from less corrupt countries with less profound experience in corruption (Egger & Winner, 2005; Cuervo-Cazurra, 2006; Arita, 2013). This argumentation supports the preference of investors to invest in countries with corruption levels similar to the home country, with familiar economic and institutional environments, regardless of the perceived degree of corruption, and thus exhibiting a type of "home country bias" in their choice of international R&D location. This home country bias discourages firms from low-corruption countries to invest in more corrupt countries, and firms from high-corruption countries to invest in less corrupt countries, assuming that firms prefer to stay within familiar environments. We therefore propose the following two hypotheses:

Comfort Hypothesis ***H2a****: Firms from countries with low corruption are more likely to invest in countries of similarly low corruption.*

Familiarity Hypothesis ***H2b****: Firms from countries with high corruption are more likely to invest in countries of similarly high corruption.*

These four hypotheses constitute our theoretical framework as represented in Figure 1. We propose to label international investment flows as

- "trading up" for firms investing from a more corrupt to a less corrupt country,
- "trading down" for firms investing from a less corrupt to a more corrupt country, and
- "trading lateral" for firms investing in a country with similar corruption.

---- Insert Figure 1 about here ----

Moderator Hypotheses

International R&D investments are influenced by a multitude of factors that can be classified in numerous ways (von Zedtwitz and Gassmann, 2002; Gammeltoft 2006). Corruption—whether in the host country or at home—is just one of many contributing factors. In this section, we consider possible moderators influencing the role corruption may have on crossborder R&D flows. These moderators can unveil further home country qualities that motivate certain behavior in international R&D investment.

Given the importance that innovation and R&D has in generating competitive advantage, R&D-related investments in foreign countries are regarded as especially risky. If a firm's competitive advantage rests on relatively few patents, exposing its technological know-how to countries with poor IP protection is riskier compared to a firm that has a deep IP portfolio and is able to afford intelligent disclosing of parts of its IP. Invoking the argument of diminishing returns (Brue, 1993), we would expect firms from countries with many patents per capita to not only work on breakthrough innovations, but on localization and adaption research and development in a given host country. Therefore, we would assume a country's

R&D to be less sensitive towards disruptive factors such as corruption. Countries whose companies rely on fewer patents (or even trade secrets) are more vulnerable with regards to the dangers of IP theft, whereas countries whose companies produce a relatively larger amounts of patents are more diversified and, as a result, able to protect their sources of competitive advantage better. Firms with greater pre-existing R&D expertise also develop more defensible IP from their international R&D (Penner-Hahn & Shaver, 2005). Thus, firms with large patent portfolios can more easily afford to enter more corrupt countries. Hence, we hypothesize that countries with fewer patents per capita behave more cautiously and, subsequently, are more reluctant to invest in countries whose overall context does not provide the same stability and security as the home country. Therefore, the lower the amounts of patents per million inhabitants in a country, the greater its strategic exposure of R&D, the more likely it should seek R&D-conducive environments for its outbound R&D investments, and the more likely it will go into less corrupt countries, i.e. countries with a positive corruption distance. Hence, we propose:

*IP Sensitivity Hypothesis **H3a**: The lower the number of patents per million inhabitants of a country, the greater the tendency to trade up.*

Analogously, a country is likely more sensitive about corruption, if its economy is built on businesses that are more vulnerable to corruption. One simple country-level distinction is Fisher's (1939) three-sector classification that differentiates between the primary, secondary, and tertiary sector, which roughly represents agriculture and raw materials, manufacturing, and service businesses, respectively. All sectors are vulnerable to IP theft but the tertiary sector, which comprises industries such as financial services, software, education, etc., is characterized by the production of intangibles, and intangibles are notoriously hard to protect. The primary and secondary sector, by virtue of being more labor intensive, both in terms of manual and machine-driven labor (Caves & Porter, 1977; Aghion et al., 2005b), have higher barriers of entry (Amaral & Quintin, 2006; Saviotti & Pyka, 2011). In the case of the primary sector, for example, resources and assets are highly immobile, and even the knowledge of how to extract and harvest goods does not allow easy copying without also acquiring the underying assets and machinery. Moreover, many companies that historically were rooted firmly in the first or secondary sector have added significant service portions to their businesses, and nowadays invest heavily service-related activities such as software development, consulting and training, maintenance, logistics and financial services. The service industry, which builds on the ability to develop, manage and apply know-how and information—core processes in innovation and R&D—is therefore more exposed to conditions that increase IP uncertainty, such as unstable institutional context and corruption. Accordingly, we hypothesize that countries whose economies largely build on the tertiary sector exhibit stronger tendencies to trade up.

Service Sensitivity Hypothesis ***H3b****: The higher the tertiary sector's contribution to a country's GDP, the greater the tendency to trade up.*

METHODS AND DATA

Dependent Measure

RDS. For the purposes of our study on R&D-related foreign investments we focus on individual crossborder R&D establishment decisions by firms. The extraction of R&D-related investments from general FDI would introduce a number of unwanted difficulties: FDI data are highly skewed, partially because tax havens distort the quality of the data, and partially because FDI stock data are based on capital flow data derived from balance of payments (Beugelsdijk et al., 2010), and thus not necessarily related to what firms do in terms of strategic R&D decision-making. We therefore focused on the actual establishments of R&D centers as a manifestation of foreign R&D investments by MNEs, an approach that is well established in international business research (e.g., Kuemmerle, 1999; von Zedtwitz & Gassmann, 2002; Ito & Wakasugi, 2007; Di Minin et al., 2012; Awate et al., 2015), and as suggested by Sauvant (2017) for this type of FDI research.

We use a proprietary dataset that contains domestic and international R&D centers of 500 multinational technology-intensive firms representing approximately 65% of global industrial R&D. The 500 parent MNCs were chosen by size of global revenue, irrespective of their country of origin. For each firm R&D centers were compiled by analyzing annual reports, press releases, official media communications, corporate websites, and interviews with company representatives, arriving at 10,106 individual R&D centers with known location at the country level. We include all such centers opened in or before 2017 to avoid any recency bias, with more than 90.8% of all centers established after 1980.

After aggregating the number of R&D centers per country, we focused on those 15 countries that were either a top-10 home or a top-10 host country of crossborder R&D (excluding R&D investments into their own countries): United States of America (US), Germany (DE), Japan (JP), Switzerland (CH), France (FR), Netherlands (NL), China (CN), South Korea (KR), Finland (FI), Sweden (SE), United Kingdom (UK), India (IN), Canada (CA), Italy (IT), and Brazil (BR). Overall, this yielded 7,753 datapoints and unique R&D center investments, representing 76.7% of all R&D centers in the dataset. 4,652 R&D center establishments conformed to the requirement of being crossborder, i.e. different home and host countries.

In order to establish an absolute measure of crossborder R&D from a source to a host country, irrespective of the reverse inflow of R&D centers from host to the source country, we define the **crossborder R&D Stock (RDS)** of the number of R&D centers established in country B as invested by a multinational firm headquartered in country A, with the optional parameter of a time span given by [T], i.e.,

RDS (A, B, [T]) = *Sum of all R&D centers established during time period [T] in country B by a company with HQ in country A*

RDS is always positive or zero. RDS is also non-commutative, i.e., RDS (A, B) is not necessarily RDS (B, A), except if A = B, when RDS is the number of domestic R&D centers in a country. RDS is a quantifiable measure of the crossborder R&D flow between countries and allows us to compare the results with other crossborder measures at the country-level, most notably corruption distance.

This generated 210 transnational country pairings or dyads, including mirror country pairs in which home and host countries were swapped, representing reciprocal R&D investments between those two countries (Table 1).[1] For instance, RDS (DE, US) indicates that there are 263 German R&D centers in the United States (e.g., Siemens Research in Princeton, NJ). The figures at the bottom of the columns indicate the respective country's share of R&D centers hosted in the total database, i.e. the 14 countries other than the US account for 91% of the origin of all foreign R&D centers in the US. Analogously, the US R&D centers in the 14 other countries in the RDS dataset account for 61% of all outbound R&D from the United States (horizontal rows in Table 1). Some countries are top 10 source and recipient countries, whereas others are only in one of them. For instance, Brazil was included in our list of 15 countries because it is a top 10 recipient country, with only 5 R&D centers of Brazilian MNCs outside Brazil.

---- Insert Table 1 about here ----

This set of 15 countries is fairly comprehensive in terms of describing the global R&D ecosystem, as it represents 70.7% of total outgoing and 93.6% of total incoming crossborder RDS, meaning that the majority of global R&D investments is concentrated in this club of top-investing and top-receiving countries. This finding is reminiscent of Hirst's (1997) observation that the world economy, global

[1] Our focus on the major emitters and receivers of RDS is further supported by the observation that FDI can be a biased measure for economically relevant capital flows. Around 60% of China's outward FDI stock is in Hong Kong. By considering only the 15 major countries in terms of crossborder R&D investments, we avoid FDI-distorting countries such as tax havens. Also, Rosen and Hanemann (2009) described the danger of "round-tripping", namely the process where Chinese funds are externalized and "exported" to Hong Kong and then "re-imported" to make use of specially granted financial benefits to foreign capital inflows into China. As a result, reported outgoing FDI can be overstated by approximately 50% (Zhang, 2005). Our RDS data avoids this issue altogether, as we consider only realized firm-level R&D investments.

development, and FDI sources as well as FDI recipients are heavily concentrated. We thus focus on countries that are important sources and recipients of global R&D investments, and avoid noise from countries with no or little R&D inflow and generally higher levels of corruption, i.e. we reduce the possible bias towards accepting corruption as an investment-repellent factor due to many underdeveloped countries with low chances of receiving R&D investments and overall low inbound FDI. Table 2 reveals that this measure is robust for RDS split along different time-intervals.

---- Insert Table 2 about here ----

Independent Measures

CPI. Cuervo-Cazurra (2006, p. 807) defines corruption as "the abuse of public power for private gain, [which] creates uncertainty regarding the costs of operation in the country." Corruption can be measured in many ways. One widely accepted tool is Transparency International's Corruption Perception Index (CPI), which is considered a representative, comprehensive and accurate account of corruption in a country, as it captures both public and private dimensions of corruption on a global scale. CPI values are recorded as a number between one [1] and one hundred [100], with 1 denoting complete corruption and 100 describing absence of corruption. As a non-ranking normalized score, CPI values permit comparison of the degree of corruption between countries.

In 2017, CPI values were available for a total of 180 countries (Transparency International, 2018). The composition of the CPI index has been repeatedly improved since its first release in 1995 and was upgraded to a 100-point scale in 2012. Since CPI scores per country have not varied widely (Kwok & Tadesse, 2005), we use the averages of country CPI scores from 2012 to 2017. As a result, two countries rarely have matching scores, allowing us to capture even small degrees of variability inherent in this variable.

The countries within our RDS dataset account for an average CPI score of 68.0. The high and low CPI home country groups used later in this analysis are each one standard deviation from this average (σ_{CPI} = 18.5). Depending on the model, conditional effects for high-corruption countries refer to countries with CPI values as low as 49.5, while conditional effects for low-corruption countries refer to countries with CPI values of 86.5.

DCD. Distance measures (e.g., geographical, cultural, administrative, and economic) are central in understanding the international dimensions of foreign direct investments (Zaheer et al., 2012). Distance properties can be either symmetrical or asymmetrical (i.e., whether distance is reciprocal and identical for both countries in a dyad, see Shenkar et al., 2001) or relative or absolute (i.e. whether distance exerts a different influence depending on the home country's viewpoint, see e.g. Håkanson & Ambos, 2010). As a means to investigate dyadic relationships between two countries and their possible relationship with corruption, we define the **Directional Corruption Distance (DCD)** as the arithmetic difference between the CPI values of two countries A (Home) and B (Host), i.e.

$$DCD\ (A, B) = \overline{CPI}_B - \overline{CPI}_A \qquad [1]$$

We inherit the simplification that each country is characterized by a single corruption score, even though corruption most likely varies within countries (Brada et al., 2012). Compared to Habib and Zurawicki's (2002) distance measures of corruption, the DCD value is directional, i.e. it is positive if the host country has a higher CPI (lower corruption) than the home country, zero if the CPI values are identical, and negative otherwise. In essence, we follow the Qian & Sandoval-Hernandez (2016) operationalization of corruption distance, but as our DCD is calculated over the averages of CPI values per country from 2012 to 2017 (analogous to the RDS measure), we face no selection bias from a potentially large presence of zeros in the table (Heckman, 1979), and therefore use absolute rather than log-normalized values. DCD values range between -99 and +99, and form a matrix over all countries with available CPI scores. Our DCD value is symmetric (its effects on RDS may be asymmetric, however) and relative. As it is calculated as the arithmetic difference between two values, we assume an inherent linear relationship (for its consequences, see Shenkar et al., 2001).

We are in line with a large body of research using similarly calibrated indices interpreting arithmetic difference as distance effects. Our approach offers directional symmetry for the corruption measure, and directional asymmetry for the crossborder R&D measure. Together with RDS, DCD defines the investments from a home to a host country as either upward or downward trading. Negative DCD values indicate trading down, as the host country receiving an investment features a lower CPI than the home country where the investment originates. Positive DCD values signal trading up, if a home country with a lower CPI score invests in another country with a higher CPI score. Table 3 presents the averaged DCD scores of the various country dyads analyzed in this paper.

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Moderators

***CPI Home*.** In order to operationalize the home-country perspective and differentiate between companies from high- and low-corruption home countries, we utilize the home country's corruption level (CPI Home) as a primary moderator of the relationship between DCD and RDS. As the other CPI scores, this variable is taken from Transparency International (2018) and averaged over 2012 to 2017.

Patents per Million Inhabitants. As a measure of a country's inventiveness, this variable represents the natural log +1 of the total number of patents (average from 2012 until 2017) a country's residents are granted both in their country of residence and abroad (WIPO, 2020).

Tertiary GDP Contribution. This variable represents the share of a country's gross domestic product that is contributed by the tertiary sector (Central Intelligence Agency, 2018) and thus constitutes a degree of a country's exposure towards protection and safe-guarding of intangibles.

We use 2012-2017 averages for all moderators and control variables, as crossborder R&D decisions are generally based on the assessment of longterm trends rather than shortterm variations of country context conditions. Figure 2 shows the overall conceptual model used in our analysis.

---- Insert Figure 2 about here ----

Control Variables

We also introduce a number of control variables in order to validate our empirical studies on a broad basis and to identify the actual influence of corruption on international R&D investments.

GDP. We control for the size of the country's economy receiving RDS, as we assume that larger economies would naturally attract more RDS investments. We expect firms to target large markets with market-seeking RDS to reap downstream economies of scale for individual R&D investments. We took the log-normalized averages of 2012 to 2017 Purchasing-Power-Parity GDP in USD for each of the 15 countries within our dataset (World Bank, 2018a).

GDP per Capita. We further control for GDP per capita as a measure of a country's level of development. Some countries with comparatively small economies might still be attractive in terms of technological and economic value added. These countries, such as the Netherlands or Switzerland, provide stable environments for sensitive operations such as research and development. This serves to control for the influence of technology-seeking R&D. We use log-normalized averages of 2012 to 2017 GDP per Capita data obtained from the World Bank (2018a).

GDP Growth. Given that R&D represents a future-oriented business activity, with ROI times of several years, firms may want to establish their R&D efforts in countries with a positive outlook for the economy. Economies with positive growth rates guarantee increasing demand and make the upfront investment it requires to establish R&D facilities less risky. We thus control for economic growth by using the mean of the average percentage growth each economy experienced from 2012 to 2017 (World Bank, 2018a).

Number of Graduates from Tertiary Education. The availability of scientifically trained personnel with advanced college and university degrees may act as a factor promoting RDS into an economy. As economies vary with regard to the number of citizens with tertiary education, we approximate the availability of R&D trained human resources by considering the absolute number of graduates from tertiary education, i.e. universities, universities of applied sciences, and other high-ranking educational institutions. We obtained this data from the World Economic Forum's Human Capital Report, which compares 130 countries regarding the development of their human resources across the economy (World Economic Forum, 2018). We log-normalized the average of this variable's 2012 to 2017 numbers for our analysis.

Ease of Doing Business. Given the sensitive nature of R&D investments, we also control for institutional quality by employing the Ease of Doing Business score released by the World Bank. This variable quantifies the extent to which companies find it easy to set up and conduct operations in a country, including R&D centers. Ease of Doing Business is measured on a scale from 1 to 100 and involves 10 subindices such as procedures to start a business, dealing with construction permits, and investor protection (World Bank, 2018b). It serves as a proxy for stability and procedural uncertainty for foreign firms entering a new market. We use the averages of the 2012 to 2017 values.

OECD Membership. OECD membership can be attained once a country gives up its developing nation status. As Mauro (1995) stated, developing countries tend to be more corrupt. To control for this, we assigned a score of 1 if the country was an OECD member state, and 0 otherwise. Information regarding current memberships was retrieved directly via the OECD's list of member countries (OECD, 2018). Although imperfect (e.g., Brazil is part of the OECD while China is not), it still represents a measure to differentiate country developmental levels.

Geographic Distance. We further control for the distance between two countries, as travel costs, overlap in timezones and ease of remote coordination may influence propensity of crossborder R&D (von Zedtwitz & Gassmann, 2002; Castellani et al., 2013). As European countries represent the majority of countries in our dataset, this would also control for the effects of ease of intra-European R&D

internationalization. Using the average latitudinal and longitudinal degrees of each country as seen from the prime meridian (Stavish, 2011), we used the spherical distance between countries as our geographic distance control variable.

Share of International Patents Received Host. A bandwagon effect is present when a large number of imitators follows a few opinion leaders in setting up R&D centers in certain locations, either due to information or rivalry-based imitation efforts to compete on the best resources (Lieberman & Asaba, 2006; Nikolaeva & Bicho, 2011). This effect has been observed in company crossborder investment-related decision making (Sethi, Guisinger, Phelan, & Berg, 2003; Rose & Ito, 2008). Therefore, to control for a 'winner-takes-it-all' bandwagon effect, we calculate the ratio of patents granted to foreign applicants over patents granted to resident applicants in a given host country (WIPO, 2020). A higher value means a higher internationality of patent applicants in the host country.

---- Insert Table 4 about here ----

Procedure

In accordance with Egger and Winner (2005), we run Weighted Least Squares Regressions using the entire country sample, including possible outliers such as China and India, for a complete picture of crossborder R&D behavior. This choice accepts the possibility of corruption being either an investment-repellent or an investment-conducive factor. Many transition economies receive high FDI despite their relatively high degrees of corruption (Cuervo-Cazurra, 2008). Our country sample includes a wide array of countries, ranging across the CPI spectrum. All our models control for heteroscedasticity (Hayes & Cai, 2007).

As this research does not seek to explain the whole array of factors forecasting international investment flows, our models do not aim at reaching a higher R^2 than previous research (e.g. 0.2 as in the case of Habib and Zurawicki, 2002), but at identifying a significant interaction between the degree of corruption in home countries and their Directional Corruption Distance to respective host countries. We calculate five models (1, 2, 3, 4a, and 4b). The first three models all analyze the interaction between CPI Home and Directional Corruption Distance on RDS among the 210 country dyads. Each of the first three models sequentially introduces more control variables to solidify the findings; each model thereby includes the controls included in the prior model. Model 1 controls for economic attractiveness of a host country, as larger markets might attract more investments. As controls we chose the host country's GDP, GDP per Capita, GDP Growth, and Number of Graduates from Tertiary Education, which all act as strong incentives to invest in a certain country. Model 2 adds variables that are concerned with institutional quality. We control for a host country's score in the Ease of Doing Business index and its OECD membership. Model 3 controls for internationality, represented by the geographic distance between two countries and the degree to which a country grants patents to foreign applicants vs. residential ones. Models 4a and 4b introduce moderators that can further break down and explain country investment behavior. In two separate models, which both include all control variables from Model 3, we introduce the moderators of Patents per Million Inhabitants (Model 4a) and GDP Contribution by Tertiary Sector (Model 4b) in order to test whether country inventiveness and exposure to intangibles affects crossborder R&D in the context of corruption and uncertainty.

We report standardized coefficients and standard errors of five main terms: (i) the interaction effect between CPI Home and CPI Distance, (ii) the separate direct effects of Home Country CPI scores and Directional Corruption Distance on RDS, and (iii) conditional effects of Directional Corruption Distance on RDS for countries with low, mid, and high CPI scores. In Models 1, 2, and 3, the conditional effects represent spotlight analyses one standard deviation above and below the mean Home Country CPI. The conditional effect for home countries with medium CPI scores are thus equal to the main effect of Directional Corruption Distance on RDS. Models 4a and 4b include the moderator variables and add the respective conditional effects for high, mid, and low levels of the moderators. Here we report nine conditional effects, crossing the three spotlights for home countries of high, mid, and low CPI with the three spotlights for home countries with high, mid, and low degrees of Patents per Million Inhabitants (Model 4a) and GDP Contribution by Tertiary Sector (Model 4b). All interaction terms within our models were mean-centered prior to analysis. For readability, control variables are reported directly in the results table rather than in the text itself (Table 5).

We calculated interaction terms and conditional effects using Hayes' (2013) process macro for SPSS. Hayes, Montoya, & Rockwood (2017) argue that the decision whether to use their process macro or SEM is inconsequential, as both means of analysis yield the same results, especially if all variables in the model are observed variables—which is the case in our analysis. Hayes et al. (2017) also argue that the process macro delivers the same results even in regressions involving mediating variables. If mediation were relevant in our analysis, calculating path and measurement models using SEM would be helpful to further solidify the results from the process macro, given that the existence of mediation depends on other conditions, such as a non-significant direct effect of the independent on the dependent variables. However, as we de not calculate mediation but only moderations, this does not apply in our case. Our analysis focuses solely on direct and indirect effects, whose significance does not depend on model-relevant factors and is only subject to control variables, which are expounded throughout the models calculated.

For sake of completeness, we also report R^2, Standard Error, and F-Values for each model. Hayes' process macro only yields regular R^2 values instead of adjusted R^2 measures. But as we do not seek to show a complete model to explain RDS but rather the underlying influence that corruption distance and the home country perspective exert on R&D investments, these measures—although convincing in size—are not central to our analysis.

---- Insert Table 5 about here ----

ANALYSIS

Model 1: Economic Attractiveness

We find the interaction between CPI Home and DCD to be statistically significant ($t(201) = 2.04$, $p < .05$). DCD has a marginally significant direct effect on RDS ($t(201) = 1.84$, p = .07), which shows that, on average, there is a marginal tendeny for countries to trade up with regard to RDS. We obtain a highly significant direct effect of CPI Home on RDS ($t(201) = 3.56$, $p < .001$), which shows that countries with higher CPI scores, on average, emit more crossborder RDS than countries with lower CPI scores.

The conditional effects of DCD on RDS show that high CPI countries exhibit a significant tendency to trade up ($t(201) = 2.47$, $p < .05$), while low CPI countries do not exhibit a significant preference ($t(201) = 1.09$, *n.s.*). These results support H1a for high CPI countries (Trading Up Hypothesis) and H2b for low CPI countries (Familiarity Hypothesis), showing that the relevance of corruption is relative to the observer and does not, per se, discourage investments. The home-based perception of corruption (CPI Home) does influence the perception of corruption distance.

Model 2: Institutional Quality

The interaction between CPI Home and DCD is significant ($t(199) = 2.04$, $p < .05$). The direct effect of CPI Home on RDS is highly significant ($t(199) = 3.94$, $p < .001$), while DCD's effect is also significant ($t(199) = 2.25$, $p < .05$). Consistent with the prior model, less corrupt countries are the ones emitting more RDS, while all countries taken together, on average, tend to trade up. Conditional effects, as shown in Model 1, have proven robust, such that high CPI countries exhibit a highly signifcant tendency to trade up ($t(199) = 2.87$, $p < .01$), while low CPI countries do not show a significant preference ($t(199) = 1.48$, *n.s.*). This further supports H1a for high CPI countries (Trading Up Hypothesis) and H2b for low CPI countries (Familiarity Hypothesis).

Model 3: Geographic Distance

This model shows a marginally significant interaction between DCD and CPI Home ($t(197) = 1.82$, $p = .07$). The direct effect of CPI Home ($t(197) = 3.35$, $p < .01$) is highly significant, while DCD is marginally significant ($t(197) = 1.78$, $p = .08$). This supports the general tendency of RDS to trade up, whereby most RDS is emitted by higher CPI countries. Conditional effects, as shown before, have replicated: high CPI countries exhibit a signifcant tendency to trade up ($t(197) = 2.26$, $p < .05$), while low CPI countries do not show a significant trend ($t(197) = 1.16$, *n.s.*). These results yield further support for H1a for high CPI countries (Trading Up Hypothesis) and H2b for low CPI countries (Familiarity Hypothesis).

Model 4a: Patents per Million Inhabitants

The moderation model produces interesting insights with regard to the investment behavior of countries with low and high degrees of inventiveness. DCD and CPI Home interact significantly ($t(193) = 2.44$, $p < .05$). Neither direct effects of CPI Home ($t(193) = 1.29$, *n.s.*) nor DCD ($t(193) = 1.43$, *n.s.*) are significant this time, which is due to the introduction of the moderator as a process variable. Patents per Million Inhabitants trumps the other direct effects and significantly impacts RDS ($t(193) = 4.30$, $p < .001$). While neither the threeway interaction between DCD, CPI Home, and Patents per Million Inhabitants ($t(193) = .37$, *n.s.*) nor the interaction between the moderator and CPI Home are significant ($t(193) = -.83$, *n.s.*), the moderator interacts significantly with DCD ($t(193) = 2.41$, $p < .05$). This means that Patents per Million Inhabitants alters home country perceptions of DCD.

This becomes evident in the conditional effects, for which we find statistically significant results. Interestingly, countries with low levels of Patents per Million Inhabitants, across all CPI groups, significantly trade up ($t_{MidCPI}(193) = 2.30$, $p < .05$). The effect is stronger for high CPI countries ($t_{HighCPI}(193) = 2.28$, $p < .05$) than for low CPI countries ($t_{LowCPI}(193) = 1.82$, $p = .07$). Conversely, countries with high levels of Patents per Million Inhabitants, across all CPI groups, do not exhibit a significant trading tendency ($t_{LowCPI}(193) = -.89$, *n.s.*; $t_{MidCPI}(193) = .03$, *n.s.*; $t_{HighCPI}(193) = 1.39$, *n.s.*).

High inventiveness, expressed by high levels of Patents per Million Inhabitants, thus makes countries of all corruption groups less sensitive towards uncertainty. But low inventiveness, expressed by low levels of Patents per Million Inhabitants, increases sensitivity to such an extent that even low CPI countries exhibit a marginally significant tendency to trade up. This provides support for H3a (IP

Sensitivity Hypothesis). The high inventiveness condition yields support for H2a (Comfort Hypothesis) and H2b (Familiarity Hypothesis). The low inventiveness condition yields support for H1a (Trading Up). Overall, the moderator´s influence on the model yields support for H3a (IP Sensitivity Hypothesis). An R^2 of around 54% shows that the variables we employ to discuss international R&D investments manage to capture a large portion of variation.

Model 4b: GDP Contribution by Tertiary Sector

Moderating the relationships under scrutiny with the GDP contribution by a country's tertiary sector yields further support for our hypotheses. In this model, DCD and CPI Home interact significantly ($t(193) = 2.22$, $p < .05$). The direct effect of CPI Home is significant ($t(193) = 3.62$, $p < .001$), which again shows that high CPI countries are the main emitters of crossborder RDS. DCD is not significant ($t(193) = 1.61$, *n.s.*), which shows that—in this model more than in others—the impact of DCD is relative to each CPI group. Tertiary GDP Contribution has a highly significant effect on RDS ($t(193) = 3.88$, $p < .001$). There is also a significant threeway interaction between CPI Home, DCD, and the moderator at hand ($t(193) = 2.30$, $p < .05$). GDP contribution also interacts significantly with CPI Home ($t(193) = 3.02$, $p < .01$), while the interaction with DCD is insignificant ($t(193) = .47$, *n.s.*).

We find statistically significant results in the conditional effects. High CPI countries trade up significantly, if they possess a high Tertiary GDP Contribution ($t(193) = 2.51$, $p < .05$) or an average one ($t(193) = 2.32$, $p < .05$). This yields further support for H1a (Trading Up Hypothesis). Interestingly, high CPI countries with a low degree of Tertiary GDP Contribution do not exhibit a significant tendency to trade up any more ($t(193) = .7045$, *n.s.*). This shows that lower Tertiary GDP Contribution reduces sensitivity towards corruption. In this particular situation H2a (Comfort Hypothesis) is supported. Low CPI countries, consistent with prior models, do not show any tendency to trade up or down ($t(193) = .3094$, *n.s.*). This supports H2a (Familiarity Hypothesis). Overall, the moderator´s influence on the model yields support for H3b (Service Sensitivity Hypothesis). The R^2 of around 57% underlines the significant explanatory power of our model.

Figure 3 shows the conditional and direct effects of DCD on RDS in these models.

---- Insert Figure 3 about here ----

The Validity of Our Models

Our analysis was guided by a focus on relevance and conservatism, as outlined below. Empirical phenomena in economic research and social science will often 'violate' theory in some way, and it is important to include sanity checks on both ends of the equation to ensure that our methods and assumptions were reasonable. Our choices below provide us with some reassurance that our results are meaningful and reliable:

- Our 15 sample countries have an average CPI of 64. Had we included all available countries, many of which did not receive any RDS, the average CPI would have dropped to 43 (Transparency International, 2018), with two thirds below 50, which would have given even more support for our trading up hypothesis.
- We did not include randomly chosen countries, as some prior research has done, but included only the top RDS investors of the past decades. Using only the top investors reduces variance between countries regarding their invested crossborder RDS.
- We compressed the individual RDS data of more than 10,000 R&D centers into only 210 dyadic data points and log-normalized all one-sided open variables. We thus avoid misleading significance effects based on an inflated number of observations.
- We can alleviate concerns that the particular choice of countries involved in this study drives any trading-tendencies. Firstly, there are no multicollinearity issues, and the validity of our models was not artificially inflated. The statistical method we employed (Hayes, 2013; Hayes & Cai, 2007; Hayes & Preacher, 2013; Hayes, Montoya, & Rockwood, 2017) checks for multicollinearity and only delivers results in its absence. Secondly, our analysis is not trying to

conduct a macro-level analysis, optimizing a model for its ultimate fit to explain a dependent variable, but a micro-level analysis, seeking to single out the impact of specific independent variables and their interaction terms. We statistically account for the diversity of high- and low-corruption countries in our dataset through mean-centering process variables prior to calculating interaction terms (mean-centering reduces 'micro'-multicollinearity, i.e., multicollinearity between the process variables constituting an interaction term, see Iacobucci et al. (2016)). As our country set is fairly balanced, with a similar number of countries in high-, mid-, and low-corruption groups, mean-centering reduces imbalances caused by an imperfect spacing of countries across the corruption scale, and allows us to rule out trading-tendencies due to a surplus of countries on one or the other end of the corruption continuum.

- We did not include intra-country R&D center investments of the RDS (A, A) kind. Domestic R&D center establishments account for a significant share of a company's global R&D footprint, and one could argue that within-country R&D investment is tantamount to crossboder R&D if this country has multiple time zones, and is culturally and linguistically diverse. Certainly, long-distance country-internal investments are often plagued by similar challenges as regular FDI. Since the majority of RDS stems from low-corruption countries, had we included intra-country investments, our models would exhibit even stronger aversions to trade down, and would have led to an overestimation of the Comfort and Familiarity Hypotheses.
- An important factor speaking in favor of the effects shown in our analysis is that none of the control variables are significant, except for the variable measuring the number of graduates from tertiary education, which is mostly only marginally significant. Only the interplay between our main process variables, namely CPI Home, DCD and the chosen moderators, can explain the direction of crossborder RDS investment.

DISCUSSION

Reflections on the Trading-Up/Down Framework

The preceding analysis permits drawing conclusions about the prevalence of crossborder R&D investments given international business theory and corruption in home and hosts countries. First, we summarize the results in the context of the trading up / down framework (see Table 6).

---- Insert Table 6 about here ----

The trading up hypothesis was partially accepted, as countries of low corruption showed a strong tendency to trade up across our statistical models. The trading down hypothesis could not be supported, as no country group traded down significantly. We see the same results when we slice the data with such moderators as a country's degree of inventiveness or tertiary sector contribution. This suggests that corruption, generally, is a repellent rather than an attractor for incoming international R&D investments, in agreement with the findings by e.g. Mauro (1998), Wei (2000) and Habib & Zurawicki (2002) on general FDI. This result refines the early work by Huntington (1968), Leff (1989) and Wheeler & Mody (1992), and more recently by Henisz (2000) and Egger & Winner (2005), who suggested the existence of an investment-conducive effect on FDI: Generally, this is not the case for crossborder R&D.

We were able to differentiate crossborder R&D investment behavior by corruption similarity among countries and found lateral trading tendencies across virtually all of our statistical models for high-corruption countries. This means that the investment-repellent effect is lower for firms investing in crossborder R&D from other already corrupt countries. Specifically, we found support for the Familiarity hypothesis, qualifying results obtained by Cuervo-Cazurra (2006) and Arita (2013) based on general FDI data. Its logical complement—the Comfort hypothesis—for countries of low corruption trading laterally into countries with similarly low corruption levels, only occurred in models involving the moderators and was only be partially supported. This result is consistent with expectations of investment-conducive behavior, but qualifies established research by e.g. Wei (2000) and Henisz (2000) on the attractiveness of low-corruption countries with the added perspective on R&D-related crossborder investments. However, given the overall strong support for trading laterally in countries of both low and high corruption, we can support both the Comfort and the Familiarity hypotheses. The causes behind each lateral trading may be different, but the results are still the same.

The moderators in our models help explain the behavior of firms within both country groups of high and low corruption in our framework. While we would expect all countries to trade up, this tendency is especially strong for countries with relatively low inventiveness. Even countries with high corruption traded up, which supports the IP Sensitivity hypothesis. Among countries with many patents per capita, there is no trading up effect for either high- or low-corruption countries, perhaps because they are already inventive and therefore less economically affected by a potential loss of IP. They might also be less reliant on only few key technologies, which may allows them to accept more risk and uncertainty in crossborder investments.

The Service Sensitivity hypothesis was supported for low-corruption countries, which—in case of higher tertiary sector GDP contributions—exhibited stronger tendencies to trade up than in models without moderators. Countries with high levels of corruption, however, do not trade up, regardless of their GDP tertiary sector contributions. The same is true for low-corruption countries with relatively lower tertiary sector contribution, perhaps because R&D in the primary and secondary sectors is more easily protectable (Cullmann et al., 2012). The same line of reasoning explains why a high tertiary sector GDP contribution made low-corruption countries even more likely to invest in less corrupt countries.

Contributions to the International Business Literature

These findings are significant with respect to the ongoing market-seeking vs capability-seeking discussion in global R&D research (e.g., Kuemmerle, 1999; Le Bas & Sierra, 2002; von Zedtwitz & Gassmann, 2002) in the context of corruption influence on policy-making by recipient or origin countries of global R&D (e.g., Kwok & Tadesse, 2006; Cuervo-Cazurra et al., 2018), and with respect to strategy in innovation-intensive MNCs (e.g., Rodriguez et al., 2005; Goerzen et al, 2013; Meyer 2015). They also appear to be counter-intuitive for two reasons: The first is the apparent attractiveness of China in particular, and India to a somewhat lesser extent, as hosts of foreign R&D. In fact, the global R&D

investment community listed China repeatedly as their most important destination for new R&D establishment, and consider China as the new “must-have” location for their global R&D footprint (e.g., PwC’s Global Innovation Index). Estimates for the number of foreign R&D centers in China vary between 1,800 to more than 3,000, as no official list is publicly available. Our own database lists 813 foreign R&D centers in China, or 12.2% of the global crossborder R&D establishments, and 433 centers for India at 6.3% of the global total, respectively. This is an impressive achievement for these countries, but given the support for our trading-up hypothesis, we conclude that they have so far underperformed in their attraction of foreign R&D because of their relatively high levels of corruption. Countries such as China and India therefore should not be blinded by the current inflow of R&D investments from abroad, as this may represent R&D that the investing firms consider isolated from possible corruption effects (which likely constitutes a small share of overall R&D) or R&D that is less important at the global strategic level and “hedged” by imperfect local competition in the countries’ local markets.

The second counter-intuitive observation relates to Brouthers et al.’s (2008) finding that firms also conduct significant production-related FDI in corrupt countries (see also Egger & Winner, 2005). They showed that overall economic attractiveness can trump the perils associated with corruption as perceived by the investors. We also detected the compensatory influence of market attractiveness on corruption. At face value, i.e., without considering control variables, R&D seemed to be heavily attracted to corrupt countries. However, after controlling for economic attractiveness, RDS trades up toward less corrupt countries. This finding is an important cornerstone in accepting the reasons of crossborder R&D to countries that fundamentally—in terms of protection of IP, transparency of ownership and decision-making, fair appropriability of longterm investments—are poor hosts for R&D and innovation.

Research on motivational aspects of FDI (see, e.g., Meyer, 2015) may offer some insight from the international business literature. While market-seeking strategies are concerned with tailoring products for a certain market, for example in terms of consumer goods fit to local customs and habits, technology- or capability-seeking strategies seek to tap into specific talent, technology and know-how pools mostly with the aim to repatriate those proceeds for global benefit of the MNC. Our analysis shows that markets trump technology considerations. If market attractiveness were factored out, crossborder R&D would to go towards countries with lower corruption.

Our research also contributes to the literature covering developing countries as sources of international R&D and innovation. For instance, AlAzzawi (2012) suggested that firms from developing countries have strong incentives to invest in R&D in advanced economies in order to better monitor their international competitors at their home bases. Habib and Zurawicki (2002) already speculated that the influence of corruption might vary with the nature of a project or investment. Specifically, we identify under what conditions crossborder R&D would trade laterally to other corrupt countries, qualifying more general FDI research by Cuervo-Cazurra (2006) and Arita (2013).

Representing an investment where returns are in the distant future, R&D carries a higher degree of uncertainty than FDI, which generally is composed of asset purchases or equity takeovers. While the uncertainty in non-R&D and tangible asset-centered FDI can be reduced through due diligence risk assessments that yield a substantiated ad-hoc value of an equity at stake, the proceeds from R&D investments are much more uncertain to be valued accurately at time of the investment. This explains why knowledge-intense capability-seeking R&D is sensitive to negative externalities such as corruption.

The tendency of firms from low-corruption countries to trade up in terms of RDS, both under market-seeking and capability-seeking conditions, indicates a preference for safe environments. While firms from high-corruption countries also exhibit a slight tendency to trade up in terms of capability-seeking RDS under certain conditions, they show a strong tendency to invest market-seeking RDS in countries with similar corruption levels. Our Familiarity Hypothesis—firms from high-corruption countries striving for R&D in environments similar to theirs—constitutes an exciting opportunity for further research at the overlap between international business and innovation research.

Our research contributes to the discussion of home vs. host country conditions on international investment streams. Corruption is neither an absolute deterrent nor catalyst for incoming FDI, and moderated by market attractiveness of the recipient country. The difference in corruption perception-related investment decisions depends on two factors: the type of investment and the corruption of the home country. While prior research has focused on general undifferentiated FDI (subsuming, among others, R&D-related investment), we considered crossborder R&D separately. The varying effects researchers have so far discovered about corruption derive from the large differences in country samples, control variables, and model designs (e.g., Mauro, 1998; Wei, 2000; Cuervo-Cazurra, 2008). We not only confirm that R&D-related crossborder investments are often moderated by corruption, but also show that this depends not exclusively on the level of corruption in the host country but also on the relative distance between host and home country of the investor. At least among highly developed and less corrupt countries, it appears adequate to assume a home country bias in global R&D flows, which is in agreement with the Comfort Hypothesis, i.e., a preference for firms from low-corrupt countries to invest in other low-corrupt countries. This will allow to extend research taking a home-base perspective (e.g., Cuervo-Cazurra et al., 2018) and future research differentiating better between drivers and implications for global investment flows of different types, especially those that are either capability-seeking or market-seeking.

IMPLICATIONS AND LIMITATIONS

Implications

The benefits and drawbacks of corruption lie indeed in the eye of the beholder. Apart from country-internal regional differences, there are two more caveats: (i) individual decision makers have their own ethical standards and may be more or less corrupt than the countries they are affiliated with, and (ii) they may also perceive the level of corruption in target host countries differently from the CPI scores which are, after all, merely average perception indices. Nevertheless, our analysis shows that the perception of corruption is shaped, to a large extent, by the viewpoint from where one looks, as exhibited by the differing trading tendencies of firms from countries of high and low corruption.

The results spell out clear implications for countries of relatively high levels of corruption: everything else being equal, they are less attractive for high value-added FDI. Although much of current-day R&D investment lands in relatively more corrupt countries—developing behemoths such as China—those countries' attractiveness is likely just a temporary comparative advantage fueled by unsaturated markets and emerging market growth.

Low-corruption countries ought to retain their FDI attractiveness by maintaining low degrees of corruption. This can become a competitive advantage in attracting foreign investments, especially once growth in large developing countries slows down. Countries of low corruption should refrain from sliding down the corruption ladder, at least not relative to their peer group of preferred investors. For firms from low-corruption countries to invest comfortably in more corrupt countries, it may be necessary to use subsidiaries in countries of intermediate corruption levels, in an attempt to exploit the implications from the Familiarity Hypothesis. Of course, this is not meant to circumvent legal requirements, rather this should help leverage firm-internal familiarity with adjacent corruption conditions. In fact, this cascading strategy may already be employed by some MNCs (more likely those with extensive global networks and sufficiently far-sighted internationalization strategies) and account for some of the observed lateral trading and some of the unobserved down trading. As investigating the prevalence of such a strategy would require a firm-level analysis, we have to defer to future research in this matter.

Since the investments in our R&D-focused dataset vary in terms of financial commitment, IP exposure, and content (e.g., basic vs. applied research), the logic that discerns different patterns between R&D and general FDI likely replicates within international R&D investments as well. We postulate that, despite the attractiveness of markets due to their size and growth, the more valuable and ground-breaking crossborder investments are made in such safe nests as identified by Di Minin & Bianchi (2011). Again, from a host country standpoint, it pays to be less corrupt, as it allows a country to attract significantly more valuable R&D investments than highly corrupt countries.

Multinational firms seem to be drawn to R&D investing in high-corruption countries more than might be good for R&D, either because the decision-making process of initiating transnational R&D investment is specifically prone to corruption-related influences, or because countries of high corruption provide more incentives for foreign firms, e.g., favorable endowment factors or a large market. Our research suggests that MNCs should balance their global R&D ambitions carefully between capability-seeking strategies (with location-independent R&D conducted for global customers) and market-seeking strategies (when R&D follows the call of the customer and develops local products) in the context of exposure to host-based corruption. As mitigation strategies do not always work well for international R&D (Keupp et al., 2012), MNCs may also need to employ nonmarket strategies (Baron, 1995) that work well in the context of regimes that leverage local country conditions in the attempt to extract sensitive IP from foreign MNCs (Prud'homme and von Zedtwitz, 2019).

Our research also provides an additional explanation for the observed differences between international R&D strategies of MNCs from advanced and emerging markets (Awate et al., 2015). Given that corruption is more prevalent in developing countries (Mauro, 1995), and given that country corruption levels are relatively stable (based on our own analysis of CPI values as reported by Transparency International (2018)), we expect that emerging markets MNCs will, by and large, continue to trade laterally in terms of crossborder R&D, especially as far as their own expansionary R&D internationalization (von Zedtwitz, 2006) is concerned. For the same reasons (and supported by the qualifying results of Hypotheses H1a and H3a), we expect that MNCs from corrupt countries will decrease their trading up tendencies once their home countries' level of inventinveness increases. Any counteracting effects of an expanding service sector would only become apparent once the home country's level of corruption decreases (based on the partial support of Hypothesis H3b). In anticipation of this expected shift in emerging market MNC strategy, global collaboration partners as well as the governments of the host countries will have to adjust how they incorporate foreign R&D input from firms from more corrupt countries. However, analoguously to their advanced country counterparts, in the attempt to bypass the liability of relatively corrupt country origins, emerging market MNCs may engage in reverse cascading, provided they have established and matured longterm R&D internationalization beyond Awate et al.'s (2015) characterization.

LIMITATIONS AND CONCLUSIONS

Limitations and Future Research

Our crossborder R&D database has its own limitations, e.g. with respect to granularity at the R&D unit level rather than monetary equivalents more accepted in FDI research. If some of the disadvantages of FDI data were overcome, it would be possible to study the effects of corruption on R&D investments at a more refined level. For instance, it would be possible to differentiate asset vs non-asset-specific R&D FDI flows, and variations within different types of R&D, e.g. long-term vs short-term R&D.

Although our models already include several control variables, future research could consider the influence of costs of highly skilled labor. Lower costs of hiring highly skilled graduates of academic fields in the STEM area might be a major factor attracting RDS. Due to data limitations, this study did not include a control variable in this regard.

The level of analysis was the country, respectively, country pairings. Much of the underlying investment decisions are taken at the firm level, and therefore one cannot generalize crossboder investments at the country level. Future research should investigate firm-level decision-making in the context of country-paring specific conditions, such as the pursuit of cascading strategies on firms driving investments from and to certain countries. There may also be industry-related effects on firm-level investment choices that could be controlled for, e.g., differences in propensity for R&D internationalization of firms in high vs. low R&D intensive industries. In the previous sections we have proposed several strategic responses of MNCs to the conditions that shape their preferences for transnational R&D, and investigating them as well as the underlying antecedents are at the core of international business and innovation research. As this requires a different analytical lens from the one chosen in this study, we defer such work to future research.

Conclusions

We examined crossborder R&D investments between 15 countries in relationship to the relative directional corruption distance between home and host country. Introducing R&D Stock (RDS) and Directional Corruption Distance (DCD) as new variables, we revisit conflicting observations on the role of corruption as an investment-repellent and investment-conducive factor. Overall, crossborder R&D

flows follow global investment patterns, however, they are moderated by their greater sensitivity to corruption-specific characteristics in a country's innovation ecosystem. We find support for trading up, familiarity, and comfort hypotheses, but no support for a trading down hypothesis that would have explained why some countries invest in more corrupt countries. We further find support for two sensitivity hypotheses, such that firms from low-corruption countries with low inventiveness (IP Sensitivity Hypothesis) and high tertiary sector contribution (Service Sensitivity Hypothesis) strongly tend to trade up. This further shows the importance of considering the home country perspective in international business research.

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TABLES AND FIGURES

Figure 1

Four generic directions of crossborder investments given home and host corruption

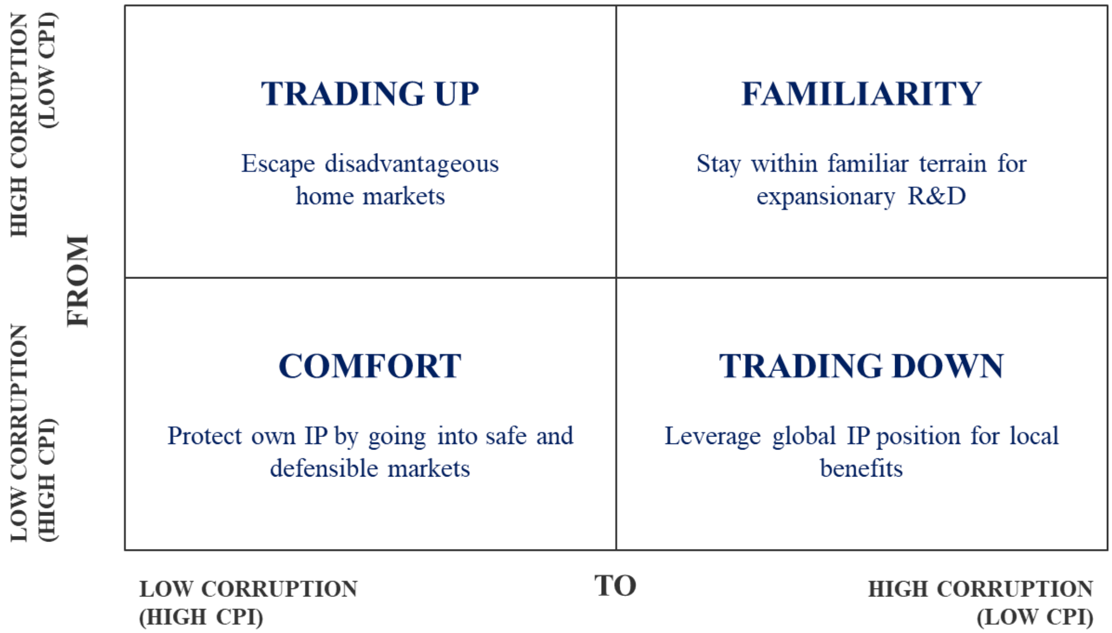


Figure 2

The Conceptual Model

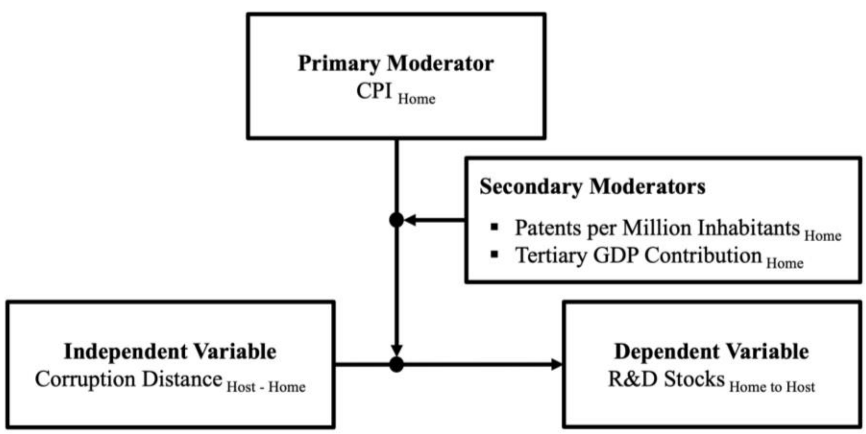
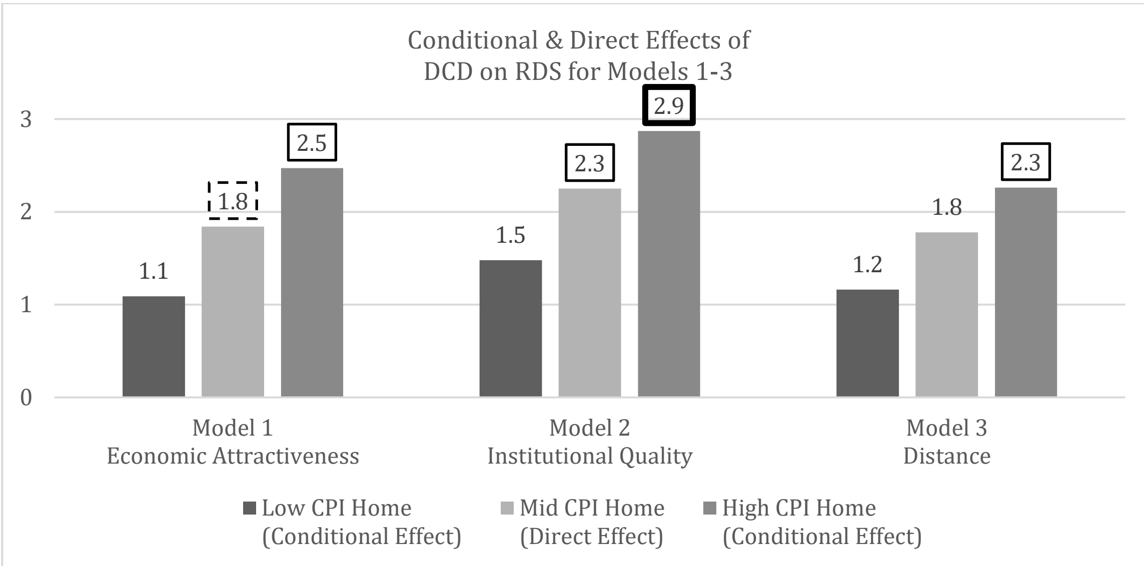
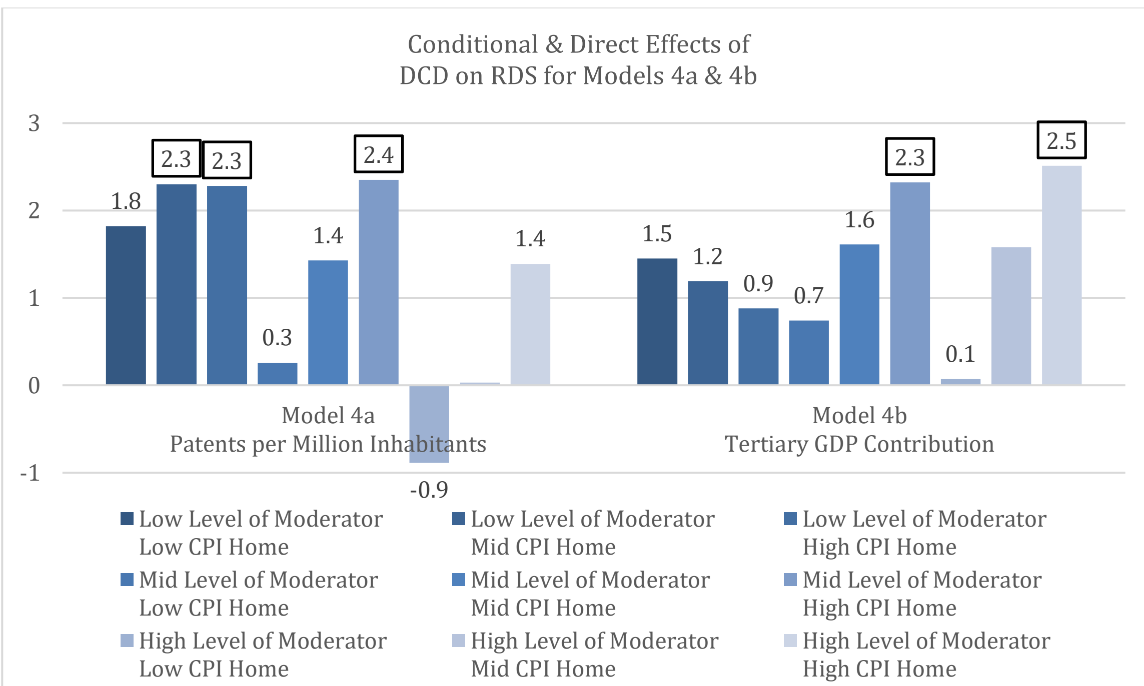


Figure 3

Conditional & direct effects of Directional Corruption Distance (DCD) on R&D Stock (RDS)





This figure reports t-values to showcase the direction and significance of the conditional and direct effects. Boxed effect sizes are statistical significant: solid bold line ($p < .01$), solid line ($p < .05$), and dotted line ($p < .10$).

Table 1

Crossborder R&D centers, i.e. RDS (host, home, [1900-2017])

RDS	**Host Countries**															
Home Countries	**US**	**DE**	**JP**	**CH**	**FR**	**NL**	**CN**	**KR**	**FI**	**SE**	**UK**	**IN**	**CA**	**IT**	**BR**	**Share of Country's Total Outgoing Transnational-R&D *(rounded)***
US		187	128	30	119	39	311	60	10	25	183	214	112	56	77	*61%*
DE	263		75	21	49	12	122	30	4	8	33	50	27	35	33	*75%*
JP	204	50		3	12	5	99	13	1	3	43	20	7	9	8	*79%*
CH	126	53	21		38	10	50	4	2	7	28	24	12	28	13	*77%*
FR	77	38	21	3		6	43	14	2	8	18	21	8	14	11	*73%*
NL	79	34	13	4	31		38	3	4	11	32	16	13	10	12	*78%*
CN	52	18	13	2	18	5		6	1	10	14	7	4	11	4	*71%*
KR	45	12	14	0	5	1	34		0	0	8	10	0	1	2	*84%*
FI	38	15	2	1	9	0	27	4		6	5	12	4	13	6	*76%*
SE	23	7	6	2	5	2	27	3	3		12	13	3	7	2	*79%*
UK	41	12	6	4	5	2	12	1	0	3		8	6	3	1	*79%*
IN	17	10	4	0	1	2	9	1	1	0	10		6	0	3	*75%*
CA	32	13	1	1	4	2	7	2	0	2	8	6		2	1	*83%*
IT	16	8	1	2	5	1	6	0	0	0	3	3	2		7	*74%*
BR	2	1	0	0	0	0	0	0	0	0	0	0	2	0		*100%*
Share of Country's Total Incoming Foreign RDS *(rounded)*	*91%*	*94%*	*95%*	*92%*	*95%*	*89%*	*95%*	*93%*	*93%*	*94%*	*96%*	*93%*	*95%*	*96%*	*95%*	

Table 2

Correlation table of all RDS variables (log-normalized)

Descriptive Statistics

RDS	Mean	Std. Deviation	N
Overall	2.1967	1.38543	210
1980-1989	0.1819	0.46446	210
1990-1999	0.4890	0.74743	210
2000-2009	0.8732	1.02934	210
2010-2019	0.7007	0.89664	210
2012-2017	0.5006	0.75795	210

Correlations

		RDS (Overall)	RDS 1980-1989	RDS 1990-1999	RDS 2000-2009	RDS 2010-2019	RDS 2012-2017
RDS (Overall)	Pearson Correlation	1	.548**	.725**	.798**	.770**	.722**
	Sig. (2-tailed)		0.000	0.000	0.000	0.000	0.000
	N	210	210	210	210	210	210
RDS 1980-1989	Pearson Correlation	.548**	1	.677**	.470**	.457**	.422**
	Sig. (2-tailed)	0.000		0.000	0.000	0.000	0.000
	N	210	210	210	210	210	210
RDS 1990-1999	Pearson Correlation	.725**	.677**	1	.680**	.683**	.646**
	Sig. (2-tailed)	0.000	0.000		0.000	0.000	0.000
	N	210	210	210	210	210	210
RDS 2000-2009	Pearson Correlation	.798**	.470**	.680**	1	.783**	.741**
	Sig. (2-tailed)	0.000	0.000	0.000		0.000	0.000
	N	210	210	210	210	210	210
RDS 2010-2019	Pearson Correlation	.770**	.457**	.683**	.783**	1	.933**
	Sig. (2-tailed)	0.000	0.000	0.000	0.000		0.000
	N	210	210	210	210	210	210
RDS 2012-2017	Pearson Correlation	.722**	.422**	.646**	.741**	.933**	1
	Sig. (2-tailed)	0.000	0.000	0.000	0.000	0.000	
	N	210	210	210	210	210	210

** Correlation is significant at the 0.01 level (2-tailed).
Note: 2012-17 period given in compliance with CPI data available.

Table 3

DCD Directional Corruption Distance ($CPI_{Host} - CPI_{Home}$) between the countries represented in this study based on CPI scores averages from 2012 until 2017

DCD	Host Countries														
Home Countries	**US**	**DE**	**JP**	**CH**	**FR**	**NL**	**CN**	**KR**	**FI**	**SE**	**UK**	**IN**	**CA**	**IT**	**BR**
US		5.7	-0.2	11.5	-4.2	9.0	-35.3	-19.7	14.5	13.3	4.5	-36.2	8.0	-29.3	-33.7
DE	-5.7		-5.8	5.8	-9.8	3.3	-41.0	-25.3	8.8	7.7	-1.2	-41.8	2.3	-35.0	-39.3
JP	0.2	5.8		11.7	-4.0	9.2	-35.2	-19.5	14.7	13.5	4.7	-36.0	8.2	-29.2	-33.5
CH	-11.5	-5.8	-11.7		-15.7	-2.5	-46.8	-31.2	3.0	1.8	-7.0	-47.7	-3.5	-40.8	-45.2
FR	4.2	9.8	4.0	15.7		13.2	-31.2	-15.5	18.7	17.5	8.7	-32.0	12.2	-25.2	-29.5
NL	-9.0	-3.3	-9.2	2.5	-13.2		-44.3	-28.7	5.5	4.3	-4.5	-45.2	-1.0	-38.3	-42.7
CN	35.3	41.0	35.2	46.8	31.2	44.3		15.7	49.8	48.7	39.8	-0.8	43.3	6.0	1.7
KR	19.7	25.3	19.5	31.2	15.5	28.7	-15.7		34.2	33.0	24.2	-16.5	27.7	-9.7	-14.0
FI	-14.5	-8.8	-14.7	-3.0	-18.7	-5.5	-49.8	-34.2		-1.2	-10.0	-50.7	-6.5	-43.8	-48.2
SE	-13.3	-7.7	-13.5	-1.8	-17.5	-4.3	-48.7	-33.0	1.2		-8.8	-49.5	-5.3	-42.7	-47.0
UK	-4.5	1.2	-4.7	7.0	-8.7	4.5	-39.8	-24.2	10.0	8.8		-40.7	3.5	-33.8	-38.2
IN	36.2	41.8	36.0	47.7	32.0	45.2	0.8	16.5	50.7	49.5	40.7		44.2	6.8	2.5
CA	-8.0	-2.3	-8.2	3.5	-12.2	1.0	-43.3	-27.7	6.5	5.3	-3.5	-44.2		-37.3	-41.7
IT	29.3	35.0	29.2	40.8	25.2	38.3	-6.0	9.7	43.8	42.7	33.8	-6.8	37.3		-4.3
BR	33.7	39.3	33.5	45.2	29.5	42.7	-1.7	14.0	48.2	47.0	38.2	-2.5	41.7	4.3	

Table 4

Variables, measures, and sources of data

	Variable	Measure	Source
Dependent Variables	R&D Stock (RDS)	Natural log of R&D stock a host country has received prior to 2017 in absolute numbers of R&D center establishments	R&D Center Database (2019)
Independent Variables	Directional Corruption Distance (DCD)	Distance between home and host country's CPI values (average from 2012 to 2017) calculated using $CPI_{Host} – CPI_{Home}$	Transparency International (2018)
Moderators	CPI Home	CPI value of home country measured on a scale from 1 to 100 (average from 2012 until 2017)	Transparency International (2018)
	Patents per Million Inhabitants	Natural log of the total number of patents (average from 2012 to 2017) a country's residents are granted both in their country of residence and abroad	WIPO (2020)
	Tertiary GDP Contribution	The share of a country's gross domestic product that is contributed by the tertiary sector (average from 2012 to 2017)	Central Intelligence Agency (2018)
Control Variables for Economic Attractiveness	GDP Host	Natural log of gross domestic product of host country, applying purchasing power parity, in US$ (average from 2012 to 2017)	World Bank (2018a)
	GDP per Capita Host	Natural log of gross domestic product per capita of host country, applying purchasing power parity, in US$ (average from 2012 to 2017)	World Bank (2018a)
	GDP Growth Host	GDP growth rate of host country (average from 2012 to 2017)	World Bank (2018a)
	Population Host	Natural log of number of inhabitants of the host country (average from 2012 to 2017)	World Bank (2018a)
	Graduates Host	Natural log of overall number of graduates from tertiary education (average from 2012 to 2017)	World Economic Forum (2018)

Control Variables for Institutional Quality	Ease of Doing Business	Quantifies business regulations and intellectual property protection, measured on a scale from 1 to 100 (average from 2012 until 2017)	World Bank (2018b)
	OECD Host	Dummy variable (0/1-coded) for membership of host country in the OECD for the year 2017	OECD (2018)
Control Variables for Distance & Internationality	Geographic Distance	The spherical distance between two points given a metric environment with latitude and longitude coordinates in degrees (Haversine Formula)	Stack-overflow (2019)
	Share of International Patents Received Host	Ratio of patents granted to foreign applicants over patents granted to resident applicants in a given host country (average from 2012 until 2017)	WIPO (2020)

Table 5

Summary of all statistical models

Regression Model	**Model 1** *Economic Attractiveness*	**Model 2** *Institutional Quality*	**Model 3** *Distance & Internationality*	**Model 4a** *Moderator Patents per Million Inhabitants*	**Model 4b** *Moderator GDP Contribution by Tertiary Sector*
n	210	210	210	210	210
Interaction					
CPI_{Home}*DCD	.0004 * (.0002)	.0004 * (.0002)	.0003 † (.0002)	.0007 * (.0003)	.0004 * (.0002)
DCD*PatentsPerMillion				-.0087 * (.0036)	
CPI_{Home}*PatentsPerMillion				-.0031 (.0037)	
CPI_{Home}*DCD*PatentsPerMillion				.0000 (.0001)	
DCD*TertiaryGDP					.0004 (.0008)
CPI_{Home}*TertiaryGDP					.0029 ** (.0010)
CPI_{Home}*DCD*TertiaryGDP					.0001 * (.0000)
Direct Effects					
CPI Home	.0420 *** (.0117)	.0467 ** (.0119)	.0415 ** (.0124)	.0173 (.0135)	.0420 *** (.0116)
DCD	.0187 † (.0102)	.0235 * (.0105)	.0197 † (.0111)	.0163 (.0113)	.0157 (.0098)
Patents Per Million Inhabitants				.3646 *** (.0848)	
GDP Contribution by Tertiary Sector					.0615 *** (.0159)
Conditional Effects (Spotlight Analysis)					
DCD for High CPI_{Home}	.0253 * (.0102)	.0301 ** (.0105)	.0259 * (.0114)		
DCD for Mid CPI_{Home}	.0187 † (.0102)	.0235 * (.0105)	.0157 † (.0111)		
DCD for Low CPI_{Home}	.0121	. 0169	.0095		

		(.0111)	(.0114)	(.0117)		
	Conditional Effects via Moderation (Spotlight Analysis)					
High Level of Moderator *1 σ Above Average*	High CPI$_{Home}$				.0148	.0359 *
					(.0107)	(.0143)
	Mid CPI$_{Home}$				.0004	.0184
					(.0122)	(.0117)
	Low CPI$_{Home}$				-.0141	.0009
					(.0159)	(.0126)
Mid Level of Moderator *Average*	High CPI$_{Home}$				.0293 *	.0236 *
					(.0124)	(.0102)
	Mid CPI$_{Home}$				.0163	.0157
					(.0113)	(.0098)
	Low CPI$_{Home}$				.0033	.0078
					(.0126)	(.0106)
Low Level of Moderator *1 σ Below Average*	High CPI$_{Home}$				.0439 *	.0113
					(.0192)	(.0129)
	Mid CPI$_{Home}$				.0324 *	.0130
					(.0141)	(.0109)
	Low CPI$_{Home}$				.0209 †	.0147
					(.0115)	(.0101)
	Control Variables					
	Ln GDP Host	27.1849	-167.1014	-110.1554	-105.0977	-80.6646
		(135.3699)	(168.3200)	(194.8910)	(188.1263)	(174.7596)
	Ln GDP per Capita Host	-26.6589	167.1340	110.2680	105.2629	80.8221
		(135.3854)	(168.2138)	(194.7654)	(187.9954)	(174.6655)
	GDP Growth Host	-.0018	-.0193	-.0263	-.0151	-.0291
		(.0735)	(.0819)	(.0825)	(.0789)	(.0776)
	Ln Population Host	-26.2133	168.7967	111.7306	106.6276	82.8221
		(135.3177)	(168.4337)	(194.9819)	(188.2234)	(174.8307)
	Ln Graduates Host	-.2453	-.9139 *	-.8081 †	-.7674 †	-.8096 *
	(Tertiary Education)	(.2665)	(.4159)	(.4345)	(.4124)	(.3748)
	Ease of Doing Business		.0416	.0417	.0413	.0412 †
			(.0279)	(.0280)	(.0266)	(.0241)
	OECD Membership Host		.4812	.3705	.3715	.3470
			(.3707)	(.3846)	(.3701)	(.3615)
	Geographic Distance			-.1054	-.0933	-.1225
				(.0841)	(.0826)	(.0792)
	Share of International			.2078	.1361	.2754
	Patents Received Host			(.4473)	(.4165)	(.4007)
	Model Estimates					
	R^2	.4375	.4516	.4556	.5382	.5727

Standard Error	1.1226	1.1056	1.1086	.9599	.8882
F-Value	22.9735 ***	20.5675 ***	17.1994 ***	20.1089 ***	19.6514 ***
df1	8	10	12	16	16
df2	201	199	197	193	193

This table reports unstandardized coefficients and standard errors for direct effects calculated via the WLS regressions alongside goodness-of-fit statistics for each individual regression throughout models 1, 2, 3, and 4. Moderation analysis was manifested using Hayes' (2013) process macro. All standard errors for continuous outcome models are based on the HC3 estimator and correct for heteroskedasticity (Hayes & Cai, 2007).

† $p < 0.1$; * $p < 0.05$; ** $p < 0.01$; *** $p < 0.001$

Table 6

Hypotheses and their results

Hypothesis	Title	Description	Result
H1a	*Trading Up Hypothesis*	Firms from more corrupt countries are more likely to invest in less corrupt countries.	Partially Supported [1]
H1b	*Trading Down Hypothesis*	Firms from less corrupt countries are more likely to invest in more corrupt countries.	Not Supported
H2a	*Comfort Hypothesis*	Firms from countries with low corruption prefer to invest in countries of similarly low corruption.	Partially Supported [2]
H2b	*Familiarity Hypothesis*	Firms from countries with high corruption prefer to invest in countries of similarly high corruption.	Supported
H3a	*IP Sensitivity Hypothesis*	The lower the number of patents per million inhabitants of a country, the greater the tendency to trade up.	Supported
H3b	*Service Sensitivity Hypothesis*	The higher the tertiary sector's contribution to a country's GDP, the greater the tendency to trade up.	Partially Supported [3]

[1] For low-corruption countries with a high CPI. Also for countries of all corruption groups when home country's variable Patents per Million Inhabitants is low.
[2] Only when home country's variable Patents per Million Inhabitants is high or when GDP Contribution by Tertiary Sector is low.
[3] For countries of low corruption.