

### **AUTHORS**

### Makram El-Shagi (Corresponding Author)

HenU Center for Financial Development and Stability Henan University

E-mail: makram.el-shagi@cfds.henuecon.education

Tel: +86 155 6511 5281

#### **Bashir Muhammad**

HenU Center for Financial Development and Stability Henan University

E-mail: <u>bashir.muhammad@cfds.henuecon.education</u>

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HenU Center for Financial Development and Stability Dongliuzhai Building, 85 Minglun Street Henan University, Minglun Campus Shunhe, Kaifeng, Henan, China Tel. +86 (30) 897 89-0 http://cfds.henuecon.education

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## Institutional similarity and bilateral FDI

Makram El-Shagi\*a and Bashir Muhammada

<sup>a</sup>Center for Financial Development and Stability, Henan University, China.

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#### Abstract

In this paper we assess the effect of institutional similarity on foreign direct investment. In a large panel of bilateral FDI stocks that covers roughly 190 countries both as host and source country of FDI we demonstrate that it is not similarity in general, but similarity with respect to government involvement in markets and with respect to corruption that matters. Our finding is robust to a large set of different panel estimators and specifications of the gravity model that is underlying our estimation.

Keywords: FDI, institutions, similarity, gravity model

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<sup>\*</sup>Corresponding author. Email: makram.el-shagi@cfds.henuecon.education. The authors are indebted to Peter Egger for fruitful discussions about gravity models and to Tamara Gurevich for valuable comments on the data she coauthored and which is used in this paper.

### 1 Introduction

Attracting foreign direct investment (FDI) seems to be the holy grail of economic achievements, especially for emerging markets.

FDI has been shown to bolster growth (De Mello, 1999; Nair-Reichert and Weinhold, 2001), and although this view has been challenged for example by Herzer et al. (2008) it seems that it is still a staple of the narrative of FDI. The seminal paper by Potterie and Lichtenberg (2001) and a range of country studies have shown that FDI can facilitate technological transfer, see e.g. Kokko et al. (1996) for Uruguay, Sinani and Meyer (2004) for Estonia and Blomström and Sjöholm (1999) for Indonesia. On top of all that, it allows for increased international risk sharing (Albuquerque, 2003).

So it comes at no surprise that the factors driving FDI have been the subject of some academic interest. In particular since bilateral FDI data became more readily available through the OECD and UNCTAD, there has been a surge of interest in the analysis of FDI. With the exception of few papers, which assess FDI between a single country (usually the US) and its partners, see e.g. Baltagi et al. (2007), bilateral FDI is assessed in a standard gravity framework borrowed from the trade literature.

Because a huge portion of FDI is flowing from the developed world to developing countries it comes at no surprise that a large part of the literature deals with FDI to developing countries in general (see for example Busse et al., 2010, 2011), or groups of developing countries such as emerging Asia (Hattari and Rajan, 2009; Mengistu and Adhikary, 2011; Petri, 2012), the Middle East (Bannaga et al., 2013) or the transition economies in Eastern Europe (Brenton et al., 1999; Egger and Merlo, 2007). The majority of the literature explores potential key drivers of bilateral FDI flows, that go beyond the staple push and pull factors (such as GDP) and multilateral resistance factors (such as distance, etc.) traditionally included in gravity models. A fairly sizable chunk of that literature deals with bilateral investment treaties (Neumayer and Spess, 2005; Egger and Pfaffermayr, 2004; Egger and Merlo, 2007; Busse et al., 2010) and trade agreements (Jang, 2011). Bénassy-Quéré et al. (2005) explore the potential role of corporate taxation; Abbott and De Vita (2011) and Barrell et al. (2017) and have a closer look at exchange rates and exchange rate regimes; Razin et al. (2008) look at productivity shocks; and Tong (2005) tests whether ethnic networks (of Chinese) can improve FDI, to name just a few examples of other indicators considered.

Our study is mostly inspired by the large literature that considers governance and other institutional factors as determinants of FDI (Mishra and Daly, 2007; Guerin and Manzocchi, 2009; Mengistu and Adhikary, 2011; Bannaga et al., 2013). Interestingly, institutions have mostly been considered as push for pull factors for investment flows. Although the role of cultural familiarity is well established in gravity models used for both trade and FDI as can easily be seen by the frequent inclusion of common language dummies or language distance measures, institutional similarity — and thereby familiarity with institutions — is mostly ignored, the notable exception being a recent paper by Cezar and

Escobar (2015). We add to this new line of literature, and aim to dig deeper in the aspects of institutional similarity that matter for FDI flows.

Contrary to the single previous study, we take a disaggregated perspective and assess individual institutions in addition to broader measures of general institutional development. We apply a broader econometric toolbox to guarantee robust results, and last but not least we extend the sample quite substantially using the most recent vintage of merged UNCTAD and OECD data for bilateral FDI data, and a newly developed gravity database by the USITC (Gurevich and Herman, 2018). This does not only include the sample size considerably, but also allows us to include FDI between emerging markets which has been widely ignored by the previous literature.

The remainder of the paper is structured as follows. In Section 2, we present our data including some stylized facts. In Section 3, we briefly introduce the models we estimate, and in Section 4 we discuss our results. Section 5 concludes.

### 2 Data

#### 2.1 Bilateral FDI data

Our bilateral FDI database includes the most current versions of the FDI data reported by the United Nations Conference on Trade and Development (UNC-TAD) and Organization for Economic Cooperation and Development (OECD). In case of divergent reports between sources or between information based on different reporting countries, we always use the largest number provided, assuming that it is more likely that a specific type of FDI slips through the gaps of one countries reporting system, than a country reporting non existing FDI.

It covers 191 countries – both as hosts and recipients – from 2002 to 2012. What makes our database special is that contrary to many previous studies (including Cezar and Escobar (2015)) it covers FDI from emerging markets in emerging markets. Figure 1 summarizes the total global FDI stocks separated into FDI within the groups of emerging markets, OECD countries, and between the groups.

#### 2.2 Institutions and institutional distance

#### 2.2.1 World governance indicators

Governance is primarily measured based on the World bank's Worldwide Governance Indicators (WGI) introduced by Kaufmann et al. (2011). The WGI data distinguishes six different dimensions of governance quality, namely control of corruption (COC), government effectiveness (GE), political stability and

<sup>&</sup>lt;sup>1</sup>The UNCTAD OECD data includes instocks and outstocks as reported by all countries. That is, each FDI stock is reported twice; once as instock by the host country, then as outstock by the source country. The same is true for FDI between OECD countries in the OECD data. In rare cases this leads to different numbers for the same stock even in one database.

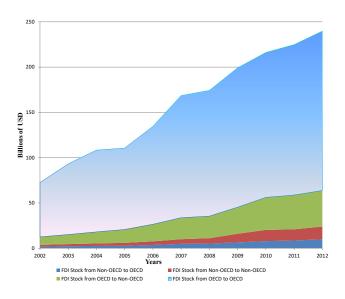


Figure 1: Composition of global FDI stocks

	Full sample		OECD			Non OECD		
$\operatorname{Indicator}$	Mean	Std. Dev.	Mean	Std. Dev.		Mean	Std.Dev.	
CPI	41.196	21.695	69.325	18.694		32.846	14.218	
CC	0	0.998	1.297	0.783		-0.264	0.813	
GE	0	0.998	1.334	0.569		-0.273	0.833	
PSAV	0	0.998	0.728	0.648		-0.148	0.992	
RQ	0	0.998	1.289	0.415		-0.264	0.869	
$\operatorname{RL}$	0	0.998	1.289	0.591		-0.258	0.852	
NAVAA	0	0.998	1.174	0.391		-0.236	0.913	

Table 1: Distribution of institutional indicators by country group

absence of violence (PSAOV), regulatory quality (RQ), rule of law (RL), voice and accountability (VAA).

Control of corruption captures corruption or – since many of the measures included are survey based – corruption perception. That is, despite its name "control" of corruption, it focuses more on the actual extent of corruption (which can be read as the governments success in controlling corruption) than on the government's attempts to limit corruption. The indicators included capture every type of corruption from petty corruption on the administrative level to grand corruption in parliament.

Governance effectiveness measures the quality of public good provision and the independence of the civil service from political pressure. However, the first component clearly dominates the index, which mostly aggregates over individual measures that focus on the quality of specific public goods such as infrastructure, education, health services and sanitation.

The *Political stability and absence of violence* indicator is mostly focused on the second component it is named after, i.e. the existence (or absence) of terrorism, riots, internal and external conflict, etc. In other words, the "stability" part of the indicator mostly describes the risk of the government being violently overthrown rather than general instability (for example with frequent non violent changes in administration that might make policies hard to predict), and thus should be interpreted primarily as indicator of political violence.

Regulatory quality is mostly an index of economic freedom and low government involvement, aggregating indicators on (the lack of) barriers to trade, entry, and investment, government regulated prices, etc. In other words, unlike governance effectiveness, it does not describe whether or not the government achieves its objectives, but evaluates the governments' objectives.

Rule of law summarizes both indicators of crime in general (i.e. the inability of the government to enforce it's law) and the governments' abuse of law in its dealings with citizens. However, the vast majority of indicators included measures the former aspect, making RL mostly an indicator of crime rather than government arbitrariness.

Voice and accountability aggregates over individual indicators that capture democratic institutions on the one hand and government transparency and ar-

bitrariness on the other side (effectively making this a second "rule of law" indicator).

A summary of the data by country group is reported in Table 1. Each of the six composite WGI indicators is constructed to be standard normal latent factor underlying the individual indicators included in the respective indicator. Unsurprisingly we find worse institutional quality in non OECD countries than in OECD countries. Typically the variance is much smaller for OECD countries. Given that the non OECD group ranges from the poorest economies of the globe to countries on the brink of being considered "developed", this seems plausible.

#### 2.2.2 Corruption perception

In addition to the WGI database, we measure corruption as reported in Transparency International's Corruption Perception Index (CPI). Theoretically, the CPI measures almost the exact same problem as CC. However, when developing the CC, the Worldbank considered a larger range of sources and uses a more sophisticated approach than the simple averaging done for the CPI. <sup>2</sup> However, CPI has established itself as the dominant indicator of corruption in the empirical literature (used for example in Méon and Weill, 2010; Barassi and Zhou, 2012; Huang, 2016; Liu, 2016). Therefore, we include it in our analysis despite its similarity and indeed find it to perform much more strongly than the Worldbank indicator. Like governance, CPI is summarized in Table 1. Since CPI is measured on a scale from 0 (fully corrupt) to 100 (not corrupt) rather than being standard normal, the numerical values differ starkly. However, the key message is the same: OECD countries are typically by far less corrupt than non OECD countries. It is interesting to note that for CPI, we find a higher variance for OECD countries, which seems to be counter-intuitive at first glance.

#### 2.2.3 Institutional distance

We compute institutional distance for each of the six WGI indicators and CPI as absolute distance. This absolute distance is then normalized to allow for an easier comparison of coefficient magnitudes between WGI indicators and CPI. In addition we compute a simple Euclidean distance measure based on the WGI indicators, that is defined as:

$$Dist_{i,j,t} = \sqrt{\frac{\sum_{k=1}^{6} (WGI_{i,t}^{(k)} - WGI_{j,t}^{(k)})^{2}}{6}},$$
(1)

where  $WGI^{(k)}$  is the  $k^{th}$  WGI indicator.

### 2.3 Other "gravity" data

Our control variables are taken from the recent gravity data set provided by Gurevich and Herman (2018). Since our different specifications use a relative

 $<sup>^2\</sup>mathrm{For}$  an excellent comparison of CPI and CC see Rohwer (2009).

rich set of dummy variables, to capture unobserved heterogeneity, we only include some of the key parameters found in the gravity literature in (some of) our specifications, in particular (log) per capita GDP and (log) population, distance, and a common language. Experiments with further indicators included in the gravity data did not yield systematically different results than those reported in the paper.

### 3 Model and method

### 3.1 Model specification

We adapt a standard gravity framework to assess the relevance of institutional similarity. Our models primarily differ in the fixed effects that we consider in addition to the variable of interest, i.e. the respective indicator of institutional distance.

We start from a basic model, that includes country-pair and time specific effects  $(\eta \text{ and } v)$ . Since most of the typical distance terms (such as geographical distance, cultural distance, etc.) are non time varying, they are omitted in the model. We do, however, control for the absolute difference in log GDP (y), to guarantee that we do not mistake economic similarity for institutional similarity. Adding the push and pull factors (Z) for each country that vary over time, we obtain the model:

$$fdi_{i,j,t} = |I_{j,t} - I_{i,t}|\phi + |y_{j,t-1} - y_{i,t-1}|\psi + Z_{i,t}A_1 + Z_{j,t}A_2 + \eta_{i,j} + \tau + \varepsilon_{i,j,t},$$
(2)

where  $fdi_{i,j,t}$  is log FDI from country i to country j at time t, I measures institutions and Z includes both (log) GDP, (log) population and the institutional quality measures themselves.

In a second specification, we use a version of the gravity model that became state of the art in recent years, where time-country specific effects are included for both the origin and the destination country of the considered flows. Contrary to specification 2 this specification obviously no longer includes the country variables, but does account for distance indicators (captured in D):

$$fdi_{i,i,t} = |I_{i,t} - I_{i,t}|\phi + |y_{i,t-1} - y_{i,t-1}|\psi + D_{i,j}B_1 + u_{i,t} + v_{j,t} + \varepsilon_{i,i,t}.$$
(3)

We then move to dynamic specifications for both models to account for the potential path dependency in FDI. I.e., we estimate

$$fdi_{i,j,t} = fdi_{i,j,t-1}\gamma + |I_{j,t} - I_{i,t}|\phi + |y_{j,t-1} - y_{i,t-1}|\psi + Z_{i,t}A_1 + Z_{j,t}A_2 + \eta_{i,j} + \tau + \varepsilon_{i,j,t}, \tag{4}$$
 and

$$fdi_{i,j,t} = fdi_{i,j,t-1}\gamma + |I_{j,t} - I_{i,t}|\phi + |y_{j,t-1} - y_{i,t-1}|\psi + D_{i,j}B_1 + u_{i,t} + v_{j,t} + \varepsilon_{i,j,t}.$$
(5)

It has to be kept in mind that the interpretation of coefficient magnitude changes drastically, when a lagged dependent is included. Over time, while the system overcomes its inbuilt persistence, the impact of a change in institutional difference is much larger than the initial impact of a change. More precisely, rather than looking at  $\phi$ , we have to look at  $\phi/(1-\gamma)$  to get an idea of the long run coefficient.

#### 3.2 Estimation

#### 3.2.1 GMM or no GMM

For the nondynamic models 2 and 3 estimation can be done through simple OLS without too much trouble. Things become more complicated for the dynamic models 4 and 5.

GMM (Arellano and Bond, 1991) and system GMM (Arellano and Bover, 1995; Blundell and Bond, 1998) estimators are well known to overcome the bias that is inherent to fixed effects models with a lagged dependent variable (where the strict exogeneity assumption required for fixed effects estimators no longer holds). Yet, the instrumentation necessary for both GMM and system GMM comes with a massive loss of information. It has therefore been a longgoing debate in the literature, in which situation overcoming a bias (that is fairly small for large T) is worth the loss of efficiency. In their widely cited paper, Judson and Owen (1999) demonstrate in a simulation exercise that the uncertainty introduced by instrumentation overcompensates the finite sample bias roughly when the time dimension hits 30, i.e. substantially more than our sample size. However, Moral-Benito (2013) demonstrates, that in particular for time series that exhibit a unit root<sup>3</sup>. simple fixed effects estimators might be more desirable in much smaller sample sizes, especially when the parameter of interest is not the autoregressive coefficient itself, but the coefficient of one of the exogenous variables.<sup>4</sup> Therefore, we rely on simple fixed effects or more precisely "least square dummy variable" estimators in our paper. However, the dynamic baseline model (see Equation 4) is estimated with both GMM and system GMM estimators as robustness test.

#### 3.2.2 The Wooldridge selection estimator

In an additional robustness test, we account for the large amount of zeros (i.e. no foreign direct investment) in our dataset. It is not quite certain, whether

 $<sup>^3</sup>$  A simple Fisher test (as proposed by Maddala and Wu, 1999), strongly rejects the stationarity null hypothesis for log FDI.

<sup>&</sup>lt;sup>4</sup>The main point by Moral-Benito (2013) is to introduce a new maximum likelihood base estimator. For a more detailed summary of the result that is highlighted here refer for example to El-Shagi and Shao (2017).

those zeroes and missing values actually represent zero investment or missing data, but it seems fair to assume that the flows where they are not reported are miniscule (and thus the quantitative interpretation of 0 as "no fdi" is still valid). To correct for those zeros we employ a Wooldridge (1995) selection estimator. This estimator, which is essentially a panel version of the seminal approach introduced by Heckman (1979). This approach does, however, have one downside for samples with a relatively large time dimension. The correction term is based on probit estimations for each individual period, where each variable for every period is used as regressor. Those auxiliary regressions quickly run out of degrees of freedom if T and/or the number of regressors in the equation of interest is large. Therefore, we have to omit most of our controls when using this approach, and exclusively focus on institutional difference and the level of the institutional indicators in each country. While we omit most controls, the model still accounts for unobserved heterogeneity through the implicit inclusion of country pair fixed effects. Yet, we still consider this limitation severe enough to merely apply the Wooldridge (1995) approach as robustness test, rather than relying on it as our baseline model.

### 4 Results

Since we estimate our model with a fairly large battery of estimators, the detailed results for each of those are reported in the appendix (Tables A2 to A14). Table 2 summarizes the core results, regarding the sign and significance of results. We find that only CPI and voice and accountability are robustly negatively correlated with FDI. For regulatory quality we find less clearcut but still fairly strong results. For all others, there is no conclusive evidence.

$\frac{1 \text{ model}}{\sqrt{0/0/0}}$	individual
/n /n /n	10 10 10 10
/ 0/ 0/ 0	13/0/0/0
0/9/3	6/0/7/0
(2/1/9)	7/0/2/4
5/0/5	7/3/0/3
1/1/2	10/1/0/2
6/2/2	7/3/1/2
/0/0/0	11/2/0/0
	6/1/1/5

Note: From left to right the numbers count significantly negative, insignificantly negative, insignificantly positive, and significantly positive coefficient estimates. The "Full model" column refers to estimations with all governance indicators, the "individual" column refers to the specifications where only one governance indicator is used. The Wooldridge estimator has only been used for individual governance indicators.

Table 2: Summary of results

Our most puzzling result clearly is the huge difference between the findings regarding CPI and CC. While CPI performs clearly best in terms of confirming our key hypothesis (i.e. that similarity increases FDI flows), CC is among the worst. Given a correlation of more than 90% (see Table A1 in the appendix) this seems impossible at first glance. However, this correlation is almost exclusively driven by the cross country component. When account for fixed effects, the "within" correlation drops to a meager 20%. Given that CPI yields much more economically plausible results, it seems that focusing on a few, very well established individual corruption measures, as done by transparency international, might be a better methodology than the broader approach chosen by the Worldbank after all.

Regarding the subcomponents of governance as measured by the WGI, of findings are highly intuitive. Both VAA and RQ mostly describe "how" the government and the economic system of a country functions rather than "whether or not" it functions. Familiarity with those aspects, such as government involvement in general, wide reaching government involvement, and even government discretion can help navigating the pitfalls of a system that exhibits those features. Being able to deal with red tape gives investors from countries with a similar background a comparative advantage that they exploit. Contrarily, issues like crime (as measured by RL), absence of key public goods (as measured by GE) or the threat of violence (as measured by PSAV) are quite unequivocally bad. Even when having experience with violence in your own country, this does not make it more attractive to invest in a country that has the same problems. Whether or not you understand a terrorist threat, does not increase the probability of successfully avoiding it. Similarity thus does not provide a comparative advantage in those cases. Correspondingly, our composite indicator (that aggregates all six WGI variables including the four that perform badly) does not perform very well.

Our lack of conclusive evidence for some of the indicators considered is not necessarily reflecting their irrelevance, but might be due to the large variation in the data explained by other factors. However, it is telling that the indicators where the results we find are robust, are those where it is economically intuitive.

For all three indicators we typically find coefficients in the order of magnitude between 0.05 and 0.3, clustered around 0.15. For dynamic models we usually find an AR coefficient between 0.5 and 0.6, i.e. the results have to be doubled to obtain "long run" coefficients that are comparable with the static models. After doing so, the dynamic models imply results in the upper tail of this distribution. In other words, it seems an increase in similarity with regards to corruption and government involvement by one standard deviation most likely increases FDI 15% or even more. This finding is robust to including development differences (measured as difference in log GDP per capita) in the model.

### 5 Conclusion

In a uniquely large sample of bilateral FDI data, we can show that institutional similarity does indeed matter for foreign direct investment decisions. However, it is not similarity per se. As can be expected, it is familiarity with issues that create transaction costs that can be lowered by experiences. This applies mostly to corruption (measured by CPI), and a few indicators of governance quality, in particular voice and accountability and regulatory quality, both effectively measuring the degree of government involvement in decisions relevant for business. The size of the effect is considerable, and speaks for further increases in FDI between emerging markets (with oftentimes similar institutions) in the future as those countries keep growing.

### References

- Abbott, A. J. and De Vita, G. (2011). Evidence on the Impact of Exchange Rate Regimes on Bilateral FDI Flows, *Journal Of Economic Studies* **38**(3): 253–274.
- Albuquerque, R. (2003). The Composition of International Capital Flows: Risk Sharing Through Foreign Direct Investment, Journal of International Economics 61(2): 353–383.
- Arellano, M. and Bond, S. (1991). Some Tests of Specification for Panel Data: Monte Carlo Evidence and An Application to Employment Equations, *The Review of Economic Studies* 58(2): 277–297.
- Arellano, M. and Bover, O. (1995). Another Look at the Instrumental Variable Estimation of Error-components Models, *Journal of Econometrics* **68**(1): 29–51.
- Baltagi, B. H., Egger, P. and Pfaffermayr, M. (2007). Estimating Models of Complex FDI: Are there third-Country Effects?, *Journal of Econometrics* **140**(1): 260–281.
- Bannaga, A., Gangi, Y., Abdrazak, R. and Al-Fakhry, B. (2013). The Effects of Good Governance on Foreign Direct Investment Inflows in Arab Countries, *Applied Financial Economics* **23**(15): 1239–1247.
- Barassi, M. R. and Zhou, Y. (2012). The Effect of Corruption on FDI: A Parametric and Non-parametric Analysis, *European Journal of Political Economy* **28**(3): 302–312.
- Barrell, R., Nahhas, A. and Hunter, J. (2017). Exchange Rates and Bilateral FDI: Gravity Models of Bilateral FDI in High Income Economics, *Economics and Finance Working Paper Series* (17-07).

- Bénassy-Quéré, A., Fontagné, L. and Lahrèche-Révil, A. (2005). How Does FDI React to Corporate Taxation?, *International Tax and Public Finance* 12(5): 583–603.
- Blomström, M. and Sjöholm, F. (1999). Technology Transfer and Spillovers: Does Local Participation with Multinationals Matter?, *European Economic Review* **43**(4-6): 915–923.
- Blundell, R. and Bond, S. (1998). Initial Conditions and Moment Restrictions in Dynamic Panel Data Models, *Journal of Econometrics* 87(1): 115–143.
- Brenton, P., Di Mauro, F. et al. (1999). The Potential Magnitude and Impact of FDI Flows to CEECs, *Journal of Economic Integration* **14**: 59–74.
- Busse, M., Königer, J. and Nunnenkamp, P. (2010). FDI Promotion through Bilateral Investment Treaties: More than a Bit?, *Review of World Economics* **146**(1): 147–177.
- Busse, M., Nunnenkamp, P. and Spatareanu, M. (2011). Foreign Direct Investment and Labour Rights: A Panel Analysis of Bilateral FDI Flows, *Applied Economics Letters* **18**(2): 149–152.
- Cezar, R. and Escobar, O. R. (2015). Institutional Distance and Foreign Direct Investment, *Review of World Economics* **151**(4): 713–733.
- De Mello, L. R. (1999). Foreign Direct Investment-led Growth: Evidence from Time Series and Panel Data, Oxford Economic Papers 51(1): 133–151.
- Egger, P. and Merlo, V. (2007). The Impact of Bilateral Investment Treaties on FDI Dynamics, World Economy **30**(10): 1536–1549.
- Egger, P. and Pfaffermayr, M. (2004). The Impact of Bilateral Investment Treaties on Foreign Direct Investment, *Journal of Comparative Economics* **32**(4): 788–804.
- El-Shagi, M. and Shao, L. (2017). The Impact of Inequality and Redistribution on Growth, *Review of Income and Wealth*.
- Guerin, S. S. and Manzocchi, S. (2009). Political Regime and FDI from Advanced to Emerging Countries, *Review of World Economics* **145**(1): 75–91.
- Gurevich, T. and Herman, P. (2018). The Dynamic Gravity Dataset: 1948–2016, US International Trade Commission Office of Economics Working Paper .
- Hattari, R. and Rajan, R. S. (2009). Understanding Bilateral FDI Flows in Developing Asia, *Asian-Pacific Economic Literature* **23**(2): 73–93.
- Heckman, J. J. (1979). Sample Selection Bias as a Specification Error, *Econometrica: Journal of the Econometric Society* pp. 153–161.

- Herzer, D., Klasen, S. et al. (2008). In Search of FDI-led Growth in Developing Countries: The Way Forward, *Economic Modelling* **25**(5): 793–810.
- Huang, C.-J. (2016). Is Corruption Bad for Economic Growth? Evidence from Asia-pacific Countries, The North American Journal of Economics and Finance 35: 247–256.
- Jang, Y. J. (2011). The Impact of Bilateral Free Trade Agreements on Bilateral Foreign Direct Investment among Developed Countries, *The World Economy* **34**(9): 1628–1651.
- Judson, R. A. and Owen, A. L. (1999). Estimating Dynamic Panel Data Models: A Guide for Macroeconomists, *Economics Letters* **65**(1): 9–15.
- Kaufmann, D., Kraay, A. and Mastruzzi, M. (2011). The Worldwide Governance Indicators: Methodology and Analytical Issues, *Hague Journal on the Rule* of Law 3(2): 220–246.
- Kokko, A., Tansini, R. and Zejan, M. C. (1996). Local Technological Capability and Productivity Spillovers from FDI in the Uruguayan Manufacturing Sector, *The Journal of Development Studies* **32**(4): 602–611.
- Liu, X. (2016). Corruption Culture and Corporate Misconduct, *Journal of Financial Economics* **122**(2): 307–327.
- Maddala, G. S. and Wu, S. (1999). A Comparative Study of Unit Root Tests with Panel Data and A New Simple Test, Oxford Bulletin of Economics and statistics 61(S1): 631–652.
- Mengistu, A. A. and Adhikary, B. K. (2011). Does Good Governance Matter for FDI Inflows? Evidence from Asian Economies, *Asia Pacific Business Review* 17(3): 281–299.
- Méon, P.-G. and Weill, L. (2010). Is Corruption an Efficient Grease?, World Development 38(3): 244–259.
- Mishra, A. and Daly, K. (2007). Effect of Quality of Institutions on Outward Foreign Direct Investment, *The Journal of International Trade & Economic Development* 16(2): 231–244.
- Moral-Benito, E. (2013). Likelihood-based Estimation of Dynamic Panels with Predetermined Regressors, *Journal of Business & Economic Statistics* **31**(4): 451–472.
- Nair-Reichert, U. and Weinhold, D. (2001). Causality Tests for Cross-country Panels: A New Look at FDI and Economic Growth in Developing Countries, Oxford Bulletin Of Economics And Statistics 63(2): 153–171.
- Neumayer, E. and Spess, L. (2005). Do Bilateral Investment Treaties Increase Foreign Direct Investment to Developing Countries?, *World Development* **33**(10): 1567–1585.

- Petri, P. A. (2012). The Determinants of Bilateral FDI: Is Asia Different?, *Journal of Asian Economics* **23**(3): 201–209.
- Potterie, B. v. P. d. l. and Lichtenberg, F. (2001). Does Foreign Direct Investment Transfer Technology Across Borders?, *Review of Economics and Statistics* 83(3): 490–497.
- Razin, A., Sadka, E. and Tong, H. (2008). Bilateral FDI Flows: Threshold Barriers and Productivity Shocks, *CESifo Economic Studies* **54**(3): 451–470.
- Rohwer, A. (2009). Measuring Corruption: A Comparison Between the Transparency International's Corruption Perceptions Index and the World Bank's Worldwide Governance Indicators, *CESifo DICE Report* 7(3): 42–52.
- Sinani, E. and Meyer, K. E. (2004). Spillovers of Technology Transfer from FDI: The Case of Estonia, *Journal of Comparative Economics* **32**(3): 445–466.
- Tong, S. Y. (2005). Ethnic Networks in FDI and the Impact of Institutional Development, *Review of Development Economics* **9**(4): 563–580.
- Wooldridge, J. M. (1995). Selection Corrections for Panel Data Models Under Conditional Mean Independence Assumptions, *Journal of Econometrics* **68**(1): 115–132.

# Appendix

	CPI	CC	GE	PSAV	RQ	RL	VAA
CPI	1.000						
CC	0.975	1.000					
GE	0.935	0.948	1.000				
PSAV	0.730	0.757	0.726	1.000			
RQ	0.870	0.884	0.936	0.693	1.000		
RL	0.938	0.957	0.963	0.774	0.936	1.000	
VAA	0.743	0.785	0.799	0.638	0.637	0.825	1.000

Table A1: Correlation of governance indicators

		Table A2:	Country pai	r fixed effe	cts; time fix	xed effects;	static mod	el	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.122***	-0.0607**							
	(0.0291)	(0.0249)							
CC	0.305***		0.169***						
	(0.0386)		(0.0306)						
GE	0.0600*			0.0423					
	(0.0336)			(0.0292)					
PSAV	-0.00344				-0.0346*				
	(0.0210)				(0.0198)				
RQ	-0.117***				`	-0.0494*			
•	(0.0346)					(0.0289)			
RL	-0.174***					,	-0.0406		
	(0.0487)						(0.0385)		
VAA	-0.138***						,	-0.0611*	
	(0.0405)							(0.0361)	
Dist.	(0.0.200)							(0.000-)	0.0346*
									(0.0196)
Observations	32,700	32,700	36,025	36,022	36,024	36,022	36,029	36,029	36,020
R-squared	0.264	0.258	0.246	0.246	0.244	0.245	0.246	0.244	0.245
*									

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.135***	-0.0828***							
	(0.0290)	(0.0250)							
CC	0.321***	,	0.160***						
	(0.0386)		(0.0306)						
GE	0.0423		, ,	0.0133					
	(0.0336)			(0.0294)					
PSAV	0.0123			,	-0.0275				
	(0.0210)				(0.0197)				
RQ	-0.157***					-0.0841***			
	(0.0347)					(0.0290)			
RL	-0.171***						-0.0477		
	(0.0486)						(0.0384)		
VAA	-0.156***							-0.0799**	
	(0.0405)							(0.0361)	
$\operatorname{Dist.}$									0.0213
									(0.0196)
Observations	32,700	32,700	36,025	36,022	36,024	36,022	36,029	36,029	36,020
R-squared	0.266	0.260	0.248	0.247	0.246	0.247	0.248	0.247	0.247
Number of id	4 319	4 319	4.737	4 737	4.737	4737	4.737	4.737	4737

Number of id 4,319 4,319 4,737 4,737 4,737 4,737 4,737 4,737 4,737 4,737 4,737 4,737  $\overline{}$  Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1, and the absolute lagged distance of log GDP per capita.

Table A4: Country pair fixed effects; time fixed effects; dynamic model
(2) (3) (4) (5) (6) (7) (8) (9)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.114***	-0.0741***							
CC	(0.0235) $0.166***$	(0.0203)	0.0713***						
	(0.0310)		(0.0246)						
GE	0.0254			0.0114					
	(0.0272)			(0.0238)					
PSAV	0.0199				0.00187				
	(0.0170)				(0.0159)				
RQ	-0.0582**					-0.0283			
	(0.0280)					(0.0234)			
RL	-0.0630						-0.00229		
	(0.0404)						(0.0319)		
VAA	-0.0731**							-0.0423	
	(0.0329)							(0.0292)	0.04.00
Dist.									0.0138
									(0.0162)
Observations	30,079	30,079	32,883	32,881	32,880	32,881	32,884	32,884	32,879
R-squared	0.503	0.501	0.496	0.496	0.495	0.496	0.496	0.496	0.496
Number of id	4,036	4,036	4,402	4,402	4,402	4,402	4,402	4,402	4,402

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1.

Table A5: Country pair fixed effects; time fixed effects; controls for development difference; dynamic model

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.119***	-0.0807***							
	(0.0235)	(0.0203)							
CC	0.173***		0.0693***						
	(0.0310)		(0.0246)						
GE	0.0205			0.00402					
	(0.0272)			(0.0239)					
PSAV	0.0253				0.00419				
	(0.0170)				(0.0159)				
RQ	-0.0740***					-0.0392*			
-	(0.0281)					(0.0235)			
RL	-0.0580					,	-0.00153		
	(0.0404)						(0.0319)		
VAA	-0.0813**						,	-0.0488*	
	(0.0329)							(0.0292)	
Dist.	, ,							,	0.0102
									(0.0162)
Observations	30,079	30,079	32,883	32,881	32,880	32,881	32,884	32,884	32,879
R-squared	0.503	0.501	0.496	0.496	0.496	0.496	0.496	0.496	0.496
Number of id	4,036	4,036	4,402	4,402	4,402	4,402	4,402	4,402	4,402

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1, and the absolute lagged distance of log GDP per capita.

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.135***	-0.288***							
	(0.0323)	(0.0205)							
CC	$0.0650^{'}$	,	-0.295***						
	(0.0415)		(0.0228)						
GE	-0.0115		, ,	-0.311***					
	(0.0375)			(0.0241)					
PSAV	0.0263			,	-0.118***				
	(0.0216)				(0.0192)				
RQ	-0.136***					-0.353***			
	(0.0384)					(0.0255)			
RL	-0.0709						-0.351***		
	(0.0464)						(0.0257)		
VAA	-0.407***							-0.478***	
	(0.0346)							(0.0270)	
Dist.									-0.238***
									(0.0137)
Observations	34,692	34,692	40,182	40,182	40,177	40,182	40,196	40,191	40,165
Number of id	4,334	4,334	$5,\!010$	$5,\!010$	5,008	5,010	$5,\!011$	$5,\!010$	5,007

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are (log) distance and a common language dummy

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.144***	-0.278***							
	(0.0333)	(0.0212)							
CC	0.0727 *	,	-0.291***						
	(0.0429)		(0.0242)						
GE	0.0418		,	-0.295***					
	(0.0392)			(0.0256)					
PSAV	0.00458				-0.144***				
	(0.0225)				(0.0204)				
RQ	-0.174***					-0.377***			
	(0.0399)					(0.0270)			
RL	-0.0564						-0.353***		
	(0.0484)						(0.0268)		
VAA	-0.394***							-0.491***	
	(0.0356)							(0.0284)	
Dist.									-0.238***
									(0.0143)
Observations	32,704	32,704	36,004	36,004	36,008	36,004	36,008	36,008	36,004
Number of id	4,319	4,319	4,737	4,737	4,737	4,737	4,737	4,737	4,737

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are (log) distance, a common language dummy, and the absolute lagged distance of log GDP per capita.

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.0530**	-0.0415***							
	(0.0236)	(0.00595)							
CC	0.0407		-0.0419***						
	(0.0271)		(0.00593)						
GE	-0.000857			-0.0509***					
	(0.0196)			(0.00684)					
PSAV	-0.00197				-0.0334***				
	(0.00866)				(0.00682)				
RQ	-0.0647***					-0.0671***			
	(0.0173)					(0.00758)			
RL	0.0406*						-0.0451***		
	(0.0215)						(0.00631)		
VAA	-0.0452***							-0.0597***	
	(0.0106)							(0.00706)	
Dist.									-0.0271***
									(0.00331)
Observations	30,109	30,109	34,294	34,294	34,295	34,294	34,303	34,301	34,286
Number of id	4,043	4,043	$4,\!617$	4,617	$4,\!617$	$4,\!617$	4,618	$4,\!618$	4,616

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are (log) distance and a common language dummy

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.0530**	-0.0413***							
	(0.0236)	(0.00594)							
CC	0.0377		-0.0422***						
	(0.0271)		(0.00598)						
GE	0.00553			-0.0491***					
	(0.0196)			(0.00691)					
PSAV	-0.00516				-0.0381***				
	(0.00867)				(0.00694)				
RQ	-0.0681***					-0.0698***			
	(0.0173)					(0.00769)			
RL	0.0412*						-0.0445***		
	(0.0215)						(0.00635)		
VAA	-0.0430***							-0.0604***	
	(0.0106)							(0.00717)	
Dist.									-0.0276**
									(0.00334)
Observations	30,083	30,083	$32,\!865$	$32,\!865$	32,866	$32,\!865$	32,866	32,866	$32,\!865$
Number of id	$4,\!036$	4,036	4,402	4,402	4,402	$4,\!402$	4,402	4,402	4,402

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are (log) distance and a common language dummy, and the absolute lagged distance of log GDP per capita.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.0967***	-0.0850***							
	(0.0335)	(0.0326)							
CC	0.0995**	,	0.100**						
	(0.0462)		(0.0409)						
GE	0.0635			0.0772**					
	(0.0409)			(0.0368)					
PSAV	-0.0131				-0.0195				
	(0.0260)				(0.0246)				
RQ	0.00458					0.0362			
	(0.0426)					(0.0378)			
$\operatorname{RL}$	-0.0605						0.00922		
	(0.0616)						(0.0514)		
VAA	-0.0873*							-0.0813*	
	(0.0473)							(0.0430)	
$\operatorname{Dist.}$									0.0338
									(0.0272
Observations	25,667	25,667	28,154	28,152	28,151	28,152	28,155	28,155	28,150
Number of id	3,790	3,790	4,136	4,136	4,136	$4,\!136$	4,136	4,136	4,136

Number of id 3,790 3,790 4,130 4,130 4,130 4,130 4,130 4,130 4,130 4,130  $\frac{1}{1}$  Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1

Table A11: Country pair fixed effects; time fixed effects; controls for development differece; dynamic model (GMM)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.100***	-0.0885***							
011	(0.0334)	(0.0326)							
CC	0.101**	()	0.0999**						
	(0.0461)		(0.0408)						
GE	$0.0605^{'}$		,	0.0732**					
	(0.0408)			(0.0368)					
PSAV	-0.0113			,	-0.0184				
	(0.0260)				(0.0245)				
RQ	-0.000167				, ,	0.0308			
-	(0.0426)					(0.0378)			
RL	-0.0620						0.00807		
	(0.0615)						(0.0512)		
VAA	-0.0850*							-0.0787*	
	(0.0471)							(0.0429)	
Dist.									0.0318
									(0.0271)
Observations	25,667	25,667	28,154	28,152	28,151	28,152	28,155	28,155	28,150
Number of id	3,790	3,790	4,136	$4,\!136$	$4,\!136$	4,136	$4,\!136$	$4,\!136$	$4,\!136$

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1, and the absolute lagged distance of log GDP per capita.

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	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.157***	-0.100***							
	(0.0218)	(0.00681)							
CC	0.134***	,	-0.0891***						
	(0.0242)		(0.00621)						
GE	0.0101			-0.0820***					
	(0.0166)			(0.00615)					
PSAV	-0.0374***				-0.0735***				
	(0.00780)				(0.00665)				
RQ	0.0228					-0.0829***			
	(0.0139)					(0.00636)			
RL	0.000222						-0.0955***		
	(0.0184)						(0.00629)		
VAA	-0.166***							-0.147***	
	(0.0111)							(0.00790)	
Dist.									-0.0417***
									(0.00285)
Observations	30,079	30,079	32,883	32,881	32,880	32,881	32,884	32,884	32,879
Number of id	4,036	$4,\!036$	4,402	4,402	4,402	$4,\!402$	4,402	4,402	4,402

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1

Table A13: Country pair fixed effects; time fixed effects; controls for development differece; dynamic model (sysGMM)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
CPI	-0.166***	-0.104***							
	(0.0218)	(0.00689)							
CC	0.122***	`	-0.0918***						
	(0.0241)		(0.00624)						
GE	0.0183		,	-0.0806***					
	(0.0166)			(0.00613)					
PSAV	-0.0513***				-0.0811***				
	(0.00804)				(0.00676)				
RQ	0.0274**					-0.0810***			
	(0.0139)					(0.00633)			
RL	0.0158						-0.0951***		
	(0.0184)						(0.00627)		
VAA	-0.164***							-0.146***	
	(0.0110)							(0.00786)	
Dist.									-0.0420***
									(0.00285)
Observations	30,079	30,079	32,883	32,881	32,880	32,881	32,884	32,884	32,879
Number of id	4,036	4,036	4,402	4,402	4,402	$4,\!402$	4,402	$4,\!402$	4,402

Note: Panel robust standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1; controls included are origin and destination log GDP per capita and population in t-1, and the absolute lagged distance of log GDP per capita.

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	(1)	(0)	Table A14					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
CPI	-0.241***							
	(-3.708)							
aa	( 0.100)	0.194**						
CC		0.134**						
		(1.674)						
GE			-0.227***					
			(-2.992)					
-0.177			(-2.992)	0.010				
PSAV				0.013				
				(0.255)				
RQ				` /	-0.138*			
100								
					(-1.752)			
RL						-0.189*		
						(-1.630)		
VAA						( =:)	-0.016	
VAA								
							(-0.171)	
Dist.								-0.077
								(-1.358

Note: Standard errors in parantheses. \*\*\* = Sig at 0.01, \*\* = Sig at 0.05, \* = Sig at 0.1