Barriers to Global Capital Allocation

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Abstract

This paper presents a theory of international capital allocation in which cross-border investment is subject to policy distortions (taxation, political risk) as well as information frictions, which reflect geographic and cultural barriers among countries. We develop a novel structural, multi-country dynamic general equilibrium model with rationally-inattentive investors that yields an exact gravity equation for bilateral gross investment positions. We calibrate the model by estimating the gravity equation on nationality-based foreign investment data. While parsimonious, our model rationalizes several important stylized facts about the international investment network. It predicts large differences in capital returns across countries in the steady-state (a sign of capital misallocation), which correlate with the level of development. Our model also predicts, out of sample, a significant home bias. Finally, we find that frictions to international capital allocation account for a large share of the observed cross-country differences in capital per employee, and therefore play a significant role in producing persistent income differences among countries.

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1 Introduction

International capital flows have increased greatly in recent decades (Lane and Milesi-Ferretti, 2018). However, economists have been asking why we do not observe much larger flows from capital-abundant to capital-scarce economies (Lucas, 1990; Alfaro, Kalemli-Ozcan, and Volosovych, 2008), while portfolios continue to be disproportionately allocated towards domestic assets ("home bias" in international financial markets - French and Poterba, 1991; Lau et al., 2010; Coeurdacier and Rey, 2013). Whether frictions to international capital flows can explain these patterns has been widely debated in the literature. Some landmark studies (Caselli and Feyrer, 2007) have contributed to this debate by measuring capital returns for different countries, and found that do not differ significantly: this is consistent with an efficient international allocation of capital. For this reason, research has moved away from frictional models of international capital allocation.

Recently, however, multiple studies have overturned this result, by applying the same methodology to more recent releases of the same data (Monge-Naranjo et al., 2019; David et al., 2014).[1]. The new evidence that has emerged is that there *are* indeed large and (perhaps even more puzzlingly) *persistent* capital returns differentials across countries, suggesting that capital is *not* efficiently allocated.

This motivates our research question: what are the sources of this global capital misallocation? What barriers have the largest effect on income and welfare? Can they be built into a theory of international capital allocation that can *quantitatively* predict capital return differentials, home bias, as well as the lack of net flows to developing countries?

In this paper, we address such questions with a novel theoretical framework, which we bring to new data. Specifically, we make three main contributions. First, we provide a dynamic general-equilibrium model in which cross-border investment by rationally-inattentive agents is subject to information and policy frictions. Second, we employ the model to empirically estimate what factors prevent capital from flowing freely from one country to another, using updated measures of international investment that take into account offshore investment and financing vehicles. Third, we use our empirical estimates to assess the impact of these barriers on the allocation of capital across countries, as well as cross-country inequality.

In our model, international investment is subject to both information and policy frictions. We model information frictions in cross-border investment using insights from the literature on rational inattention and flexible information acquisition (Sims, 2003; Denti, 2015; Yang, 2015). While agents can acquire unlimited information by asset returns, they have an informational advantage for domestic assets, and this leads to home bias. Incidentally, we also make a general contribution to the rational inattention literature, by finding a first closed-form solution to rational inattention logit model (Matějka and McKay, 2015; Caplin et al., 2019) for the case where agents are ex-ante not equally informed about choices. Cross-border investment is also affected by expropriation risk and taxation.

The model yields a gravity equation for foreign assets demand. Equilibrium allocations of capital from each origin country to each destination country are characterized as a function of investment frictions and other fundamentals. To calibrate the model, we estimate the gravity equation using recently-developed

[1]In this paper we apply the same methodology using to most recent version of the data (Penn World Table 10, World Bank Wealth of Nations 2018) and we confirm that the findings of MNS and DHS hold in the latest releases.

foreign investment data that have been restated by Damgaard, Elkjaer, and Johannesen (2019) and Coppola, Maggiori, Neiman, and Schreger (2020) from a residency to a nationality basis. These databases account for the presence of offshore investment and financing vehicles located in tax havens, such as Bermuda and the Cayman Islands.[2] Intermediation costs and other obstacles to capital flows are captured using a parsimonious specification, with four types of barriers: geographic distance, cultural distance, foreign investment taxes, and political risk.

We obtain three sets of empirical results. First, our measures of barriers exert substantial effects on international financial positions, controlling for origin and destination fixed effects. The effects are similar for different subcategories of foreign investment (equity vs. debt, foreign direct investment vs. foreign portfolio investment). They are robust to using different specifications, and remain quantitatively large irrespective of the estimation method (OLS regressions, Poisson regression, and IV regressions). Our IV approach, used to ensure that our estimates are not amplified by reverse causality, is based on the assumption that deeply-rooted factors, such as measures of ancestral and religious distance between populations, have an impact on contemporary measures of cultural distance. These in turn act as current barriers to the global allocation of capital.

Second, we find that a conservative calibration of our model predicts, out-of-sample, allocations of domestic capital that are consistent with the home bias in international investment documented in the literature (French and Poterba, 1991; Coeurdacier and Rey, 2013). Our estimates also match independently-measured differences in rates of return across countries. In particular, our model predicts that emerging economies should exhibit higher rates of return on capital, consistent with the empirical evidence (David et al., 2014). Also, while our model predicts persistent (steady-state) global imbalances, the predicted net asset positions do not correlate with country income levels, consistent with Lucas's observation that capital fails to flow from rich to poor countries.

Third, we conduct a counterfactual analysis, using the model to study the quantitative implications of removing barriers to global capital allocation. We find that our estimated barriers introduce significant capital misallocation across countries. Compared to a situation without barriers, World GDP is 4.4% lower. Interestingly, the effect of cultural distance is of a similar magnitude as the effect of geographic distance. Barriers to global capital allocation also contribute significantly to cross-country inequality. We find that the standard deviation of log capital per employee is 84% higher than it would be in a world without barriers to international financial flows, and the dispersion in output per employee is 30% higher.

Our novel contributions can be summarized along the following lines: 1) we provide a first structural, multi-country model of international capital allocation that can generate *persistent* (i.e. steady state) capital misallocation and global imbalances; 2) we build inside our theory a rigorous micro-foundation for gravity and home bias in terms of information frictions, which is based on the rational inattention logit model (for which we find a new closed-form solution); 3) we take our model *quantitatively* to the data and use it to rationalize old stylized facts, as well as new evidence.

We also build on and incorporate, in our own work, insights from previous research. To begin with, we bring together, in a structural framework, the theoretical and empirical literatures on gravity equations

[2]The first paper restates IMF and OECD data on foreign direct investment, while the latter restates IMF data on portfolio investment.

in finance. Two seminal theoretical contributions in this area are Martin and Rey (2004) and Okawa and Van Wincoop (2012). The first provided a two-country, two-period model of international investment capturing a number of features of empirical gravity in financial flows. The latter provided the first rigorous theoretical underpinnings for gravity regressions in finance, using a two-period multi-country model. Among the early empirical papers that use gravity regressions to study international assets there's Ghosh and Wolf (1999), De Ménil (1999), Di Giovanni (2005) as well as Portes and Rey (2005), who provided an interpretation of this empirical regularity in terms of information costs. An early contribution that combines theory and data is Head and Ries (2008), who focused specifically on M&A transactions.

We also build on previous seminal work on natural resources and capital misallocation by Caselli and Feyrer (2007) and subsequent research (Monge-Naranjo et al., 2019). We incorporate natural (non-reproducible) capital explicitly in our theory and dataset, ensuring that our model-based estimates of country marginal revenue product of capital (MRPK) are consistent, in terms of measurement, with their methodology. The differences are driven by country-level capital stocks, which in their case is measured, while in our case it is generated endogenously by the model. One way we judge our model is by its ability to match MRPK estimates computed by MNS, based on the methodology first developed by CF.

A related line of research has studied to what extent international financial integration can speed up the process of convergence to steady-state (for capital-scarce countries) in a neoclassical framework, and how large the resulting welfare gains are. Gourinchas and Jeanne (2006) found these welfare gains to be tiny, seemingly contrasting our results. While our two studies belong to the same literature, they answer rather different research questions: GJ focus entirely on transition dynamics, whilst we focus exclusively on steady-state capital misallocation. Hence, far from contradicting each other, our findings complement each other: what we learn from the combination of the two, is that international capital frictions only have significant welfare effects if they affect the steady state equilibrium.

Our paper also expands, in a new direction, the literature on rational inattention in macro-finance (Mackowiak et al., 2020; Veldkamp, 2011): we find a new closed-form solution to the rational inattention logit model (Matějka and McKay, 2015; Caplin et al., 2019) and use it to micro-found an international asset demand system (Koijen and Yogo, 2020; Jiang, Richmond, and Zhang, 2020) where investors hold an information advantage for domestic assets: this is a key component of several existing theoretical models of home bias (Van Nieuwerburgh and Veldkamp, 2009; Dziuda and Mondria, 2012).

Our paper also connects to a large empirical literature on the geographic, historical and cultural determinants of international financial flows. Burchardi et al. (2019) documented a causal effect of the ancestry composition of US counties on foreign direct investment sent and received by local US firms to and from the immigrants' nations of origin, and interpreted this effect as also resulting from lower information frictions. Similarly, Leblang (2010) found that diaspora networks affect international investment, and argued that cultural ties increase trust and reduce information frictions. Other contributions t include Guiso et al. (2009); Lane and Milesi-Ferretti (2008); Rose and Spiegel (2009); Blonigen and Piger (2014).

Last but not least, since we find that barriers to international investment amplify cross-country dispersion of capital and output per worker, our study provides new evidence on the origins of cross-country income differences (Hall and Jones, 1999; McGrattan and Schmitz Jr, 1999; Spolaore and Wacziarg, 2009, 2012, 2018 - among many others).

2 A Theory of Imperfect International Capital Markets

In this section, we present a multi-country, general equilibrium overlapping generations (OLG) model with rationally-inattentive heterogeneous investors and imperfect capital mobility.

2.1 Firms

Time is discrete and indexed by t. There is a set of n countries $i \in \{1, 2, , \ldots, n\}$. Each country has a a representative firm (also called i) that acts competitively and produces a perfectly-substitutable, tradable good using a 3-factor Cobb-Douglas production function:

$$y_{it} \;=\; \omega_i \cdot x_{it}^{\xi_i} \cdot \ell_{it}^{\lambda_i} \cdot k_{it}^{(1-\lambda_i-\xi_i)} \tag{2.1}$$

where y_{it} is the level of output; x_{it} is the input of natural (non-reproducible) capital; ℓ_i is the labor input; k_{it} is the input of reproducible capital; ω_i is country i's total factor productivity. The production function parameters λ_i and ξ_i, which in equilibrium are equal to labor and natural capital income shares, are allowed to vary across countries. Human and natural capital are immobile (cannot be moved across countries) and reproducible capital is the only mobile factor.

Each unit produced of the final good can either be used for consumption or saved and transformed into $1/\delta$ units of capital to be used for production in the next period.[3] The global resource constraint is:

$$\sum_{i=1}^{n} y_{it} \;=\; \sum_{i=1}^{n} (c_{it} + \delta k_{it+1}) \tag{2.2}$$

where c_{it} is the current-period consumption of country i's agents. The final homogeneous good is assumed to be the numéraire of the economy (we normalize its price to one).

We make the additional assumption that production takes place in entities called *plants*. We identify a generic plant with the index q. We assume that plants can be built and decommissioned costlessly, but each plant contains a maximum capital stock of α. In short, plants are a discretization of country i's capital stock. This implies that the number of plants in each country is k_{it}/α, and that there are a total of $N_t = K_t/\alpha$ plants distributed over n countries, where K_t is the world capital stock at time t:

$$K_t \;\stackrel{\text{def}}{=}\; \sum_{i=1}^{n} k_{it} \tag{2.3}$$

The equilibrium rental rate on natural capital (m_{it}) reproducible capital (r_{it}), and wage rate (w_{it}) are determined as usual:

$$m_{it} \;=\; \xi_i \frac{y_{it}}{x_{it}}; \qquad w_{it} \;=\; \lambda_i \frac{y_{it}}{\ell_{it}}; \qquad r_{it} \;=\; \kappa_i \frac{y_{it}}{k_{it}} \tag{2.4}$$

$$\text{where} \qquad \kappa_i \;\stackrel{\text{def}}{=}\; 1 - \lambda_i - \xi_i \tag{2.5}$$

In addition, each country i imposes a tax equal to τ_i on capital income, so that the net return on

[3] We combine, inside the parameter δ a "transformation rate " as well as a depreciation rate.

capital in country i is $\tau_i r_i$. The wedge τ_i is a comprehensive measure, which also includes political risk.

2.2 Consumers-Workers-Investors

In what follows, we use the index i to refer to the country where production takes place (the *destination* country), and the index j to refer to the country that provides the capital (the *investor* country).

In each country j, a continuum of agents $z \in [0,1]$ is born every period t. They live for two periods: they are endowed with ℓ_j units of labor in period t and they inherit natural capital x_j from the previous generation. In the first period (when they are young) they supply labor and natural capital inelastically. In the second period (when they are old) the return on the capital saved at time t is their only source of income. The investors are atomistic, and invest their "atom" of capital in a single plant that can be located anywhere in the world; while they are allowed to invest in foreign plants, international investment is subject to information and policy frictions, which we model explicitly.

We model information frictions in cross-border investment using insights from the literature on rational inattention and flexible/unrestricted information acquisition (Matějka and McKay, 2015; Denti, 2015; Yang, 2015): agents make their asset allocation decisions using limited information about asset returns. We represent this imperfect knowledge by assuming that assets returns are ex-ante stochastic from the investors' point of view, and represented by a random vector $\tilde{\mathbf{r}}_{t+1} \in \mathbb{R}_+^N$. We use the tilde $(\tilde{\cdot})$ symbol to distinguish the random variable from the realized value $(\mathbf{r})$.

Investors from country j are endowed a prior distribution for the vector of returns that we call G_{jt}, but can acquire additional information about asset returns, in the form of a signal $\tilde{\mathbf{s}}(z)$ that takes realized value $\mathbf{s}(z)$. This signal induces a posterior distribution for asset returns that we call $F_t(\tilde{\mathbf{r}}_{t+1}|j, \mathbf{s}(z))$. Consistent with the literature above, we assume that the agents' information choice set is unrestricted – i.e. they can acquire any signal they wish (the signal is not restricted to have a specific distribution). They do however incur an effort to acquire the additional information – and the resulting disutility is proportional to the informativeness of the signal.

The preferences of agent z, born in country j at time t, are described by the following intertemporal utility function:

$$\mathcal{U}(z) \;=\; (1-\theta_j)\log c_t(z) + \theta_j\left[\mathbb{E}_t \log c_{t+1}(z) - \mathcal{I}(z)\right] \tag{2.6}$$

where $c_t(z)$ is agent z's consumption at time t and the patience parameter θ is allowed to vary by country. $\mathcal{I}(z)$ is the information acquisition cost incurred by z. Following the literature, we assume it to be proportional to the incremental information content of the signal acquired by investor z, measured as the expected reduction in Shannon Entropy $(\mathcal{H})$ between the posterior F and the prior G:

$$\mathcal{I}(z) \quad \stackrel{\text{def}}{=} \quad \frac{1-\sigma}{\sigma}\cdot\left[\mathcal{H}\left(G_{jt}(\cdot)\right) - \mathbb{E}_t\,\mathcal{H}\left(F_t(\cdot|j,\mathbf{s}(z))\right)\right] \tag{2.7}$$

The parameter $\sigma \in (0,1)$ captures the efficiency of the information processing technology, with a higher value of σ being associated with a lower information processing cost. There is no fundamental risk in the model. All uncertainty is driven by the noisiness contained in the signals received by the investors, as well as their priors.

Let $s_t(z)$ be the amount saved by investor z at time t. Thus, agent z's intertemporal budget constraint is defined by the following two equations:

$$w_{jt}\ell_j + m_{jt}x_j \;=\; c_t(z) + s_t(z) \tag{2.8}$$

$$c_{t+1}(z) \;=\; \delta R_{t+1}(z)\, s_t(z) \tag{2.9}$$

where $R_{t+1}(z)$ is the return earned by agent z. Then, the Euler equation is:

$$\mathbb{E}_t^F\left[\frac{\theta_j}{c_{t+1}(z)}\cdot \delta R_{t+1}(z)\right] \quad = \quad \frac{1-\theta_j}{c_t(z)} \tag{2.10}$$

We look for a steady-state equilibrium, with constant consumption, output, capital and saving $(\mathbf{c}_t, \mathbf{y}_t, \mathbf{k}_t, \mathbf{s}_t)$. Thus, we will drop time subscripts when referring to steady-state solutions. By plugging (2.8) and (2.9) inside (2.10), we find that, in equilibrium, all investors save a constant share θ_j of their earnings in the initial period:

$$s_t(z) \quad \equiv \quad s_j \quad = \quad \theta_j\left(w_j\ell_j + m_j x_j\right) \quad = \quad \theta_j\left(\lambda_j + \xi_j\right) y_j \qquad \forall j,t \tag{2.11}$$

Define a_{ij} as the total claims to country i capital by investors in country j. Capital markets clearing implies the following two accounting relationships: 1) Country i's supply of physical capital k_i equals the sum of all units of financial capital invested from all countries j

$$k_i \;=\; \sum_{j=1}^{n} a_{ij}\;; \tag{2.12}$$

2) Total claims by country j towards all countries i must equal country j's total savings:

$$s_j \;=\; \frac{1}{\delta}\sum_{i=1}^{n} a_{ij} \tag{2.13}$$

We next describe how investors allocate their capital across different plants/securities. Define π_{ij}, the share of capital invested in country i as a percentage of country$j$'s aggregate saving:

$$\pi_{ij} \;\stackrel{\text{def}}{=}\; \frac{a_{ij}}{s_j} \tag{2.14}$$

In matrix form, the following equation describes the flow of capital from country to country:

$$\mathbf{k} \;=\; \delta\,\mathbf{\Pi}\,\mathbf{s} \quad : \qquad \begin{bmatrix} k_1 \\ k_2 \\ \vdots \\ k_n \end{bmatrix} \;=\; \delta \begin{bmatrix} \pi_{11} & \pi_{12} & \cdots & \pi_{n1} \\ \pi_{21} & \pi_{22} & \cdots & \pi_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{n1} & \pi_{n2} & \cdots & \pi_{nn} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_n \end{bmatrix} \tag{2.15}$$

2.3 Information Acquisition and Asset Allocation

We next describe how agents acquire information and allocate capital across countries – that is, how the matrix $\mathbf{\Pi}$ is determined in the steady-state equilibrium. We assume that capital investment is lumpy: an atomistic investor z in country j invests their savings by buying claims to the return on the capital from of one plant q, which can be located in any country i.

Investors receive the noisy signal they previously acquired, update their priors into posteriors in a Bayesian fashion, and then choose the plant that offers, in expectation, the highest log return. This is because the saving problem is separable from the information acquisition/asset allocation problem. Because investors within the same country have the same prior, they will buy identical signals $\tilde{\mathbf{s}}$. However, because the *realized* value $\mathbf{s}$ of these signals will differ across investors, the choice of each individual investors is stochastic, even when we condition on the vector of *realized* country returns $\mathbf{r}$. Define the conditional probability that a generic investor from country j invests in plant q, located in country $i\left(q\right)$

$$\mathcal{P}_j\left(q\right) \;=\; \Pr\left(z \in j \text{ selects plant } q \in i \mid \tilde{r}_{q'} = \tau_{i(q')} r_{i(q')} \;,\; q' = 1, 2, ...n\right) \tag{2.16}$$

where the conditioning is on the vector of *realized* returns $\mathbf{r}$. By the seminal result of Matějka and McKay (2015), this probability is equal to:

$$\mathcal{P}_j\left(q\right) \quad = \quad \frac{\left[\tau_{i(q)} r_{i(q)}\right]^{\frac{\sigma}{1-\sigma}} \cdot \mathcal{P}_j^0\left(q\right)}{\sum_{q'} \left[\tau_{i(q')} r_{i(q')}\right]^{\frac{\sigma}{1-\sigma}} \cdot \mathcal{P}_j^0\left(q'\right)} \tag{2.17}$$

where $\mathcal{P}_j^0\left(q\right)$ is the *unconditional* probability of investing in plant q, defined as follows:

$$\mathcal{P}_j^0\left(q\right) \;\overset{\text{def}}{=}\; \int_{\tilde{\mathbf{r}} \in \mathbb{R}_+^N} \mathcal{P}_j\left(q\right) \,\mathrm{d}G_j\left(\tilde{\mathbf{r}}\right) \tag{2.18}$$

In order to derive an expression for $\mathcal{P}_j^0\left(q\right)$, the unconditional probability, we need at this point to make a parametric assumption on prior distribution G. It has been known since Sims (2003) that, for the continuous action, quadratic-gaussian rational inattention choice problem, there is a closed-form solution. However (to the best of our knowledge) no closed-form solutions have been found for the rational inattention logit model, except for symmetric or limiting cases[4].

We therefore make a theoretical contribution to the literature on rational inattention, by finding a specification of the prior G that produces a closed form solution for the unconditional probability $\mathcal{P}_j^0\left(q\right)$.

Proposition 1. *Assume that by j investors' prior beliefs (G_j), the vector $\tilde{\mathbf{r}}^{\frac{\sigma}{1-\sigma}}$ follows a multivariate independent[5] Gamma (Γ) distribution with common mean ρ_j and heterogeneous precision $\varphi_{i(q)j}$. The*

[4]Matějka and McKay (2015) proved that the unconditional probabilities $\mathcal{P}_j^0\left(q\right)$ simplify out (i.e. they are constant) if all choices are ex-ante exchangeable (i.e. undistinguishable from the prior alone). Dasgupta and Mondria (2018) provide a closed form-expression for the case where the prior is a 1-parameter Cardell C-distribution and the single parameter coincides with the information acquisition cost $\left(\frac{1-\sigma}{\sigma}\right)$.

[5]As is widely known in the RI literature, the assumption that returns be independently distributed is not controversial in this setting. The reasons is that what we are specifying here are the investors' *prior* beliefs, not the statistical properties of a stochastic return process. As we already clarified, the actual returns are not stochastic: they are simply unknown to

unconditional probability $\mathcal{P}_j^0(q)$ *is then equal to:*

$$\mathcal{P}_j^0(q) \;=\; \frac{\varphi_{i(q)j}}{\sum_{q'}\ \varphi_{i(q')j}} \tag{2.19}$$

Proof. See Appendix A. □

Because the probability of investing in any of the k_i/α plants in country i is the same, we can then sum these probabilities at the level of destination country to obtain π_{ij} - the share of country j's savings that are invested in destination country i:

$$\pi_{ij} \;\overset{\text{def}}{=}\; \sum_{q\in i}\mathcal{P}_j(q) \;=\; \frac{k_i}{\alpha}\cdot\mathcal{P}_j(q) \qquad \forall\, x\in j\in\{1,2,...n\} \tag{2.20}$$

Hence, the portfolio shares take the following equilibrium value[6]:

$$\pi_{ij} \;=\; \frac{(\tau_i r_i)^{\frac{\sigma}{1-\sigma}}\ k_i\,\varphi_{ij}}{\sum_{\iota=1}^{n}\ (\tau_\iota r_\iota)^{\frac{\sigma}{1-\sigma}}\ k_\iota\,\varphi_{\iota j}} \tag{2.21}$$

An improvement in the information processing technology (that is, a higher value of the parameter σ) increases the elasticity of the portfolio shares π_{ij} with respect to the country returns r_i and decreases their elasticity with respect to prior information. In the limit where information becomes freely available ($\sigma\to 1$), the investors' utility becomes deterministic and they simply invest in the country that offers the highest after-tax return. Vice-versa, when signals become prohibitively costly, the investors' utility also becomes deterministic, and they invest in the country for which they have the most precise prior information.

2.4 Geography and Information

The fact that the prior precision φ_{ij} varies by i,j implies that, depending on their origin country, investors might have an informational advantage from investing in certain destination countries. If we stack all the φ_{ij} inside a matrix $\mathbf{\Phi}$, we can think of this matrix as the adjacency matrix of a network, where the network links represent informational advantages. In order to go and measure this network we shall impose some structure on $\mathbf{\Phi}$. We assume that it depends linearly on a $n\times n\times D$ array of distances:

$$\log\mathbf{\Phi} \;\overset{\text{def}}{=}\; \log\begin{bmatrix}\varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n}\\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n}\\ \vdots & \vdots & \ddots & \vdots\\ \varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nn}\end{bmatrix} = \begin{bmatrix}\mathbf{d}'_{11}\beta & \mathbf{d}'_{12}\beta & \cdots & \mathbf{d}'_{1n}\beta\\ \mathbf{d}'_{21}\beta & \mathbf{d}'_{22}\beta & \cdots & \mathbf{d}'_{2n}\beta\\ \vdots & \vdots & \ddots & \vdots\\ \mathbf{d}'_{n1}\beta & \mathbf{d}'_{n2}\beta & \cdots & \mathbf{d}'_{nn}\beta\end{bmatrix} \tag{2.22}$$

the investor.

[6]This expression does not depend on plant size (α). Hence, in practice, we can ignore the fact that k_i may not be divisible by α, because we can make plants arbitrarily small ($\alpha\to 0$) without affecting country portfolios.

$$\text{where} \qquad \mathbf{d}_{ij} \;=\; \left[\begin{array}{cccc} d_{ij}^1 & d_{ij}^2 & \cdots & d_{ij}^D \end{array}\right]' \tag{2.23}$$

is a D-dimensional vector of distances between country i and country j and $\beta < \mathbf{0}$ is a $\mathbb{R}_-^D$ vector of investor-distance semi-elasticities.

What the assumption above means in practice is that the country j's investors are born with less accurate information about returns in far away countries, and the precision of their prior decays with distance. The reason we let $\mathbf{d}_{ij}$ be a vector (as opposed to a scalar) is that we want it to encompass not just geographic distance, but cultural distance as well.

2.5 Calibrating the elasticity parameter σ

The parameter σ governs the elasticity of substitution among different countries' assets, and is therefore an important determinant of the representative investors' portfolios.

We calibrate $\sigma = 1/2$, based on several considerations. First, this value allows our equation for the portfolio shares to match an important institutional feature of international portfolio investment – namely, that multi-country funds invest in (or are benchmarked against) market cap or GDP-weighted portfolios (take for example the MSCI World Index). Imposing $\sigma = 1/2$ and assuming no prior bias against distant countries, the portfolio share equation simplifies to:

$$\pi_{ij} \;=\; \frac{\tau_i \, r_i \, k_i}{\sum_{\iota=1}^{n} \tau_\iota \, r_\iota \, k_\iota} \tag{2.24}$$

Because, in steady state, the present discounted value of country i's capital is proportional to $\tau_i r_i k_i$, the portfolio share equation above is consistent with market value-weighting. In addition, if we assume no taxes and a common capital share κ_i, the equation above reduces to simple GDP weighting ($\pi_{ij} \propto y_i$).

The recent literature on demand estimation in asset pricing also supports calibrating σ to $1/2$. Using the fact that for a small open economy i the elasticity of investment with respect to return is equal to:

$$\frac{\partial \log \sum_j a_{ij}}{\partial \log r_i} \quad = \quad \frac{\sigma}{1-\sigma} \sum_j \frac{a_{ij}}{k_i} \left(1 - \pi_{ij}\right) \quad \approx \quad \frac{\sigma}{1-\sigma} \tag{2.25}$$

we can compare $\frac{\sigma}{1-\sigma}$ to empirical estimates of the demand elasticity with respect to returns[7]. $\sigma = 1/2$ implies approximately a unit demand-returns elasticity.

Koijen and Yogo (2020) estimate a demand system for international assets for the period 2002-2017, and report the following (semi-)elasticities. For long-term and short-term debt, they report demand-yield semi-elasticities of 42 and 10.5 respectively. To convert these values into elasticities, we multiply by average interest rates (3.6% and 1.8%, respectively, using OECD data), thus obtaining an average elasticity for debt securities of 0.85. For equity, they report a demand-*price* elasticity of 1.9. We can use the Gordon constant dividend growth model to convert this demand-price elasticity into a demand-return

[7]Because we have 70 countries in our dataset, this approximation appears to be accurate even in the presence of significant domestic investment. For a country with a zero net foreign asset position, a 30% share of domestic investment, and with foreign assets and liabilities that are allocated uniformly across the remaining countries, the demand-return elasticity is $\frac{.9\sigma}{1-\sigma}$.

elasticity. To do so, we multiply it by one minus the ratio between the dividend growth rate to the rate of return. Using the average MSCI World Return (9.3%) and a dividend growth rate of 2.9% (equal to the World GDP growth), we obtain an elasticity of 1.3. Because the elasticities for debt and equity fall immediately to the left and right of 1, it seems therefore natural to set $\frac{\sigma}{1-\sigma} = 1$.

2.6 Gravity

Since, in equilibrium, the capital income is equal to $\kappa_i y_i$, equation (2.21) can be rearranged as follows:

$$\pi_{ij} \;=\; \frac{\tau_\iota\, \kappa_i\, y_i\, \varphi_{ij}}{\sum_{\iota=1}^{n} \tau_\iota\, \kappa_\iota\, y_\iota\, \varphi_{\iota j}} \tag{2.26}$$

The denominator of equation 2.26 can be interpreted as a frictions-adjusted measure of the global market for capital that is available to country j investors. We shall call it M_j:

$$M_j \;\stackrel{\text{def}}{=}\; \sum_{\iota=1}^{n} \tau_\iota\, r_\iota\, k_\iota\, \varphi_{\iota j} \tag{2.27}$$

Multiplying both sides of equation (2.26) by s_j and using the fact that $s_j = (\lambda_j + \xi_j)\, y_j$, equation (2.26) can be rearranged as a gravity equation[8]:

$$\boxed{\textbf{Gravity}} \;:\quad a_{ij} \;=\; \tau_i \cdot \kappa_i \cdot \delta \cdot \theta_j \cdot \frac{\lambda_j + \xi_j}{M_j} \cdot \frac{y_i \cdot y_j}{\mathscr{D}_{ij}^2} \tag{2.28}$$

where $\mathscr{D}_{ij}^2 \stackrel{\text{def}}{=} 1/\varphi_{ij}$ is the j-investors' prior precision for the return to capital in country i, as implied by the distance vector $\mathbf{d}_{ij}$.

2.7 Global Capital Markets Clearing

To close the model, we find the vector of capital stocks $\mathbf{k}$ that simultaneously clears the market for inputs and assets. First, the matrix of country shares $\mathbf{\Pi}$ is a function of the capital stock vector ($\mathbf{k}$), of the parameters and the distortions:

$$\mathbf{\Pi} \;=\; \mathbf{\Pi}\left(\mathbf{r}\left(\mathbf{k}\right), \mathbf{k}; \mathbf{T}, \mathbf{\Lambda}, \mathbf{\Xi}, \mathbf{\Phi}\right) \tag{2.29}$$

$$\text{with} \qquad \mathbf{\Phi} \;\stackrel{\text{def}}{=}\; \exp\begin{bmatrix} \mathbf{d}'_{11}\beta & \mathbf{d}'_{12}\beta & \cdots & \mathbf{d}'_{1n}\beta \\ \mathbf{d}'_{21}\beta & \mathbf{d}'_{22}\beta & \cdots & \mathbf{d}'_{2n}\beta \\ \vdots & \vdots & \ddots & \vdots \\ \mathbf{d}'_{n1}\beta & \mathbf{d}'_{n2}\beta & \cdots & \mathbf{d}'_{nn}\beta \end{bmatrix}; \qquad \mathbf{T} \;\stackrel{\text{def}}{=}\; \begin{bmatrix} \tau_1, & 0, & \ldots & 0 \\ 0 & \tau_2 & \ldots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \ldots & \tau_n \end{bmatrix} \tag{2.30}$$

[8] A gravity equation obtains even if $\sigma \neq 1$, in which case τ_i is replaced, within equation (2.28), by $\tau_i^{\frac{\sigma}{1-\sigma}} r_i^{\frac{\sigma}{1-\sigma}-1}$.

$$\boldsymbol{\Theta} \overset{\text{def}}{=} \begin{bmatrix} \theta_1, & 0, & \dots & 0 \\ 0 & \theta_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \theta_n \end{bmatrix}; \quad \boldsymbol{\Lambda} \overset{\text{def}}{=} \begin{bmatrix} \lambda_1, & 0, & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix}; \quad \boldsymbol{\Xi} \overset{\text{def}}{=} \begin{bmatrix} \xi_1, & 0, & \dots & 0 \\ 0 & \xi_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \xi_n \end{bmatrix} \tag{2.31}$$

Since $\mathbf{s}$ can be written as $\boldsymbol{\Theta}(\boldsymbol{\Lambda}+\boldsymbol{\Xi})\mathbf{y}$ and $\mathbf{y}$ in turn can be written as a function of $\mathbf{k}$, equation (2.15) can be re-written as:

$$\mathbf{k} \quad = \quad \delta\,\boldsymbol{\Pi}(\mathbf{r}(\mathbf{k}),\mathbf{k}) \cdot \boldsymbol{\Theta} \cdot (\boldsymbol{\Lambda}+\boldsymbol{\Xi}) \cdot \mathbf{y}(\mathbf{k}) \tag{2.32}$$

The market-clearing vector of equilibrium capital stocks $\mathbf{k}^*$ is then determined as the fixed point of equation (2.32). Notice that there is a trivial equilibrium at $\mathbf{k} = \mathbf{0}$. When we solve equation (2.32) numerically, we can rule out the trivial equilibrium by taking logs of both sides of the equation.

The consumption of final good by country j (by old and young agents) balances the domestic consumers' budget:

$$c_j \;=\; \mathbf{r}'\mathbf{a}_j + (1-\theta_j)(w_j\ell_j + m_j x_j) \tag{2.33}$$

and the following equation balances country j's current account:

$$\underbrace{c_j + s_j - y_j}_{\text{Net Imports}} \quad = \quad \mathbf{r}'\mathbf{a}_j - \theta_j(w_j\ell_j + m_j x_j) - r_j k_j + s_j \quad = \quad \underbrace{\mathbf{r}'\mathbf{a}_j - r_j k_j}_{\text{Net Foreign Income}} \tag{2.34}$$

That is, all consumption and saving in excess of production (or equivalently, net imports) are financed by a positive net foreign capital income. Conversely, a negative net foreign income has to be balanced by a trade surplus.

2.8 Theoretical Results on Capital Allocation Efficiency

Let Y be World GDP:

$$Y \overset{\text{def}}{=} \sum_{i=1}^{n} Y_i \tag{2.35}$$

and let us call a vector $\mathbf{k} = (k_1, k_2, ..., k_n)'$, a *capital allocation.* Because labor and natural resources are immobile, Y is a function of $\mathbf{k}$ alone.

Definition 1 (Efficient Capital Allocation)**.** We say that an allocation $\mathbf{k}$ is *efficient* if it maximizes World GDP Y for a given level of world capital $K \overset{\text{def}}{=} \sum_{i=1}^{n} k_i$, that is:

$$\mathbf{k} \;\in\; \arg\max_{\mathbf{k}'} Y(\mathbf{k}') \quad \text{s.t.} \quad \sum_{i=1}^{n} k_i' = \sum_{i=1}^{n} k_i \tag{2.36}$$

Definition 2. We say that investors are ex-ante unbiased if φ_{ij} is constant over i – that is, the investors' prior beliefs over returns are *iid.*

Consistent with Proposition 1 of Matějka and McKay (2015), if investors' are ex-ante unbiased the unconditional probability $\mathcal{P}_j^0(q)$ drops out of equation (2.17). The effect of that is a CAPM-type result,

whereby all investor countries hold similar portfolios.

Lemma 1. *If asset markets are in equilibrium and international investment is undistorted, all origin countries j hold identical portfolios of foreign assets (π_{ij} is independent of j)*

Proof. If $\varphi_{i(q)j}$ is a constant, equation (2.21) simplifies to an expression that does not depend on the origin country:

$$\pi_{ij} \;=\; \frac{(\tau_i r_i)^{\frac{\sigma}{1-\sigma}}\, k_i}{\sum_{\iota=1}^{n} (\tau_\iota r_\iota)^{\frac{\sigma}{1-\sigma}}\, k_\iota} \;\forall\, j \tag{2.37}$$

□

One implication of Lemma 1 is that, in the absence of international investment distortions, we should observe no home bias. Armed with this fact, we can now proceed to show that equilibrium in input and asset markets implies a direct equivalence between the absence of international frictions and efficient capital allocation. We call this a "dual" efficiency theorem to emphasize the fact that asset markets efficiency translates in factor markets efficiency and vice-versa.[9]

Theorem (Dual Efficiency)**.** *Provided that companies and investors are optimizing, the following three statements are equivalent (if and only if):*

1. *capital is efficiently allocated;*
2. *rates of returns are equalized across countries ($r_i = r \quad \text{for} \quad i = 1, 2, ..., n$)*
3. *international investment is undistorted*

Corollary. *For a fixed global capital stock K, there is a unique efficient allocation $\mathbf{k}^*$.*

Proof. Appendix A. □

Having shown that efficient capital allocation is equivalent to rates of return being equalized, we can next show formally that capital *misallocation* manifests itself as cross-country dispersion in the rate of return on capital.

Lemma 2. *Consider a generic allocation $\mathbf{k}$ and the corresponding efficient allocation $\mathbf{k}^*$. The difference in world GDP between the two allocations is equal – to a second order Taylor Approximation, to:*

$$\frac{Y(\mathbf{k}) - Y(\mathbf{k}^*)}{Y(\mathbf{k}^*)} \quad \approx \quad -\frac{1}{2} \cdot \mathbb{E}^{y_i}\left(\frac{\kappa_i}{1-\kappa_i}\right) \cdot \mathbb{V}^{\mathcal{W}_i}(\log r_i) \tag{2.38}$$

where the operator $\mathbb{E}^{y_i}(\cdot)$ represents taking the GDP-weighted average across countries and the operator $\mathbb{V}^{\mathcal{W}_i}$ represent taking the variance across countries with weights $\mathcal{W}_i$, where

$$\mathcal{W}_i \;\overset{\text{def}}{=}\; \frac{\kappa_i}{1-\kappa_i} \cdot y_i \tag{2.39}$$

Proof. Appendix A. □

This latter lemma is important because it sets a bar for our model. For our model to capture international capital misallocation, it needs to generate meaningful variation in capital returns across countries.

[9] This is not a re-statement of the First Welfare Theorem, because it is a statement about GDP, not welfare.

2.9 Extensions

Our model can be extended to accommodate additional barriers and frictions to global capital allocation. In Section 6, we present three extensions: we model capital controls, the presence of currency hedging costs, and risky asset returns in destination countries. In that section, we also explore the empirical implications of allowing for these additional frictions.

3 Econometric Model and Data

3.1 Econometric Model

Having already calibrated σ, we only have to calibrate β, the semi-elasticities of the investors' prior precision with respect to distances. We estimate these econometrically. Assume that capital flows are observed with a multiplicative error term:

$$\hat{a}_{ij} \;=\; a_{ij} \cdot \exp\left(\varepsilon_{ij}\right) \qquad \text{with} \qquad \varepsilon_{ij} \perp \mathbf{d}_{ij} \tag{3.1}$$

we can then re-write the gravity equation (2.28) as the following fixed effects linear regression model for the log of foreign investment:

$$\log \hat{a}_{ij} \;=\; \mu_i + \nu_j + \mathbf{d}_{ij}'\beta + \varepsilon_{ij} \tag{3.2}$$

where μ_i is a country of origin fixed effect and ν_j is a country of origin fixed effect.

This is our main econometric specification. The dependent variable is measured using data on *Foreign Equity Investment*, *Foreign Debt Investment*, and the sum of the two (*Total Foreign Asset*s). [10] To capture $\mathbf{d}$, we propose a parsimonious specification based on two measures of distance, hypothesized to capture information asymmetries in international investment: *Geographic Distance* and *Cultural Distance.*

Because the vector of distances $\mathbf{d}$ varies at the level of the *undirected* country pair, in our regression analysis we compute standard errors clustered by undirected country pair. Additional bilateral variables are used either as instruments or control variables, depending on the specific empirical model under consideration. We now turn to describing these variables in more detail.

3.2 Dependent Variables: Restated Foreign Investment Data

Our analysis improves upon the empirical literature on the determinants of foreign investment by using recently-developed foreign investment data that account for the existence of tax havens. These tax havens may serve as indirect conduits between the origin and destination countries. For instance, the Cayman Islands are often used to transit funds between origin and destination countries in a tax-efficient manner. In recent work, Damgaard, Elkjaer, and Johannesen (2019) combined FDI data from the IMF's Coordinated Direct Investment Survey (CDIS) and the OECD's Foreign Direct Investment statistics. They restated

[10] In the Appendix, we also consider the determinants of global asset holdings, dinstinguishing between *Foreign Direct Investment* and *Foreign Portfolio Investment*, as is often done in the literature. We prefer to focus on the debt / equity distinction in the main analysis because the distinction between FDI and equity FPI is somewhat arbitrary. See for instance Blanchard and Acalin (2016) and Alfaro and Chauvin (2020).

the data in order to account for the fact that some countries act as offshore investment centers. In such countries, there is a high concentration of investment companies that only act as investment vehicles, and do not actually engage in productive activities. Damgaard, Elkjaer, and Johannesen (2019) used cross-border entity ownership data from Bureau Van Dijk's Orbis to reallocate asset ownership from country of residence of the investment vehicle to the nationality country of the ultimate investor, thereby correcting for artificially inflated numbers pertaining to offshore tax havens. This is the source of our FDI data.

Regarding portfolio investment, our main source is data from Coppola, Maggiori, Neiman, and Schreger (2020). They use data from IMF's Coordinated Portfolio Investment Survey (CPIS), and restate them to account for the presence of shell companies in tax havens - often used to issue securities. To do so, they use *reallocation matrices* based on fund holdings data from Morningstar. Using these reallocation matrices, they converted international portfolio data from CPIS from a residency basis to a nationality basis. Their Foreign Portfolio Investment (FPI) data is further broken down between debt and equity. This is the source of our FPI data.[11]

To obtain a measure of *Total Foreign Assets* (or *Foreign Total Investment*, FTI), we sum the FPI and FDI series (both are in current international US Dollars). Further, we create a series of *Foreign Equity Investment* by adding up FDI and the equity portion of FPI, and a series for *Foreign Debt Investment* by isolating the debt portion of the FPI series.

For both *Foreign Debt Investment* and *Foreign Equity Investment*, we base our econometric estimates on cross-sectional data from 2017 (the equity series starts in 2013). Figure 1 displays the two series for 2017, plotted against each other on a logarithmic scale. The plot reveals some interesting facts. First, there is a great deal of variation in both foreign debt and equity investment across countries. These two variables range from a few hundred thousand dollars to over a trillion dollars. This is the variation we seek to explain. Second, the two variables correlate very strongly ($\rho = 0.73$), and line up neatly on the 45° line, indicating that they are similar in size and tend to track each other closely. This suggests that they might be driven by a similar set of underlying factors, an issue that our econometric analysis will clarify. Similar observations hold for the distinction between FDI and FPI, which are considered as alternative dependent variables in the Appendix.

3.3 Main Explanatory Variables

Barriers to global capital allocation are captured in our model by the distance metric $\mathbf{d}$. We operationalize these barriers by modeling them in a parsimonious way as the result of cultural distance and geographic distance. Other impediments to global capital flows are considered in the counterfactual analysis (taxes on foreign investment, political risk) as well as in the Appendix (currency risk, capital controls).

3.3.1 Cultural and Geographic Distance

Our vector of distances $\mathbf{d}_{ij}$ includes two distances: *Cultural Distance* and *Geographic Distance*.

[11] Coppola et al. (2020) combine all European Monetary Union countries into a single entity. We use un-restated FPI data from CPIS to break down aggregate EMU figures into investment data corresponding to each individual member country.

FIGURE 1: FOREIGN EQUITY AND DEBT INVESTMENT (2017)

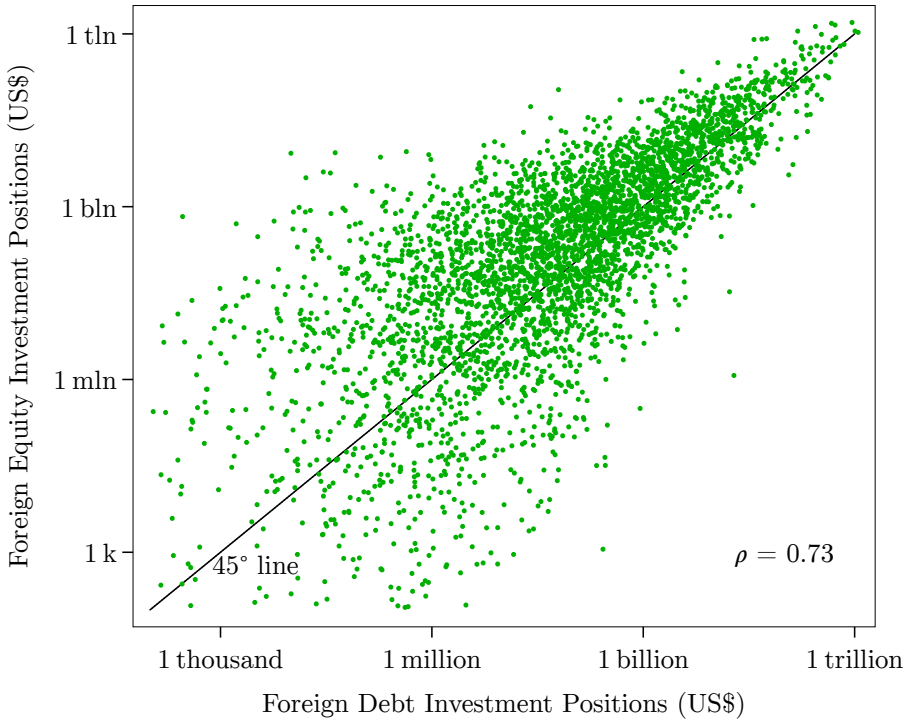


FIGURE NOTES: This figure plots restated Foreign Equity Investment against restated Foreign Debt Investment. Each observation is a country pair and all data refer to the year 2017. The unit of measurement is US dollars at current prices. Log scale on both axes.

Our measure of *Cultural Distance* captures distance in contemporary values and beliefs, introduced by Spolaore and Wacziarg (2016). It is constructed using a set of 98 questions from the World Values Survey 1981- 2010 Integrated Questionnaire, reflecting the following question categories: a) perceptions of life; b) environment; c) work; d) family; e) politics and society; f) religion and morale; g) national identity. These questions are a subset of a broader set of 740 questions, where the subset was chosen to ensure that the set of questions used to compute bilateral distances remains relatively similar across pairs. For each question, the measure consists of the Euclidian distance in answers between country pairs. Distances are then averaged over questions to obtain a summary index. Averages can be computed by question category, but here we use the average over all underlying 98 questions. We re-scaled this index to span the $[0, 3]$ interval, so that the magnitude of its effect can be compared to that of *Geographic Distance*.

We obtained country dyad-level data on physical distance from CEPII's GeoDist dataset (Mayer and Zignago, 2011). *Geographic Distance* measures the geodesic distance between any two countries, based on a population-weighted average of the distances between individual cities. As for *Cultural Distance*, we have re-scaled this variable (whose maximum value is equal to half the earth's circumference) to the $[0, 3]$ interval, so that the magnitude of the two effects can be compared.

3.3.2 Taxes and Political Risk

Our measure of policy barriers, τ_i, captures four factors: 1) corporate income taxes; 2) taxes on dividends; 3) taxes on interest income; 4) political risk (i.e. probability of expropriation). This composite tax rate is constructed using the formula:

$$\tau_i \;=\; \tau_i^{\text{Tax}} \times \tau_i^{\text{PR}} \tag{3.3}$$

$$\text{where} \qquad \tau_i^{\text{Tax}} \;=\; \left(\frac{\text{EBT}}{\text{EBIT}} \times \tau_i^{\text{Corp}} \times \tau_i^{\text{Div}} + \frac{\text{Interest}}{\text{EBIT}} \times \tau_i^{\text{Int}} \right) \tag{3.4}$$

τ_i^{Corp} is the corporate tax rate which we measure (in order, depending on availability) using OECD effective average tax rates, or statutory corporate tax rates from the KPMG's Tax Rates Database and the Tax Foundation's Global Tax Database.

τ_i^{Div} and τ_i^{Int} are measured as withholding tax rates on (respectively) dividends and interests from the Tax Research Platform of the International Bureau of Fiscal Documentation (IBFD).

The formula above implies that, in order to combine the tax rates on equity and interest income we need to impute some weights, which depend on how much of the corporate capital income goes to equity-holders (EBT) and how much goes to debt-holders (Interest Expense). We base our choice on the US Census' quarterly financial reports, where (for a broad set of industries) during 2017 EBT and Interest made up, respectively, 4/5 and 1/5 of all earnings before interests and taxes. Hence these are the weights that we apply to (respectively) equity and debt tax rates.

Our formula also includes τ_i^{PR}, which reflects political risk. We measure it by combining a composite measure produced by the International Country Risk Group (ICRG) with empirical estimates from Alfaro, Kalemli-Ozcan, and Volosovych (2008, henceforth AKV), who estimate econometrically the sensitivity of foreign investment inflows (in millions of US$) to this measure of country risk. The ICRG index ranges from zero (extreme political risk) to ten (virtually no political risk).[12]

We compute the shadow tax on political risk using the following equation:

$$\log \tau_i^{\text{PR}} \;=\; \beta_{\text{AKV}} \left(\text{ICRG}_i - 10 \right) \tag{3.5}$$

where β_{AKV} is a semi-elasticity coefficient that can be computed from AKV's tables. We show how to do so in Appendix C.

3.4 Instruments and Control Variables

We consider additional variables as direct determinants of capital flows, to be used either as instruments or as control variables, depending on the specification under consideration.

3.4.1 Linguistic, Ancestral and Religious Distances

The first category of variables consists of measures of historical distinctiveness that are deep determinants of contemporary cultural distances. We use measures of linguistic distance and religious distance

[12] The political risk index is missing for a handful of countries, for whom we input a political risk score of 5.

introduced in Fearon (2003), Mecham, Fearon, and Laitin (2006) and Spolaore and Wacziarg (2016). We also use measures of ancestral distance initially developed by Spolaore and Wacziarg (2009) and later updated in Spolaore and Wacziarg (2018). As these contributions discuss in detail, linguistic distance, religious distance, and ancestral distance can all be interpreted as measures of historical relatedness between populations.

Consider first *Linguistic Distance*. Different contemporary languages have descended from common ancestral languages over time. For instance, German, Italian and French all descend from a common proto-Indoeuropean language. In turn, Italian and French descend from more recent common ancestral languages (Romance languages stemming from Latin), while German does not. Thus, Italian and French are more closely related to each other than either is to German. Intuitively, this is analogous to our concept of relatedness between individuals: two siblings are more closely related to each other than they are to their first cousins, because they share more recent common ancestors (their parents) with each other, while they share more distant ancestors with their first cousins (their grandparents) and second cousins (great-grandparents).[13] Formally, our measures of linguistic distance are computed by counting the number of different linguistic nodes separating any pair of languages, according to their classification from Ethnologue.

Religious Distance is also constructed considering number of nodes in historical trees. In this case, the trees consist of religions grouped in related historical categories. For instance, Near Eastern monotheistic religions are subdivided into Christianity, Islam and Judaism. These are further divided into finer levels of disaggregation. The number of common nodes between religions is our metric of religious proximity. Thus, Baptists are closer in religious space to Lutherans than they are to the Greek Orthodox.

Ancestral Distance, like *Linguistic Distance* and *Religious Distance*, can be interpreted as a measure of long-term historical separation times between groups. However, while linguistic distance captures how far back one must go in order to find the common ancestral language from which two modern languages descend, *Ancestral Distance* captures how far in the past one must go in order to find the common ancestral population from which two contemporary populations descend. In this respect, the measure is intuitively closer to the concept of relatedness between individuals, as applied to whole populations. *Ancestral Distance*, here, is computed using a genomic dataset on human microsatellite variation from Pemberton et al. (2013), covering 267 world populations. These populations were matched to 1,120 ethnic groups from Alesina et al. (2003).

Microsatellites are tracts of DNA in which specific sequences of base pairs are repeated. Microsatellites tend to mutate rapidly and randomly - that is, microsatellite variation mostly captures neutral change that is not subject to natural selection. Their variation provides no direct information about overall differences in genetic endowments, so it would not be appropriate to interpret the effects of ancestral distance on economic or societal outcomes as a direct causal effect of genetic factors. Rather, measures of distance based on microsatellite variation provide information on historical relatedness between populations. This neutral feature of *Ancestral Distance* is crucial for the interpretation of the relationship between historical

[13]The analogy is not perfect because individuals have two parents, while languages typically evolve sequentially from "ancestor" languages. For example, the ancestors of the Italian language, according to Ethnologue are, in order: Indo-European, Italic, Romance, Italo-Western, and Italo-Dalmatian.

relatedness and contemporary cultural distance. As populations separate over time, they are more likely to diverge in cultural traits that are transmitted randomly and with variation from one generation to the next (Appendix A provides a formal treatment of this idea). Hence, we should expect a positive relationship, on average, between ancestral distance and cultural or institutional distance, whereas there is no reason to expect ancestral distance to directly affect financial flows. Consequently, we can use ancestral distance as an instrument for the proximate determinants of financial flows.

3.4.2 Additional Variables

We use a variety of additional bilateral measures either as instruments or control variables. Among them are several measures of geographic distance - contiguity, access to a common sea or ocean, latitudinal distance, longitudinal distance, and whether the two countries in pair are on the same continent. Additionally, we consider the length of the diplomatic relationship between the two countries in a pair, as a measure of the depth of their historical links. We also consider variables called *Colonial Relationship* - capturing whether two countries in a pair were ever in a colonizer-colonized relationship, and *Common Colonizer*, denoting whether the two countries in a pair ever had a common colonizer.[14]

We obtain the control variable *Currency Peg* from the dataset of exchange rate arrangements constructed by Ilzetzki, Reinhart, and Rogoff (2019). The dataset coverage ends in 2016. We carry over the last year of data to 2017. The variable *Currency Peg* captures the presence of a currency peg as well as the presence of a common currency. We also obtained, from the World Bank's International Center for the Settlement of Investment Disputes (ICSID), data on the presence of bilateral investment treaties, which we code as the dummy variable *Investment Treaty*.[15]

To control for trade policy, we obtain data on regional trade agreements (RTAs) and their member countries from the WTO websites. We construct bilateral dummy variables representing joint memberships in *Customs Union*, *Free Trade Agreements*, and *Economic Integration Agreements* as of 2017. Finally, we control for a measure of *Trade Costs*, because trade costs can induce changes in international investment. For instance, high trade costs can spur FDI in an effort to "jump" tariffs. Or, on the contrary there may be complementarities between trade in capital and trade in goods: the return to investment in a foreign country may be lower if exporting from the destination is costly, or if the investment requires paying tariffs to import capital goods into the destination country. The source of the trade cost data is the ESCAP-World Bank Trade Cost Database (2020), as initially developed in Novy (2013). This paper derives time-varying bilateral trade costs from a gravity model, which is solved analytically so that trade costs can be inferred using observed trade data. The ESCAP-World Bank Trade Cost Database[16] updates these calculations periodically, and estimates of trade costs are now available for a wide set of country pairs over the 1995-2018 period.

[14]The data are from CEPII and can be obtained at http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=6

[15]https://icsid.worldbank.org/resources/publications/investment-treaty-series

[16]https://www.unescap.org/resources/escap-world-bank-trade-cost-database

Table 1: Summary Statistics

Panel A: Directed Variables

	Observations	Mean	StDev	Min	Max
Foreign Assets (US$ mln)	1,512	66,708	907,000	0	34,700,000
Foreign Equity Assets (US$ mln)	1,694	36,094	487,000	0	19,600,000
Foreign Debt Assets (US$ mln)	2,260	17,738	322,000	0	15,100,000
Currency Hedging Cost	4,900	0.000	0.069	-0.209	0.209
Trade Costs	4,828	0.048	0.046	0.000	0.717

Panel B: Undirected Variables

	Undirected Pairs	Mean	StDev	Min	Max
Cultural Distance	2,485	4.196	1.746	0.000	10.000
Geographic Distance	2,485	3.069	2.339	0.004	9.764
Ancestral Distance	2,346	0.021	0.016	0.000	0.074
Border Contiguity	2,485	0.036	0.187	0.000	1.000
Colonial Relationship	2,485	0.025	0.156	0.000	1.000
Common Colonizer	2,485	0.030	0.171	0.000	1.000
Common Legal Origin	2,485	0.357	0.479	0.000	1.000
Common Sea	2,415	0.110	0.313	0.000	1.000
Currency Peg	2,485	0.379	0.485	0.000	1.000
Custom Union	2,485	0.173	0.379	0.000	1.000
Economic Integration Agreement	2,485	0.272	0.445	0.000	1.000
Free Trade Area	2,485	0.377	0.485	0.000	1.000
Investment Treaty	2,485	0.488	0.500	0.000	1.000
Latitudinal Distance	2,415	28.857	25.699	0.000	106.000
Linguistic Distance	2,281	0.935	0.193	0.000	1.000
Longitudinal Distance	2,415	58.708	51.576	0.000	276.000
Religious Distance	2,281	0.786	0.209	0.000	0.999
Tax Treaty	2,485	0.532	0.499	0.000	1.000

3.5 Coverage and Summary Statistics

After merging all the variables above, we are left with a dataset of 68 countries, i.e. $68 \times 68 = 4{,}624$ directed country pairs-observations (including diagonal i-to-i pairs) or 2,278 undirected country pairs.[17]

[17]We exclude Venezuela and Ukraine who display suspect data on capital and GDP for 2017, our baseline year, likely due to the political events in these two countries at that specific time.

The 68 countries in our dataset cover 85.56% of the World GDP (based on 2017 data from the Penn World Tables, version 10.0). Table 1 displays summary statistics for the data described above.

4 Econometric Analysis

In this section, we estimate the parameter vector β, the effect of geographic and cultural distances on log foreign investment (two semi-elasticities). Our objective is not only to provide a quantitative assessment of the statistical impact of cross-border investment frictions, but also to retrieve structural parameters for the model of Section 2, in order to conduct counterfactual analysis.

4.1 Least Squares Analysis

We begin by performing an OLS regression of the log of foreign investment (debt, equity or total) on the two main measures of distance, for the 2017 cross-section. Table 2 reports the estimates. Column (1) presents estimation results with for the log of total assets (i.e. Foreign Total Investment or FTI), as the dependent variable. We find that *Cultural Distance* and *Geographic Distance* are both statistically and economically significant predictors of FTI: the slope coefficients corresponding to these two variables are negative, sizable in magnitude (-0.362 and -0.424 respectively) and statistically significant at the 99% confidence level. To get a notion of relative magnitudes, the coefficients can be expressed as the effect of a one standard deviation change in the independent variables in terms of a percentage change in FTI ($\%\Delta FTI = e^{\beta_x \Delta x} - 1$). We find large effects of both barriers: a one standard deviation increase of geographic distance (2.339 units) is associated with a 62.9% decrease in FTI, while a one standard deviation increase in cultural distance (1.746 units) is associated with a 46.7% decrease in FTI.

In Column (2) we present estimation results using log foreign equity investment as the dependent variable. We find again that both barriers are statistically and economically significant: the standardized effects as defined above are slightly larger than those for log FTI. Column (3) considers log foreign debt investment as the dependent variable. We find effects of geographic distance (a standardized effect of -55.2%) and cultural distance (with a standardized effect of -54.4%), both statistically significant at the 5% level, that are commensurate with the effects on log FTI.

Finally, columns (4) through (6) repeat the analysis of the first three columns, but depart from our very parsimonious specification by adding controls for a variety of measures of geographic distance (contiguity, access to a common sea, latitudinal distance, longitudinal distance), common history variables (linguistic distance, past colonial relationship, common colonizer, common legal origins), as well as variables possibly capturing bilateral facilitators of capital exchange (currency peg, customs union, economic integration agreement, free-trade agreement, foreign investment tax, investment treaty and trade costs). The coefficient estimates on cultural and geographic distances are similar in magnitude to those in the parsimonious specification of columns (1) - (3): for FTI, we find standardized effects of cultural distance and geographic distance equal, respectively, to -32.6% and -64.9%. We again find that these two barriers have similar quantitative effects on foreign equity investments and foreign debt investment. In sum, adding control variables does not fundamentally alter the inferences drawn from the more parsimonious specification.

Table 2: OLS Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable in logs:	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-0.362**	-0.367**	-0.450**	-0.226**	-0.223**	-0.377**
	(0.042)	(0.049)	(0.039)	(0.044)	(0.053)	(0.043)
Geographic Distance	-0.424**	-0.541**	-0.343**	-0.448**	-0.386**	-0.362**
	(0.026)	(0.033)	(0.028)	(0.089)	(0.102)	(0.079)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	1,484	1,642	2,259	1,353	1,491	2,077
R-squared	0.818	0.780	0.782	0.845	0.813	0.797
Within R-squared	0.306	0.257	0.188	0.422	0.386	0.267

Table Notes: This table reports OLS estimates of a linear regression of a linear regression of the log of the variable listed on the top row (*Foreign Assets*, *Foreign Equity Assets*, *Foreign Debt Assets*) on the variables in the leftmost column, using data from 2017. Each observation is a directed country pair. All regressions include origin country (i) fixed effects and destination country (j) fixed effects. Additional controls in columns 4-6 are *Border Contiguity, Common Sea, Latitudinal Distance, Longitudinal Distance, Colonial Relationship, Common Colonizer, Common Legal Origin, Linguistic Distance, Currency Peg, Customs Union, Economic Integration Agreement, Free-Trade Agreement, Investment Treaty, Tax Treaty* and *Trade Costs*. Standard errors (clustered by undirected country pair) in parentheses. $^{*}p < .05$; $^{**}p < .01$

4.2 Pseudo-Poisson Regressions

One shortcoming of the econometric model described by equation (3.2) is that, being written in logs, it can only accommodate strictly positive capital positions ($\hat{a}_{ij} > 0$). In order to incorporate country pairs with zero investment, we can re-write the regression equation (3.2) as:

$$\hat{a}_{ijt} \;=\; \exp\left(\mu_i + \nu_j + \mathbf{d}'_{ij}\beta + \varepsilon_{ij}\right) \tag{4.1}$$

thereby converting the log-linear specification into a Poisson regression. This type of model has been applied to gravity models of trade by Santos Silva and Tenreyro (2006) and Correia, Guimaraes, and Zylkin (2019). We apply the same statistical model to our model of financial positions. In order to avoid using a highly-inefficient estimator (as a consequence of the high degree of heteroskedasticity that is present in the residuals of this equation), we weigh observations by the inverse of the geometric mean of the GDPs of countries i and j (un-weighted estimates, which have larger standard errors, are shown in Appendix I). Including the zero investment pairs, the size of the sample rises a bit compared to that in Table 2 (by about 3% for equity, though the increase is smaller for total investment, at about 1.6%).

Table 3: Pseudo-Poisson Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-0.595**	-0.436**	-0.745**	-0.174**	-0.152*	-0.246**
	(0.071)	(0.059)	(0.097)	(0.056)	(0.064)	(0.052)
Geographic Distance	-0.249**	-0.277**	-0.260**	-0.314*	-0.352*	-0.105
	(0.035)	(0.033)	(0.054)	(0.129)	(0.146)	(0.085)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	1,508	1,690	2,259	1,375	1,534	2,077

Table Notes: This table reports Iteratively-Reweighted Least Squares (IRLS) estimates of a Pseudo-Poisson regression of the variables listed on the topmost row (*Foreign Assets*, *Foreign Equity Assets*, *Foreign Debt Assets*) on the variables in the leftmost column. Each observation is a directed country pair. All regressions include origin country (i) fixed effects and destination country (j) fixed effects. Additional controls in columns 4-6 are *Border Contiguity, Common Sea, Latitudinal Distance, Longitudinal Distance, Colonial Relationship, Common Colonizer, Common Legal Origin, Linguistic Distance, Currency Peg, Customs Union, Economic Integration Agreement, Free-Trade Agreement, Investment Treaty, Tax Treaty* and *Trade Costs*. Observations are weighted by the inverse of the geometric average of destination and origin country GDP. Standard errors (clustered by undirected country pair) in parentheses. $^{\dagger}p < .10$; $^{*}p < .05$; $^{**}p < .01$

Table 3 displays the resulting estimates. In general, we find that the standardized magnitude of Poisson estimate on geographic distance is slightly smaller than the corresponding OLS estimate, and the standardized effect of cultural distance is now sometimes larger than that of geographic distance. For instance, in the specification of column 1, the standardized effect of cultural distance is to reduce total foreign assets by 64.6% while that of geographic distance is -44.1%. The effects on debt are again commensurate with those for equity foreign investment. Broadly speaking, a consideration of the extensive margin does not greatly affect our basic finding that both geographic and cultural barriers exert quantitatively meaningful and statistically significant negative effects of foreign asset holdings - and that their respective effects are similar to each other.

4.3 Instrumental Variables Regressions

A challenge in estimating the effect of cultural distance on bilateral investment positions is the potential for reverse causality: it is conceivable that two countries may converge culturally (by adopting more similar values and norms) as a consequence of more intense cross-border investment.[18] In that case,

[18]For obvious reasons, reverse causality is not an issue for geographic distance.

Table 4: First-Stage Regressions

	(1)	(2)
	Cultural Distance	Cultural Distance
Ancestral Distance	32.712**	17.790**
	(4.548)	(3.887)
Religious Distance	3.847**	2.521**
	(0.431)	(0.349)
Control Variables	No	Yes
Observations	1,346	1,346
R-squared	0.707	0.802
Within R-squared	0.218	0.471
Cragg-McDonald Wald F statistic	1067.358	793.211
Kleibergen-Paap Wald F statistic	100.663	93.913
Stock & Yogo Critical Value (r=10%)	19.93	19.93

Table Notes: This table reports Ordinary Least Squares (OLS) estimates of a linear regression of the variables listed on the topmost row on the variables in the leftmost column. These correspond to the first stage of the IV regressions (1) and (4) presented in Table 5. Each observation is an undirected country pair. All regressions include origin country (i) fixed effects and destination country (j) fixed effects. All regressions control for *Geographic Distance*. Additional controls in columns 3 and 4 are *Border Contiguity, Common Sea, Latitudinal Distance, Longitudinal Distance, Colonial Relationship, Common Colonizer, Common Legal Origin, Linguistic Distance, Currency Peg, Customs Union, Economic Integration Agreement, Free-Trade Agreement, Investment Treaty, Tax Treaty* and *Trade Costs*. Robust standard errors in parentheses. $^{*}p < .05$; $^{**}p < .01$

the OLS estimates of the gravity equation (3.2) could not be interpreted as causal. To address this issue, we turn to an IV strategy. We rely on the distinction between *proximate* and *deep* determinants of foreign financial positions. We assume that historically-determined factors only influence financial flows indirectly, through their effect on contemporary cultural distance. Consistent with this exclusion restriction, we consider two instruments for cultural distance: *Ancestral Distance* and *Religious Distance* (other measures of historical relatedness, like *Linguistic Distance* or *Colonial Relationship*, are used as controls rather than instruments out of concern about their excludability from the second stage). A stronger argument for excludability can be made for *Ancestral Distance*, because it is very plausible that such a variable - capturing intergenerational relatedness and based on neutral genetic changes - might only impact contemporary outcomes through its historical effects on the cultural transmission of traits and

Table 5: Instrumental Variables Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable in logs:	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-0.519**	-0.642**	-0.488**	-0.324*	-0.410**	-0.343**
	(0.107)	(0.124)	(0.096)	(0.139)	(0.146)	(0.126)
Geographic Distance	-0.395**	-0.492**	-0.332**	-0.454**	-0.399**	-0.364**
	(0.033)	(0.041)	(0.034)	(0.092)	(0.107)	(0.079)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	1,346	1,483	2,064	1,346	1,483	2,064
Within R-squared	0.283	0.235	0.186	0.417	0.378	0.265
Kleibergen-Paap χ P-value	0.000	0.000	0.000	0.000	0.000	0.000
Sargan-Hansen J P-value	0.295	0.246	0.013	0.925	0.914	0.083

Table Notes: This table reports Instrumental Variable (IV) estimates of a linear regression of the log of the variable listed on the top row (*Foreign Assets*, *Foreign Equity Assets*, *Foreign Debt Assets*) on the variables in the leftmost column. *Cultural Distance* is the endogenous regressor and the excluded instruments are *Ancestral Distance* and *Religious Distance.* Each observation is a directed country pair. All regressions include origin country (i) fixed effects and destination country (j) fixed effects. The additional controls in columns 4-6 are *Border Contiguity, Common Sea, Latitudinal Distance, Longitudinal Distance, Colonial Relationship, Common Colonizer, Common Legal Origin, Linguistic Distance, Currency Peg, Customs Union, Economic Integration Agreement, Free-Trade Agreement, Investment Treaty, Tax Treaty* and *Trade Costs*. Standard errors (clustered by undirected country pair) in parentheses. $^{*}p < .05$; $^{**}p < .01$

beliefs, captured by our measure of *Cultural Distance.*[19] A similar argument can be made for *Religious Distance*, which is also constructed using a branching tree, tracing the historical splits of different religious denominations. It is plausible that the contemporary effects of such splits on our dependent variable should operate (mainly or exclusively) through contemporary differences in values and beliefs (including, but not limited to, religious beliefs), measured by *Cultural Distance.*

Table 4 presents estimation results for the first-stage regressions. We present results for the parsimonious specification (column 1), and for the specification with additional controls (column 2). First stage regressions lead to interesting results. Consistent with findings in Spolaore and Wacziarg (2016), ancestral and religious distances are both positively and significantly correlated with cultural distance: the instruments are strongly predictive of the endogenous variable in the first stage, as shown by the two first stage F-statistics presented on Table 4.

[19]We provide a simple model of the relationship between *Ancestral Distance* and *Cultural Distance* in Appendix A.

Results for the second stage appear in Table 5. As before, there are 6 columns, corresponding to three dependent variables (log total foreign assets, log foreign equity investment and log debt investment) and to whether we include additional controls or not. *Cultural Distance* is treated as endogenous. Compared to the OLS results of Table 2, we find that the magnitude of the effect of cultural distance rises.[20] Take for instance the effect of cultural distance on log FTI (column 1). The effect of a one standard deviation increase in *Cultural Distance* was -46.8% under OLS, and it rises in magnitude to -59.6% under IV. Similar differences are seen across specifications. On the other hand, across specifications the standardized magnitude of the effect of geographic distance is roughly unchanged compared to OLS (in column 1, it is -60.3% versus -62.9% under OLS, for instance).

The bottom line from the IV results is that both distance metrics continue to remain statistically and economically significant, with a larger effects of cultural distance compared to OLS. These findings do not depend greatly on whether we control for additional determinants of foreign investment, and is robust across log total foreign assets, log foreign debt assets and log foreign equity assets. Since the IV results control for possible endogeneity of cultural distance, we rely on them for the counterfactual analysis conducted in Section 5.

5 Counterfactual Analysis: Global Capital Misallocation

In this section, we calibrate the model of Section 2 using the econometric estimates of Section 4, to provide a quantitative assessment of the welfare impact of barriers to international investment. If we could hypothetically set to zero all intermediation costs associated with geographic and cultural distances between countries, and let market forces reallocate capital, how would the sum and the cross-country distribution of output change? It is important to note that, in our counterfactual exercise, we are not assuming that all distances themselves would disappear. Societal differences in locations, values, beliefs, norms, and other cultural traits, may continue to matter indirectly through their effects on productivities and other variables that differ across countries (empirically, such effects will continue to be captured by country fixed effects). Rather, our counterfactual assumption is that the world can now have access to new "intermediation technologies", affecting factors such as transportation, communication, cultural translation, international cooperation, and so on, which would completely eliminate all intermediation costs associated with geographic and cultural distances. Thus, we will look at a world where geopolitical and cultural differences between countries persist, but they no longer act as barriers to global capital allocation.

Two reasons motivate this exercise. The first is to provide a deeper understanding of the quantitative implications of the model. The second reason is related to policy. Of course, policy-makers cannot directly eliminate geographic distance. And, even if they could directly affect cultural distance, they probably should not for ethical, political, and economic reasons - including, for instance, the fact that geographic and

[20]Finding IV estimates on the instrumented variables that are larger in magnitude than OLS estimates is quite common in the literature, even in cases (like ours) where we expect reverse causality to bias OLS estimates away from zero. A common explanation is that IV estimation helps address attenuation bias coming from measurement error, if error in measurement of the instrumental variables is uncorrelated with error in measurement of the instrumented (endogenous) regressor.

cultural diversity across societies may have a positive impact on potential gains from trade, growth, and innovation. However, there can exist policies that reduce the *effect* of geographic and cultural distances on intermediation costs - for example, policies that facilitate travel, communication, and inter-cultural exchanges. The counterfactual exercise can be interpreted as capturing the potential benefits from such barrier-reducing policies.

5.1 Model Mapping and Calibration

The main source of country-level macroeconomic data is the Penn World Tables (PWT, version 10). The first variable that we obtain from PWT is country output (y_i), which is measured as GDP at current PPP US dollars. The second is labor input (ℓ_i), which is measured as total employment. From the Penn-World tables we also obtain a measure of the capital stock (k_i) at current PPP dollars, which we use for model validation purposes (our model generates capital stocks endogenously).

The third variable obtained from the PWT is the labor income share of GDP (λ_i). We complement this data, when missing, with estimates from the International Labor Office (ILO) Department of Statistics. Finally, we calibrate θ_i, the savings rate, using savings rates from the Penn World Tables (consumption as a ratio of consumption plus investment)[21]

The last data ingredient is the income compensation share of natural capital (ξ_i) : this is obtained from the most recent version (2018) of the World Bank's *Wealth of Nations* dataset.

Our regression estimates for β vary somewhat depending on the estimator. We calibrate the investment to-distance semi-elasticities (β) using the estimates of column 4 of Table 5 (which includes the full set of controls, and instruments for cultural distance): -0.324 for *Cultural Distance,* and -0.454 for *Geographic Distance*. We also use data on τ_i, composed of both investment taxes and risk of expropriation, as described in Section 3.3.2.

The model components that remain to be identified are the matrix of portfolio shares $\mathbf{\Pi}$, the vector of (destination country) capital stocks $\mathbf{k}$, the vector of savings $\mathbf{s}$ and total factor productivities ω_i. These objects are identified given the previously-measured variables and parameters: the matrix $\mathbf{\Pi}$ is identified given $\mathbf{y}$ and $\mathbf{\Phi}$ (equation (2.26)). The vector of savings $\mathbf{s}$ is identified by equation (2.11). $\mathbf{k}$ is then obtained as $\mathbf{\Pi s}$. Finally, the Cobb-Douglas production function pins down total factor productivity ω_i given k_i, ℓ_i and y_i.

5.2 Empirical Performance of the Gravity Equation

The first question is how well the gravity equation actually fits the restated data on cross-border investment positions. After calibrating the model, we can use the gravity equation (2.21) to predict international investment by origin and destination-country.

The model-implied foreign investment positions are shown in Figure 2 against the actual data on Foreign Total Investment. Model-implied values are *not* fitted values from the regressions in Section 4.

[21]The parametrization of α is inconsequential from an economic standpoint (it does not affect any of our counterfactuals): all it does is to scale the overall level of capital across all countries).

FIGURE 2: EMPIRICAL PERFORMANCE OF THE GRAVITY MODEL

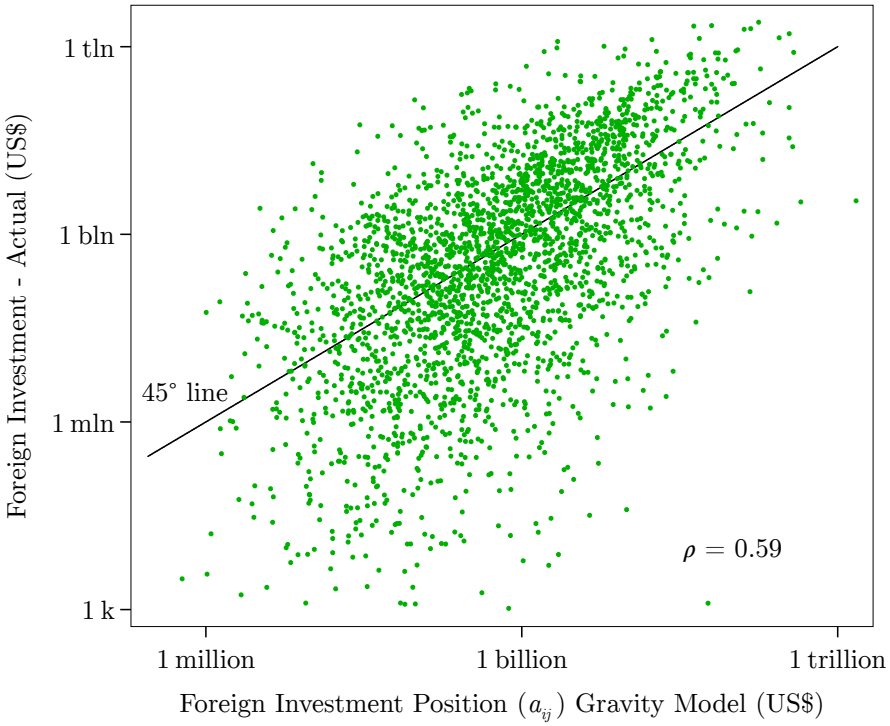


FIGURE NOTES: This figure plots the log of Foreign Total Investment against the log of predicted international investment from the gravity model (a_{ij}). The data are for 2017.

The difference between the two lies in the fixed effects: while in the econometric model they are fitted, in the model they are computed as a function of model parameters and observables.

The gravity equation performs satisfactorily: the actual and fitted values line up neatly along the 45° line, and their correlation is 0.59, which is high considering that the equation above is not fitted using fixed effects. We conclude that the calibrated gravity equation predicts cross-sectional variation in total investment quite well.

5.3 Model Fit: Country-Level Capital Stocks

We now consider another way to validate our model empirically. When taking the model to the data, we have not used any domestic capital data. To further validate our model, we can compare capital stock per employee from the Penn World Tables to our model-based estimates of the same variable. We take these two variables in logs, subtract the mean, and then plot the two series in a scatter plot in in Figure 3.[22]

[22]The OLG model does not differentiate between investment and capital stock, hence the level is not comparable. This is not important, since the model is isomorphic to scaling up or down all capital stocks (productivity ω_i adjusts to preserve the level of GDP).

FIGURE 3: MODEL FIT: CAPITAL STOCK PER EMPLOYEE

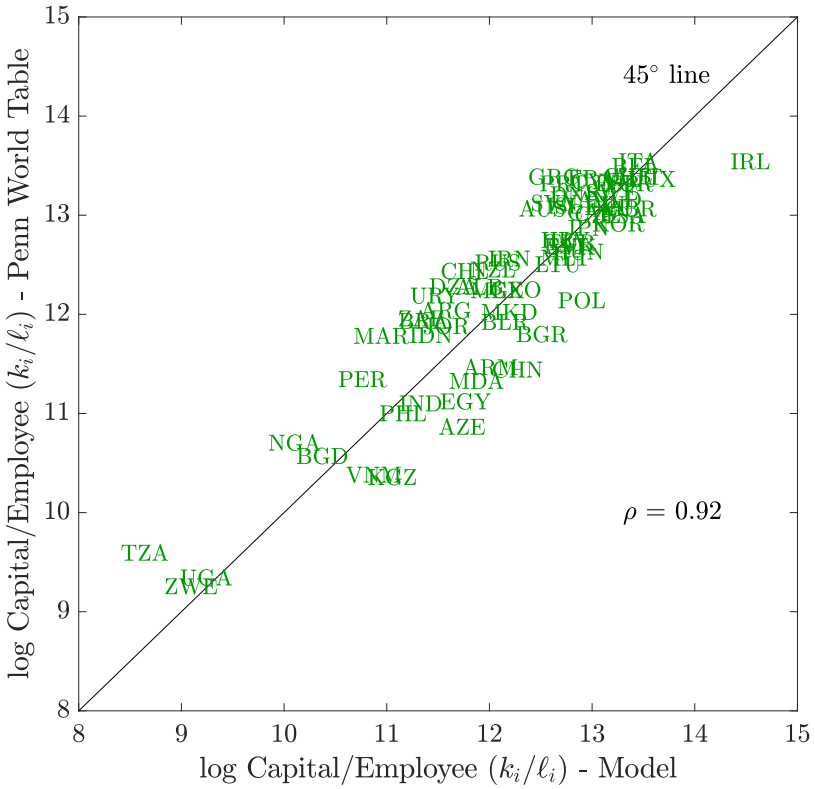


FIGURE NOTES: This figure plots the log of capital stock per employee (k_i/ℓ_i) from the against the corresponding model estimate. Both measures are in differences from the mean. Each observation is a country and data refer to the year 2017.

The graph shows that our model-based estimates correlate very strongly with their counterparts from Penn World Tables (the correlation is 0.92), and line up tightly around the 45-degree line. Thus, our model performs well in terms of predicting the cross-section of capital stocks across the 70 countries we are able to cover. Repeating the exercise without dividing by employment (ℓ_i) yields a stronger correlation (0.97).

5.4 Rates of Return

An key endogenous variable in our model is the objective rate of return on capital (r_i). As described in sub-section (2.8), the cross-country dispersion in rates of returns arises as a consequence of capital market imperfections (variation in $\mathbf{d}'\beta$ and τ_{ij}), and can be related to the resulting GDP loss. As already shown in subsection 2.8, if we set $\beta = \mathbf{0}$ and $\mathbf{T} = \mathbf{0}$, rates of return would be equalized and capital would be efficiently allocated across countries. It is therefore useful, in order to evaluate the empirical performance of the model, to investigate how the rates of returns produced by our model compare to those independently estimated by other researchers.

FIGURE 4: MODEL-IMPLIED RATES OF RETURN ON CAPITAL

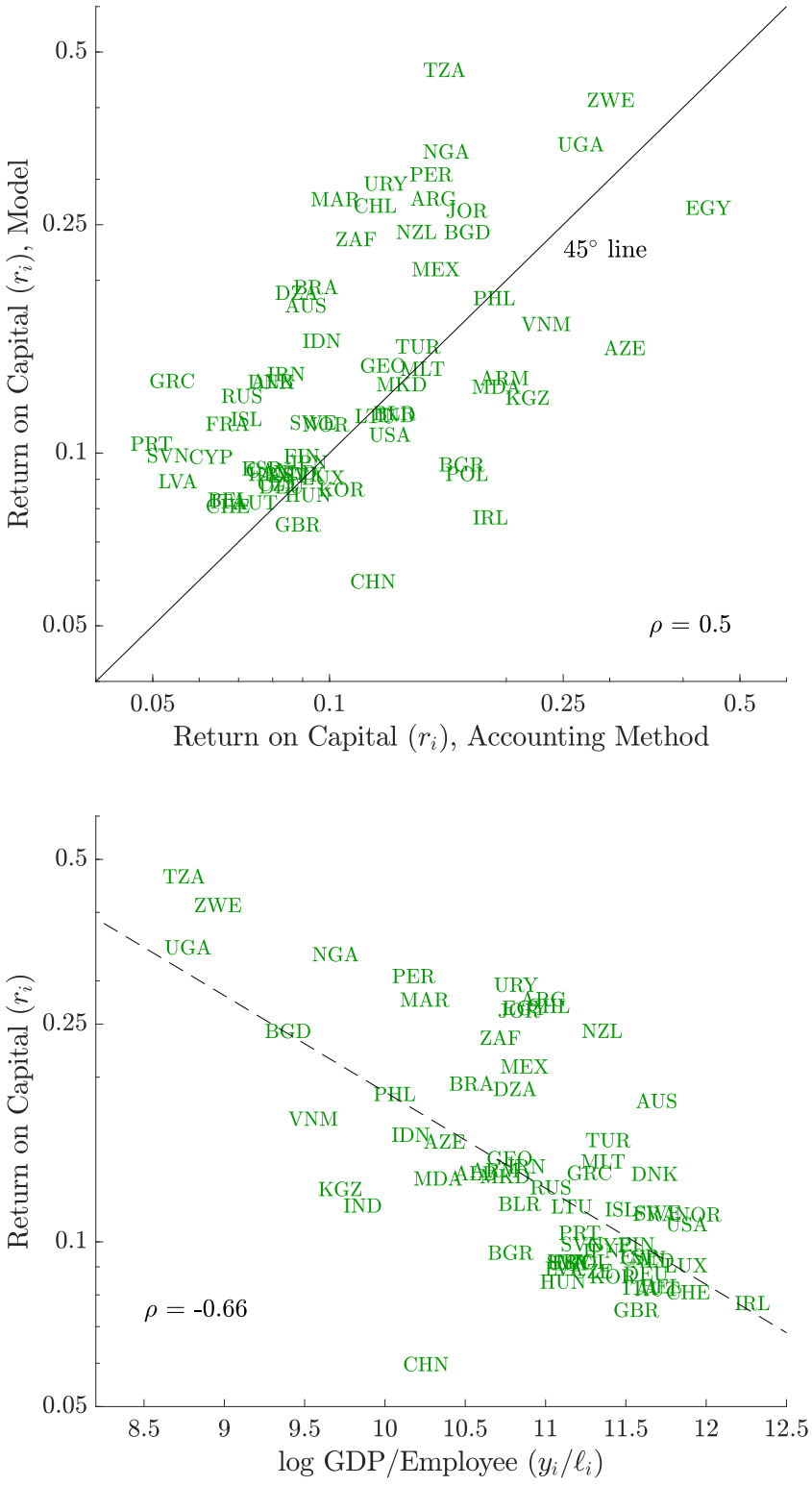


FIGURE NOTES: This figure plots the model-implied rate of return on capital, as a ratio to its median value, against the corresponding estimates of rates of return computed using the Penn World Tables, using the methodology in Caselli and Feyrer (2007), as amended by Monge-Naranjo et al. (2019), and against the log of GDP per employee (lower panel). Each observation is a country and the data are for 2017.

To do so we compare our model-implied relative rates of return to those obtained by applying the methodology in Caselli and Feyrer (2007) (augmented to allow for natural resources along the lines of Monge-Naranjo et al., 2019) to data from the Penn World Tables (version 10). By "relative", we mean that we normalize each of the two estimates by their respective median values (the levels are not comparable, because in our model there is no capital depreciation).[23]

In Figure 4 (upper panel) we produce a scatter plot of the rates of returns estimated from the Penn World Tables against those implied by our gravity model. We find that the two series are strongly correlated ($\rho = 0.5$). We argue that this correlation should be considered high because, again, cross-country variation in rates of returns generated by our model is driven entirely by bilateral metrics of investment taxes as well as geographic and cultural distances. If we were to set $\beta = 0$ and $\tau_i = 1$ for all i, the upper panel of Figure 4 would display a vertical line. Hence, the observed correlation between our model-implied values and estimates based on actual data arises exclusively from our four explanatory variables.

Another desirable property of the capital returns generated by our model is that they are consistent with a stylized fact, previously documented by DHS: rates of returns on capital correlate negatively, at the country level, with the level of economic development. We document this in the lower panel of Figure 4, where we plot the relationship between the rates of return from our model against the log of GDP per employee. The correlation between these two variables is -0.66. This is consistent with the observation that rates of return are much higher in developing countries. Therefore, if differentials in such rates were the only driver of international investment, one should expect large flows of capital from richer to poorer country. This raises the important question, originally emphasized by Lucas (1990) and later studied in depth by Alfaro, Kalemli-Ozcan, and Volosovych (2008), of why we do not observe such flows in the data. Barriers to global capital allocation, which are at the center of our empirical analysis, can help explain the absence of large movements of capital towards developing countries, thus shedding light on Lucas's question.[24]

5.5 Home Bias

Finally, we consider the out-of-sample performance of the model. As measured in the data, the matrix of investment portfolio shares $\mathbf{\Pi}$ has a significant number of missing observations, which can be filled

[23] In a recent paper, David, Henriksen, and Simonovska (2014, henceforth DHS) produce estimates of the return on capital for 144 countries, 65 of which overlap with countries in our dataset. DHS's measurement of returns to aggregate capital builds on those of (Caselli and Feyrer, 2007) and Gomme, Ravikumar, and Rupert (2011). In their seminal paper, Caselli and Feyrer found that, after accounting for differences in the the relative price of investment goods and after adjusting capital shares for land and other natural resources, capital returns were approximately equal across countries in the year they considered (1996). DHS have confirmed such finding for that specific year, but found large return differentials over longer periods. Similar differences between returns in developed and developing markets have been found by Daly (2010) for the period 1981-2008. In previous version of this paper, we compared our model-implied rates of return to those of DHS, finding results similar to those reported here.

[24] DHS also develop a model to explain this stylized fact. In their theoretical framework, capital yields higher returns in emerging economies due to risk and diversification (emerging assets are a worse hedge for global risk). In our framework, returns to capital are higher in emerging markets due to asset market frictions. It is not possible to judge the relative importance of these two factors based on our two models in isolation. A more general model – incorporating both risk and asset market frictions – would be needed. Also, a systematic methodology to measure asset return variances and covariances would likely be required. This is a promising avenue for future research.

TABLE 6: MATRIX OF G20 COUNTRIES INVESTMENT SHARES (BASED ON GRAVITY MODEL)

				Country of Origin - j																	
	Group	**Country**	**Code**	**AUS**	**CAN**	**USA**	**IND**	**RUS**	**TUR**	**ZAF**	**ARG**	**BRA**	**MEX**	**DEU**	**FRA**	**GBR**	**ITA**	**CHN**	**IDN**	**JPN**	**KOR**	**RoW**
Destination Country - i	1	Australia	AUS	27%	0%	0%	0%	0%	0%	1%	1%	0%	0%	0%	0%	0%	0%	0%	1%	0%	0%	0%
	1	Canada	CAN	1%	8%	7%	0%	1%	1%	1%	2%	2%	4%	1%	1%	2%	1%	0%	0%	0%	0%	1%
	1	United States	USA	10%	61%	67%	1%	4%	5%	6%	20%	15%	41%	6%	6%	12%	7%	1%	1%	3%	2%	7%
	2	India	IND	4%	1%	1%	48%	6%	10%	15%	1%	2%	1%	2%	2%	2%	3%	2%	13%	2%	4%	7%
	2	Russia	RUS	1%	1%	0%	2%	18%	3%	1%	1%	1%	1%	2%	2%	2%	2%	1%	1%	1%	1%	3%
	2	Turkey	TUR	1%	1%	1%	3%	3%	30%	4%	1%	1%	1%	2%	2%	2%	3%	0%	2%	1%	1%	4%
	2	South Africa	ZAF	1%	0%	0%	0%	0%	0%	12%	1%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
	3	Argentina	ARG	0%	0%	0%	0%	0%	0%	1%	14%	3%	1%	0%	0%	0%	0%	0%	0%	0%	0%	0%
	3	Brazil	BRA	1%	1%	1%	0%	0%	1%	6%	18%	43%	4%	0%	1%	1%	1%	0%	0%	0%	0%	2%
	3	Mexico	MEX	1%	3%	4%	0%	1%	1%	1%	6%	6%	25%	1%	1%	1%	1%	0%	0%	0%	0%	1%
	4	Germany	DEU	1%	3%	2%	1%	5%	3%	3%	2%	2%	2%	24%	10%	10%	10%	1%	1%	1%	1%	7%
	4	France	FRA	1%	2%	1%	1%	3%	2%	2%	2%	2%	1%	6%	17%	7%	6%	0%	0%	0%	0%	4%
	4	United Kingdom	GBR	2%	4%	3%	1%	3%	3%	3%	2%	2%	2%	8%	10%	17%	7%	0%	0%	1%	1%	6%
	4	Italy	ITA	1%	2%	2%	2%	4%	6%	6%	4%	3%	2%	8%	9%	7%	17%	0%	1%	1%	1%	7%
	5	China	CHN	25%	3%	3%	21%	23%	9%	12%	2%	2%	4%	7%	5%	5%	6%	84%	21%	36%	48%	13%
	5	Indonesia	IDN	4%	0%	0%	3%	1%	1%	3%	0%	0%	0%	0%	0%	0%	0%	1%	45%	1%	1%	1%
	5	Japan	JPN	8%	1%	1%	2%	3%	2%	1%	1%	0%	1%	2%	1%	1%	1%	4%	4%	40%	13%	2%
	5	South Korea	KOR	4%	1%	1%	3%	3%	1%	1%	0%	0%	1%	1%	1%	1%	1%	3%	3%	8%	21%	2%
	6	Rest of the World	RoW	9%	10%	7%	11%	22%	23%	23%	21%	15%	9%	30%	32%	30%	32%	3%	7%	4%	5%	32%

TABLE NOTES: This table presents, for G20 countries (except Saudi Arabia, for which we do not have data) matrix of investment shares $\mathbf{\Pi} = [\pi_{ij}]$, based on the gravity model of Section 2. $\mathbf{\Pi}$ lists, for every country pair (i, j), the share of capital owned by j that is invested in country i. G20 countries are officially sorted in 5 groups which are loosely based on country locations. We group countries in this matrix based on their official G20 group membership, and impute missing shares based on the gravity model we estimate in Section 4. All of the diagonal elements are imputed.

in using our gravity equation. Among the missing values are the entire diagonal of $\mathbf{\Pi}$, which represents domestic investment. Based on the literature on home bias, we can predict that these diagonal elements should be large relative to non-diagonal elements. Hence, one of the strictest tests of our gravity model would be its ability to predict, out-of-sample, a significant home bias.

Table 6 displays the matrix of portfolio shares $\mathbf{\Pi}$, based on restated IMF data, with missing values imputed using our gravity model. To avoid having to display 68 countries, the table includes only the G20 plus the rest of the world. Two features of this matrix are of note. The first is the dominance of the United States as a receiving country, which is consistent with its role as a "financial supermarket", previously documented by Martin and Rey (2004). The second striking pattern is the prominence of the diagonal elements, whose average value is over 50%, pointing to very significant home bias.

Given that our gravity equation loads negatively on measures of cultural and geographic distance, the fact that it predicts at least some degree of home bias is not entirely surprising. What is unexpected is the large size of the home bias predicted by our model: hence, another strength of our structural gravity model is its ability to predict, out-of-sample, a significant domestic bias.

The magnitudes of the home bias we calculate are comparable to those documented by French and Poterba (1991) and (more recently) Coeurdacier and Rey (2013), albeit it should be noted that we focus on a wider range of assets and our data are more recent.[25] Moreover, our data come from a different source.

Another stylized fact that our model is able to account for is that home bias correlates positively with rates of return. This fact was robustly documented by Lau, Ng, and Zhang (2010) who used, as a measure of home bias for country i, the share of domestic fund holdings in i's stock market capitalization divided by their i's world-market capitalization weight, expressed in logs.

To show that our general equilibrium model is capable of reproducing this correlation, we compute our own model-consistent version of this measure:

$$\text{Home Bias}_i \quad \stackrel{\text{def}}{=} \quad \log \pi_{ii} - \log \frac{k_i}{K} \tag{5.1}$$

and plot it against the model-implied return to capital (r_i) in Figure 5. As visible from the graph, the two correlate strongly and positively.

5.6 Counterfactual Analysis

We now move to the core of this section: the counterfactual analysis. Counterfactuals allow us to gain a sense of the economic impact of the barriers. In our setting, simulating a counterfactuals means changing the vector β (the semi-elasticity of investment with respect to the distance vector) and/or the diagonal matrix of investment taxes ($\mathbf{T}$), and studying how all other variables (as well as statistics of interest) change in equilibrium as a result. For each of the counterfactuals, we compute the corresponding World GDP. We also compute the percentage difference between the counterfactual and an undistorted (*zero-gravity*) equilibrium in terms of three statistics: World GDP, the standard deviation of the log of capital

[25] Coeurdacier and Rey (2013) document that home bias is slowly weakening.

FIGURE 5: RATES OF RETURN AND HOME BIAS

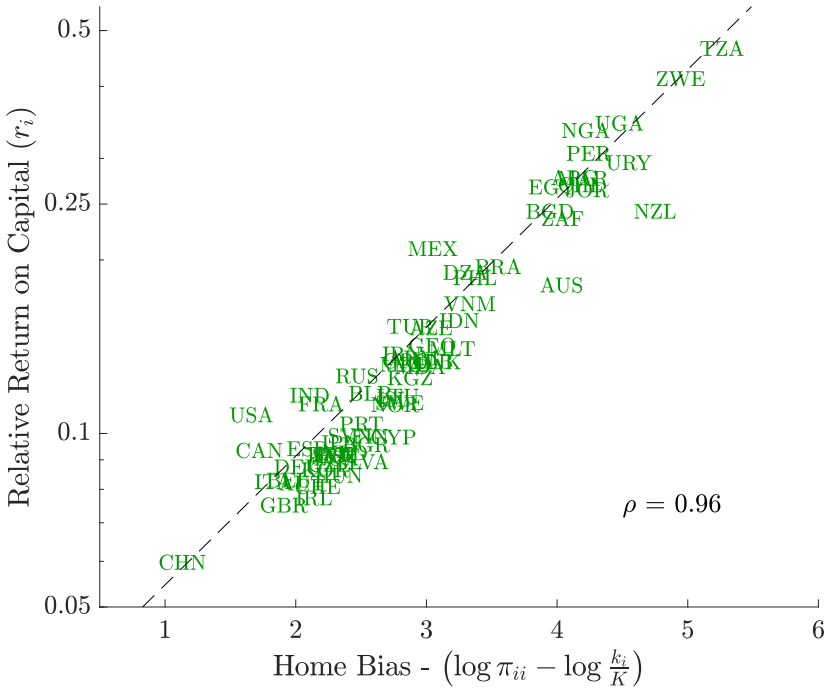


FIGURE NOTES: This figure plots the model-implied rate of return on capital, as a ratio to its median value, against a measure of home bias - the ratio of the shares of country i investment in country i portfolio and in the World Portfolio $\left(\log \pi_{ii} - \log \frac{k_i}{K}\right)$. Each observation is a country and data refer to the year 2017.

per employee and the standard deviation of log of output per employee.

Table 7 presents the main results from the counterfactual analysis. In column (1), we present the observed, distorted equilibrium, with investment taxes, geographic distance and cultural distance as observed. In column (2), we present the *zero-gravity* equilibrium, from which all distortions – except those at the level of the individual investors – have been removed ($\beta = \mathbf{0}$, $\mathbf{T} = \mathbf{0}$). In column (3) to (5), we consider equilibria in which the effect of *Cultural Distance*, *Geographic Distance* and investment taxes are respectively re-introduced in isolation (that is, all other distortions except the one indicated are removed). These three counterfactuals allow to gain a sense of the marginal impact of each individual distortion.

The upper panel shows results of our counterfactual, computed under the assumption that the supply of capital is inelastic (that is, the vector of savings $\mathbf{s}$ cannot react to the removal of the distortions). This set of results is meant to isolate the effect of capital misallocation, and reflects a "one-period" change in our model economy following the addition or removal of distortions. The lower panel shows results based on the assumption that the supply of capital can adjust in response to the removal of the distortions. These results reflect instead how the steady state equilibrium changes: they account for the fact that, when capital is reallocated away from some countries and towards some other countries, the total capital stock may need to adjust in order for steady-state conditions to be satisfied.

TABLE 7: COUNTERFACTUALS (2017)

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Cultural Distance*	*Geographic Distance*	*Political Risk & Taxes*
Welfare Statistics (Fixed Capital Stock)	(1)	(2)	(3)	(4)	(5)
World GDP (US$ trillions)	103.5	111.7	108.5	108.4	111.1
World GDP, % Difference in GDP from Zero-Gravity	-7.3%	0%	-2.8%	-2.9%	-0.5%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+83.1%	0%	+33.8%	+33.9%	+19.0%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+29.6%	0%	+14.1%	+4.6%	+8.1%
Welfare Statistics (Endogenous Capital Stock)					
World GDP (US$ trillions)	103.5	108.3	107.1	107.1	108.4
World GDP, % Difference in GDP from Zero-Gravity	-4.4%	0%	-1.2%	-1.1%	0.0%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+83.8%	0%	+34.8%	+34.3%	+19.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+29.6%	0%	+14.7%	+4.3%	+8.1%

TABLE NOTES: This table presents welfare statistics for four counterfactuals of the model described in Section 2. Each of columns (2)-(5) is a counterfactual, and the rows represent different welfare statistics of interest. *Observed* is the equilibrium allocation with all measured barriers. *Zero-Gravity* is the counterfactual in which all three barriers (*Cultural Distance*, *Geographic Distance* and *Political Risk & Taxes*) have been removed. Columns (3)-(5) illustrate three counterfactuals from which only the corresponding distortion is in place. (k_i/ℓ_i) is the capital stock per employee, while (y_i/ℓ_i) is output (GDP) per employee. Actual World PPP$ GDP (including countries not in the model) in 2017 was $121 trillion.

FIGURE 6: DISTRIBUTION OF CAPITAL AND OUTPUT PER EMPLOYEE

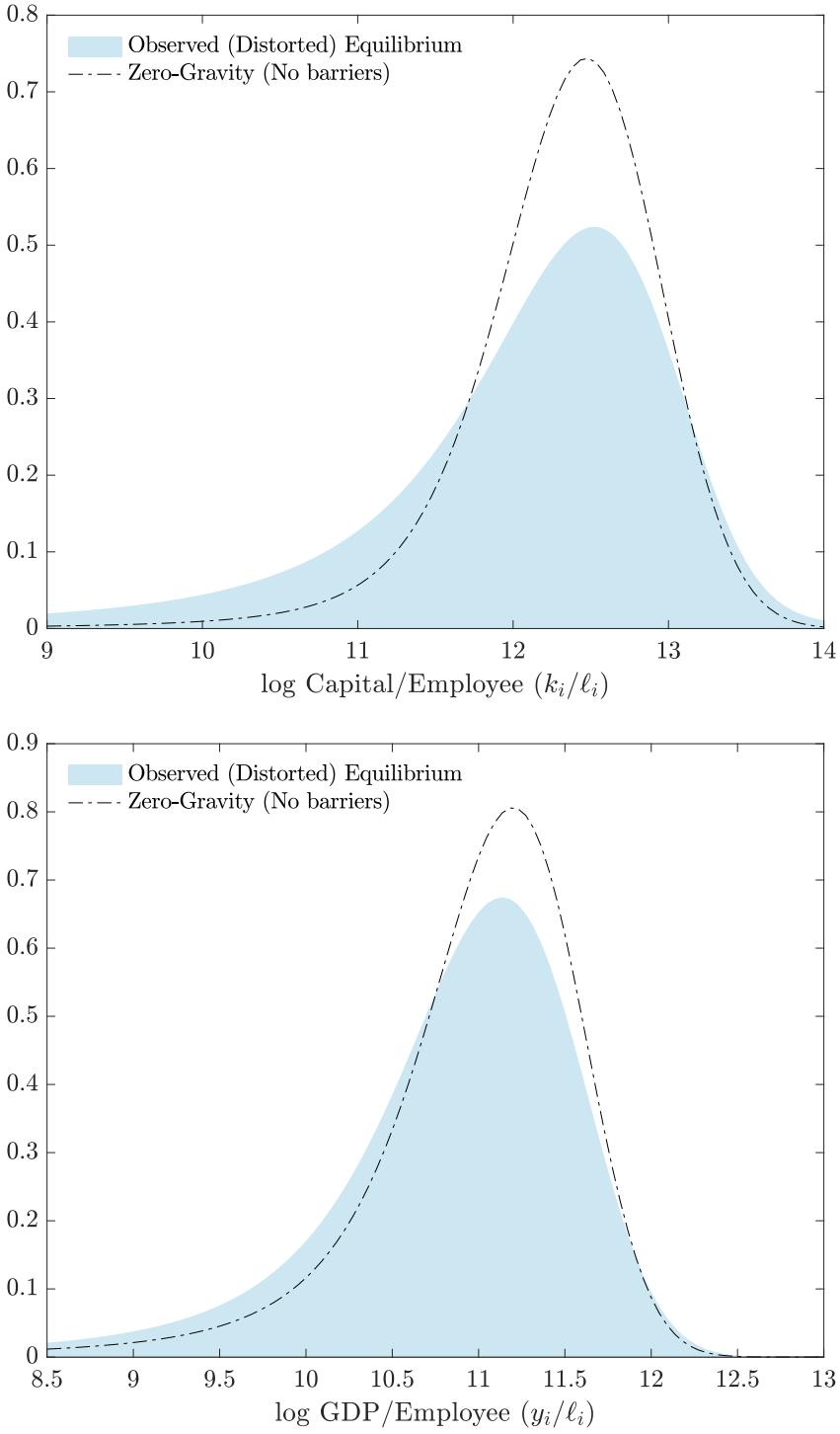


FIGURE NOTES: This figure fits the probability density function of a *stable* distribution (a 4-parameter family of distributions with flexible skewness and fat tails) to country-level capital stock per employee (upper panel) and GDP per employee (bottom panel). In each panel, the lighter area is the distribution in the observed, distorted equilibrium. The dotted black line is the distribution in a counterfactual scenario in which all measured distortions to capital movement (geographic and cultural distances, as well as investment taxes) have been removed.

We find that barriers to the global allocation of capital have quantitatively important effects on the level of output produced globally. World GDP in the observed equilibrium of our model is measured at 103.5 US$ billion. That is 7.3% lower than in the *zero-gravity* counterfactual (column 2) under the assumption of an inelastic capital supply, and 4.4% lower when we assume that the supply of capital can respond.

We also find that the three distortions have quantitatively meaningful effects on World GDP when considered in isolation. When all distortions except those due to *Cultural Distance* are removed, GDP is 2.8% lower than in the Zero-Gravity scenario; this figure becomes 1.2% if capital is allowed to respond. When *Geographic Distance* alone is considered, the GDP losses are 2.9% (inelastic capital) and 1.1% (elastic capital). Investment taxes and political risk have a more muted impact when considered in isolation: they reduce World GDP by 0.5% when capital supply is inelastic.[26]

One common theme of these counterfactual is that GDP losses appear slightly smaller when we allow the capital stock to react. A potential explanation for this finding is that we allow countries to vary in their capital income shares (θ_i). When distortions are removed, capital generally tends to be reallocated to countries with higher capital shares, and country savings (s_i) are smaller for countries with a larger capital share. Hence, with an elastic capital supply, aggregate saving tends to be slightly lower in the zero-gravity counterfactual due to compositional effects.

While the overall effects of these three distortions on allocative efficiency and World GDP appear substantial, their effect on cross-country inequality is even more sizable. We can gain a sense of country heterogeneity by looking at how much these distortions change the distribution of capital and output per employee. When capital misallocation resulting from barriers to international investment are removed, we observe a significant decrease in dispersion of both capital and output per employee. When moving from the zero-gravity equilibrium to the observed (distorted) equilibrium, the standard deviation of (log) capital per employee increases by 83.1%, while the standard deviation of log output per employee increases by 29.6%. These numbers are not sensitive to whether capital supply is assumed to be inelastic.

When *Cultural Distance* alone is maintained, dispersion in log capital per employee is 33.8%-34.8% higher than in the zero-gravity benchmark (depending on whether capital supply is elastic or not). The dispersion of log output per employee is 14.1%-14.8% higher. For *Geographic Distance*, the magnitudes are commensurate with these numbers. Finally, we find that maintaining only investment taxes and political risk, dispersion in log capital per employee is about 19% higher compared to the zero-gravity benchmark, while dispersion in log output per employee is 8% higher. In other words, cultural distance appears to have the largest marginal effect, followed by geographic distance. Investment taxes and political risk have smaller, but still sizable effects on cross-country inequality.

Figure 6 provides a graphical representation of the effect of removing barriers to international investment on cross-country inequality. It shows how the (fitted) cross-country distribution of capital per employee and output per employee changes in response to the removal of the barriers. For both variables, we observe a significant reduction in dispersion, but also in skewness (the left tail becomes thinner). We also can notice a general rightward shift, reflecting an increase of capital and income per employee for the

[26]When we allow capital supply to adjust, we find that the removal of this friction in isolation leads to no change in world GDP. This is explained by a reallocation of economic activity towards countries with lower savings rates.

FIGURE 7: CAPITAL REALLOCATION GAINS BY COUNTRY

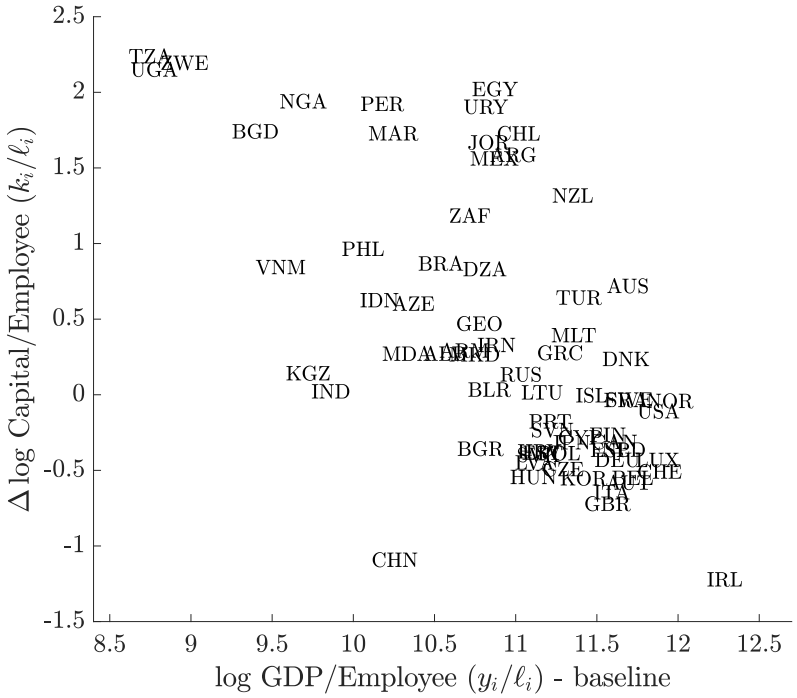


FIGURE NOTES: This figure displays the baseline level of log output per capita (horizontal axis), against the log change in capital stock per employee (left axis) following the removal of all measured barriers to global capital allocation. Each observation is a country, and the data are from 2017.

median country.

What lies beyond this reduction in inequality under zero-gravity? When capital distortions are removed, capital tends to be reallocated to countries that had higher rates of returns on capital in the distorted equilibrium. As discussed previously, these tend to be countries with lower capital stock per employee and lower output per employee. Figure 7 illustrates this effect: it is a scatter plot of the baseline level of GDP per employee (horizontal axis) against the log change in GDP per employee from moving to a zero-gravity world (vertical axis). The latter number can also be read, on the right axis scale, as the log change in capital per employee. As can be seen from the graph, there are significant "winners" and "losers" among the countries in our dataset – albeit on average most countries experience an increase in capital and output per capita. The strong negative correlation between the country-level gains and the initial level of output per employee implies that the removal of barriers leads to a substantial reduction in cross-country inequality. In other words, poorer countries benefit disproportionately from capital reallocation. Some of them, such as Zimbabwe or Uganda, see capital per employee more than double, and their income per employee jump by over half.

Finally, we consider a comparison of net foreign asset positions (defined here as the difference between country i's supply of physical capital k_i and the total financial capital supplied by country i to all other countries), under the observed equilibrium and the zero-gravity equilibrium (i.e. when we set $\beta = 0$ and

FIGURE 8: NET FOREIGN ASSETS AND DEVELOPMENT

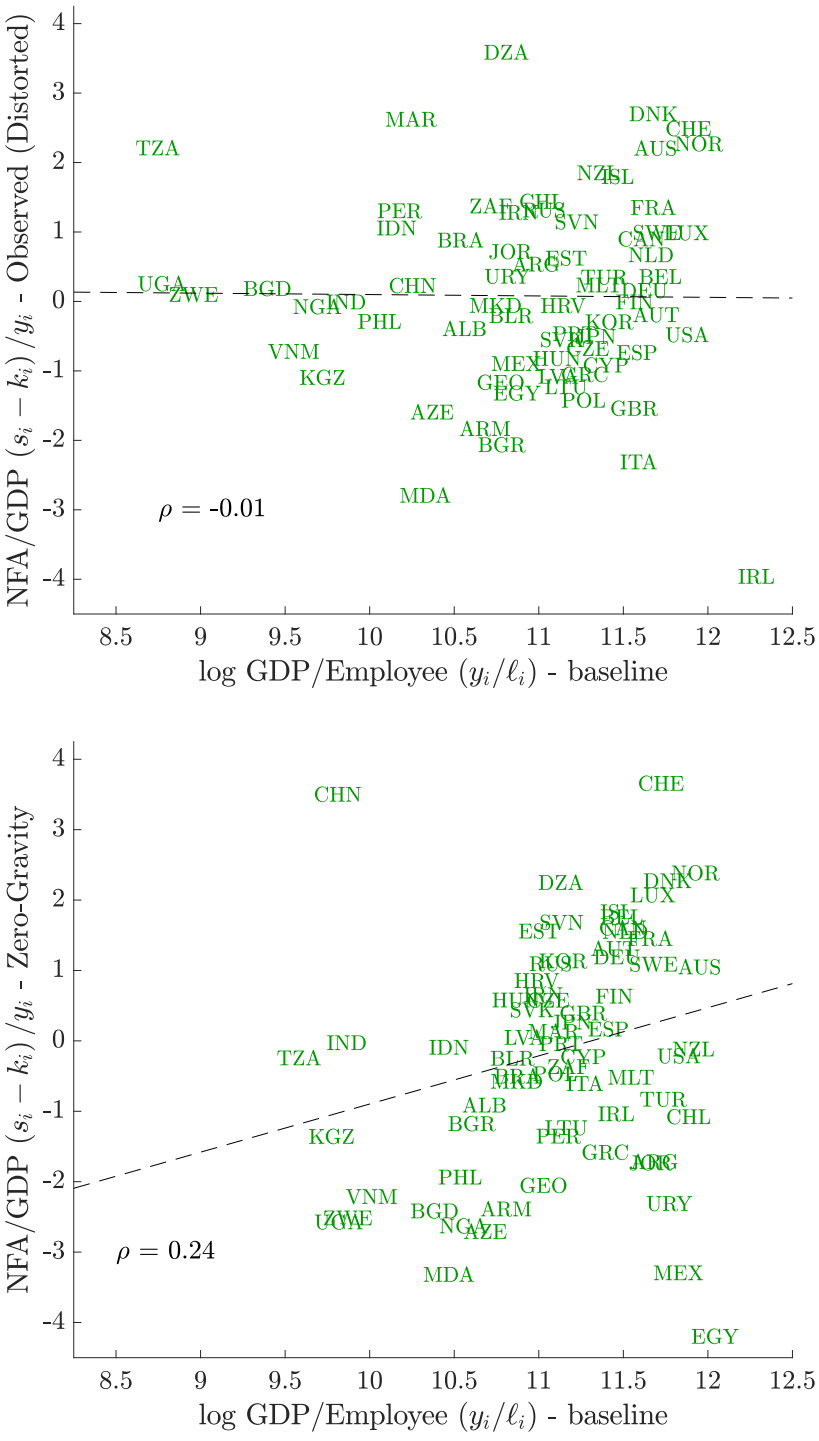


FIGURE NOTES: the figure above plots the model-implied Net Foreign Assets $(s_i - k_i)$ as a share of GDP (y_i), against the log of GDP per employee. The top panel plots NFA/GDP in the observed distorted equilibrium, while the bottom panel plots NFA/GDP in the Zero-Gravity counterfactual, in which all barriers are removed.

$\tau_i = 1$ for all i). One attractive feature of our model is that it generates persistent (steady-state) global imbalances.

Figure 8 displays scatterplots of the resulting net foreign assets against log GDP per employee. Under the observed equilibrium, there are large deviations in net investment positions ($s_i - k_i$); yet, these net asset positions correlate very weakly (and negatively) with the level of development: this is consistent with Lucas's observation that capital fails to flow from rich to poor countries. When frictions are removed (bottom panel), the relationship turns positive and becomes stronger in magnitude, as the absolute value of the correlation between net foreign assets and the level of development doubles. In the zero-gravity equilibrium, capital indeed flows from rich to poor countries. The presence of international barriers to capital flow (geographic, cultural and tax-based) can help explain the lack of a positive correlation, in the data, between a country's net asset positions and its level of development.

In summary, using counterfactual analysis, we find that misallocation of capital across countries – induced by investment taxes as well as geographic and cultural distances – imposes quantitatively important output losses for the majority of countries, and in general for World GDP, and can potentially account for a significant share of the observed cross-country dispersion in capital/employee.

6 Robustness Checks and Extensions

6.1 Coefficients Stability

How stable are the coefficient estimates on *Cultural Distance* and *Geographic Distance* over time? Appendix D, Figure D.1 plots coefficient estimates from a variation of our baseline regression specification (Table 2, column 1). The dependent variables is still the log of foreign total investment, but the right hand side variables (*Cultural Distance*, *Geographic Distance*) are interacted with year fixed effects to produce time-varying coefficients. The 95% confidence interval is plotted together with the calibrated coefficients (dotted line). The dotted line always falls within the confidence interval, and close to its center for both variables. This time-stability of the main regression estimates of interest provides evidence that our choice of calibrated effects of cultural and geographic distance is well-founded.

6.2 Alternative Breakdown of Foreign Investment Statistics

In our main estimation, we broke down FTI into debt and equity components. Here we consider instead another conventional breakdown of capital flows: between Foreign Direct Investment (FDI) and Foreign Portfolio Investment (FPI). Appendix E, Table E.1 presents the results, using the same specification as that of Table 2. We find that cultural and geographic distances exert negative, statistically significant and economically meaningful negative effects on FDI and FPI, whether one does not include additional controls (columns 2 and 3) or whether one includes them (columns 5 and 6).

6.3 Restated vs. Un-restated Data

In our main estimation exercise, we use foreign investment data that are restated to account for the effect of tax havens. Appendix F, Table F.1 replicates the regressions of Table 2 using non-restated (residency-

based) data on foreign total investment, foreign debt investment and foreign equity investment. The sample involves a substantially larger number of observations, especially when no control variables are added (columns 1-3). Nonetheless, the standardized magnitudes of the estimates are very close to those obtained from Table 2. Across the six specifications, with non-restated data the effect of cultural distance is slightly smaller, while that of geographic distance is slightly larger than when using data that are restated on a nationality basis.

6.4 Capital Controls

One type of barrier that we have deliberately omitted from our model is capital account policy restrictions. We did so because our model is not designed to address questions of macro-prudential policy, i.e. short-term considerations about macroeconomic stability (we focus instead on a long-run steady-state). Nonetheless, capital controls are enacted in order to affect capital flows, and thus we worry whether their effect may interact with that of our variables in a way that might change our results in a meaningful way.

A simple way to theoretically model the effect of capital controls is to add a bilateral component to the tax wedge τ:

$$\tau_{ij} \;=\; \tau_i^{\text{Tax}} \cdot \tau_i^{\text{PR}} \cdot \tau_{ij}^{\text{KC}} \tag{6.1}$$

τ_{ij}^{KC} is defined over the interval $[0, 1]$: it captures the degree of capital account openness (the lack of capital controls) facing j-investors seeking to invest in country i. $\tau_{ij}^{\text{KC}} = 1$ implies that investment from j to i is unrestricted. For domestic investors ($i = j$) τ_{ij}^{KC} is always 1 by definition.

Turning to the empirical implementation, we measure the degree of *de jure* capital account openness between country i and country j using data from Jahan and Wang (2016), which is based on qualitative information from the IMF's Annual Report on Exchange Arrangements and Exchange Restrictions (AREAER). Their dataset consists in a set of dummy variables that encode the presence of inflow or outflow capital account restrictions on specific types of investments. We use data for the most recent year in their dataset, 2013.

For each country in their dataset, we use the following set of ten dummy variables. The first two dummies represent, respectively, restrictions on inflowing and outflowing direct investment. The next set of four dummies represent restrictions on equity portfolio investment: two represent restrictions on (respectively) the sale and purchase of domestic equity by non-residents, while the other two represent restrictions on (respectively) the sale and purchase of foreign equity by residents. The third and last set of four dummies covers restrictions on debt portfolio investment: two reflect, respectively, restrictions on sale and purchase of domestic debt securities by non-residents; the other two represent restrictions on sale and purchase of foreign debt securities by residents.

To estimate τ_{ij}^{KC}, we consider the five inflow restrictions dummies for country i (1 for FDI, 2 for portfolio equity and 2 for debt) as well as the five outflow restrictions dummies for country i (1 for FDI, 2 for portfolio equity and 2 for debt). We model each restriction as a (shadow) tax on foreign investment. To be conservative in our analysis, we assume that these taxes take on large values. In particular, we assume that both dummies corresponding to FDI investment restrictions are equivalent to a tax of 50%,

while each of the four dummy variables corresponding to FPI restrictions is equivalent to a tax of 25%. We first compute the total tax (compounding both i inflow restrictions and j outflow restrictions) at the asset class level (FDI, equity portfolio and debt), and then take the simple average across the three asset classes. Formally:

$$\tau_{ij}^{\text{KC}} \;=\; \frac{1}{3}\left[(1-50\%)^{N_{\text{FDI}}} + (1-25\%)^{N_{\text{Equity FPI}}} + (1-25\%)^{N_{\text{Debt}}}\right] \tag{6.2}$$

where N indicates the number of dummy variables in AREAER for each asset class/country pair (two, four and four respectively).

In Appendix G, Table G.1 we repeat our counterfactual analysis for the extended model with capital controls. To make the exercise symmetric to the baseline one, capital controls remain in place in each of the five scenarios being studied – that is, we do not remove the effect of capital controls in any of the estimated counterfactuals, not even when we move to "zero-gravity". The percentage world GDP losses is little changed with respect to our baseline exercise, both when the capital stock is fixed (7.5% vs. 7.3%) as well as when the world capital stock is endogenous (4.8% – very close to our baseline estimate of 4.4%). The marginal effects of the individual frictions are also very similar to the one found in the baseline exercise.

6.5 Currency Hedging Costs and Risk Premia

Another aspect of international investment that we have left out of the model is currency risk. In our basic model, there is no explicit notion of money. However, there is a tractable way to incorporate currency risk in our framework. We start from the observation that the vast majority of international investors hedge currency risk. Sialm and Zhu (2020) find that over 90% of US-based international fixed income funds hedge currency risk with derivatives. A similar stylized fact holds for equity investments. According to the EU-EFIGE survey (a survey of 15,000 manufacturing firms from the EU and the UK), about two-thirds of the firms engaging in foreign direct investment are hedged against currency risk, either through derivatives or because the foreign subsidiaries invoices in the same currencies as their parent company. This percentage rises to 85% when responses are weighted by firm employment size.

Based on these facts, a parsimonious way to incorporate currencies in our theory is to model the currency hedging cost directly. An agent investing from country j to country i that hedges with forward contracts will exchange j currency for i currency at a spot exchange rate, and will then repatriate their investment return at the forward rate. This implies that the investor is subjected to a multiplicative cost (or gain) equal to the forward premium on the j/i exchange rate.

Thus, a simple way to introduce this hedging cost in our model (without modeling currency risk explicitly) is to add an additional component in the international investment wedge τ paid to the intermediating agent based in j's domestic country:

$$\tau_{ij} \;=\; \tau_i^{\text{Tax}} \cdot \tau_i^{\text{PR}} \cdot \tau_{ij}^{\text{Ccy}} \tag{6.3}$$

Here τ_{ij}^{Ccy} represents, rather than taxes or political risk, the currency hedging cost, which we estimate

using exchange rate forward premia.

$$\tau_{ij}^{\text{Ccy}} \;=\; \frac{F_{ij}}{S_{ij}} \;=\; \frac{1+r_i^f}{1+r_j^f} \tag{6.4}$$

We can also define a currency risk-adjusted return:

$$\bar{r}_{ij} \;\stackrel{\text{def}}{=}\; \tau_{ij}^{\text{Ccy}} r_i \tag{6.5}$$

This is because, if *covered* interest parity holds, the forward premium is given by the risk-free return differential between in country i and j. This is in turn related, by the fundamental exchange rate valuation equation (Campbell and Clarida, 1987; Froot and Ramadorai, 2005), to the risk premium on i's currency from the point of view of a j investor. In other words, the cost of hedging a high-yielding currency is equal to the forgone currency risk premium, and this allows us to interpret $\bar{r}_{ij}$ as the foreign investment return, adjusted for currency risk.

In order to incorporate currency hedging costs in our model, we use forward premia on exchange rates. We download, from Bloomberg, spot as well as 1-year forward rates against the US dollar for the currencies of the countries covered in our foreign investment data. We use the earliest available data for the year 2017. We then compute cross-rates for all available currency pairs. For currency pairs where data is unavailable or unreliable, we estimate forward premia using the covered interest rate parity. We use 1-year interbank rate differentials where available, and central bank rates differentials as a last resort. Interest rate data (for January 2017) is sourced from TradingEconomics.com. Finally, we fill the data for the remaining currency pairs (which are missing because the forward premia were estimated using different methodologies) using a linear regression of log forward premia on i and j fixed effects. For pegged currency pairs, we assume that the currency hedging cost is zero.

In Appendix G, Table G.2 we repeat our counterfactual analysis for the extended model with currency hedging costs. As in the previous robustness exercise with capital controls, currency hedging costs remain in place throughout the four scenarios. The world GDP loss that we find according to this extended model is larger, but only slightly: -7.6% when the capital stock is fixed and -4.9% when the capital stock is endogenous. As for the capital controls extension, the marginal effect of the three set of barriers remains very close to the baseline level.

6.6 Risky Country Returns

A third factor ignored thus far is the intrinsic riskiness of the investment (both domestic and foreign) undertaken. Our third extension aims to tractably introduce a notion of risk in our otherwise non-stochastic model. To do that, we introduce risk in the conversion of final good at time t into productive capital at time $t+1$. In particular, each unit of final good saved by z becomes $\exp\zeta\left(x,z\right)$ units of productive capital in the next period. We assume that the within-country shock ζ cannot be learned about by investors, and is assumed to be conditionally Gaussian, with mean $-v_i^2/2$ and standard deviation v_i, so that the shocks average out and do not change the overall level of capital.

Because agent z holds log sub-utility and choose the plant with the highest expected log return, this

leads to the following amended expression for the portfolio shares:

$$\pi_{ij} = \frac{\tau_i \cdot r_i k_i \cdot \exp\left(\mathbf{d}'_{ij}\beta - \frac{1}{2}v_i^2\right)}{\sum_{c=1}^{n} \tau_c \cdot r_i k_i \cdot \exp\left(\mathbf{d}'_{cj}\beta - \frac{1}{2}v_i^2\right)} \tag{6.6}$$

This treatment of investment risk is simplified, in that there is no aggregate risk, and hedging motives are assumed away. However, an advantage of this simplification is that it only requires us to find an estimate of v_i. To estimate the country-level variance of the asset returns $\left(v_i^2\right)$, we download country equity volatility indices from FRED (the original source of the data is Bloomberg). For the few (emerging) countries for which this is unavailable, we use the CBOE Emerging Markets ETF Volatility Index as a proxy.

In Appendix G, Table G.3 we repeat our counterfactual analysis for the extended model with risky investment. As for the previous robustness exercises with capital controls and currency hedging costs, the effect of risk on portfolio allocations remains in place in all four scenarios being considered. Our results are virtually unchanged when we account for risky returns.

6.7 Sensitivity Analysis on Coefficient Estimates

It is reasonable to ask how the results of our counterfactual analysis would change if we were to utilize our OLS estimates or the Pseudo-Poisson estimates to calibrate β: this is the semi-elasticity of foreign investment with respect to cultural and geographic distance.

We address this question in Appendix H, Tables H.1-H.2. There we present the analysis of Table 7, using these alternative estimates for β. We find that the steady-state GDP loss induced by capital misallocation would be 3.4% if we were to use the Pseudo-Poisson coefficients, and 2% if we were to use the IV estimates. The variable whose marginal effect is most sensitive to this choice is *Cultural Distance.* We continue to find that the removal of barriers would result in significant reductions in world inequality under both Poisson and IV estimates.

7 Conclusion

In this paper, we focused on how barriers to international financial flows affect the efficiency of capital allocation across countries. To study such barriers, we developed a novel multi-country overlapping-generations general equilibrium model of international capital allocation that yields a gravity equation for foreign assets demand as an equilibrium outcome. The model features atomistic agents with objective and subjective returns to investing in various markets. The returns depend crucially on factors that hinder the flows of information across societies and affect intermediation costs, reducing the return from investing in distant markets. These costs result from geographic and cultural barriers to capital allocation.

We estimated our gravity model empirically, using foreign investment data that have been restated from a residency to a nationality basis, in order to account for the presence of offshore investment and financing vehicles (Coppola et al., 2020; Damgaard et al., 2019). Using a variety of estimation approached (OLS,

Poisson, IV), we found that geographic and cultural barriers have substantial effects on the allocation of capital across different societies. The estimated effects are large in magnitude, suggesting that the removal of barriers to international capital allocation could have important effects on output, welfare and inequality across countries. Our parsimonious implementation of the model - based on cultural and geographic barriers, foreign investment taxes and political risk - explains a significant share of the observed variation in foreign investment.

Our model reproduces several features of international asset markets. First, it produces large and meaningful variation in rates of returns across countries. These rates of returns correlate negatively with the level of economic development, a realistic feature of the model. Second, our model produces, out-of-sample, a large home bias in a multi-country setting. While previous research has emphasized diversification and hedging as crucial to understanding these patterns, our analysis suggests that geographic and cultural factors are also likely to play an important role.

To quantify the influence of these factors on the international allocation of capital and their real impact, we performed a number of counterfactual exercises using our model. We studied how World GDP and the cross-country distribution of capital and output per worker would change if the effects of geographic and cultural distances on foreign investment were zeroed out. This quantitative exercise suggests that capital misallocation associated with barriers to the global allocation of capital has a sizable impact on the distribution of capital across countries, in terms of efficiency as well as inequality. World GDP is 7% lower than it would be if the effect of these barriers could be neutralized. The cross-country standard deviation of capital per employee is 80% higher, while the dispersion of output per employee is 42% higher. Conversely, the hypothetical removal of frictions would lead to substantial economic gains and reductions in cross-country inequality, by reallocating capital from richer countries (where the rate of return on capital is lower) to poorer countries (where the rate of return is higher). At the same time, in our estimation, some countries "lose out" (output and capital per employee drop), following the removal of international capital distortions.

Our study contributes to the literature on open economy financial macroeconomics, by making theoretical as well as empirical progress in modeling international asset markets in a multi-country, general-equilibrium setting. It also connects to the macroeconomics literature on resource misallocation, by studying the real effects of international asset market frictions.

We end by suggesting directions for future research. Our work departs significantly from the existing small open economy macro-financial literature: it focuses on geo-cultural and policy frictions, as opposed to diversification and hedging, as potential drivers of international capital allocation. A potential goal of future research could be to produce a unified theory of international investment, which incorporates asset market imperfections as well as currency and risk considerations in a multi-country environment.

A second, interesting potential direction for future research is to incorporate a richer specification of the goods sector, which we deliberately chose to keep simple in our model. A fully-integrated model for international trade and investment would make it possible to study the combined effect of asset market imperfections and of goods markets distortions, accounting for possible ways in which the two interact with each other.

Finally, another direction for future research would be to enrich the model along the dimension of

consumer/investor heterogeneity. In our framework, all agents have the same saving rate. An interesting question, which could be investigated with a richer household sector, is how financial globalization might affect *within*-country income inequality.

In 1990, Robert Lucas asked: "Why doesn't capital flow from rich to poor countries?". This paper sheds new light on this question. Geographic, cultural and policy barriers are important determinants of cross-country investment positions. They have major effects on efficiency and distribution, including hindering the flow of capital from richer to poorer societies.

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Online Appendix
Barriers to Global Capital Allocation

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A Proofs and Derivations

Proof to Proposition 1. By Proposition 1 in Caplin, Dean, and Leahy (2019), $\mathcal{P}_j^0(q)$ solves the rational inattention logit problem if and only if equation (2.17) and the following condition both hold:

$$\mathbb{E}_{\tilde{\mathbf{r}}}^{G_j} \frac{\tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}}}{\sum_{q'} \tilde{r}_{i'(q)}^{\frac{\sigma}{1-\sigma}} \cdot \mathcal{P}_j^0(q')} \leq 1 \tag{A.1}$$

where the relationship holds with equality if plant q is selected with positive probability. We therefore need to show that this second condition is satisfied by:

$$\mathcal{P}_j^0(q) = \frac{\varphi_{i(q)j}}{\sum_{q'=1}^{N} \varphi_{i(q')j}} \tag{A.2}$$

We guess and later verify that every plant is selected with positive probability. This implies that we can re-write condition A.1 as:

$$\mathbb{E}_{\tilde{\mathbf{r}}}^{G_j} \frac{\tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}} \cdot \mathcal{P}_j^0(q)}{\sum_{q'} \tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}} \cdot \mathcal{P}_j^0(q')} = \mathcal{P}_j^0(q) \tag{A.3}$$

Next, we note that if $\tilde{r}_i$ follows a Gamma (Γ) distribution, we can write its scale and shape parameters in terms of the mean and the variance. If the mean is ρ_j and the precision is φ_{ij} we have:

$$\tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}} \overset{G_j}{\sim} \Gamma\left(\rho_j^2 \varphi_{ij}, \frac{1}{\rho_j \varphi_{ij}}\right) \tag{A.4}$$

Using the scaling property of the Γ distribution:

$$\tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}} \varphi_{i(q)j} \overset{G_j}{\sim} \Gamma\left(\rho_j^2 \varphi_{ij}, \frac{1}{\rho_j}\right) \tag{A.5}$$

this in turn implies, by a well-known result, that:

$$\frac{\tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}} \varphi_{i(q)j}}{\sum_{q'} \tilde{r}_{i(q')}^{\frac{\sigma}{1-\sigma}} \varphi_{i(q')j}} \overset{G_j}{\sim} \text{Dirichlet}\left(\rho_j^2 \varphi_{i(1)j}, \rho_j^2 \varphi_{i(2)j}, \ldots, \rho_j^2 \varphi_{i(N)j}\right) \tag{A.6}$$

we can now verify whether whether A.2 respects A.3 by plugging it in, and solving the expectation on the

left hand side as the mean of a Dirichlet-distributed variable:

$$\mathbb{E}^{G_j}_{\tilde{\mathbf{r}}} \frac{\tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}} \cdot \frac{\varphi_{i(q)j}}{\sum_{q'=1}^{N}\varphi_{i(q')j}}}{\sum_{q'} \tilde{r}_{i(q')}^{\frac{\sigma}{1-\sigma}} \cdot \frac{\varphi_{i(q')j}}{\sum_{q''=1}^{N}\varphi_{i(q'')j}}} = \mathbb{E}^{G_j}_{\tilde{\mathbf{r}}} \frac{\tilde{r}_{i(q)}^{\frac{\sigma}{1-\sigma}}\varphi_{i(q)j}}{\sum_{q'} \tilde{r}_{i(q')}^{\frac{\sigma}{1-\sigma}}\varphi_{i(q')j}} = \frac{\rho_j^2\varphi_{i(q)j}}{\sum_{q'=1}^{N}\rho_j^2\varphi_{i(q')j}} = \frac{\varphi_{i(q)j}}{\sum_{q'=1}^{N}\varphi_{i(q')j}} \tag{A.7}$$

Because $\varphi_{i(q)j} > 0$ for all i, j by assumption, it is thus verified that all plants are selected with positive probability. □

Proof to Theorem (Dual Efficiency) and Corollary. Input markets equilibrium implies that the marginal product of capital in country i is equal to the objective rate of return on capital r_i. We start by showing that a necessary and sufficient condition for World GDP maximization is that the rates of returns on capital are equalized across countries. To show necessity, consider the first-order Taylor approximation for the change in Y following a change $\Delta\mathbf{k}$ such that $\sum_i \Delta k_i = 0$:

$$\Delta Y \approx \sum_{i=1}^{n} r_i \Delta k_i \tag{A.8}$$

then, if $r_i > r_j$ for some (i, j), we can construct a $Y-$increasing $\Delta\mathbf{k}$ by simply reallocating an arbitrarily-small amount of capital from j to i. To show sufficiency, notice that we can write country i's capital stock as a strictly-decreasing function of the common rate of return r:

$$k_i = r^{-\frac{1}{1-\kappa_i}} \left(\kappa_i\omega_i\right)^{\frac{1}{1-\kappa_i}} \ell_i \tag{A.9}$$

This implies that K and Y are also strictly-decreasing functions of r. As a consequence, it is not possible to vary r and increase Y without also increasing K. We have thus shown the equivalence between statements (1) and (2). In addition, this also implies the corollary statement that the efficient allocation is unique.

To show equivalence between statements (2) and (3), we use the proof of Lemma 1, by which statement (3) obtains if and only if:

$$\pi_{ij} = \frac{r_i^{\frac{\sigma}{1-\sigma}} k_i}{\sum_{c=1}^{n} r_c^{\frac{\sigma}{1-\sigma}} k_c} \tag{A.10}$$

If capital markets clear these portfolio shares must be equal to

$$\pi_{ij} = \frac{k_i}{K} \quad \forall\ (i, j) \tag{A.11}$$

The portfolio allocation above is optimal, from the investors' point of view, if and only if rate of returns are equalized, implying the equivalence of statements (2) and (3). □

Proof to Lemma (2). Consider a second-order Taylor approximation of the change in World GDP around an efficient $\mathbf{k}$:

$$\Delta Y \quad \approx \quad r \sum_{i=1}^{n} \Delta k_i - \frac{1}{2} \sum_{i=1}^{n} (1 - \kappa_i) \frac{r}{k_i} (\Delta k_i)^2 \tag{A.12}$$

This expression is derived using the fact that, in equilibrium, the rate of return r is equal to the marginal product of capital. In order to focus on capital misallocation, we consider a $\Delta\mathbf{k}$ that leaves K unaffected. This implies that the first-order term of the equation above is zero. We can then divide both sides by world GDP and rearrange the second-order term as:

$$\frac{\Delta Y}{Y} \approx -\frac{1}{2} \sum_{i=1}^{n} (1 - \kappa_i) \frac{r k_i}{Y} (\Delta \log k_i)^2 \tag{A.13}$$

We then use the following facts

$$\Delta \log r_i = -(1 - \kappa_i) \Delta \log k_i \tag{A.14}$$

$$r_i k_i = \kappa_i y_i \tag{A.15}$$

to derive:

$$\begin{aligned} 0 = \sum_{i=1}^{n} \Delta k_i = \sum_{i=1}^{n} \frac{r k_i}{1 - \kappa_i} \cdot \Delta \log r_i \quad &= \quad \sum_{i=1}^{n} \frac{\kappa_i}{1 - \kappa_i} \cdot \frac{y_i}{Y} \cdot \Delta \log r_i \\ = \quad \frac{\sum_{i=1}^{n} \frac{\kappa_i y_i}{1 - \kappa_i}}{Y} \cdot \mathbb{E}^{\mathcal{W}_i} (\Delta \log r_i) \quad &= \quad \left[\mathbb{E}^{\mathcal{W}_i} (\Delta \log r_i)\right]^2 \end{aligned} \tag{A.16}$$

We finally plug equations (A.14) and (A.15) inside equation (A.13) to obtain:

$$\frac{\Delta Y}{Y} \quad \approx \quad -\frac{1}{2} \sum_{i=1}^{n} \frac{\kappa_i}{1 - \kappa_i} \cdot \frac{y_i}{Y} (\Delta \log r_i)^2 \quad = \quad -\frac{1}{2} \cdot \frac{\sum_{i=1}^{n} \frac{\kappa_i y_i}{1 - \kappa_i}}{Y} \cdot \mathbb{E}^{\mathcal{W}_i} (\Delta \log r_i)^2 \tag{A.17}$$

Equation (A.16) implies that the last expectation on the right is the $\mathcal{W}_i$-weighted variance of log-returns:

$$\frac{\Delta Y}{Y} \quad = \quad -\frac{1}{2} \cdot \frac{\sum_{i=1}^{n} \frac{\kappa_i y_i}{1 - \kappa_i}}{Y} \cdot \mathbb{V}^{\mathcal{W}_i} (\log r_i) \quad = \quad -\frac{1}{2} \cdot \mathbb{E}^{y_i} \left(\frac{\kappa_i}{1 - \kappa_i} \right) \cdot \mathbb{V}^{\mathcal{W}_i} (\log r_i) \tag{A.18}$$

□

B A Model of Ancestral and Cultural Distance

As documented in our empirical analysis, we observe a strong positive relation between *Ancestral Distance* and *Cultural Distance* (Table 4). In this Appendix, we present a simple analytical framework that formally illustrates how such relation would naturally emerge in a setting where: 1) ancestral distance measures the time since two populations have been separated (that is, they are no longer the same population), and 2) cultural change takes place as the result of random shocks. The framework builds on Spolaore and Wacziarg (2009, 2012) and Becker, Enke and Falk (2020).

Assume that at time 0 there exists only one population, with cultural traits denoted by a real number C^0. At time 1, the population splits into $P^1 > 1$ populations. Each new population $i = 1, 2, ..., P^1$ inherits the cultural traits of its ancestral population plus a shock ϵ_i^1 , so that

$$C_i^1 = C^0 + \epsilon_i^1 \tag{B.1}$$

We assume that the shocks are non-degenerate integrable random variables, independent and identically distributed across time and space. This assumption is a useful benchmark simplification, consistent with the view of cultural change as mainly due to random drift. This assumption is sufficient to obtain our main result (for discussions of more general assumptions, see Spolaore and Wacziarg, 2009 and Becker, Enke and Falk, 2020).

At time 2, populations split into $P^2 > P^1$ populations. Again, each new population $i = 1, 2, ..., P^2$ inherits the culture of its parental population the previous period plus a random shock ϵ_i^2. Let $a_{mt}(i)$ denote the ancestral population, living at time m, from which a population $i$living at time t descended., where $a_{tt}(i) = i$. Therefore, at time 2 we have:

$$C_i^2 = C^0 + \epsilon_{a_{12}(i)}^1 + \epsilon_i^2 \tag{B.2}$$

In general, at time t, the cultural traits of each population $i = 1, 2, ..., P^t$ are equal to the sum of all previous shocks experienced by population i's ancestral populations plus the new shock:

$$C_i^t = C^0 + \sum_{m=1}^{t} \epsilon_{a_{mt}(i)}^m \tag{B.3}$$

Let $d_C^t(i,j) \equiv |C_i^t - C_j^t|$ denote the cultural distance between population $i$and population j at time t. Let $d_A^t(i,j)|$ denote the ancestral distance between between population $i$and population j, which is defined as the number of periods $N(i,j)$ in which population $i$and population j have different ancestors - that is, the number of periods when $a_m(i) \neq a_m(j)$. Assuming that the shocks are independent and identically distributed random variables, it follows that two populations at a larger ancestral distance from each other can also be expected to be at a higher cultural distance from each other. That is

$$d_A^t(i,j) > d_A^t(k,l) \Longleftrightarrow E[d_C^t(i,j)] > E[d_C^t(k,l)] \tag{B.4}$$

This relation is formally analogous to Proposition 1 in Becker, Enke and Falk (2020, online appendix,

Section 3), and a formal derivation can be obtained along similar lines. Specifically, let n_{ij} be the number of periods up to time T when population $i$and population j were separated, and n_{kl}be the number of periods up to time T when population $k$and population l. Then, we can re-write the above preposition as:

$$n_{ij} > n_{kl} \Longleftrightarrow E[|C_i^T - C_j^T|] > E[C_k^T - C_l^T|] \tag{B.5}$$

By definition:

$$C_i^T - C_j^T = \sum_{a_{mT}(i) \neq a_{mT}(j)}^{T} (\epsilon_{a_{mt}(i)}^m - \epsilon_{a_{mt}(i)}^m) \tag{B.6}$$

where the sum of shocks is taken for all periods $m = 1, 2, ...T$ where the two populations do not share a common ancestral population. By defining $\eta_1, ...\eta_T, \nu_1, ...\nu_T$ as i.i.d. random variables having the same distribution as the shocks above, implying:

$$E[|C_i^T - C_j^T|] = E[|\sum_{q=1}^{n_{ij}} (\eta_q - \nu_q)|] \tag{B.7}$$

By the same token, we have:

$$E[|C_k^T - C_l^T|] = E[|\sum_{q=1}^{n_{kl}} (\eta_q - \nu_q)|] \tag{B.8}$$

Thus, our claim follows if we can show that:

$$n_{ij} > n_{kl} \Longleftrightarrow E[|\sum_{q=1}^{n_{ij}} (\eta_q - \nu_q)|] > E[|\sum_{q=1}^{n_{kl}} (\eta_q - \nu_q)|] \tag{B.9}$$

The right-hand side of this equivalence is formally identical to equation (1) in Becker, Enke and Falk (2020), online appendix, Section 3, page 10, and can be derived in the same way, using their Lemma 1 (the details are available upon request).

C Measuring Political Risk'

We model the expropriation wedge τ_i^{PR} as a function of the ICRG index:

$$\tau_i^{\text{PR}} \;=\; \tau_i^{\text{PR}}\left(\text{ICRG}_i\right) \tag{C.1}$$

We use again the fact that, for a small open economy i:

$$\frac{\partial \log \sum_{j\neq i} a_{ij}}{\partial \log \tau_i^{\text{PR}}} \quad = \quad \frac{\sigma}{1-\sigma}\sum_{j\neq i}\frac{a_{ij}}{k_i}\left(1-\pi_{ij}\right) \quad \approx \quad \frac{\sigma}{1-\sigma} \tag{C.2}$$

AKV regress capital inflows per capita on ICRG. From AKV's regression and summary statistics tables, we can compute:

$$\frac{\mathrm{d}\log \sum_{j\neq i} a_{ij}}{\mathrm{dICRG}_i} \;=\; \beta_{\text{AKV}} \;\overset{\text{def}}{=}\; \left[\frac{\partial\left(k_i/\text{Population}_i\right)}{\mathrm{dICRG}_i}\right]\cdot\left[\frac{k_i}{\text{Population}_i}\right]^{-1} \tag{C.3}$$

where ICRG_i is ICRG's measure of political risk and the first term in square brackets is the regression coefficient estimated by AKV, while the second term in square brackets (foreign investment per capita) can be obtained from AKV's summary statistics table. From the chain rule:

$$\frac{\mathrm{d}\log k_i}{\mathrm{dICRG}_i} \;=\; \frac{\partial \log k_i}{\partial \log \tau_i^{\text{PR}}}\cdot\frac{\partial \log \tau_i^{\text{PR}}}{\mathrm{dICRG}_i} \tag{C.4}$$

Combining the two equations above, and assuming that $\tau_i^{\text{PR}} = 0$ when $\text{ICRG}_i = 10$ (implying the expropriation risk is zero for a country with the maximum ICRG score) we then have the following trivial ODE for τ_i^{PR}:

$$\frac{\mathrm{d}\log \tau_i^{\text{PR}}}{\mathrm{dICRG}_i} \;=\; \frac{1-\sigma}{\sigma}\cdot\beta_{\text{AKV}} \tag{C.5}$$

with boundary condition

$$\tau_i^{\text{PR}}\left(\text{ICRG}_i\right)\big|_{\text{ICRG}_i=10} \;=\; 1 \tag{C.6}$$

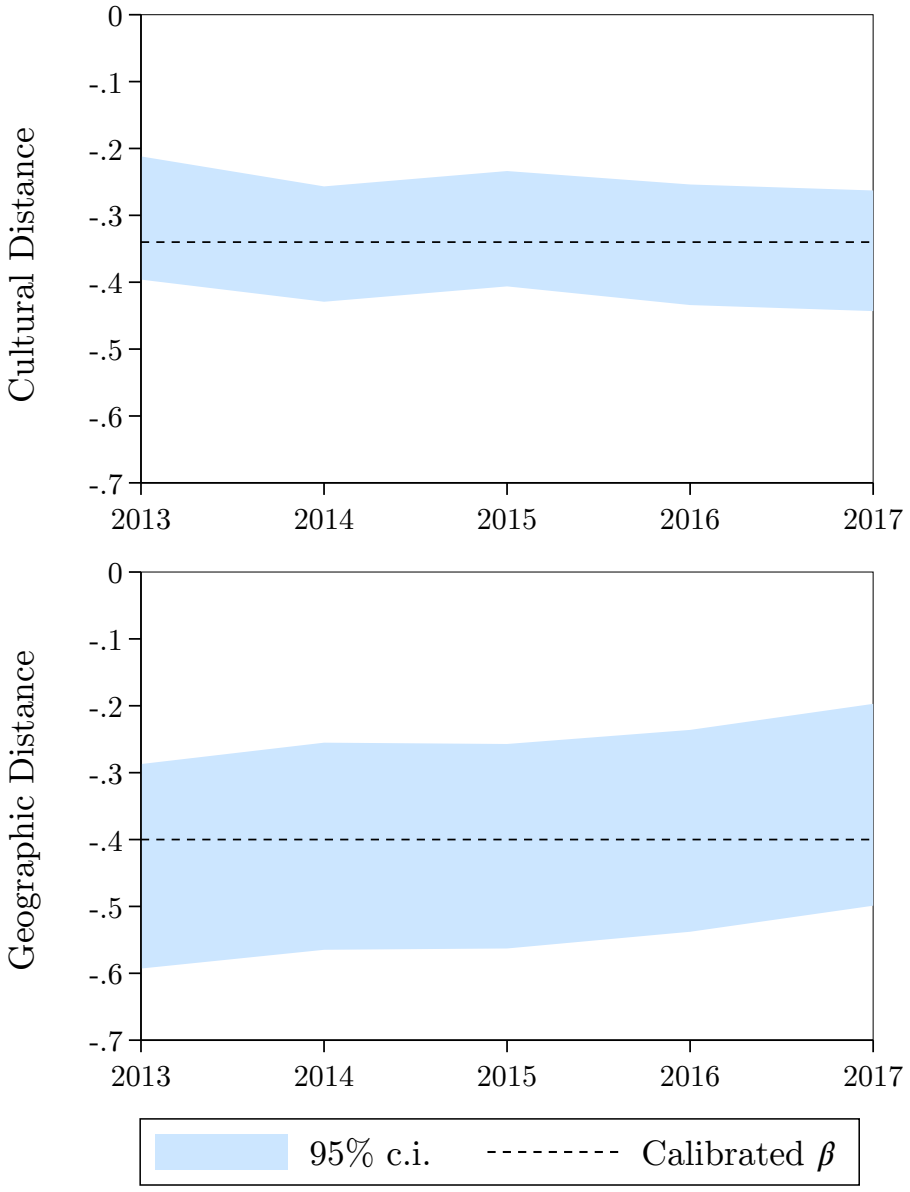
Using our calibrated value of σ, the solution yields the following calibrated value for the expropriation rate:

$$\log \tau_i^{\text{PR}} \;=\; \beta_{\text{AKV}}\left(\text{ICRG}_i - 10\right) \tag{C.7}$$

AKV perform instrumental variable regressions using two different datasets in their analysis (IMF and KLSV). For each of the two datasets, we use the β_{AKV} estimate that controls for the initial level of GDP per capita. This leads to two different estimates for β_{AKV}. To calibrate our model, we take the simple average of the two.

D Regression Coefficients Stability

Figure D.1: Coefficients Stability over Time



E Robustness Check: alternative Breakdown of Foreign Investment

Table E.1: OLS Regressions using FDI/FPI breakdown instead of Equity/Debt

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable in logs:	Assets	FDI	FPI	Assets	FDI	FPI
Cultural Distance	-0.362**	-0.430**	-0.402**	-0.226**	-0.285**	-0.305**
	(0.042)	(0.041)	(0.041)	(0.044)	(0.049)	(0.045)
Geographic Distance	-0.424**	-0.600**	-0.344**	-0.448**	-0.567**	-0.418**
	(0.026)	(0.037)	(0.025)	(0.089)	(0.105)	(0.084)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	1,484	2,685	1,728	1,353	2,438	1,576
R-squared	0.818	0.712	0.828	0.845	0.754	0.849
Within R-squared	0.306	0.220	0.239	0.422	0.312	0.338

F Robustness Check: Residency-Based Foreign Investment Data

Table F.1: OLS Regressions using un-restated data

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable in logs:	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-0.322**	-0.354**	-0.450**	-0.218**	-0.234**	-0.377**
	(0.045)	(0.051)	(0.039)	(0.046)	(0.053)	(0.043)
Geographic Distance	-0.448**	-0.553**	-0.343**	-0.536**	-0.422**	-0.362**
	(0.028)	(0.035)	(0.028)	(0.098)	(0.106)	(0.079)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	1,487	1,634	2,259	1,366	1,495	2,077
R-squared	0.810	0.768	0.782	0.838	0.804	0.797
Within R-squared	0.289	0.248	0.188	0.425	0.392	0.267

G Counterfactual Analysis using Model Extensions

The following tables replicate Table 7 for the three model extensions presented in Section 6: Capital Controls, Currency Hedging Costs, and Risky Asset Returns.

Table G.1: Counterfactuals with Capital Controls (2017)

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Cultural Distance*	*Geographic Distance*	*Political Risk & Taxes*
Welfare Statistics (Fixed Capital Stock)	(1)	(2)	(3)	(4)	(5)
World GDP (US$ trillions)	103.5	111.9	107.3	107.8	111.0
World GDP, % Difference in GDP from Zero-Gravity	-7.5%	0%	-4.1%	-3.6%	-0.8%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+63.8%	0%	+26.8%	+24.8%	+18.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+29.0%	0%	+13.7%	+6.2%	+9.4%
Welfare Statistics (Endogenous Capital Stock)					
World GDP (US$ trillions)	103.5	108.7	106.8	107.4	108.2
World GDP, % Difference in GDP from Zero-Gravity	-4.8%	0%	-1.8%	-1.2%	-0.5%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+63.1%	0%	+26.4%	+25.3%	+18.3%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+28.6%	0%	+13.7%	+5.6%	+9.5%

TABLE G.2: COUNTERFACTUALS WITH CURRENCY HEDGING COSTS (2017)

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Cultural Distance*	*Geographic Distance*	*Political Risk & Taxes*
Welfare Statistics (Fixed Capital Stock)	(1)	(2)	(3)	(4)	(5)
World GDP (US$ trillions)	103.5	112.0	108.7	108.6	111.3
World GDP, % Difference in GDP from Zero-Gravity	-7.6%	0%	-2.9%	-3.1%	-0.6%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+82.6%	0%	+33.4%	+34.6%	+19.6%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+29.1%	0%	+13.8%	+4.6%	+8.1%
Welfare Statistics (Endogenous Capital Stock)					
World GDP (US$ trillions)	103.5	108.9	107.5	107.4	108.6
World GDP, % Difference in GDP from Zero-Gravity	-4.9%	0%	-1.3%	-1.3%	-0.2%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+83.1%	0%	+34.3%	+35.2%	+19.8%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+29.0%	0%	+14.5%	+4.4%	+8.1%

TABLE G.3: COUNTERFACTUALS WITH RISKY ASSET RETURNS (2017)

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Cultural Distance*	*Geographic Distance*	*Political Risk & Taxes*
Welfare Statistics (Fixed Capital Stock)	(1)	(2)	(3)	(4)	(5)
World GDP (US$ trillions)	103.5	111.7	108.5	108.4	111.1
World GDP, % Difference in GDP from Zero-Gravity	-7.3%	0%	-2.9%	-2.9%	-0.5%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+83.0%	0%	+33.8%	+33.8%	+19.0%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+29.5%	0%	+14.1%	+4.5%	+8.1%
Welfare Statistics (Endogenous Capital Stock)					
World GDP (US$ trillions)	103.5	108.3	107.0	107.1	108.3
World GDP, % Difference in GDP from Zero-Gravity	-4.4%	0%	-1.2%	-1.1%	+0.0%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+83.7%	0%	+34.8%	+34.2%	+19.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+29.5%	0%	+14.7%	+4.2%	+8.0%

H Counterfactual Analysis with Alternate Coefficient Estimates

The following tables replicates Table 7, using alternative estimates instead of the baseline IV estimates for the investment-distance semi-elasticities (β). Table H.2 uses OLS estimates, while Table H.1 uses Pseudo-Poisson regression estimates.

Table H.1: Counterfactuals using OLS regression Estimates (2017)

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Cultural Distance*	*Geographic Distance*	*Political Risk & Taxes*
Welfare Statistics (Fixed Capital Stock)	(1)	(2)	(3)	(4)	(5)
World GDP (US$ trillions)	103.5	110.2	108.7	107.0	109.7
World GDP, % Difference in GDP from Zero-Gravity	-6.1%	0%	-1.3%	-3.0%	-0.5%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+74.3%	0%	+23.0%	+30.8%	+19.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+25.0%	0%	+10.3%	+3.2%	+8.0%
Welfare Statistics (Endogenous Capital Stock)					
World GDP (US$ trillions)	103.5	107.2	106.9	106.0	107.2
World GDP, % Difference in GDP from Zero-Gravity	-3.4%	0%	-0.3%	-1.1%	-0.0%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+74.7%	0%	+24.1%	+29.7%	+19.3%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+24.9%	0%	+10.8%	+2.3%	+7.9%

Table H.2: Counterfactuals using Pseudo-Poisson Estimates (2017)

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Cultural Distance*	*Geographic Distance*	*Political Risk & Taxes*
Welfare Statistics (Fixed Capital Stock)	(1)	(2)	(3)	(4)	(5)
World GDP (US$ trillions)	103.5	108.2	107.4	106.1	107.8
World GDP, % Difference in GDP from Zero-Gravity	-4.3%	0%	-0.8%	-2.0%	-0.5%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+61.7%	0%	+18.1%	+19.4%	+20.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+21.1%	0%	+8.4%	+1.4%	+8.4%
Welfare Statistics (Endogenous Capital Stock)					
World GDP (US$ trillions)	103.5	105.6	105.6	105.2	105.4
World GDP, % Difference in GDP from Zero-Gravity	-1.9%	0%	+0.0%	-0.4%	-0.1%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+62.0%	0%	+18.5%	+17.8%	+20.3%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+20.9%	0%	+8.5%	+0.6%	+8.3%

I Unweighted Poisson Regressions

In this Appendix, we replicate Table 3 without applying weights to the observations.

Table I.1: Poisson Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-0.475**	-0.360**	-0.658**	-0.095*	-0.067	-0.179**
	(0.081)	(0.068)	(0.102)	(0.048)	(0.061)	(0.048)
Geographic Distance	-0.232**	-0.218**	-0.304**	-0.332**	-0.392**	-0.060
	(0.036)	(0.029)	(0.049)	(0.085)	(0.087)	(0.106)
Controls	No	No	No	Yes	Yes	Yes
Observations	1,508	1,690	2,259	1,375	1,534	2,077