Abstract

Observed patterns of international investment are difficult to reconcile with frictionless capital markets. In this paper, we provide a novel multi-country dynamic general equilibrium model with rationally-inattentive investors, where cross-border investment is subject to both information and policy frictions. The presence of these frictions results in persistent (steady-state) misallocation of capital across countries. We estimate model parameters using nationality-based, bilateral investment data, and find a major role for information barriers, which we capture using measures of geographic, linguistic and cultural distance. Our unifying theoretical–empirical framework can account for several stylized facts: the gravity structure of investment flows, home bias, persistent global imbalances and capital return differentials across countries, as well as the paucity of net flows from rich to poor economies. We then perform counterfactual analysis: we find that information and policy barriers to international investment greatly amplify the capital gap between rich and poor countries, and result in a large reduction in world output.

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Keywords: Capital Allocation, Capital Flows, Foreign Investment, Culture, Geography, Gravity, International Finance, Misallocation, Open Economy, Rational Inattention.

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1 Introduction

International capital flows have increased greatly in recent decades (Lane and Milesi-Ferretti, 2018). Yet, several features of international investment data remain difficult to reconcile with frictionless capital markets (Maggiori, 2021). We fail to observe large capital flows from capital-abundant to capital-scarce economies, even though there are large and persistent capital-return differentials across countries (Lucas 1990; Alfaro, Kalemli-Ozcan, and Volosovych 2008, David et al. 2014; Monge-Naranjo et al. 2019). At the same time, portfolios continue to be disproportionately allocated towards domestic assets ("home bias" - French and Poterba 1991; Coeurdacier and Rey 2013). How can we explain these patterns? Are they related to specific barriers to international investment flows? If there are different obstacles to efficient global capital allocation, which ones have the largest effects on income and welfare?

In this paper, we provide a structural model of international capital allocation in which cross-border investment is subject to informational and policy frictions. The model endogenously produces equilibrium allocations of capital (from each origin country to each destination country) that obey a gravity equation. The equilibrium investment “network” is shaped by information frictions (which we proxy by geographical, linguistic and cultural distance), foreign investment taxes, and political risk. We estimate our gravity equation empirically using updated measures of international investment that have been restated by Damgaard, Elkjaer, and Johannesen (2019) and Coppola, Maggiori, Neiman, and Schreger (2020) from a residency to a nationality basis, accounting for offshore investment and financing vehicles located in tax havens, such as Bermuda and the Cayman Islands;\(^1\) updated measures of foreign investment taxation and political risk; and recently-developed measures of cultural distance, capturing a broad set of differences in values and beliefs across countries. Finally, we use our empirical estimates to calibrate our model and assess the income and welfare impact of barriers to the allocation of capital across countries.

In our theory, we model informational barriers using insights from the literature on flexible information acquisition (Matějka and McKay, 2015; Denti, 2015; Yang, 2015). Specifically, we propose a rational-inattention logit model, for which we find a new closed-form solution. Investors from each country are endowed with a prior distribution for the vector of returns, but can obtain additional information about asset returns by acquiring any signal they wish (the signal is not restricted to have a specific distribution). However, they incur an effort whose disutility is proportional to the informativeness of the signal. In the baseline version of our model, all uncertainty is driven by the noisiness contained in the signals received by the investors, as well as their priors (in an extension of the model, we allow for intrinsic investment risk). While agents can acquire information about all asset returns, they have an informational advantage for assets at a closer geographical and cultural distance from themselves. As a result, equilibrium portfolios are biased towards assets that are “closer” to them. While they could overcome such biases by acquiring signals about more distant investment prospects, such additional information comes at a cost. Thus, geographical and cultural distances act as barriers to a more efficient and better-informed allocation of global capital. Intuitively, the countries that bear the highest costs from such barriers and biases are those that, on average, happen to be farther from where most investors are geographically and culturally.

\(^1\)The first paper restates IMF and OECD data on foreign direct investment, while the latter restates IMF data on portfolio investment.
located (the “periphery”), while more “central” countries tend to benefit, in relative terms, from the biases associated with informational obstacles. We extend our model along several dimensions, namely: 1) we add frictions in good trade; 2) we introduce capital controls as an additional barrier; 3) we extend our model to incorporate country-differences in fundamental risk; 4) we introduce currency hedging costs as an additional friction to international investments.

Turning to the empirical analysis, we obtain three sets of results. First information (proxied by geographic, cultural and linguistic distances) exerts 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 Instrumental Variables (IV) regressions. Our IV approach, used to ensure that our estimates are not amplified by reverse causality, is based on the assumption that religious distance between populations has an impact on contemporary measures of cultural distance. These in turn act as current barriers to the global allocation of capital. In our robustness analysis, we check that our gravity estimates are robust to: 1) using different available time periods; 2) using residency-based data; 3) using alternative methods of estimation.

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 only correlate weakly with country income levels, consistent with the data and Robert Lucas’s observation that capital fails to flow from rich to poor countries (Lucas, 1990).

Third, we carry out 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 5.9% lower. An important result is that barriers to global capital allocation contribute significantly to cross-country inequality. We find that the standard deviation of log capital per employee is 77% higher than it would be in a world without barriers to international financial flows, and the dispersion in output per employee is 24% higher. Consistent with the intuition of our theory, the largest gains from removing informational biases associated with geographical and cultural barriers would accrue to developing countries in Africa, Asia and Latin America, which happen to be farther from the “center” where most investors are currently located.

To summarize our contribution: we provide a first structural, multi-country model of international capital allocation that generates persistent (i.e. steady-state) capital misallocation and global imbalances as a result of specific, measurable barriers and biases. While those barriers and biases stem from rational decisions at the individual level (because of costs associated with informational acquisition), they generate large worldwide inefficiency losses that disproportionally impact poorer countries. Thus, our theoretical and empirical framework can explain, within a unified and coherent setting, multiple important stylized
facts - the gravity structure of investment flows, home bias, return differentials, and the lack of large capital flows from the richer center to the poorer periphery. Finally we also characterize why and by how much the global misallocation of capital associated with such phenomena matters in terms of worldwide income, welfare, and cross-country inequality.

We add to several distinct literatures. To begin with, we bring together, in a structural framework, the theoretical and empirical literatures on gravity equations 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. Early empirical papers using gravity regressions to study international assets include Ghosh and Wolf (1999), De Ménil (1999), Di Giovanni (2005), and Portes and Rey (2005), who provided an interpretation of the findings in terms of information costs. The key difference between these approaches and ours is that our gravity estimates have a structural interpretation, and thus allow us to calibrate our model. An early contribution that combines theory and data is Head and Ries (2008), who focused specifically on cross-border M&A. Other related models are those by Sellin and Werner (1993) and Jin (2012).

In addition, our paper expands, in a new direction, the literature on rational inattention in macrofinance (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 (Kojien and Yogo, 2020; Jiang, Richmond, and Zhang, 2020) where investors hold an information advantage for domestic assets - a feature that links our contribution to several existing theoretical models of home bias (Van Nieuwerburgh and Veldkamp, 2009; Dziuda and Mondria, 2012).

We also build on previous 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 marginal product of capital in each country are consistent with the methodology of those contributions, while using the most up-to-date available data (Penn World Table 10, World Bank Wealth of Nations 2018). Consistent with the more recent findings by Monge-Naranjo et al. (2019) and David et al. (2014), which differ from the original estimates by Caselli and Feyrer (2007), our model generates large and persistent differentials in capital returns across countries, implying that capital is *not* efficiently allocated across countries.

A related line of research has studied to what extent international financial integration can speed up the process of convergence to the steady state in capital-scarce countries in a neoclassical framework, and how large the resulting welfare gains can be. Gourinchas and Jeanne (2006, GJ) found these welfare gains to be small. Our findings of large income and welfare effects from global capital misallocation do not contradict GJ, but complement their approach. While GJ focus entirely on transition dynamics, we exclusively study steady-state capital misallocation. Hence, what we learn from the combination of the

\[\text{2The difference between our estimates of the marginal product of capital and those of (Monge-Naranjo et al., 2019) lies in the country capital stocks: our model generates them endogenously, while (Monge-Naranjo et al., 2019) estimate them using the Penn World Tables.}\]
two studies is that international capital frictions only have significant welfare effects insofar as they affect the steady-state equilibrium.

Our paper also connects to a large empirical literature on the geographical, 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 include Lane and Milesi-Ferretti (2008); Rose and Spiegel (2009); Blonigen and Piger (2014). More broadly, our paper relates to the literature on historical and cultural barriers to international exchanges and the spread of innovations and development across countries (Spolaore and Wacziarg, 2009; Guiso et al., 2009; Felbermayr and Toubal, 2010; Spolaore and Wacziarg, 2012; Fensore et al., 2017; Bove and Gokmen, 2018; Spolaore and Wacziarg, 2018).

Finally, as we find that barriers to international investment amplify cross-country dispersion of capital and output per worker, this study provides new evidence on the origins of cross-country income differences, therefore contributing to a large empirical literature on this topic, which includes Hall and Jones (1999); McGrattan and Schmitz Jr (1999), among many others.
2 A Theory of Imperfect International Capital Markets

2.1 Firms

In this section, we present a multi-country, general equilibrium overlapping generations (OLG) model with rationally-inattentive heterogeneous investors and imperfect capital mobility. In the interest of streamlining exposition, our baseline model will assume away frictions in goods markets as well as fundamental sources of risk (the only source of uncertainty in the model is the noisiness in the information acquired by the investors). We will re-introduce these features as model extensions in Section 7.

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

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

where $y_{it}$ is the level of output; $x_{it}$ is the input of natural (non-reproducible) capital; $\ell_{it}$ is the labor input; $k_{it}$ is the input of reproducible capital; and $\omega_i$ is country $i$'s total factor productivity. The production function parameters $\lambda_i$ and $\xi_i$, which in equilibrium are equal to labor and natural capital income shares, are allowed to vary across countries. Human and natural capital cannot be moved across countries. 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. The global resource constraint is:

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

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 $\alpha$. In short, plants are a discretization of country $i$'s capital stock. This implies that the number of plants in each country is $k_{it}/\alpha$, 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 $t$:

$$K_t \overset{\text{def}}{=} \sum_{i=1}^{n} k_{it} \quad (2.3)$$

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

$$m_{it} = \frac{\xi_i y_{it}}{x_{it}}; \quad w_{it} = \frac{\lambda_i y_{it}}{\ell_{it}}; \quad r_{it} = \frac{\kappa_i y_{it}}{k_{it}} \quad (2.4)$$

Thus, the parameter $\delta$ captures both a “transformation rate” as well as a depreciation rate.
where \( \kappa_i \overset{\text{def}}{=} 1 - \lambda_i - \xi_i \) \hspace{1cm} (2.5)

In addition, each country \( i \) imposes a tax equal to \((1 - \tau_i)\) on capital income, so that the net return on capital in country \( i \) is \( \tau_i r_i \). The wedge \( \tau_i \) 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 \( \ell_j \) 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 they 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. 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 \( \tilde{r}_{t+1} \in \mathbb{R}_+^N \). We use the tilde (\( \tilde{\cdot} \)) symbol to distinguish the random variable from the realized value \( (\tau_i r_i) \).

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. This signal induces a posterior distribution for asset returns that we call \( F_t(z) \). 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:

\[
U(z) = (1 - \theta_j) \log c_t(z) + \theta_j [E_t \log c_{t+1}(z) - I(z)]
\]  

(2.6)

where \( c_t(z) \) is agent \( z \)'s consumption at time \( t \) and the patience parameter \( \theta \) is allowed to vary by country. \( I(z) \) 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 (\( H \)) between the posterior \( F \) and the prior \( G \):

\[
I(z) \overset{\text{def}}{=} \frac{1 - \sigma}{\sigma} \cdot [H(G_{jt}) - E_t H(F_t(z))]
\]  

(2.7)

The parameter \( \sigma \in (0,1) \) captures the efficiency of the information processing technology, with a higher value of \( \sigma \) being associated with a lower information processing cost. In this basic version of our model, for simplicity, we assume that there is no fundamental risk: all uncertainty is driven by the noisiness
contained in the signals received by the investors, as well as their priors. In an extension of the model, presented in Section 7, we extend the model to allow for intrinsic investment risk.

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:

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

$$c_{t+1}(z) = \delta R_{t+1}(z) s_t(z)$$

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

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

We look for a steady-state equilibrium, with constant consumption, output, capital and saving ($c_t$, $y_t$, $k_t$, $s_t$). 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 $\theta_j$ of their earnings in the initial period:

$$s_t(z) \equiv s_j = \theta_j (w_{jt} \ell_j + m_{jt} x_j) = \theta_j (\lambda_j + \xi_j) y_j \quad \forall j, t$$

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

$$k_i = \sum_{j=1}^{n} a_{ij}; \quad s_j = \delta \sum_{i=1}^{n} a_{ij}$$

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

$$\pi_{ij} \stackrel{def}{=} \delta \cdot \frac{a_{ij}}{s_j}$$

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

$$\delta k = \Pi s : \begin{bmatrix} \delta k_1 \\ \delta k_2 \\ \vdots \\ \delta k_n \end{bmatrix} = \begin{bmatrix} \pi_{11} & \pi_{12} & \ldots & \pi_{1n} \\ \pi_{21} & \pi_{22} & \ldots & \pi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{n1} & \pi_{n2} & \ldots & \pi_{nn} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_n \end{bmatrix}$$
2.3 Information Acquisition and Asset Allocation

We next describe how agents acquire information and allocate capital across countries – that is, how the matrix $\Pi$ 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 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 $\tilde{s}$. However, because the realized value $s$ 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 $r$.

Define the conditional probability that a generic investor from country $j$ invests in plant $q$, located in country $i$ ($q$):

$$P_j(q) \overset{\text{def}}{=} \Pr(z \in j \text{ selects plant } q \in i \mid \tilde{r}_q = \tau_{i(q)} r_{i(q)}', q' = 1, 2, \ldots n)$$

(2.15)

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

$$P_j(q) = \left[ \frac{\tau_{i(q)} r_{i(q)}'}{\sum_{q'} \tau_{i(q')} r_{i(q')}'} \right]^{\frac{\sigma}{1-\sigma}} \cdot P_0(j, q)$$

(2.16)

where $P_0(j, q)$ is the unconditional probability of investing in plant $q$, defined as follows:

$$P_0(j, q) \overset{\text{def}}{=} \int_{\tilde{r} \in \mathbb{R}^N} P_j(q) \ dG_j(\tilde{r})$$

(2.17)

In order to derive an expression for $P_0(j, q)$ we need to make a parametric assumption on the 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 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 $P_0(j, q)$.

**Proposition 1.** Assume the following prior beliefs for $j$-investors: $[\tilde{r}(q)]^{1-\sigma}$ follows a Gamma distribution with common mean $\rho_j$ and heterogeneous precision $\varphi_{i(q), j}$. Then the unconditional probability is

$$P_0(j, q) = \frac{\varphi_{i(q), j}}{\sum_{q'} \varphi_{i(q'), j}}$$

(2.18)

**Proof.** See Appendix A. \(\square\)

\(^4\)Matějka and McKay (2015) proved that the unconditional probabilities $P_0(j, q)$ simplify out if all choices are ex-ante exchangeable. 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 $\left( \frac{1-\sigma}{\sigma^2} \right)$. 

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This specification of the prior beliefs allows country $j$’s investors to have an informational advantage for certain assets: namely, $j$—investors have an information advantage for $i$—assets if the precision parameter $\varphi_{ij}$ is high. The share of $j$—savings that are invested in $i$-domiciliated assets are thus proportional to $\varphi_{ij}$.

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

$$\pi_{ij} \overset{\text{def}}{=} \sum_{q \in i} P_j(q) = \frac{k_i}{\alpha} \cdot P_j(q) \quad \forall \ x \in \{1, 2, \ldots n\} \quad (2.19)$$

Hence, the portfolio shares take the following equilibrium value:\footnote{This expression does not depend on plant size ($\alpha$). Hence, in practice, we can ignore the fact that $k_i$ may not be divisible by $\alpha$, because we can make plants arbitrarily small ($\alpha \to 0$) without affecting country portfolios.}

$$\pi_{ij} = \frac{(\tau_i r_i)^{1-\sigma} k_i \varphi_{ij}}{\sum_{i=1}^{\alpha} (\tau_i r_i)^{1-\sigma} k_i \varphi_{ij}} \quad (2.20)$$

An improvement in the information processing technology (that is, a higher value of the parameter $\sigma$) increases the elasticity of the portfolio shares $\pi_{ij}$ with respect to net returns ($\tau_i r_i$) and decreases their elasticity with respect to prior information. The intuition behind this result is that the more easily investors can acquire information about return fundamentals, the more these fundamentals will affect equilibrium portfolios. In the limit, where information becomes freely available ($\sigma \to 1$), 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 $\varphi_{ij}$ 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 $\varphi_{ij}$ inside a matrix $\Phi$, 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 impose some structure on $\Phi$. We assume that it depends linearly on a $n \times n \times D$ array of distances:

$$\log \Phi \overset{\text{def}}{=} \log \begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\
\varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n} \\
\vdots & \vdots & \ddots & \vdots \\
\varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nn} \end{bmatrix} = \begin{bmatrix} d_{11}^\beta & d_{12}^\beta & \cdots & d_{1n}^\beta \\
d_{21}^\beta & d_{22}^\beta & \cdots & d_{2n}^\beta \\
\vdots & \vdots & \ddots & \vdots \\
d_{n1}^\beta & d_{n2}^\beta & \cdots & d_{nn}^\beta \end{bmatrix}$$

where $d_{ij} = \begin{bmatrix} d_{i1}^\beta & d_{i2}^\beta & \cdots & d_{i}^D \end{bmatrix}$

$$\log \Phi \overset{\text{def}}{=} \begin{bmatrix} d_{11}^\beta & d_{12}^\beta & \cdots & d_{1n}^\beta \\
d_{21}^\beta & d_{22}^\beta & \cdots & d_{2n}^\beta \\
\vdots & \vdots & \ddots & \vdots \\
d_{n1}^\beta & d_{n2}^\beta & \cdots & d_{nn}^\beta \end{bmatrix}$$
is a \( D \)-dimensional vector of distances between country \( i \) and country \( j \) and \( \beta < 0 \) 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 \( d_{ij} \) be a vector (as opposed to a scalar) is that we want it to encompass not just geographic distance, but cultural and linguistic distance as well.

2.5 Calibrating the elasticity parameter \( \sigma \)

The parameter \( \sigma \in (0,1) \) 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 two considerations. First, this value rationalizes an pervasive feature of international portfolio investment – namely, that multi-country funds (such as the MSCI World Index) are benchmarked against market cap-weighted portfolios. Imposing \( \sigma = 1/2 \) and assuming no prior bias against distant countries, the portfolio share equation simplifies to:

\[
\pi_{ij} = \frac{\tau_i r_i k_i}{\sum_{i=1}^n \tau_i r_i k_i} \tag{2.23}
\]

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.

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

\[
\frac{\partial \log \sum_j a_{ij}}{\partial \log r_i} = \frac{\sigma}{1 - \sigma} \sum_j \frac{a_{ij}}{k_i} (1 - \pi_{ij}) \approx \frac{\sigma}{1 - \sigma} \tag{2.24}
\]

we can compare \( \frac{\sigma}{1 - \sigma} \) to empirical estimates of the demand elasticity with respect to returns.\(^6\) \( \sigma = 1/2 \) implies a unit demand-returns elasticity close to one.

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 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 over the period), we obtain an elasticity of 1.3. Because the elasticities for debt and equity

---

\(^6\)Because we have 62 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 approximately \( \frac{\sigma}{1 - \sigma} \).
fall immediately to the left and right of 1, it seems natural to set $\frac{\sigma}{1-\sigma} = 1.7$

### 2.6 Gravity

Since, in equilibrium, the capital income is equal to $\kappa_i y_i$, equation (2.20) can be rearranged as follows:

$$\pi_{ij} = \frac{\tau_i \kappa_i y_i \varphi_{ij}}{\sum_{i=1}^{n} \tau_i \kappa_i y_i \varphi_{ij}}$$  \hspace{1cm} (2.25)

The denominator of equation (2.25) 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 $M_j$:

$$M_j \overset{\text{def}}{=} \sum_{i=1}^{n} \tau_i r_i k_i \varphi_{ij}$$  \hspace{1cm} (2.26)

Multiplying both sides of equation (2.25) by $s_j$ and using the fact that $s_j = (\lambda_j + \xi_j) y_j$, equation (2.25) can be rearranged as a gravity equation:\footnote{A gravity equation obtains even if $\sigma \neq 1$, in which case $\tau_i$ is replaced, within equation (2.27), by $\tau_i^{\frac{\sigma}{1-\sigma}} r_i^{\frac{\sigma}{1-\sigma}-1}$.}

$$a_{ij} = \tau_i \cdot \kappa_i \cdot \theta_j \cdot \frac{\lambda_j + \xi_j}{\delta M_j} \cdot \frac{y_i \cdot y_j}{\varphi_{ij}^2}$$  \hspace{1cm} (2.27)

where $\varphi_{ij}^2 \overset{\text{def}}{=} 1/\varphi_{ij}$ is the prior variance of the return to capital in country $i$ from the point of view of $j$-investors', as implied by the distance vector $d_{ij}$.

### 2.7 Global Capital Markets Clearing

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

$$\Pi = \Pi (r(k), k, T, \Lambda, \Xi, \Phi)$$  \hspace{1cm} (2.28)

with $\Phi \overset{\text{def}}{=} \exp \left[ \begin{array}{cccc} d'_{11} & d'_{12} & \cdots & d'_{1n} \\ d'_{21} & d'_{22} & \cdots & d'_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ d'_{n1} & d'_{n2} & \cdots & d'_{nn} \end{array} \right]$; $\ T \overset{\text{def}}{=} \left[ \begin{array}{cccc} \tau_1 & 0 & \cdots & 0 \\ 0 & \tau_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \tau_n \end{array} \right]$;

$$\Theta \overset{\text{def}}{=} \left[ \begin{array}{cccc} \theta_1 & 0 & \cdots & 0 \\ 0 & \theta_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \theta_n \end{array} \right]$; $\ \Lambda \overset{\text{def}}{=} \left[ \begin{array}{cccc} \lambda_1 & 0 & \cdots & 0 \\ 0 & \lambda_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \lambda_n \end{array} \right]$; $\ \Xi \overset{\text{def}}{=} \left[ \begin{array}{cccc} \xi_1 & 0 & \cdots & 0 \\ 0 & \xi_2 & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \xi_n \end{array} \right]$  \hspace{1cm} (2.29)

\footnote{The last (and most trivial) reason why we calibrate $\sigma = 1/2$ is that $\sigma$ is restricted to be between 0 and 1: from a Bayesian perspective, if we impose a maximum entropy (uniform) prior for $\sigma$ over this interval, any estimate of $\sigma$ should be shrunk towards the mid-point of the range.}
Since \( s \) can be written as \( \Theta (\Lambda + \Xi) y \) and \( y \) in turn can be written as a function of \( k \), equation (2.14) can be re-written as:

\[
\delta k = \Pi (r(k), k) \cdot \Theta \cdot (\Lambda + \Xi) \cdot y(k)
\] (2.31)

The market-clearing vector of equilibrium capital stocks \( k^* \) is then determined as the fixed point of equation (2.31). Notice that there is a trivial equilibrium at \( k = 0 \). When we solve equation (2.31) 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:

\[
c_j = r' a_j + (1 - \theta_j)(w_j \ell_j + m_j x_j)
\] (2.32)

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

\[
c_j + s_j - y_j = r' a_j - \theta_j(w_j \ell_j + m_j x_j) - r_j k_j + s_j = r' a_j - r_j k_j
\] (2.33)

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

In this next subsection we present a series of theoretical results that help us understand under what conditions the competitive equilibrium of our model produces an efficient allocation of capital, and how we can infer allocative inefficiencies from the cross-section of returns to capital. Let \( Y \) be World GDP:

\[
Y = \sum_{i=1}^{n} Y_i
\] (2.34)

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

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

\[
k \in \arg \max_{k'} Y(k') \quad \text{s.t.} \quad \sum_{i=1}^{n} k_i' = \sum_{i=1}^{n} k_i
\] (2.35)

**Definition 2.** We say that investors have no informational advantage \( i \) if \( \varphi_{ij} \) is constant over \( i \) – that is, the investors’ prior beliefs over returns are iid.

If there is no informational advantage, the unconditional probability \( \mathcal{P}_j^0 (q) \) drops out of equation (2.16). This yields a CAPM-type result, whereby all investor countries hold similar portfolios.
Lemma 1. If asset markets are in equilibrium and there is no informational advantage, all origin countries \(j\) hold identical portfolios of foreign assets \((\pi_{ij} \text{ is independent of } j)\).

Proof. Follows directly from Proposition 1 in Matějka and McKay (2015). \(\square\)

One implication of Lemma 1 is that, in the absence of informational advantage, 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 the effective absence of asset markets frictions 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 return are equalized across countries \((r_i = r \text{ for } i = 1, 2, \ldots, n)\)
3. taxes are optimally set – that is, the vector of taxes \(\tau\) satisfies the following condition:

\[
\sum_j \frac{\tau_i \varphi_{ij} \kappa_j}{\sum_{i=1}^n \tau_i \varphi_{ij} \kappa_i} = \mathcal{C} \quad \text{for } i = 1, 2, \ldots, n \tag{2.36}
\]

where \(\mathcal{C}\) is some strictly-positive constant.

Corollary 1. For a fixed global capital stock \(K\), there is a unique efficient allocation \(k^*\).

Corollary 2. The absence of information advantage and a uniform tax \((\tau_i = \tau \forall i)\) are jointly sufficient (but not necessary) for statements (1)-(3) to obtain.

Proof. Appendix A. \(\square\)

Intuitively, the condition outlined in equation (2.36) requires that taxe rates perfectly offset the effect of informational advantage: a benevolent global planner should impose lower capital taxes in countries that are more peripheral in the network of cultural and geographic distances, and who therefore find it harder to attract capital due to information frictions. This implies that it is possible to attain the first-best allocation without necessarily having to remove information advantage altogether. Corollary 2 simply says that, when there is no informational advantage, the optimal tax is a uniform tax.

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 (gross) rate of return on capital.

Lemma 2. Consider a generic allocation \(k\) and the corresponding efficient allocation \(k^*\). The percent difference in world GDP between \(k\) and \(k^*\) is equal – to a second order Taylor approximation, to:

\[
\frac{Y(k) - Y(k^*)}{Y(k^*)} \approx -\frac{1}{2} \cdot E_{\mu} \left( \frac{\kappa_i}{1 - \kappa_i} \right) \cdot \mu_{i\omega} (\log r_i) \tag{2.37}
\]

\(^9\)This is not a re-statement of the First Welfare Theorem, because it is a statement about GDP, not welfare.
where the operator $E \gamma_i (\cdot)$ represents taking the GDP-weighted average across countries and the operator $\mathbb{V}^{W_i}$ represent taking the variance across countries with weights $W_i$, where

$$W_i \equiv \frac{\kappa_i}{1 - \kappa_i} y_i \quad (2.38)$$

Proof. Appendix A.

This latter lemma provides an important insight: for our model to capture international capital misallocation, it needs to generate meaningful dispersion in returns to capital across countries.

2.9 Extensions

Our model can be extended to accommodate additional barriers and frictions to global capital allocation. In Section 7, we present four extensions: we model goods trade frictions, capital controls, currency hedging costs, and fundamental risk in asset returns. In that section, we also explore the empirical implications of allowing for these additional frictions.

3 Data and Econometric Specification

In this section, we present the data used in our quantitative analysis: country-level variables, used to take the model to the data, as well as bilateral data used in the econometric estimation of $\beta$, the vector of semi-elasticities capturing information frictions. We conclude the section by outlining our econometric strategy to recover $\beta$.

3.1 Country-Level Variables

3.1.1 Macroeconomic Data

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 ($\ell_i$), which is measured as total employment. From the Penn-World tables we also obtain a measure of the stock of reproducible capital ($k_i$) at current PPP dollars, used only for model validation purposes (our model generates capital stocks endogenously).

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

The last data ingredient is the natural capital share ($\xi_i$): this is obtained from the most recent version (2018) of the World Bank’s *Wealth of Nations* dataset.

3.1.2 Taxes and Political Risk

Our measure of policy barriers, $\tau_i$, 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:

\[ \tau_i = \tau_i^{\text{Tax}} \times \tau_i^{\text{PR}} \]  

(3.1)

where

\[ \tau_i^{\text{Tax}} = \left( \frac{\text{EBT}}{\text{EBIT}} \times \tau_i^{\text{Corp}} \times \tau_i^{\text{Div}} + \frac{\text{Interest}}{\text{EBIT}} \times \tau_i^{\text{Int}} \right) \]  

(3.2)

\( \tau_i^{\text{Corp}} \) is the statutory corporate tax rate which we obtain (in order, depending on availability) from the OECD Tax Database, KPMG’s Tax Rates Database and the Tax Foundation’s Global Tax Database.

\( \tau_i^{\text{Div}} \) and \( \tau_i^{\text{Int}} \) 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 of weights on the US Census’ quarterly financial reports, where (for a broad set of industries) during 2017 Earnings Before Taxes and Interest made up, respectively, about 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 \( \tau_i^{\text{PR}} \), 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).\(^1\)

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

\[ \log \tau_i^{\text{PR}} = \beta_{\text{AKV}} (\text{ICRG}_i - 10) \]  

(3.3)

where \( \beta_{\text{AKV}} \) is a semi-elasticity coefficient that can be computed from AKV’s tables. We illustrate how we do so in Appendix C.

### 3.2 Bilateral Variables

#### 3.2.1 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 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

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\(^1\) The political risk index is missing for a handful of countries, for which we input a political risk score of 5.
**Figure 1: Foreign Equity and Debt Investment (2017)**

![Graph showing the relationship between Foreign Equity Investment and Foreign Debt Investment](image)

### 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.

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, Foreign Assets), 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

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\(^{11}\)Coppola et al. (2020) combine all European Monetary Union countries into a single entity. We re-state the asset position of EMU individual countries using the EMU reallocation matrices.
on cross-sectional data from 2017. 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. 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.

3.2.2 Distance Metrics

Informational advantage is captured, in our model, by the distance metric $d$. Empirically, this vector includes measures of cultural, geographic and linguistic 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).

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, 1] 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, 1] interval, so that the magnitude of the two effects can be compared.

Our third category of distance metrics includes measures of linguistic distance and religious distance introduced in Fearon (2003), Mecham, Fearon, and Laitin (2006) and discussed in depth in Spolaore and Wacziarg (2016). Linguistic distance and religious distance can 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 the 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).\textsuperscript{12} 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. Since contemporary linguistic distance can capture frictions related to difficulties in communicating, we add it as a component of vector $d$. Its effect on capital positions can be interpreted more broadly as that of information frictions arising from cultural differences, to the extent these are not fully captured by \textit{Cultural Distance}.

\textit{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.\textsuperscript{13}

### 3.2.3 Control Variables

We use a variety of additional bilateral measures as control variables. Among them are several measures of geographic distance - contiguity, 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 \textit{Colonial Relationship} - capturing whether two countries in a pair were ever in a colonizer-colonized relationship, and \textit{Common Colonizer}, denoting whether the two countries in a pair ever had a common colonizer.\textsuperscript{14}

We obtain the control variable \textit{Currency Peg} from the dataset of exchange rate arrangements constructed by Ilzetzki, Reinhart, and Rogoff (2019). We use the dataset’s most recent data points, corresponding to year 2016. The variable \textit{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 \textit{Investment Treaty}.\textsuperscript{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 \textit{Customs Union}, \textit{Free Trade Agreements}, and \textit{Economic Integration Agreements} as of 2017. Finally, we control for a measure of \textit{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

\textsuperscript{12}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.

\textsuperscript{13}We use religious distance as an instrument for \textit{Cultural Distance}, i.e. we assume the only way it affects foreign assets is through its effect on differences in values, norms and attitudes.

\textsuperscript{14}The data are from CEPII and can be obtained at http://www.cepii.fr/CEPII/fr/bdd_modele/presentation.asp?id=6, except for latitude and longitude, which are obtained from Google Public Data.

\textsuperscript{15}https://icsid.worldbank.org/resources/publications/investment-treaty-series
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 updates these calculations periodically, and estimates of trade costs are now available for a wide set of country pairs over the 1995-2018 period.

3.3 Coverage and Summary Statistics

Two distinct samples are used in our analysis. At the country-level, the sample consists of 62 countries, covering 85% of World GDP (based on 2017 data from the Penn World Tables, version 10.0).

At the bilateral level, there are 67 countries, therefore $67 \times 67 = 4,556$ directed country pairs-observations (including diagonal $i$-to-$i$ pairs) or 2,211 undirected country pairs. Table 1 displays summary statistics for the bilateral data.\(^\text{17}\)

3.4 Estimating $\beta$ : the Empirical Gravity Equation

Having already calibrated $\sigma$, we only have to calibrate $\beta$, 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:

$$\hat{a}_{ij} = a_{ij} \cdot \varepsilon_{ij} \quad \text{with} \quad \varepsilon_{ij} \perp d_{ij} \quad (3.4)$$

we can then re-write the gravity equation (2.27) as the following fixed effects linear regression model for the log of foreign investment:

$$\log \hat{a}_{ij} = \mu_i + \nu_j + d_{ij}' \beta + \varepsilon_{ij} \quad (3.5)$$

where $\mu_i$ is a country of origin fixed effect and $\nu_j$ is a country of origin fixed effect and

$$\mu_i \overset{\text{def}}{=} \log (\tau_i \kappa_i y_i) + \bar{\mu}_i \quad \text{and} \quad \nu_j \overset{\text{def}}{=} \log [\theta_j (\lambda_j + \xi_j) y_j] - \log M_j + \bar{v}_j \quad (3.6)$$

Fixed effects absorb additional country of origin ($i$) and country of destination ($j$) factors or measurement error that are not explicitly modeled ($\bar{\mu}_i$ and $\bar{v}_j$).

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 Assets).\(^\text{18}\) To

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\(^{16}\)https://www.unescap.org/resources/escap-world-bank-trade-cost-database

\(^{17}\)The country-level sample is a subset of the bilateral sample. Three countries drop out due to availability of country-level data. Additionally, we exclude Venezuela and Ukraine: these display suspect data on capital and GDP for 2017, our baseline year, likely due to political and monetary events in these two countries at that specific time.

\(^{18}\)In the Appendix, we also consider the determinants of global asset holdings, distinguishing between Foreign Direct Investment and Foreign Portfolio Investment, as is often done in the literature. We prefer to focus on the debt / equity
### Table 1: Summary Statistics

#### Panel A: Directed (Dependent) Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Observations</th>
<th>Mean</th>
<th>StDev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Foreign Assets (US$ mln)</td>
<td>2,789</td>
<td>17,620</td>
<td>96,265</td>
<td>0</td>
<td>1,940,000</td>
</tr>
<tr>
<td>Foreign Equity Assets (US$ mln)</td>
<td>2,805</td>
<td>11,970</td>
<td>70,655</td>
<td>0</td>
<td>1,470,000</td>
</tr>
<tr>
<td>Foreign Debt Assets (US$ mln)</td>
<td>3,511</td>
<td>4,495</td>
<td>28,262</td>
<td>0</td>
<td>488,408</td>
</tr>
</tbody>
</table>

#### Panel B: Undirected (Independent) Variables

<table>
<thead>
<tr>
<th>Variable</th>
<th>Undirected Pairs</th>
<th>Mean</th>
<th>StDev</th>
<th>Min</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>Border Contiguity</td>
<td>2,346</td>
<td>0.038</td>
<td>0.190</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Colonial Relationship</td>
<td>2,346</td>
<td>0.026</td>
<td>0.159</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Common Colonizer</td>
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<td>0.029</td>
<td>0.168</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Common Legal Origin</td>
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<td>0.338</td>
<td>0.473</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Cultural Distance</td>
<td>2,346</td>
<td>0.434</td>
<td>0.162</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Currency Peg</td>
<td>2,346</td>
<td>0.361</td>
<td>0.481</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Customs Union</td>
<td>2,346</td>
<td>0.144</td>
<td>0.351</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Economic Integration Agreement</td>
<td>2,346</td>
<td>0.236</td>
<td>0.425</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Free Trade Agreement</td>
<td>2,346</td>
<td>0.333</td>
<td>0.471</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>2,346</td>
<td>0.330</td>
<td>0.237</td>
<td>0.003</td>
<td>0.980</td>
</tr>
<tr>
<td>Investment Treaty</td>
<td>2,346</td>
<td>0.465</td>
<td>0.499</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Latitudinal Distance</td>
<td>2,346</td>
<td>0.162</td>
<td>0.142</td>
<td>0.000</td>
<td>0.571</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>2,346</td>
<td>0.965</td>
<td>0.097</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Longitudinal Distance</td>
<td>2,346</td>
<td>0.175</td>
<td>0.150</td>
<td>0.000</td>
<td>0.781</td>
</tr>
<tr>
<td>Religious Distance</td>
<td>2,278</td>
<td>0.812</td>
<td>0.162</td>
<td>0.222</td>
<td>0.999</td>
</tr>
<tr>
<td>Tax Treaty</td>
<td>2,346</td>
<td>0.492</td>
<td>0.500</td>
<td>0.000</td>
<td>1.000</td>
</tr>
<tr>
<td>Trade Cost</td>
<td>2,274</td>
<td>0.050</td>
<td>0.045</td>
<td>0.000</td>
<td>0.382</td>
</tr>
</tbody>
</table>

capture \(d\), we propose a parsimonious specification based on three measures of distance, hypothesized to capture information asymmetries in international investment: Geographic Distance, Cultural Distance and Linguistic Distance.

Because the vector of distances \(d\) 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, described above, are used either as instruments or control variables, depending on the specific empirical model under consideration.

distinction in the main analysis because the distinction between FDI and equity FPI is somewhat arbitrary. For a discussion of this point, see for instance Blanchard and Acalin (2016) and Alfaro and Chauvin (2020).
### Table 2: OLS Regressions

<table>
<thead>
<tr>
<th>Dep. variable in logs:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultural Distance</td>
<td>-4.174** (0.449)</td>
<td>-4.307** (0.490)</td>
<td>-3.654** (0.533)</td>
<td>-3.765** (0.479)</td>
<td>-3.736** (0.504)</td>
<td>-3.374** (0.569)</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>-4.667** (0.321)</td>
<td>-4.834** (0.338)</td>
<td>-3.065** (0.444)</td>
<td>-4.819** (0.983)</td>
<td>-5.030** (0.965)</td>
<td>-2.576* (1.043)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-3.325** (0.429)</td>
<td>-3.733** (0.471)</td>
<td>-1.759* (0.769)</td>
<td>-2.242** (0.476)</td>
<td>-2.631** (0.499)</td>
<td>-0.263 (0.793)</td>
</tr>
<tr>
<td>Control Variables</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,314</td>
<td>2,287</td>
<td>1,405</td>
<td>2,285</td>
<td>2,258</td>
<td>1,381</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.772</td>
<td>0.745</td>
<td>0.795</td>
<td>0.796</td>
<td>0.776</td>
<td>0.808</td>
</tr>
<tr>
<td>Within R-squared</td>
<td>0.239</td>
<td>0.235</td>
<td>0.103</td>
<td>0.319</td>
<td>0.329</td>
<td>0.169</td>
</tr>
</tbody>
</table>

Table Notes: This table reports OLS 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, 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, Latitudinal Distance, Longitudinal Distance, Colonial Relationship, Common Colonizer, Common Legal Origin, 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 Econometric Analysis

In this section, we estimate the parameter vector \(\beta\), the effect of geographic and cultural distances on log foreign investment (three 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 Foreign Assets), as the dependent variable. We find that Cultural, Geographic and Linguistic Distance are statistically...
and economically significant predictors of Foreign Assets: the slope coefficients corresponding to these three variables are negative, sizable in magnitude (-4.174, -4.667 and -3.325 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 Foreign Assets ($\%\Delta FTI = e^{\beta x \Delta x} - 1$). We find large effects of these barriers: a one standard deviation increase of geographic distance (0.237 units) is associated with a 66.9% decrease in Foreign Assets, a one standard deviation increase in cultural distance (0.162 units) is associated with a 49.1% decrease in Foreign Assets, while a one standard deviation increase in linguistic distance (0.097 units) is associated with a 27.6% decrease in Foreign Assets.

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 Foreign Assets. Column (3) considers log foreign debt investment as the dependent variable. We find effects of geographic distance (a standardized effect of -51.6%), cultural distance (with a standardized effect of -44.7%), and linguistic distance (with a standardized effect of -15.7%) are all statistically significant: the first two at the 1% level, and the last one at 5%. These numbers are commensurate with the effects on log Foreign Assets.

Finally, columns (4) through (6) repeat the analysis of the first three columns, but depart from our 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 (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 Foreign Assets, we find standardized effects of cultural distance, geographic distance and linguistic distance to be equal respectively to -45.7%, -68.1% and -19.5%. We again find that these barriers have similar quantitative effects on foreign equity investments and foreign debt investment, though linguistic distance does not appear to be a robust predictor of log foreign debt investment. Overall, adding control variables does not fundamentally alter the inferences drawn from the more parsimonious specification.

### 4.2 Pseudo-Poisson Regressions

One shortcoming of the econometric model described by equation (3.5) 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 (3.5) as:

$$\hat{a}_{ijt} = \exp (\mu_i + \nu_j + d'_{ij} \beta + \epsilon_{ij}) \tag{4.1}$$

thereby converting the log-linear specification into a Poisson regression. This type of regression has been applied to gravity models of trade by Santos Silva and Tenreyro (2006) and Correia, Guimaraes, and Zylkin (2019), among many others. We apply the same statistical model to our model of financial
Table 3: Pseudo-Poisson Regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>Assets</td>
<td>Equity</td>
<td>Debt</td>
<td>Assets</td>
<td>Equity</td>
<td>Debt</td>
</tr>
<tr>
<td></td>
<td>(0.356)</td>
<td>(0.401)</td>
<td>(0.453)</td>
<td>(0.366)</td>
<td>(0.433)</td>
<td>(0.412)</td>
</tr>
<tr>
<td></td>
<td>(0.214)</td>
<td>(0.226)</td>
<td>(0.336)</td>
<td>(0.757)</td>
<td>(0.886)</td>
<td>(0.685)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-1.456**</td>
<td>-1.995**</td>
<td>-1.303**</td>
<td>-0.384</td>
<td>-1.101**</td>
<td>0.212</td>
</tr>
<tr>
<td></td>
<td>(0.296)</td>
<td>(0.246)</td>
<td>(0.333)</td>
<td>(0.295)</td>
<td>(0.341)</td>
<td>(0.340)</td>
</tr>
<tr>
<td>Control Variables</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,754</td>
<td>2,770</td>
<td>3,459</td>
<td>2,754</td>
<td>2,770</td>
<td>3,459</td>
</tr>
</tbody>
</table>

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, 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. \(^1p < .10; ^*p < .05; ^{**}p < .01\)

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 weight 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 H). Including the zero investment pairs, the size of the sample rises a bit compared to that in Table 2 (by about 21% for equity, though the increase is smaller for total investment, at about 19%).

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 44.7% while that of geographic distance and linguistic distance are -51.5% and -13.2%. 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
### Table 4: First-Stage Regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Cultural Distance</td>
<td>Cultural Distance</td>
</tr>
<tr>
<td>Religious Distance</td>
<td>0.341** (0.030)</td>
<td>0.305** (0.028)</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>0.097** (0.020)</td>
<td>0.048 (0.047)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>0.173** (0.035)</td>
<td>0.138** (0.031)</td>
</tr>
<tr>
<td>Control Variables</td>
<td>2,209</td>
<td>2,181</td>
</tr>
<tr>
<td>Observations</td>
<td>0.672</td>
<td>0.734</td>
</tr>
<tr>
<td>$R^2$</td>
<td>0.229</td>
<td>0.373</td>
</tr>
<tr>
<td>Within $R^2$</td>
<td>0.232</td>
<td>0.414</td>
</tr>
<tr>
<td>Kleibergen-Paap Wald $F$ statistic</td>
<td>129.450</td>
<td>115.972</td>
</tr>
<tr>
<td>Cragg-Donald Wald $F$ statistic</td>
<td>250.065</td>
<td>217.209</td>
</tr>
<tr>
<td>Stock &amp; Yogo Critical Value ($r=10%$)</td>
<td>16.38</td>
<td>16.38</td>
</tr>
</tbody>
</table>

**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, Currency Peg, Customs Union, Economic Integration Agreement, Free-Trade Agreement, Investment Treaty, Tax Treaty and Trade Costs*. Robust standard errors in parentheses. *$p < .05$; **$p < .01$*

---

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.\(^{19}\) In that case, the

\(^{19}\)For obvious reasons, reverse causality is not an issue for geographic distance.
OLS estimates of the gravity equation (3.5) could not be interpreted as causal. To address this issue, we turn to an IV strategy. We assume that Religious Distance only influences financial flows indirectly, through its effect on contemporary Cultural Distance, and is therefore a valid instrumental variable. Other measures of historical relatedness, like Colonial Relationship, are used as controls rather than instruments out of concern about their excludability from the second stage.

Religious Distance, like linguistic distance, is constructed using a branching tree that traces 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), religious distances is 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. Our instrument comfortably passes several tests for weak instruments.

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. Take for instance the effect of cultural distance on log Foreign Assets (column 1). The effect of a one standard deviation increase in Cultural Distance was -49.1% under OLS, and it rises in magnitude to -61.3% 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 -65.4% versus -66.9% under OLS, for instance). Lastly, the effect of increase of a one standard deviation in Linguistic Distance was -27.6% under OLS, and it is equal to -24.2% under IV.

The bottom line from the IV results is that all three distance metrics continue to remain statistically and economically significant as determinants of total foreign assets, 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 are similar across log total foreign assets, log foreign equity assets and log foreign debt assets (with the exception, as before, that linguistic distance is not a robust predictor of the latter).

5 Model Calibration, Fit and Predictions

5.1 Model Solution and Identification

In this section, we calibrate the model of Section 2 using the econometric estimates of Section 4 and evaluate how the calibrated model fits the data. We calibrate the distance semi-elasticities ($\beta$) using the

---

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.


Table 5: Instrumental Variables Regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Dep. variable in logs:</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Cultural Distance</td>
<td>-5.858**</td>
<td>-5.730**</td>
<td>-4.742*</td>
<td>-5.452**</td>
<td>-5.249**</td>
<td>-3.571</td>
</tr>
<tr>
<td></td>
<td>(1.386)</td>
<td>(1.433)</td>
<td>(2.111)</td>
<td>(1.589)</td>
<td>(1.631)</td>
<td>(3.117)</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>-4.484**</td>
<td>-4.694**</td>
<td>-3.072**</td>
<td>-4.707**</td>
<td>-4.934**</td>
<td>-2.567*</td>
</tr>
<tr>
<td></td>
<td>(0.373)</td>
<td>(0.389)</td>
<td>(0.462)</td>
<td>(0.992)</td>
<td>(0.970)</td>
<td>(1.054)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-2.861**</td>
<td>-3.332**</td>
<td>-1.227</td>
<td>-1.796**</td>
<td>-2.230**</td>
<td>-0.007</td>
</tr>
<tr>
<td></td>
<td>(0.548)</td>
<td>(0.582)</td>
<td>(1.050)</td>
<td>(0.599)</td>
<td>(0.614)</td>
<td>(1.292)</td>
</tr>
<tr>
<td>Control Variables</td>
<td>2,209</td>
<td>2,181</td>
<td>1,320</td>
<td>2,181</td>
<td>2,153</td>
<td>1,297</td>
</tr>
<tr>
<td>Observations</td>
<td>0.235</td>
<td>0.233</td>
<td>0.103</td>
<td>0.319</td>
<td>0.331</td>
<td>0.173</td>
</tr>
<tr>
<td>Within $R^2$</td>
<td>0.235</td>
<td>0.233</td>
<td>0.103</td>
<td>0.320</td>
<td>0.332</td>
<td>0.171</td>
</tr>
</tbody>
</table>

**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 instrument is 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, 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. *$p < .05$; **$p < .01$

estimates of column 4 of Table 2 (which includes the full set of controls): -3.765 for Cultural Distance, -4.819 for Geographic Distance, -2.242 for Linguistic Distance. We choose this specification because the magnitude of the effect of the main barrier variables tends to be smaller than in the specifications without controls, or the specifications that use IV estimation (in other words, we choose conservative estimates).21 Armed with empirical estimates for $\beta$ and having calibrated $\sigma = 1/2$, we now solve the model.

Capital being the only moving factor, to solve the model means to find the country-level total asset stocks $s$, the network of portfolio shares $\Pi$ and (by extension) the vector of capital stocks. These objects are identified given the previously-measured variables and parameters. We start by re-writing the Cobb-Douglas production function of country $i$ by grouping non-mobile factors (including technology) in one

---

21In Section 7, we examine the sensitivity of the counterfactual analysis to the use of alternative estimates of $\beta$, finding that such alternatives deliver broadly similar results to those in the benchmark exercise.
Single term $\hat{\omega}_i$:

$$y_i = \hat{\omega}_i k_i^{x_i}$$

(5.1)

where

$$\hat{\omega}_i \overset{\text{def}}{=} \omega_i x_i \xi_i$$

(5.2)

First, we compute country-level savings ($s_i$) using equation (2.11). Second, we compute the matrix of portfolio shares $\Pi$, given the income shares ($\kappa_i, \lambda_i, \xi_i$), output ($y_i$), taxes ($\tau_i$) and ($\varphi_{ij}$) using equation (2.25). $k$ is then obtained as $\frac{1}{2} \Pi \Pi$.

The residual model component that remains to be identified is $\hat{\omega}_i$: this is obtained from equation (5.1).

### 5.2 Model Fit

In order to evaluate the model fit, we naturally want to compare data moments generated by the model against their empirical counterparts. However, this may not be sufficient. As observed by Armenter and Koren (2014), some data moments are less informative than others when it comes to evaluating model fit, as they can be reproduced equally well by a rudimentary/mechanical model, and therefore (likely) by a large set of alternative models. In the case of our model, it is important to understand to what extent our matching of data moments is due to the presence of information and policy barriers, as opposed to other features of the model.

To this end, we produce two variations of our model (presented in Section 2) that will act as benchmarks in evaluating model fit. They are both identical to the baseline model, except for asset demand – i.e., the portfolio shares $\pi_{ij}$ – which we will assume to be an exogenously-determined function. In the first of these two benchmarks, the “Frictionless” model (FL), neither information nor policy frictions play a role in capital allocation. Under this benchmark, each origin country simply invests a share of its portfolio that is proportional to the destination country’s share of world capital (see Lemma 1). In the second benchmark model – the “Residuals” model (Res) – we go to the opposite extreme, and use the gravity regression residuals ($\varepsilon_{ij}, \hat{\mu}_i, \hat{\nu}_j$) as additional frictions of undetermined origin. This allows us to perfectly fit equation (3.5). That is, we perfectly match the observed portfolio shares (after imputing missing values).

The resulting portfolio shares for the two benchmark models are:

$$\pi_{ij}^{\text{FL}} = \frac{\kappa_i y_i}{\sum_{i=1}^n \kappa_i y_i}$$

$$\pi_{ij}^{\text{Res}} = \frac{\tau_i \kappa_i y_i \varphi_{ij} \cdot \exp (\hat{\mu}_i \hat{\nu}_j \varepsilon_{ij})}{\sum_{i=1}^n \tau_i \kappa_i y_i \varphi_{ij} \cdot \exp (\hat{\mu}_i \hat{\nu}_j \varepsilon_{ij})}$$

(5.3)

Table 6 presents moments of the data, against the corresponding model-generated moments for our baseline model and the two benchmarks. We look at four different key variables: rates or return ($r_i$), capital per employee ($k_i/\ell_i$) and home bias, which we define (following Lau, Ng, and Zhang, 2010) as

$$\text{Home Bias}_i \overset{\text{def}}{=} \log \pi_{ii} - \log \frac{k_i}{K}$$

(5.4)

as well as the international investment position (IIP) as percentage of GDP (measured in PPP).

---

22 For country pairs for which we have missing values in the bilateral investment position (the dependent variable $a_{ij}$), we impute the gravity residuals $\varepsilon_{ij} = 0$. When $a_{ij} = 0$, we impute $\varepsilon_{ij} = -\infty$. 27
Table 6: Model Fit: Untargeted Moments

<table>
<thead>
<tr>
<th>Variable</th>
<th>Statistic</th>
<th>Data</th>
<th>Baseline</th>
<th>Frictionless</th>
<th>Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return on Capital log (r_i)</td>
<td>Mean (exp.)</td>
<td>0.102</td>
<td>0.103</td>
<td>0.055</td>
<td>0.077</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>0.465</td>
<td>0.578</td>
<td>0.000</td>
<td>0.824</td>
</tr>
<tr>
<td></td>
<td>Correlation w/PWT</td>
<td>1.000</td>
<td>0.604</td>
<td>0.000</td>
<td>0.442</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Capital/Employee log (k_i/\ell_i)</th>
<th>Mean</th>
<th>12.270</th>
<th>12.261</th>
<th>12.880</th>
<th>12.552</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>1.062</td>
<td>1.189</td>
<td>0.761</td>
<td>1.312</td>
</tr>
<tr>
<td></td>
<td>Correlation w/PWT</td>
<td>1.000</td>
<td>0.917</td>
<td>0.922</td>
<td>0.823</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Home Bias log ((\pi ii K)/k_i)</th>
<th>Mean</th>
<th>4.247</th>
<th>4.084</th>
<th>0.000</th>
<th>3.735</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>1.760</td>
<td>1.085</td>
<td>0.000</td>
<td>1.046</td>
</tr>
<tr>
<td></td>
<td>Correlation w/LNZ</td>
<td>1.000</td>
<td>0.630</td>
<td>0.000</td>
<td>0.442</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>IIP/GDP (IIP_i/y_i)</th>
<th>Mean (GDP-weighted)</th>
<th>-0.061</th>
<th>0.005</th>
<th>0.000</th>
<th>-0.078</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>0.523</td>
<td>0.453</td>
<td>1.734</td>
<td>0.630</td>
</tr>
<tr>
<td></td>
<td>Correlation w/LMF</td>
<td>1.000</td>
<td>0.564</td>
<td>0.435</td>
<td>0.398</td>
</tr>
</tbody>
</table>

That thus far we’ve measured capital flows in our model in units of physical capital. In order to compute the international investment position of a country (foreign assets less foreign liabilities) in a way that is consistent with available international investment statistics, we need to convert these physical capital positions into dollar market values. To do so, we use the fact that, in a steady state, the net present value of position \(a_{ij}\) is equal to the one-period income \(\tau_i r_i a_{ij}\) divided by the discount rate, plus a rate of depreciation. We use, as the estimates for the discount rate and the depreciation rate (respectively) the rate of return on domestic assets \(r_j\) and the average depreciation rate of capital in the Penn World Tables (which we call \(D\), and set equal to 4.5%). The resulting measurement for the market value of position \(a_{ij}\) from the point of view of country \(i \in (i, j)\) is:

\[
a_{ij}^{(i)} = \frac{\tau_i r_i a_{ij}}{r_j + D} \tag{5.5}
\]

The international investment position of country \(i\) is then:

\[
\text{IIP}_i = \sum_{j \neq i} \left( a_{ji}^{(j)} - a_{ij}^{(i)} \right) \tag{5.6}
\]

For all four variables, we present the mean, the standard deviation and the correlation with the actual data. Our sources for the “Data” column are as follows: we use rates of return on capital, computed using the methodology of Caselli and Feyrer (2007), as updated by Monge-Naranjo et al. (2019). This computation requires output, capital stock and labor shares from the Penn World Table as well as natural resource shares from the World Bank Wealth of Nations dataset. For capital stock per employee, we use
the corresponding data from the Penn World Tables. For Home Bias, we use the estimates of Lau, Ng, and Zhang (2010). Finally, we use international investment positions (IIP), net of gold reserves, from the 2021 update of the *External Wealth of Nations* dataset of Lane and Milesi-Ferretti (2018), which we divide by PPP GDP.

Overall, the baseline model comes closest to matching the data. In this model, the mean of the log rate of return on capital is very close to its empirical counterpart. The Frictionless and Residuals models display slightly lower values. As implied by the theorem in section 2, the Frictionless model does not produce any variation in rates of return, while the Residuals model overshoots compared to the data. By contrast, the baseline model comes close to matching the dispersion in returns. In addition, the empirical rates of return correlate more closely with those from the baseline model than those from the Residuals model. Similar results obtain for capital stock per employee.

As implied by our theory, the Frictionless model does not generate any home bias. Both the Baseline and the Residuals model produce a large home bias, but the Baseline model outperforms when it comes to predicting the cross-section of 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: 4.084 for the average country. This value implies that, for the typical country, the domestic portfolio share is nearly 60 times the corresponding country’s share of the world capital stock.

### 5.3 Rates of Return Heterogeneity

In addition to matching data moments reasonably well, our model also replicates some additional stylized facts that the literature has documented. As noted by David, Henriksen, and Simonovska (2014, henceforth DHS), rates of returns on capital correlate negatively, at the country level, with the level of economic development. In Figure 2, 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 -0.63: this is consistent with DHS’s observation that rates of return are significantly higher in emerging economies.

If movements of capital were impeded, we would expect large capital flows from richer to poorer countries to rectify these return differentials. Return differentials are a reflection of Lucas’s observation (later studied empirically by Alfaro, Kalemli-Ozcan, and Volosovych, 2008) about the paucity of such flows in the data. Because (as we have shown in the previous sub-section) these return differentials are produced in our model by information and policy barriers, these barriers help explain the absence of large movements of capital towards developing countries, thus shedding light on Lucas’s puzzle.\(^{23}\)
5.4 Home Bias and Rates of Return

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). To show that our general equilibrium model is capable of reproducing this correlation, we compute our own model-consistent version of this measure (equation 5.4) and plot it against the model-implied return to capital \( (r_i) \) in Figure 3. As visible from the graph, the two correlate strongly and positively \( (\rho = 0.88) \).

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 asset betas and capital 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.
Figure 3: Rates of Return and Home Bias

Figure Notes: This figure plots the model-implied rate of return on capital, against a measure of home bias - the log difference of the shares of country $i$ investment in country $i$ portfolio and in the world portfolio ($\log \pi_{ii} - \log \frac{\bar{K}}{K}$). Each observation is a country and data refer to the year 2017.

6 Counterfactual Analysis

6.1 Capital Allocation Efficiency

In this section we perform counterfactual analyses. If we could exogenously change the set of barriers affecting international investment, and let market forces reallocate capital, how would the sum and the cross-country distribution of output change? Two motivations underlie this exercise. The first is to better quantify the effect of information and policy frictions on the world allocation of capital. The second reason is policy: as we shall see, policy and information frictions interact in interesting ways.

Our counterfactuals consist of removing or activating, within our model, the Policy Frictions and/or the Information Frictions. To remove the policy frictions we change the (previously estimated) vector of taxes $\tau$ to a uniform positive value\(^{24}\). To remove information frictions, we make the investor prior precision $\varphi_{ij}$ invariant to the distances $d_{ij}$ (i.e. we set $\beta = 0$). The hypothetical policy intervention in

\(^{24}\)It is easy to see from equation (2.20) that the resulting capital allocation is unaffected by the particular choice of this value.
this case is to equip investors from country $j$ with identical priors for all potential destination countries $i$, so that investors no longer have an informational advantage for certain assets over others. Put differently, we are by no means picturing a counterfactual world where distances themselves disappear; rather, we are thinking of a counterfactual world where distances do not play a role in the investors’ prior information (the effect of distance on information acquisition is eliminated).

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 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 the measured information and policy barriers. In column (2), we present the zero-gravity equilibrium, from which all distortions have been removed ($\tau_i = 1, \beta = 0$). In column (3), we consider a counterfactual equilibrium (Information Frictions) where policy frictions are eliminated ($\tau_i = 1$) while information frictions remain in place. In column (4), we consider a counterfactual equilibrium (Policy Frictions) where information frictions are eliminated ($\beta = 0$) while information frictions remain in place. These three counterfactuals allow us to gain a sense of the marginal impact of each individual distortion.

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 103.3 US$ billion. That is 5.9% lower than in the zero-gravity counterfactual (column 2). We find that the information frictions have the largest effect in terms of capital allocation efficiency. When all Policy Frictions alone are removed, GDP is 6.1% lower than in the Zero-Gravity scenario. When Information Frictions alone are removed, the world GDP losses is 1.3%, which is still a very large number (the dollar size of this loss is comparable to the combined GDP of Australia and New Zealand in 2017), yet not nearly as large as the GDP loss induced by cultural, linguistic and geographic barriers.

### 6.2 Capital and Income Inequality

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 this 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 steady-state 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 77%, while the standard deviation of log output per employee increases by 24.4%.

When Information Frictions alone are maintained, dispersion in log capital per employee is 55.4% higher than in the zero-gravity benchmark. The dispersion of log output per employee is 11.9% higher. Finally, we find that by only maintaining investment taxes and political risk, dispersion in log capital per employee is about 39% higher compared to the zero-gravity benchmark, while dispersion in log output per employee is 19.3% higher. In other words, both information and policy frictions significantly contribute
<table>
<thead>
<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>109.8</td>
<td>103.1</td>
<td>108.3</td>
</tr>
<tr>
<td>World GDP, % Difference from Zero-Gravity</td>
<td>-5.9%</td>
<td>0.0%</td>
<td>-6.1%</td>
<td>-1.3%</td>
</tr>
<tr>
<td>St.Dev. of log ($k_i/\ell_i$), % Difference from Zero-Gravity</td>
<td>77.0%</td>
<td>0.0%</td>
<td>55.4%</td>
<td>39.0%</td>
</tr>
<tr>
<td>St.Dev. of log ($y_i/\ell_i$), % Difference from Zero-Gravity</td>
<td>24.4%</td>
<td>0.0%</td>
<td>11.9%</td>
<td>19.3%</td>
</tr>
</tbody>
</table>

**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 barriers (both information and policy barriers) have been removed. Columns (3)-(4) illustrate two additional counterfactuals from which only the corresponding distortion is in place. ($k_i/\ell_i$) is the capital stock per employee, while ($y_i/\ell_i$) is output (GDP) per employee. Actual World PPP$ GDP (including countries not in the model) in 2017 was $121 trillion.
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.
Figure 4 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 median country.

What lies beyond this reduction in inequality? 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 5 illustrates this effect: it is a scatter plot of the baseline level of GDP per employee (horizontal axis) against the log change in capital per employee from moving to a zero-gravity world (vertical axis). 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 increase by an order of magnitude, and
their income per employee more-than-double.

6.3 Net Flows

Finally, we consider a comparison of net foreign asset positions under the observed equilibrium and the
zero-gravity equilibrium (i.e. when we set $\beta = 0$ and $\tau_i = 1$ for all $i$). We define net foreign asset positions
as the market value of net holdings of foreign assets, and present them as a fraction of GDP.

A notable feature of our model is that it generates persistent (steady-state) global imbalances. Figure 6
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 (IIP); yet, these net asset positions
correlate weakly 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
becomes much 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 information and policy barriers can thus help explain the lack of a strong
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 – in-
duced 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.

7 Robustness Checks and Extensions

7.1 Good Markets Frictions

In our baseline model, we have assumed away frictions in goods trade: all countries produced a homoge-
neneous, perfectly-tradable good. We now want to relax those assumptions. We combine our international
investment model of section 2 with an Armington model of trade: countries $i$ produce differentiated final
goods $i$ that have different prices. The numéraire good is capital, and the price of the good produced by
country $i$ is $p_i$. This price is affected by trade barriers (such as tariffs) as well as other frictions in the
goods market, and the representative consumer’s demand over all countries’ goods has constant elasticity
of substitution, with elasticity $\eta$. We still assume that 1 unit of any final good $i$ can be converted in $1/\delta$
units of capital and saved for production in the next period.\(^{25}\)

Then, the equation for the rate of return to capital in country $i$ has to be amended as follows:

$$ r_i = \kappa_i \frac{p_i y_i}{k_i} \quad (7.1) $$

\(^{25}\)This assumption can be micro-founded as follows: all final goods are identical, except for a origin country $j$-specific
characteristic, which is valued by consumers but is irrelevant for the conversion of the consumer good into a capital good.
The atomistic consumers have random utility for the $j$-characteristic, drawn from an extreme value type 1 distribution.
**Figure Notes:** The figure above plots the model-implied International Investment Position (IIP) 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.
This leads to the following updated equation for the portfolio shares:

\[
\pi_{ij} = \frac{\left(\tau_i \kappa_i p_i y_i^k\right)^{\frac{1}{1-\sigma}} k_i \varphi_{ij}}{\sum_{i=1}^{n} \left(\tau_i \kappa_i p_i y_i^k\right)^{\frac{1}{1-\sigma}} k_i \varphi_{ij}}
\]  

(7.2)

Using a logic similar to the sufficient statistics approach of Arkolakis, Costinot, and Rodríguez-Clare (2012), we can re-compute the equilibrium output, capital and rates of return for each country without having to specify the full system of bilateral trade frictions. The intuition is that information about goods market frictions is embedded in the observed prices \( p_i \). We only need two additional statistics in order to perform counterfactual analyses, namely: 1) the final good price index for each country \( p_i \) (which we obtain from the Penn World Tables, as the price level of PPP GDP); 2) the demand elasticity of substitution \( \eta \), which we set to 4 following the literature (see Imbs and Mejean, 2015).

Then, when computing counterfactuals, the term \( p_i y_i \) in the formula above, corresponding to nominal output, can be updated using the following formula:

\[
p_i'y_i = p_i y_i \left(\frac{y_i'}{y_i}\right)^{\frac{n-1}{n}}
\]

(7.3)

where \( p_i' \) and \( y_i' \) represent the new price and quantity levels following an exogenous change in \( \tau \) or \( \beta \).

In Appendix C, Table C.1, we repeat our counterfactual analysis for the extended model with goods market frictions. We find that, with respect to our baseline findings, the percentage world GDP loss is slightly higher in the presence of goods trade frictions (7.8% instead of 5.9%), and so is the effect of the information frictions on the cross-sectional dispersion of capital. As in the baseline model, information frictions still account for the majority of the distortive force.

### 7.2 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 \( \tau \)

\[
\tau_{ij} = \tau_{i}^{\text{Tax}} \cdot \tau_{i}^{\text{PR}} \cdot \tau_{ij}^{\text{KC}}
\]

(7.4)

\( \tau_{ij}^{\text{KC}} \) 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 \((i=j)\) \( \tau_{ij}^{\text{KC}} \) is always 1 by definition.

Turning to the empirical implementation, we measure the degree of \textit{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 \( \tau_{KC}^{ij} \), 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:

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

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

In Appendix C, Table C.2 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, even when we move to “zero-gravity”. The percentage world GDP losses is halved when compared to our baseline exercise (3.3% vs. 5.9%). The marginal effects of the individual frictions are also very similar to those found in the baseline exercise.

### 7.3 Currency Risk Adjustment and Hedging Costs

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 friction, in the form of a wedge to the realized investment return from the point of view of a \( j \)-based investor. Define \( \bar{r}_{ij} \), the currency risk-adjusted return:

\[
\bar{r}_{ij} \overset{\text{def}}{=} FP_{ij} \cdot r_i
\]

where \( FP_{ij} \) is a wedge that we empirically measure as the forward premium for the \((i, j)\) currency pair. This leads to the following amended equation for the portfolio shares:

\[
\pi_{ij} = \left( \frac{\bar{r}_{ij}}{\overline{r}_i} \right)^{\frac{\gamma}{\gamma-1}} k_i \phi_{ij} \sum_{i=1}^{n} \left( \frac{\bar{r}_{ij}}{\overline{r}_i} \right)^{\frac{\gamma-1}{\gamma}} k_i \phi_{ij}
\]

(7.7)

If the covered interest rate parity holds, this wedge can be measured as the risk-free return differential between in country \( i \) and \( j \):

\[
FP_{ij} = \frac{r_i^f}{r_j^f}
\]

(7.8)

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.

We obtain forward premia from the Covered Interest Parity dataset of Du and Schreger (2021). This data does not cover all the country pairs in our sample, due to the fact that the official currencies of some of the countries in our sample are illiquid. To estimate forward premia for these currencies, we exploit the fact, documented by Ilzetzki, Reinhart, and Rogoff (2019), that even countries that do not have a de-jure fixed exchange rate regime, have their currencies “de facto” anchored to a major liquid currency. Instead of matching these countries to the de jure currency, we match these countries to corresponding anchor currency (identified by the dataset of Ilzetzki, Reinhart, and Rogoff, 2019), and use the corresponding forward premia from the dataset of Du and Schreger (2021). The assumption behind this imputation is that investor who invest in or from a country where the de-jure currency is illiquid will hedge with the corresponding anchor currency. We think this is a very realistic assumption: it is indeed common practice, among currency market players, to hedge forward exposures in an illiquid currency using a (correlated) G10 currency.

In Appendix C, Table C.3 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 and inequality effects that we find according to this extended model are essentially unchanged compared to the baseline, and the marginal effect of information frictions and policy barriers remains very close to the baseline level.

7.4 Fundamental Risk

Thus far we have presented a model where there is no fundamental risk, and uncertainty only exists for individual investors, in the form of noisy signals. 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 $\zeta(q)$ units of productive capital in the next period. We assume that the within-country shock $\zeta(q)$ cannot be learned by investors, and is assumed to be conditionally log-normal, with mean one and variance $(v_i - 1)$, so that the shocks average out and do not change the overall level of capital. In addition, we assume that investors have beliefs (of the same distributional form) not over net returns, but over the ratio $(\tau_i r_i/v_i)$.

Because agent $z$ holds log sub-utility and chooses the plant with the highest expected log return, this leads to the following amended expression for the portfolio shares:

$$
\pi_{ij} = \frac{\left(\frac{\tau_i r_i}{v_i}\right)^{\frac{1}{1-\sigma}} \cdot k_i \cdot \varphi_{ij}}{\sum_{i=1}^{n} \left(\frac{\tau_i r_i}{v_i}\right)^{\frac{1}{1-\sigma}} \cdot k_i \cdot \varphi_{ij}}
$$

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 $(v_i^2)$, 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 C, Table C.4 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.

7.5 Coefficients Stability

How stable are the coefficient estimates on Cultural Distance, Linguistic 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, Linguistic 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.

7.6 Alternative Breakdown of Foreign Investment Statistics

In our main estimation, we broke down Foreign Assets 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). Linguistic Distance is negatively associated with FDI but not FPI.

7.7 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 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.

7.8 Sensitivity Analysis on Coefficient Estimates

It is reasonable to ask how the results of our counterfactual analysis would change if we were to utilize IV estimates or the Pseudo-Poisson estimates to calibrate \( \beta \) (the semi-elasticity of foreign investment with respect to cultural, linguistic and geographic distance).

We address this question in Appendix G, Tables G.1-G.2. There we present the analysis of Table 7, using these alternative estimates for \( \beta \). We find that the steady-state GDP loss induced by capital misallocation, around 6%, is essentially unchanged under both alternative choices of \( \beta \), compared to using OLS estimates as we do in the baseline. We continue to find that the removal of barriers would result in significant reductions in world inequality under both Poisson and IV estimates, with magnitudes similar to the baseline.

8 Conclusion

Information and policy barriers have large and persistent effects on global capital allocation and affect poorer countries disproportionately. This has important implications for policy at the domestic and global level: while policy cannot change geography or history, it may affect the extent that geographical and cultural distances impact individuals’ beliefs and biases, and therefore their investment choices. In our structural framework, barriers and biases stem from rational decisions at the individual level, as the result of costs associated with informational acquisition. Yet, they create large global efficiency losses and
contribute to inequality across societies. How to address such biases and inefficiencies in an effective and coordinated way remains an open area of inquiry, both theoretically and empirically.

We estimated our 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 approaches (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, taxation 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 return across countries. These rates of return correlate negatively with the level of economic development, a realistic feature of the model. Moreover, 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 information and policy barriers also 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 framework. We studied how World GDP and the cross-country distribution of capital and output per worker would change if the effects of these barriers to foreign investment were neutralized. 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 5.9% lower than it would be if the effect of these barriers could be neutralized. Notably, the effect of cultural distance is of a similar magnitude as the effect of geographical distance. The global misallocation of capital also has significant effects on world inequality. The cross-country standard deviation of capital per employee is 77% higher, while the dispersion of output per employee is 24.4% higher than under the frictionless counterfactual. The hypothetical removal of barrier effects would lead to substantial economic gains and reductions in cross-country inequality because it would lead to reallocating capital from richer countries, where the rate of return on capital is lower, to poorer countries, where the rate of return is higher. Thus, the largest gains from removing informational biases would benefit countries that happen to be farther from the “center” where most investors are currently located. This is consistent with the insights from our theory, which models decisions as taken by rationally-inattentive investors, whose priors and biases depend on geographical and cultural distances, therefore perpetuating the advantages of the center and disadvantaging societies at the periphery.

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. In 1990, Robert Lucas asked: “Why doesn’t capital flow from rich to poor countries?” This paper sheds new light on this question. Infor-
formation 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.

References


Coppola, A., M. Maggiori, B. Neiman, and J. Schreger (2020): “Redrawing the map of global capital flows: The role of cross-border financing and tax havens,” *Available at SSRN 3525169*.

Correia, S., P. Guimaraes, and T. Zylkin (2019): “PPMLHDFE: Stata module for Poisson pseudo-likelihood regression with multiple levels of fixed effects,” *Available at SSRN 3525169*.


Jiang, Z., R. Richmond, and T. Zhang (2020): “A portfolio approach to global imbalances,” Available at SSRN.


A Proofs and Derivations

Proof to Proposition 1. By Proposition 1 in Caplin, Dean, and Leahy (2019), $P^0_j(q)$ solves the rational inattention logit problem if and only if equation (2.16) and the following condition both hold:

$$E_{F}^{G_j} \frac{\tilde{r}_{i(q)}^{\sigma}}{\sum_{q'} \tilde{r}_{i(q')}^{\sigma} \cdot P^0_j(q')} \leq 1 \quad (A.1)$$

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:

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

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

$$E_{F}^{G_j} \frac{\tilde{r}_{i(q)}^{\sigma} \cdot P^0_j(q)}{\sum_{q'} \tilde{r}_{i(q')j}^{\sigma} \cdot P^0_j(q')} = P^0_j(q) \quad (A.3)$$

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

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

Using the scaling property of the $\Gamma$ distribution:

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

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

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

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:

\[
\mathbb{E}_G r_j \frac{\tilde{r}_{i(q)}^{1-\sigma}}{\sum_{q'=1}^N \tilde{r}_{i(q')^{1-\sigma}}} \cdot \frac{\varphi_{i(q)} j}{\sum_{q'=1}^N \tilde{r}_{i(q')} \varphi_{i(q')} j} = \mathbb{E}_G r_j \frac{\tilde{r}_{i(q)}^{1-\sigma}}{\sum_{q'=1}^N \tilde{r}_{i(q')}^{1-\sigma}} \cdot \frac{\varphi_{i(q)} j}{\sum_{q'=1}^N \tilde{r}_{i(q')} \varphi_{i(q')} j} = \frac{\varphi_{i(q)} j}{\sum_{q'=1}^N \tilde{r}_{i(q')} \varphi_{i(q')} j} \quad (A.7)
\]

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

---

**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 \( \Delta k \) such that \( \sum_i \Delta k_i = 0 \):

\[
\Delta Y \approx n \sum_{i=1}^n r_i \Delta k_i \quad (A.8)
\]

then, if \( r_i > r_j \) for some \( (i, j) \), we can construct a \( Y \)–increasing \( \Delta k \) 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 \( r \):

\[
k_i = r^{-1/k_i} (\kappa_i \omega_i)^{1/k_i} \ell_i \quad (A.9)
\]

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 Corollary 1 (the efficient allocation is unique).

To show equivalence between statements (2) and (3), notice that equations (2.14) and (2.20) jointly imply:

\[
\delta k_i = \sum_j \frac{(\tau_i r_i)^{1-\sigma}}{\sum_{i=1}^n (\tau_i r_i)^{1-\sigma}} k_i \varphi_{ij} s_j \quad (A.10)
\]

if we simplify out \( k_i \) and equalize the rates of return \( (r_i = r) \), this can equation reduces to (2.36).

Finally, to prove Corollary 2, notice that if \( \varphi_{ij} \) is constant over \( i \), it can be simplified out. Then, equation 2.36 further reduces to \( \tau_i \) being constant over \( i \). \( \square \)

---

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

\[
\Delta Y \approx r \sum_{i=1}^n \Delta k_i - \frac{1}{2} \sum_{i=1}^n (1 - \kappa_i) \frac{r}{k_i} (\Delta k_i)^2 \quad (A.11)
\]
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 $\Delta k$ 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:

$$\frac{\Delta Y}{Y} \approx -\frac{1}{2} \sum_{i=1}^{n} \frac{(1 - \kappa_i)}{Y} \frac{r_k}{Y} (\Delta \log k_i)^2$$

(A.12)

We then use the following facts

$$\Delta \log r_i = - (1 - \kappa_i) \Delta \log k_i$$

(A.13)

$$r_i k_i = \kappa_i y_i$$

(A.14)

to derive:

$$0 = \sum_{i=1}^{n} \Delta k_i = \sum_{i=1}^{n} \frac{r_k}{1 - \kappa_i} \cdot \Delta \log r_i = \sum_{i=1}^{n} \frac{\kappa_i}{1 - \kappa_i} \cdot \frac{y_i}{Y} \cdot \Delta \log r_i$$

$$= \sum_{i=1}^{n} \frac{\kappa_i y_i}{Y} \cdot E_{W_i} (\Delta \log r_i) = \left[ E_{W_i} (\Delta \log r_i) \right]^2$$

(A.15)

We finally plug equations (A.13) and (A.14) inside equation (A.12) to obtain:

$$\frac{\Delta Y}{Y} \approx -\frac{1}{2} \sum_{i=1}^{n} \frac{\kappa_i}{1 - \kappa_i} \cdot \frac{y_i}{Y} (\Delta \log r_i)^2 = -\frac{1}{2} \cdot \sum_{i=1}^{n} \frac{\kappa_i y_i}{Y} \cdot E_{W_i} (\Delta \log r_i)^2$$

(A.16)

Equation (A.15) implies that the last expectation on the right is the $W_i$-weighted variance of log-returns:

$$\frac{\Delta Y}{Y} = -\frac{1}{2} \cdot \sum_{i=1}^{n} \frac{\kappa_i y_i}{Y} \cdot \mathbb{V}_{W_i} (\log r_i) = -\frac{1}{2} \cdot \mathbb{E}_{y_i} \left( \frac{\kappa_i}{1 - \kappa_i} \right) \cdot \mathbb{V}_{W_i} (\log r_i)$$

(A.17)
B  Measuring Political Risk

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

$$\tau_i^{PR} = \tau_i^{PR}(ICRG_i)$$  \hspace{1cm} (B.1)

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

$$\frac{\partial \log \sum_{j \neq i} a_{ij}}{\partial \log \tau_i^{PR}} = \frac{\sigma}{1 - \sigma} \sum_{j \neq i} a_{ij} \left(1 - \pi_{ij}\right) \approx \frac{\sigma}{1 - \sigma}$$  \hspace{1cm} (B.2)

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

$$\frac{d \log \sum_{j \neq i} a_{ij}}{dICRG_i} = \beta_{AKV} \text{ def } \left[\frac{\partial (k_i/\text{Population}_i)}{dICRG_i}\right] \cdot \left[\frac{k_i}{\text{Population}_i}\right]^{-1}$$  \hspace{1cm} (B.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:

$$\frac{d \log k_i}{dICRG_i} = \frac{\partial \log k_i}{\partial \log \tau_i^{PR}} \cdot \frac{\partial \log \tau_i^{PR}}{dICRG_i}$$  \hspace{1cm} (B.4)

Combining the two equations above, and assuming that $\tau_i^{PR} = 0$ when 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 $\tau_i^{PR}$:

$$\frac{d \log \tau_i^{PR}}{dICRG_i} = \frac{1 - \sigma}{\sigma} \cdot \beta_{AKV}$$  \hspace{1cm} (B.5)

with boundary condition

$$\tau_i^{PR}(ICRG_i) |_{ICRG_i=10} = 1$$  \hspace{1cm} (B.6)

Using our calibrated value of $\sigma$, the solution yields the following calibrated value for the expropriation rate:

$$\log \tau_i^{PR} = \beta_{AKV} (ICRG_i - 10)$$  \hspace{1cm} (B.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 $\beta_{AKV}$ estimate that controls for the initial level of GDP per capita. This leads to two different estimates for $\beta_{AKV}$. To calibrate our model, we take the simple average of the two.
C Counterfactual Analysis with Model Extensions

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

Table C.1: Counterfactuals with Goods Trade Frictions (2017)

<table>
<thead>
<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>112.0</td>
<td>103.2</td>
<td>109.7</td>
</tr>
<tr>
<td>World GDP, % Difference in GDP from Zero-Gravity</td>
<td>-7.8%</td>
<td>0.0%</td>
<td>-7.9%</td>
<td>-2.1%</td>
</tr>
<tr>
<td>St.Dev. of log (k_i/ℓ_i), % Difference from Zero-Gravity</td>
<td>81.8%</td>
<td>0.0%</td>
<td>62.6%</td>
<td>37.0%</td>
</tr>
<tr>
<td>St.Dev. of log (y_i/ℓ_i), % Difference from Zero-Gravity</td>
<td>25.8%</td>
<td>0.0%</td>
<td>15.1%</td>
<td>16.7%</td>
</tr>
<tr>
<td>Welfare Statistics</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>--------------------------------------------------------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
<td>--------</td>
</tr>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>106.6</td>
<td>103.1</td>
<td>103.9</td>
</tr>
<tr>
<td>World GDP, % Difference in GDP from Zero-Gravity</td>
<td>-3.1%</td>
<td>0.0%</td>
<td>-3.3%</td>
<td>-2.6%</td>
</tr>
<tr>
<td>St.Dev. of log ((k_i/\ell_i)), % Difference from Zero-Gravity</td>
<td>35.3%</td>
<td>0.0%</td>
<td>20.8%</td>
<td>30.3%</td>
</tr>
<tr>
<td>St.Dev. of log ((y_i/\ell_i)), % Difference from Zero-Gravity</td>
<td>4.1%</td>
<td>0.0%</td>
<td>-5.4%</td>
<td>16.7%</td>
</tr>
</tbody>
</table>
Table C.3: Counterfactuals with Currency Hedging Costs (2017)

<table>
<thead>
<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>109.7</td>
<td>103.1</td>
<td>107.6</td>
</tr>
<tr>
<td>World GDP, % Difference in GDP from Zero-Gravity</td>
<td>-5.8%</td>
<td>0.0%</td>
<td>-6.0%</td>
<td>-1.9%</td>
</tr>
<tr>
<td>St.Dev. of log (k_\ell ), % Difference from Zero-Gravity</td>
<td>73.2%</td>
<td>0.0%</td>
<td>51.8%</td>
<td>39.2%</td>
</tr>
<tr>
<td>St.Dev. of log (y_\ell ), % Difference from Zero-Gravity</td>
<td>23.4%</td>
<td>0.0%</td>
<td>10.9%</td>
<td>19.4%</td>
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<tr>
<td>Welfare Statistics</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>--------------------------------------------------------</td>
<td>------</td>
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<td>------</td>
<td>------</td>
</tr>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>109.8</td>
<td>103.2</td>
<td>107.6</td>
</tr>
<tr>
<td>World GDP, % Difference in GDP from Zero-Gravity</td>
<td>-5.9%</td>
<td>0.0%</td>
<td>-6.0%</td>
<td>-2.0%</td>
</tr>
<tr>
<td>St.Dev. of log ($k_i/\ell_i$), % Difference from Zero-Gravity</td>
<td>73.0%</td>
<td>0.0%</td>
<td>51.5%</td>
<td>39.2%</td>
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<tr>
<td>St.Dev. of log ($y_i/\ell_i$), % Difference from Zero-Gravity</td>
<td>23.5%</td>
<td>0.0%</td>
<td>11.1%</td>
<td>19.5%</td>
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</tbody>
</table>
D  Regression Coefficients Stability

Figure D.1: Coefficients Stability over Time

![Graph showing regression coefficients stability over time for Cultural Distance, Geographic Distance, and Linguistic Distance. The x-axis represents years from 2013 to 2017, and the y-axis represents the coefficients. The graph includes 95% confidence intervals (95% c.i.) and calibrated coefficients (Calibrated $\beta$).]
## Robustness check: alternative breakdown of foreign investment

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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep.variable in logs:</td>
<td>Assets</td>
<td>FDI</td>
<td>FPI</td>
<td>Assets</td>
<td>FDI</td>
<td>FPI</td>
</tr>
<tr>
<td></td>
<td>(0.449)</td>
<td>(0.455)</td>
<td>(0.607)</td>
<td>(0.486)</td>
<td>(0.492)</td>
<td>(0.610)</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>-4.667**</td>
<td>-5.362**</td>
<td>-3.434**</td>
<td>-5.038**</td>
<td>-5.631**</td>
<td>-2.836*</td>
</tr>
<tr>
<td></td>
<td>(0.321)</td>
<td>(0.344)</td>
<td>(0.400)</td>
<td>(0.984)</td>
<td>(0.977)</td>
<td>(1.271)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-3.325**</td>
<td>-3.799**</td>
<td>-1.370</td>
<td>-2.288**</td>
<td>-2.559**</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>(0.429)</td>
<td>(0.508)</td>
<td>(0.885)</td>
<td>(0.470)</td>
<td>(0.503)</td>
<td>(0.879)</td>
</tr>
<tr>
<td>Control Variables</td>
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<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
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<tr>
<td>Observations</td>
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<td>2,527</td>
<td>1,475</td>
<td>2,285</td>
<td>2,467</td>
<td>1,450</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.772</td>
<td>0.722</td>
<td>0.814</td>
<td>0.797</td>
<td>0.754</td>
<td>0.834</td>
</tr>
<tr>
<td>Within R-squared</td>
<td>0.239</td>
<td>0.229</td>
<td>0.093</td>
<td>0.321</td>
<td>0.312</td>
<td>0.188</td>
</tr>
</tbody>
</table>
F Robustness check: residency-based foreign investment Data

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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Dep. variable in logs:</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.417)</td>
<td>(0.477)</td>
<td>(0.406)</td>
<td>(0.447)</td>
<td>(0.500)</td>
<td>(0.439)</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>-4.598**</td>
<td>-4.860**</td>
<td>-3.070**</td>
<td>-4.830**</td>
<td>-5.398**</td>
<td>-4.038**</td>
</tr>
<tr>
<td></td>
<td>(0.312)</td>
<td>(0.334)</td>
<td>(0.301)</td>
<td>(0.843)</td>
<td>(0.910)</td>
<td>(0.719)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-3.410**</td>
<td>-3.965**</td>
<td>-0.990*</td>
<td>-2.338**</td>
<td>-2.879**</td>
<td>-0.713</td>
</tr>
<tr>
<td></td>
<td>(0.427)</td>
<td>(0.495)</td>
<td>(0.480)</td>
<td>(0.457)</td>
<td>(0.497)</td>
<td>(0.483)</td>
</tr>
<tr>
<td>Control Variables</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,448</td>
<td>2,363</td>
<td>2,098</td>
<td>2,418</td>
<td>2,334</td>
<td>2,082</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.763</td>
<td>0.741</td>
<td>0.769</td>
<td>0.795</td>
<td>0.777</td>
<td>0.794</td>
</tr>
<tr>
<td>Within R-squared</td>
<td>0.240</td>
<td>0.240</td>
<td>0.187</td>
<td>0.341</td>
<td>0.343</td>
<td>0.271</td>
</tr>
</tbody>
</table>
G 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 ($\beta$). Table G.2 uses OLS estimates, while Table G.1 uses Pseudo-Poisson regression estimates.

### Table G.1: Counterfactuals using Poisson regression Estimates (2017)

<table>
<thead>
<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>109.9</td>
<td>105.4</td>
<td>108.3</td>
</tr>
<tr>
<td>World GDP, % Difference in GDP from Zero-Gravity</td>
<td>-6.0%</td>
<td>0.0%</td>
<td>-4.1%</td>
<td>-1.5%</td>
</tr>
<tr>
<td>St.Dev. of $\log \left( \frac{k_i}{\ell_i} \right)$, % Difference from Zero-Gravity</td>
<td>101.5%</td>
<td>0.0%</td>
<td>58.4%</td>
<td>39.4%</td>
</tr>
<tr>
<td>St.Dev. of $\log \left( \frac{y_i}{\ell_i} \right)$, % Difference from Zero-Gravity</td>
<td>37.5%</td>
<td>0.0%</td>
<td>19.0%</td>
<td>16.3%</td>
</tr>
<tr>
<td>Welfare Statistics</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>--------------------------------------------------------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
</tr>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>109.7</td>
<td>103.0</td>
<td>108.2</td>
</tr>
<tr>
<td>World GDP, % Difference in GDP from Zero-Gravity</td>
<td>-5.8%</td>
<td>0.0%</td>
<td>-6.1%</td>
<td>-1.3%</td>
</tr>
<tr>
<td>St.Dev. of log ($k_i/\ell_i$), % Difference from Zero-Gravity</td>
<td>69.8%</td>
<td>0.0%</td>
<td>52.5%</td>
<td>37.2%</td>
</tr>
<tr>
<td>St.Dev. of log ($y_i/\ell_i$), % Difference from Zero-Gravity</td>
<td>19.8%</td>
<td>0.0%</td>
<td>9.2%</td>
<td>18.5%</td>
</tr>
</tbody>
</table>
H Unweighted Poisson regressions

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

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultural Distance</td>
<td>-2.295***</td>
<td>-1.827***</td>
<td>-2.922***</td>
<td>-1.406***</td>
<td>-0.987*</td>
<td>-1.978***</td>
</tr>
<tr>
<td></td>
<td>(0.473)</td>
<td>(0.553)</td>
<td>(0.447)</td>
<td>(0.433)</td>
<td>(0.542)</td>
<td>(0.508)</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>-2.537***</td>
<td>-2.284***</td>
<td>-3.014***</td>
<td>-4.374***</td>
<td>-4.677***</td>
<td>-3.065**</td>
</tr>
<tr>
<td></td>
<td>(0.245)</td>
<td>(0.254)</td>
<td>(0.318)</td>
<td>(0.747)</td>
<td>(0.706)</td>
<td>(1.217)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-1.541***</td>
<td>-1.417***</td>
<td>-2.034***</td>
<td>-0.439</td>
<td>-0.523</td>
<td>-0.783**</td>
</tr>
<tr>
<td></td>
<td>(0.263)</td>
<td>(0.265)</td>
<td>(0.330)</td>
<td>(0.291)</td>
<td>(0.354)</td>
<td>(0.372)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>1,508</td>
<td>1,690</td>
<td>2,259</td>
<td>1,375</td>
<td>1,534</td>
<td>2,077</td>
</tr>
</tbody>
</table>