Barriers to Global Capital Allocation

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December 2021
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Abstract

Observed patterns of international investment are difficult to reconcile with frictionless capital markets. In this paper, we provide a quantitative theory of international capital allocation: a multi-country dynamic general equilibrium model with rationally-inattentive investors, where cross-border investment is subject to both information and policy frictions. These frictions result in a persistent misallocation of capital across countries. We estimate model parameters using nationality-based, bilateral investment data, and measures of geographic, linguistic and cultural distance, which capture information frictions. Our unified 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 developed to emerging economies. Finally, we perform counterfactual exercises: 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.

JEL Codes: E22, E44, F2, F3, F4, G15, O4

Keywords: Capital Allocation, Foreign Investment, Geography, Gravity, Home Bias, Information Frictions, International Finance, Misallocation, Open Economy, Rational Inattention.

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We thank Julian Di Giovanni, John Leahy, Erik Loualiche, Moritz Lenel and Dmitry Mukhin for their excellent discussions at ASSA, NBER-IFM, the Colorado Finance Summit, EFA, and the Yale Junior Finance conference. We also thank Ariel Burstein, Manos Chatzikonstantinou, Max Croce, Thomas Drechsel, Wenxin Du, Henry Friedman, Tarek Hassan, Jean Imbs, Sebnem Kalemli-Özcan, Loukas Karabarbounis, Pete Kyle, Andrei Levchenko, Hanno Lustig, Vojislav Maksimovic, Stavros Panageas, Alessandro Rebucci, Luminita Stevens, and the participants of the UChicago International Macro-Finance Conference, the NBER IFM meeting, the Online IFM Seminar and numerous other seminars and conferences for helpful comments. Pablo Roa Prieto and Michele Schincaglia provided outstanding research assistance.

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, despite 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 display a high degree of home bias (French and Poterba, 1991; Coeurdacier and Rey, 2013) – that is, a disproportionate allocation of investment toward domestic assets. Can barriers to international investment explain these patterns? If so, what is their effect on allocative efficiency and the cross-country distribution of income?

In this paper, we provide a quantitative theory of international capital allocation in which cross-border investment is subject to informational and policy frictions. The model endogenously produces equilibrium bilateral asset positions that conform with a gravity equation. The equilibrium investment network is shaped by information frictions (captured by geographical, linguistic and cultural distances), as well as policy frictions, which include country-specific capital income taxes and political risk. We estimate the gravity equation econometrically using nationality-based international investment data that has been restated by Damgaard, Elkjaer, and Johannesen (2019) and Coppola, Maggiori, Neiman, and Schreger (2020) to correct for the presence of tax havens, such as Bermuda and the Cayman Islands.[1] We then use the estimates to calibrate our model and assess the implication of these barriers for the allocation of capital across countries.

We model informational barriers using insights from the literature on flexible information acquisition (Matějka and McKay, 2015; Denti, 2015; Yang, 2015). Investors based in different locations allocate their savings across destination countries via a rational inattention logit demand system, for which we find a new closed-form solution. Investors from each country do not know *ex ante* what is the expected return to capital in each destination country. We model this lack of knowledge using a prior distribution for the vector of expected returns. Investors can however obtain additional information about asset returns by acquiring a signal. This signal is not restricted to having a specific probability distribution, and is obtained by exerting some effort. The utility cost of effort is proportional to the informativeness of the signal. While agents can acquire information about returns in any country, they have an informational advantage for assets located in countries that are closer geographically, linguistically and culturally. As a result, equilibrium portfolios are biased toward these countries. In addition, taxes and expropriation risk affect the *ex post* return to capital investment across countries, further distorting the allocation of capital.

The resulting world allocation of capital is sub-optimal (in a GDP sense) and our model allows us to quantify, using counterfactual analysis, the resulting efficiency loss, as well as the marginal effect of various distortions on individual countries. Intuitively, the countries that bear the brunt of these barriers and biases tend to be the "peripheral" ones – that is, those farther removed from where most investors are geographically and culturally located. By contrast, more "central" countries are more likely to benefit from

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

the biases associated with informational obstacles. We extend our basic model along several dimensions, by incorporating various additional frictions - namely: frictions to trade in goods across countries; capital controls; country heterogeneity in the volatility of productivity shocks; and currency hedging costs (which capture currency risk).

Turning to the empirical analysis, we take our model to the data. We obtain three sets of results. First, information frictions (captured by geographic, cultural and linguistic distances) exert a strong influence on international asset positions. The effects are quantitatively 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. The latter is used to ensure that our estimates are not amplified by reverse causality. Our IV approach exploits the fact that differences in religion between populations have an impact on contemporary measures of cultural distance. These, in turn, act as current barriers to the global allocation of capital. In all our regressions, we include origin-country and destination-country fixed effects. Controls include trade costs, international agreements (customs-union, free-trade agreements, tax treaties, etc.), and a variety of additional geographical and historical variables, such as border contiguity, colonial relationship, common legal origin, and many others. In our robustness analysis, we check that our gravity estimates are robust to using different available time periods, residency-based data, and alternative methods of estimation.

Second, we find that a conservative calibration of the model produces realistic country-level portfolios and cross-sectional variation in the rates of return to capital across countries. In addition, despite the fact that we estimate our gravity equation without using any data on domestic investment, the model predicts out-of-sample, with great accuracy, the degree of home bias in each origin country's portfolio. Intuitively, home bias can thus viewed, through the lens of our model, as a direct implication of the gravity effect – more specifically, domestic investment corresponds to the "intercept" case where all distances are set to zero. Our estimates also match independently-measured differences in rates of return across countries. In particular, our model predicts that emerging economies and countries with a higher degree of home bias should exhibit higher rates of return on capital: these predictions are consistent with the empirical evidence (David, Henriksen, and Simonovska, 2014; Lau, Ng, and Zhang, 2010). Our model predicts persistent (steady-state) global imbalances; yet the predicted net asset positions correlate only weakly with country income levels, consistent with the data and with 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 to global capital allocation, World GDP is 5.9% lower. [2] An important result is that barriers to capital movements 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, and the dispersion in output per employee is 24% higher. Consistent with the intuition of our theory, the largest gains from removing informational

[2]The World GDP loss due to barriers to global capital allocation goes up to 7.6% when the model is extended to include frictions to international trade (which are not eliminated in the counterfactual analysis).

biases associated with geographic, linguistic and cultural barriers would accrue to developing countries in Africa, Asia and Latin America, which happen to be farther from the "center" of the international investment network – i.e. where most investors are 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 efficiency losses that disproportionally impact poorer countries. Thus, our theoretical and empirical framework can explain, within a unified and coherent setting, multiple 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 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.

This paper contributes 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 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), Jin (2012) and Gârleanu, Panageas, and Yu (2020).

In addition, our paper expands, in a new direction, the literature on rational inattention in macro-finance (Veldkamp, 2011; Mackowiak, Matejka, Wiederholt et al., 2020). We find a first non-trivial closed-form solution to the rational inattention logit model (Matějka and McKay, 2015; Caplin, Dean, and Leahy, 2019) and use it to micro-found an international asset demand system (Koijen and Yogo, 2020; Jiang, Richmond, and Zhang, 2020) where investors hold an information advantage for domestic assets. Specifically, in line with previous theoretical work by Van Nieuwerburgh and Veldkamp (2009), we have rationally-inattentive investors who choose not only how much to learn but also what assets to learn about: such directed information acquisition implies that home bias will persist despite the fact that investors can theoretically perfectly learn expected returns.[3] Our analysis is also more indirectly related to Dziuda and Mondria (2012), who, using a model of delegated asset management, show that the informational advantage of retail investors will translate into home bias if investors are uncertain about the portfolio managers' abilities.[4]

[3] A technical difference between Van Nieuwerburgh and Veldkamp (2009) and our model is that, while they assume a Quadratic-Gaussian random utility, we assume a Logit-Gamma specification, allowing us to derive a gravity equation.

[4] To keep our analysis simple, we do not to incorporate delegated asset management in our model. Extending our

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 resources 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).[5] Consistent with the more recent findings by Monge-Naranjo et al. (2019) and David, Henriksen, and Simonovska (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) found these welfare gains to be small. Our findings of large income and welfare effects from global capital misallocation do not contradict Gourinchas and Jeanne, but complement their approach. While they focus entirely on transition dynamics, we exclusively study steady-state capital misallocation. Hence, the two studies combined suggest that international capital frictions may 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. Leblang (2010) found that diaspora networks affect international investment, and argued that cultural ties increase trust and reduce information frictions. Relatedly, 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. Other contributions include Lane and Milesi-Ferretti (2008), Rose and Spiegel (2009) and 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, 2012, 2018; Guiso et al. 2009; Felbermayr and Toubal 2010; Fensore et al. 2017; Bove and Gokmen 2018).

This study complements a vast literature on open-economy financial macroeconomics that has largely focused on issues of hedging, portfolio diversification and currency risk (e.g. Hassan, 2013; David, Henriksen, and Simonovska, 2014; Lustig and Richmond, 2020; Maggiori, Neiman, and Schreger, 2020; Colacito and Croce, 2010; Itskhoki and Mukhin, 2021). In our baseline model, we abstract from portfolio diversification at the individual level, although equilibrium portfolios are diversified at the country level; among the extensions, we consider currency hedging costs and risk heterogeneity across countries. However, the focus of our contribution is on information and policy frictions, which, unlike risk, remain comparatively under-investigated in this literature.

Finally, as we find that barriers to international investment amplify cross-country dispersion of capital

framework to include portfolio managers is left for further research.

[5] The 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.

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), and many others.

2 A Theory of International Capital Allocation

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. For simplicity, our baseline model assumes away frictions to trade in goods. We incorporate frictions to trade across countries as an extension of the model 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. Total output is stochastic and equal to $(y_{it} + d_{it})$. By definition, y_{it} is the deterministic part, equal to

$$y_{it} \;=\; \omega_i \cdot k_{it}^{\kappa_i} \cdot \ell_{it}^{\lambda_i} \cdot x_{it}^{\xi_i} \tag{2.1}$$

where ω_i is country i's total factor productivity; k_{it} is the input of reproducible capital; ℓ_{it} is the labor input; x_{it} is the input of natural resources [6]. The parameters κ_i, λ_i and ξ_i, which are equal to the equilibrium income shares of reproducible capital, labor and natural resources (respectively), are allowed to vary across countries. The production function satisfies constant returns to scale:

$$\kappa_i + \xi_i + \lambda_i = 1 \tag{2.2}$$

d_{it} is a mean-zero random component, proportional to y_{it} as well as the capital share κ_i :[7]

$$d_{it} \;=\; (\zeta_{it} - 1)\, \kappa_i y_{it} \tag{2.3}$$

and ζ_{it} is a lognormal shock with expectation one and uniform variance.

Labor and natural resources cannot be moved across countries. Capital is the only mobile factor. Each unit of the final good can be: 1) used for consumption; 2) saved by young households and transformed into $1/\delta$ units of capital to be used for production in the next period;[8] 3) taxed by government (not necessarily

[6] Natural resources are included in our theoretical and empirical analyses in line with contributions by Caselli and Feyrer (2007) and Monge-Naranjo et al. (2019).

[7] This specification of the random component is made for analytical tractability: the resulting random and deterministic components of the rate of return on capital are log-separable.

[8] We assume that capital fully depreciates each period, so that all the capital available for next-period production must come from current-period production.

the domestic one) and converted into one unit of a public good. The global resource constraint is thus:

$$\sum_{i=1}^{n} (y_{it} + d_{it}) \;=\; \sum_{i=1}^{n} (c_{it} + q_{it} + \delta k_{it+1}) \tag{2.4}$$

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

The representative firm issues shares, which entitle capital investors to receive a proportion of the firm's residual capital income. The firm's objective is to maximize capital income:

$$\max_{\ell_i, x_i} \mathbb{E}\,(y_{it} + d_{it} - w_{it}\ell_{it} - m_{it}x_{it}) \tag{2.5}$$

We assume that the shock ζ_{it} is realized after wages and natural resource rents have been paid, but before capital receives its reward. Thus, capital holders are the residual claimants, i.e. they are the only agents to bear the incidence of the random component d_{it}. The equilibrium rental rate of natural resources (m_{it}) and wage rate (w_{it}) are determined in competitive markets as usual:

$$m_{it} \;=\; \xi_i \frac{y_{it}}{x_{it}}; \qquad w_{it} \;=\; \lambda_i \frac{y_{it}}{\ell_{it}}; \tag{2.6}$$

and the (residual) capital income is therefore ($\zeta_{it}\kappa_i y_{it}$). In addition, each country i exogenously imposes a (time-invariant) tax rate equal to $(1 - \tau_i)$ on capital income. All tax revenues in i go towards the production of the public good q_i. τ_i can be interpreted broadly, as a comprehensive measure that includes expropriation risk.

The net income per unit of capital invested (the rate or return earned by investors) is thus:

$$R_{it} \;\stackrel{\text{def}}{=}\; \tau_i\, \zeta_{it}\, \kappa_i \frac{y_{it}}{k_{it}} \tag{2.7}$$

and is log normally-distributed. We use the corresponding lowercase letter r_{it} to denote the expected (gross of tax) return:

$$r_{it} \;\stackrel{\text{def}}{=}\; \kappa_i \frac{y_{it}}{k_{it}} \tag{2.8}$$

2.2 Consumers-Workers-Investors

In what follows, we use index i to refer to the country where production takes place (the *destination* country), and 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. Agents live for two periods. They are endowed with ℓ_j units of labor in period t and they inherit natural resources x_j from the previous generation. In the first period, when they are young, they supply labor and natural resources inelastically.[9] In the second period, the return on the capital saved at time t is the old agents' only source of income.

[9] The assumption that only the young own natural resources is made for tractability: the saving decision is made by the young, separately from the asset allocation decision, which is made by the old.

Investors are atomistic, and invest their atom of capital in a single destination country i. International investment is subject to informational 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 information acquisition (Matějka and McKay, 2015; Denti, 2015; Yang, 2015): agents make their asset allocation decisions using limited information about expected returns.

We make the following assumptions on investor behavior. First, the stochastic shock ζ_{it} is unpredictable and unlearnable; that is, investors cannot acquire any information that allows to predict ζ_{it}. Second, the equilibrium expected returns, net of taxes ($\tau_i r_i$) are neither observed nor known to investors when they make their asset allocation decisions. From the investors' point of view, the expected returns are a random vector $\tilde{\mathbf{r}}_{t+1} \in \mathbb{R}_+^n$: we use the tilde notation $(\tilde{\cdot})$ to distinguish the unknown expected net return $\tilde{r}_{it}$ from the equilibrium mean return $\tau_i r_{it}$ and the realized return R_{it}, which includes the productivity shock.

Investors from country j are endowed with a prior distribution for $\tilde{\mathbf{r}}_{t+1}$, which we call $G_{jt}\left(\tilde{\mathbf{r}}_{t+1}\right)$: this is the only freely-available information that allows them to forecast the returns.[10] In order to obtain any additional information, they must acquire a costly signal.

The signal induces a posterior distribution for asset returns that we call $F_t\left(\tilde{\mathbf{r}}_{t+1}; z\right)$. Consistent with the literature on rational inattention, 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). Agents do, however, have to exert effort in order to acquire the additional information, and the resulting disutility is proportional to the informativeness of the signal.

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

$$\mathcal{U}(z) \quad = \quad (1-\theta_j)\log c_t(z) \; + \; \theta_j\,\mathbb{E}_t\left[\log c_{t+1}(z) - \mathcal{I}(z)\right] \; + \; \mathcal{V}_j\left(q_{jt}, q_{j,t+1}\right) \tag{2.9}$$

where $c_t(z)$ is agent z's consumption at time t and the patience parameter θ is allowed to vary by country. $\mathcal{V}_j\left(q_{jt}, q_{j,t+1}\right)$ is the expected utility value of the public good supplied by country j over the two periods. Because the public good and the tax rate enter the utility in a separable way, taxation does not distort saving (although it distorts asset allocation).

$\mathcal{I}(z)$ is the information acquisition cost incurred by z. Following the literature, we assume it is proportional to the incremental information content of the signal acquired by z, measured as the expected reduction in Shannon Entropy (H) between the posterior F and the prior G:

$$\mathcal{I}(z) \quad \stackrel{\text{def}}{=} \quad \frac{1-\sigma}{\sigma}\cdot\left[\mathrm{H}\left(G_{jt}\right) - \mathbb{E}_t\,\mathrm{H}\left(F_t(z)\right)\right] \tag{2.10}$$

The parameter $\sigma \in (0,1)$ captures the efficiency of the information processing technology: a higher value of σ is associated with a lower information processing cost.

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

[10] Specifically - and consistent with the rational inattention literature - each atomistic investor does not know how much other investors save, what their priors are, and what their information cost is.

is defined by the following two equations:

$$w_{jt}\ell_j + m_{jt}x_j \;=\; c_t(z) + s_t(z) \tag{2.11}$$

$$c_{t+1}(z) \;=\; \delta R_{t+1}(z)\, s_t(z) \tag{2.12}$$

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

$$\mathbb{E}_t\left[\frac{\theta_j}{c_{t+1}(z)} \cdot \delta R_{t+1}(z)\right] \;=\; \frac{1-\theta_j}{c_t(z)} \tag{2.13}$$

We look for a steady-state equilibrium, with constant capital, saving, expected output and expected returns $(\mathbf{k}_t,\ \mathbf{s}_t,\ \mathbf{y}_t,\ \mathbf{r}_t)$. We drop time subscripts when referring to steady-state solutions. By plugging (2.11) and (2.12) inside (2.13), we find that, in equilibrium, all investors save a constant share θ_j of their earnings in the initial period:

$$s_t(z) \quad\equiv\quad s_j \quad=\quad \theta_j\left(w_j\ell_j + m_j x_j\right) \quad=\quad \theta_j\left(\lambda_j + \xi_j\right) y_j \qquad \forall\,(j,t) \tag{2.14}$$

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:

$$k_i \;=\; \sum_{j=1}^{n} a_{ij}\,; \qquad\qquad s_j \;=\; \delta \sum_{i=1}^{n} a_{ij} \tag{2.15}$$

We next describe how investors allocate their capital across different countries. Let π_{ij} be the share of capital invested in country i as a percentage of country j's aggregate saving:

$$\pi_{ij} \overset{\text{def}}{=} \delta \cdot \frac{a_{ij}}{s_j} \tag{2.16}$$

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

$$\delta\mathbf{k} \;=\; \mathbf{\Pi}\,\mathbf{s} \quad : \qquad \begin{bmatrix} \delta k_1 \\ \delta k_2 \\ \vdots \\ \delta k_n \end{bmatrix} = \begin{bmatrix} \pi_{11} & \pi_{12} & \cdots & \pi_{n1} \\ \pi_{21} & \pi_{22} & \cdots & \pi_{n2} \\ \vdots & \vdots & \ddots & \vdots \\ \pi_{n1} & \pi_{n2} & \cdots & \pi_{nn} \end{bmatrix} \begin{bmatrix} s_1 \\ s_2 \\ \vdots \\ s_n \end{bmatrix} \tag{2.17}$$

2.3 Information Acquisition and Asset Allocation

We next describe how agents acquire information and allocate capital across countries – that is, how the matrix $\mathbf{\Pi}$ is determined in the steady-state equilibrium. We assume that capital investment is lumpy: an atomistic investor z in country j invests their savings by buying claims to the return on the capital stock of one country i.[11]

Investors receive the noisy signal, update their priors into posteriors in a Bayesian fashion, and choose the country that offers the highest log return in expectation.[12] Since investors within the same country have the same priors, in equilibrium they acquire identical signals. However, because the *realized* value of these signals will differ across investors, the choice of each individual investors is stochastic, even when we condition on the equilibrium expected returns. Define π_{ij}, the conditional probability that a generic investor from country j invests in country i:

$$\pi_{ij} \stackrel{\text{def}}{=} \Pr\left(z \in j \text{ selects country } i \mid \tilde{r}_i = \tau_i r_i\right) \tag{2.18}$$

where the conditioning is on the vector of equilibrium expected returns. By the seminal result of Matějka and McKay (2015), this probability takes the form:

$$\pi_{ij} = \frac{\left(\tau_i r_i\right)^{\frac{\sigma}{1-\sigma}} \cdot \pi_{ij}^0}{\sum_{\iota=1}^n \left(\tau_\iota r_\iota\right)^{\frac{\sigma}{1-\sigma}} \cdot \pi_{\iota j}^0} \tag{2.19}$$

where π_{ij}^0 is the *unconditional* probability of investing in country i, which satisfies the following version of the Law of Total Probability

$$\int_{\mathbb{R}_+^n} \frac{\tilde{r}_i^{\frac{\sigma}{1-\sigma}}}{\sum_{\iota=1}^n \tilde{r}_\iota^{\frac{\sigma}{1-\sigma}} \cdot \pi_{\iota j}^0} \,\mathrm{d}G\left(\tilde{\mathbf{r}}\right) \le 1 \qquad \forall\, i \in \{1, 2, ..., n\} \tag{2.20}$$

which holds with equality if country i is selected with positive probability.

In order to derive an expression for π_{ij}^0 , we need to make a parametric assumption on the prior distribution G. It has been known since Sims (2003) that there is a closed-form solution for the continuous-action, quadratic-Gaussian rational inattention choice problem. However, to the best of our knowledge, no closed-form solutions have been found for the rational inattention logit model, except for limiting cases.[13]

[11] While this may seem a strong assumption (individual atomistic investors are not allowed to diversify), it can be adopted in this context without much loss of generality, because our theoretical and empirical application is not focused on studying individual household behavior, but on producing realistic portfolios at the *country* level. When we aggregate the choices of all of the atomistic investors in each country, we do obtain realistic country-level portfolios that are consistent with an aggregate investor that has a strong diversification motive. What the discrete-choice micro-foundation buys us is the ability to incorporate informational frictions in a simple and tractable way. In fact, our foundational assumptions are conceptually analogous to those required in recent contributions on empirical asset demand systems, which are similarly built on a discrete-choice micro-foundation (Koijen and Yogo, 2020; Jiang et al., 2020).

[12] This is because the saving problem is separable from the information acquisition/asset allocation problem.

[13] Matějka and McKay (2015) proved that the unconditional probabilities π_{ij}^0 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 $\left(\frac{1-\sigma}{\sigma}\right)$.

Caplin, Dean, and Leahy (2019) show that conditions (2.19) and (2.20) are jointly necessary and sufficient to characterize a solution.

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 π_{ij}^0.

Proposition 1. *Assume the following prior beliefs for j-investors: $\tilde{r}_i^{\frac{\sigma}{1-\sigma}}$ follows a Gamma distribution with common mean $\mu_j > 0$ and heterogeneous precision $\varphi_{ij} > 0$, with independent draws for each country. Then* (2.19) *solves the rational inattention logit problem with unconditional probability*:

$$\pi_{ij}^0 = \frac{\varphi_{ij}}{\sum_{\iota=1}^{n} \varphi_{ij}} \tag{2.21}$$

Proof. In Appendix A we show that this solution satisfies (2.20), which is necessary and sufficient as shown by Caplin, Dean, and Leahy (2019). □

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 φ_{ij} is high. The share of $j-$savings that are invested in i-domiciliated assets are thus proportional to φ_{ij}.

Hence, the country-level portfolio shares take the following equilibrium values:

$$\pi_{ij} = \frac{(\tau_i r_i)^{\frac{\sigma}{1-\sigma}} \varphi_{ij}}{\sum_{\iota=1}^{n} (\tau_\iota r_\iota)^{\frac{\sigma}{1-\sigma}} \varphi_{\iota j}} \tag{2.22}$$

An improvement in the information processing technology - that is, a higher value of the parameter σ - increases the elasticity of the portfolio shares π_{ij} with respect to net returns $(\tau_i r_i)$. 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 $(\sigma \to 1)$, asset demand becomes infinitely elastic to return fundamentals and agents only invest in the country that offers the highest after-tax return. Conversely, when signals become prohibitively costly, the investors' asset demand becomes completely inelastic and they simply invest in the country for which they have the most precise prior information.

2.4 Formation of Prior Beliefs and Informational Advantage

To complete our model, we need to make an assumption about the "technology" that determines the investors' prior information – specifically, the precision φ_{ij}.[14] We assume that: 1) investors do not perfectly inherit all information learned by the previous generation;[15] 2) the amount of prior information that j-investors have about country i, measured by the precision φ_{ij}, is proportional to i's share of the

[14]How μ_j is determined is inconsequential, since the portfolio shares do not depend on it.

[15]Collin-Dufresne et al. (2017), in their review of the extensive literature on age-related learning bias, argue that "the young have more dispersed prior beliefs due to their shorter personal history" and show how this insight has important consequences for asset pricing. In our context, this helps motivate our assumption that the young (investors) have limited information on asset returns and that each generation has a new set of beliefs about *ex ante* returns.

world capital stock (K) in the previous period; 3) the prior precision φ_{ij} also depends negatively on a vector of distances $\mathbf{d}_{ij}$ between i and j. Formally:

Assumption. *The prior precisions for investors from country j, who are born at time t, are determined by the following law of motion:*

$$\frac{\varphi_{ijt}}{\sum_{\iota}\varphi_{\iota jt}} \propto \frac{k_{i,t-1}}{K_{t-1}} \cdot \exp\left(\mathbf{d}_{ij}'\beta\right) \tag{2.23}$$

where $\mathbf{d}_{ij} = \begin{bmatrix} d_{ij}^1 & d_{ij}^2 & \cdots & d_{ij}^D \end{bmatrix}'$ *is a* $\mathbb{R}_+^D$ *vector of distances between country i and country j and* $\beta < \mathbf{0}$ *is a* $\mathbb{R}_-^D$ *vector of precision-distance semi-elasticities.*

This specification means that investors have more precise prior beliefs (i.e., an informational advantage) about countries that are: 1) larger and more financially developed, as measured by their share of world capital; and 2) closer to them in terms of a range of distances. In other words, the precision of investors' prior decays with distance. $\mathbf{d}_{ij}$ is a vector (as opposed to a scalar) so that it can encompass not just geographic distance, but cultural and linguistic distance as well. In the literature on cross-border financial flows, unlike in the trade literature, these distance metrics are usually interpreted as capturing information frictions between origin and destination countries (see Portes and Rey, 2005). In Appendix I, we show that the components of $\mathbf{d}_{ij}$ can, isomorphically, be interpreted as capturing asset trade costs, i.e. intermediation costs that depend on the vector of distances $\mathbf{d}_{ij}$ and are incurred when investors purchase assets in the destination countries.

This way of modeling the investors' prior thus provides an information-theoretic micro-foundation for the gravity regression in international finance. Our specification reasonably captures two features of *ex ante* (free) information availability: the fact that people, as they grow up, are more likely to know more about bigger countries with larger financial markets as well as about societies that are closer to them along geographic, linguistic, and cultural lines. For example, Spanish investors, before they do any specific research about investment opportunities, are likely to know more about the US market than about the Canadian market. They are also more likely to have an informational advantage about the Portuguese market than about the market of another country with the same financial size as Portugal's, but at larger geographic, linguistic, or cultural distances from them.

This way of specifying prior beliefs has several appealing and reasonable properties. In particular, if we impose $\beta = \mathbf{0}$, equation (2.23) simplifies to:

$$\frac{\varphi_{ijt}}{\sum_{\iota}\varphi_{\iota jt}} = \frac{k_{i,t-1}}{K_{t-1}} \tag{2.24}$$

This case is of particular interest because, as we show formally later, when there are no cross-country differences in taxation ($\tau_i = \tau\ \forall i$), a lack of informational advantage results in capital being allocated efficiently (in a GDP-maximizing sense) across countries. Hence, by imposing this prior, we can start from an efficient benchmark model. We formalize the definition as follows.

Definition 1. We say that investors have *no informational advantage* if $\beta = \mathbf{0}$.

2.5 Calibrating the elasticity parameter σ

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 a pervasive feature of international portfolio investment – namely, that multi-country funds are benchmarked against market cap-weighted portfolios (such as the MSCI World Index). Consider for example the case where $\beta = \mathbf{0}$. Imposing $\sigma = 1/2$, the portfolio share π_{ij} is then equal to:

$$\pi_{ij} \; = \; \frac{\tau_i \, r_i \, k_i}{\sum_{\iota=1}^{n} \, \tau_\iota \, r_\iota \, k_\iota} \tag{2.25}$$

Because, in steady-state, the present discounted value of country i's capital is proportional to $\tau_i r_i k_i$, the portfolio share equation above is consistent with market value-weighting (in the case where $\beta \neq \mathbf{0}$, a similar relationship between portfolio shares and market cap would hold, but more distant countries would receive a smaller weight in the portfolio).

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

$$\frac{\partial \log \sum_j a_{ij}}{\partial \log r_i} \quad = \quad \frac{\sigma}{1-\sigma} \sum_j \frac{a_{ij}}{k_i} \left(1 - \pi_{ij}\right) \quad \approx \quad \frac{\sigma}{1-\sigma} \tag{2.26}$$

we can compare $\frac{\sigma}{1-\sigma}$ to empirical estimates of the demand elasticity with respect to returns.[16] $\sigma = 1/2$ implies a demand-returns elasticity close to one.

Koijen and Yogo (2020) estimate a demand system for international assets for the period 2002-2017, and report demand-yield semi-elasticities of 42 and 10.5, respectively, for long-term and short-term debt. 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, by multiplying 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 fall immediately to the left and right of 1, it seems natural to set $\frac{\sigma}{1-\sigma} = 1$.[17]

[16] Because we have 62 countries in our dataset, this approximation will be reasonably accurate even in the presence of significant domestic investment.

[17] The last (and most trivial) reason why we calibrate $\sigma = 1/2$ is that σ is restricted to be between 0 and 1: from a Bayesian perspective, if we impose a maximum entropy (uniform) prior for σ over this interval, any estimate of σ should be shrunk towards the mid-point of the range.

2.6 Gravity

By plugging (2.23) inside (2.22), and using the fact that country i's gross capital income is, in expectation, $r_i k_i = \kappa_i y_i$, the equilibrium portfolio shares can be re-written as follows:

$$\pi_{ij} = \frac{\tau_i \, r_i \, k_i \, \exp\left(\mathbf{d}'_{ij}\beta\right)}{\sum_{\iota=1}^{n} \tau_\iota \, r_\iota \, k_\iota \, \exp\left(\mathbf{d}'_{\iota j}\beta\right)} = \frac{\tau_i \, \kappa_i \, y_i \, \exp\left(\mathbf{d}'_{ij}\beta\right)}{\sum_{\iota=1}^{n} \tau_\iota \, \kappa_\iota \, y_\iota \, \exp\left(\mathbf{d}'_{\iota j}\beta\right)} \tag{2.27}$$

The denominator of equation (2.27) can be interpreted as a frictions-adjusted measure of the global market for capital that is available to country j investors. We call it M_j:

$$M_j \stackrel{\text{def}}{=} \sum_{\iota=1}^{n} \tau_\iota \, \kappa_\iota \, y_\iota \, \exp\left(\mathbf{d}'_{\iota j}\beta\right) \tag{2.28}$$

Multiplying both sides of equation (2.27) by s_j and using the fact that $s_j = \theta_j \left(\lambda_j + \xi_j\right) y_j$, equation (2.27) can be re-written with the total asset position a_{ij} on the left-hand side. These gross asset positions obey a gravity equation:[18]

$$\boxed{\textbf{Gravity}} \; : \quad a_{ij} = \tau_i \cdot \kappa_i \cdot \theta_j \cdot \frac{\lambda_j + \xi_j}{\delta M_j} \cdot \frac{y_i \cdot y_j}{\mathscr{D}_{ij}^2} \tag{2.29}$$

where $\mathscr{D}_{ij}^2 \stackrel{\text{def}}{=} \exp\left|\mathbf{d}'_{ij}\beta\right|$ is a composite metric of distance between i and j.

2.7 Global Capital Markets Clearing

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

$$\mathbf{\Pi} = \mathbf{\Pi}\left(\mathbf{r}\left(\mathbf{k}\right), \mathbf{\Phi}\left(\mathbf{k}\right); \mathbf{T}, \mathbf{\Lambda}, \mathbf{\Xi}\right) \tag{2.30}$$

$$\text{with} \quad \mathbf{\Phi} \stackrel{\text{def}}{=} \begin{bmatrix} \varphi_{11} & \varphi_{12} & \cdots & \varphi_{1n} \\ \varphi_{21} & \varphi_{22} & \cdots & \varphi_{2n} \\ \vdots & \vdots & \ddots & \vdots \\ \varphi_{n1} & \varphi_{n2} & \cdots & \varphi_{nn} \end{bmatrix}; \quad \mathbf{T} \stackrel{\text{def}}{=} \begin{bmatrix} \tau_1, & 0, & \dots & 0 \\ 0 & \tau_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \tau_n \end{bmatrix} \tag{2.31}$$

$$\mathbf{\Theta} \stackrel{\text{def}}{=} \begin{bmatrix} \theta_1, & 0, & \dots & 0 \\ 0 & \theta_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \theta_n \end{bmatrix}; \quad \mathbf{\Lambda} \stackrel{\text{def}}{=} \begin{bmatrix} \lambda_1, & 0, & \dots & 0 \\ 0 & \lambda_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \lambda_n \end{bmatrix}; \quad \mathbf{\Xi} \stackrel{\text{def}}{=} \begin{bmatrix} \xi_1, & 0, & \dots & 0 \\ 0 & \xi_2 & \dots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \dots & \xi_n \end{bmatrix} \tag{2.32}$$

Since $\mathbf{s}$ can be written as $\mathbf{\Theta}\left(\mathbf{\Lambda} + \mathbf{\Xi}\right)\mathbf{y}$ and $\mathbf{y}$ in turn can be written as a function of $\mathbf{k}$, equation (2.17)

[18] A gravity equation obtains even if $\sigma \neq 1$, in which case τ_i is replaced, within equation (2.29), by $\tau_i^{\frac{\sigma}{1-\sigma}} r_i^{\frac{\sigma}{1-\sigma}-1}$.

can be re-written as:

$$\delta\,\mathbf{k} \quad = \quad \mathbf{\Pi}\left(\mathbf{r}\left(\mathbf{k}\right),\mathbf{\Phi}\left(\mathbf{k}\right)\right)\cdot\mathbf{\Theta}\cdot\left(\mathbf{\Lambda}+\mathbf{\Xi}\right)\cdot\mathbf{y}\left(\mathbf{k}\right) \tag{2.33}$$

The market-clearing vector of equilibrium capital stocks $\mathbf{k}^*$ is then determined as the fixed point of equation (2.33). Notice that there is a trivial equilibrium at $\mathbf{k} = \mathbf{0}$. When we solve equation (2.33) numerically (in order to perform counterfactual analysis), we can rule out this 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:

$$c_j \;=\; \sum_{i=1}^{n} R_i a_{ij} + (1-\theta_j)\left(w_j \ell_j + m_j x_j\right) \tag{2.34}$$

and given that $q_j = \frac{1-\tau_j}{\tau_j} R_j k_j$ the following equation balances country j's current account:

$$\begin{aligned}
\underbrace{c_j + q_j + s_j - Y_j}_{\text{Net Imports}} \quad &= \quad \sum_{i=1}^{n} R_i a_{ij} - \theta_j\left(w_j \ell_j + m_j x_j\right) - \frac{1}{\tau_j} R_j k_j + q_j + s_j \\
&= \quad \underbrace{\sum_{i=1}^{n} R_i a_{ij} - R_j k_j}_{\text{Net Foreign Income}}
\end{aligned} \tag{2.35}$$

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 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.

We derive our efficiency results in terms of expected output, which is constant in the steady-state – i.e. we define World GDP (Y) as the sum of the country-level expected outputs:[19]

$$Y \quad \stackrel{\text{def}}{=} \quad \sum_{i=1}^{n} y_i \tag{2.36}$$

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

Definition 2 (Efficient Capital Allocation)**.** We say that an allocation $\mathbf{k}$ is *efficient* if it maximizes World

[19]The stochastic components d_{it} have mean zero, so their sum becomes negligible as the number of countries becomes large.

GDP Y given world capital $K \stackrel{\text{def}}{=} \sum_{i=1}^{n} k_i$, that is:

$$\mathbf{k} \in \arg\max_{\mathbf{k}'} Y\left(\mathbf{k}'\right) \quad \text{s.t.} \quad \sum_{i=1}^{n} k_i' = \sum_{i=1}^{n} k_i \tag{2.37}$$

The first useful result is that the absence of informational advantage produces a CAPM-type environment, where all origin countries hold identical portfolios.

Proposition 2. *If asset markets are in equilibrium and there is no informational advantage, all origin countries j hold identical portfolios of foreign assets (π_{ij} is independent of j).*

Proof. If there is no information advantage, the portfolio shares simplify to equation (2.25), which does not depend on j. □

One implication of Proposition 2 is that, in the absence of informational advantage, we should observe no home bias. Using this fact, we can 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.[20]

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

1. *Capital is efficiently allocated*
2. *Gross rates of return are equalized across countries ($r_i = r \quad \text{for} \quad i = 1, 2, ..., n$)*
3. *Taxes are optimally set – that is, the vector of taxes τ satisfies the following condition:*

$$\sum_j \frac{\tau_i^{\frac{\sigma}{1-\sigma}} \varphi_{ij} s_j}{\sum_{\iota=1}^{n} \tau_\iota^{\frac{\sigma}{1-\sigma}} k_\iota \varphi_{\iota j}} = \mathscr{C} \qquad \text{for } i = 1, 2, ..., n \tag{2.38}$$

where $\mathscr{C}$ is some strictly-positive constant.

Corollary 1. *For a fixed global capital stock K, there is a unique efficient allocation $\mathbf{k}^*$.*

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. □

Intuitively, the condition outlined in equation (2.38) requires that tax rates perfectly offset 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 that therefore find it harder to attract capital due to information frictions. This implies that it is possible to attain the first-best allocation

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

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 next show formally that capital *misallocation* manifests itself as cross-country dispersion in the (gross) rate of return on capital (similar to Baqaee and Farhi, 2020).

Proposition 3. *Consider a generic allocation* $\mathbf{k}$ *and the corresponding efficient allocation* $\mathbf{k}^*$ *(i.e. one that entails an unchanged level of the global capital stock* K*). The percent difference in world GDP between* $\mathbf{k}$ *and* $\mathbf{k}^*$ *is equal – to a second order Taylor approximation – to:*

$$\frac{Y(\mathbf{k}) - Y(\mathbf{k}^*)}{Y(\mathbf{k}^*)} \quad \approx \quad -\frac{1}{2} \cdot \mathbb{E}^{y_i}\left(\frac{\kappa_i}{1-\kappa_i}\right) \cdot \mathbb{V}^{\mathcal{W}_i}(\log r_i) \tag{2.39}$$

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

$$\mathcal{W}_i \overset{\text{def}}{=} \frac{\kappa_i}{1-\kappa_i} \cdot y_i \tag{2.40}$$

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 trade frictions, capital controls, currency hedging costs, and country-level heterogeneity in the volatility of shocks. In that section, we also explore the empirical implications of allowing for such 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 estimation of the investment-distance semi-elasticities β. We conclude the section by outlining our econometric strategy to recover β.

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 (ℓ_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 (λ_i). We complement this data, when missing, with estimates from the International Labor Office (ILO) Department of Statistics. Finally, we calibrate θ_i, the savings rate, using savings rates from the Penn World Tables (investment as a ratio of consumption plus investment).

The last data ingredient is the natural resources rents as a percent of GDP (ξ_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, τ_i, captures four factors: 1) corporate income taxes; 2) taxes on dividends; 3) taxes on interest income; 4) political risk (i.e. probability of expropriation). This composite tax rate is constructed using the formula:

$$\tau_i \;=\; \tau_i^{\text{Tax}} \times \tau_i^{\text{PR}} \tag{3.1}$$

$$\text{where} \qquad \tau_i^{\text{Tax}} \;=\; \left(\frac{\text{EBT}}{\text{EBIT}} \times \tau_i^{\text{Corp}} \times \tau_i^{\text{Div}} + \frac{\text{Interest}}{\text{EBIT}} \times \tau_i^{\text{Int}} \right) \tag{3.2}$$

τ_i^{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. τ_i^{Div} and τ_i^{Int} are measured as withholding tax rates on (respectively) dividends and interest income from the Tax Research Platform of the International Bureau of Fiscal Documentation (IBFD).[21]

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 2017 US Census' quarterly financial reports, where (for a broad set of industries) 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 τ_i^{PR}, which reflects political risk. We measure it by combining a composite measure produced by the International Country Risk Group (ICRG) with empirical estimates from Alfaro, Kalemli-Ozcan, and Volosovych (2008, henceforth AKV), who estimate econometrically the sensitivity of foreign investment inflows (in millions of US$) to this measure of country risk. The ICRG index ranges from zero (extreme political risk) to ten (virtually no political risk).[22]

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

$$\log \tau_i^{\text{PR}} \;=\; \beta_{\text{AKV}} \left(\text{ICRG}_i - 10\right) \tag{3.3}$$

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

[21] As an alternative to statutory tax rates on corporate, dividend and interest income, we also use effective tax rates on capital recently compiled by Bachas et al. (2021). The corresponding calibration results, which are available upon request, are largely unchanged compared to those obtained using statutory rates.

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

3.2 Bilateral Variables

3.2.1 Dependent Variables: Restated Foreign Investment Data

One way we update the empirical literature on gravity in foreign investment is by using recently-developed foreign investment data that accounts 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 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, to convert 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.[23]

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 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.

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[23] 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.

Figure 1: Foreign Equity and Debt Investment (2017)

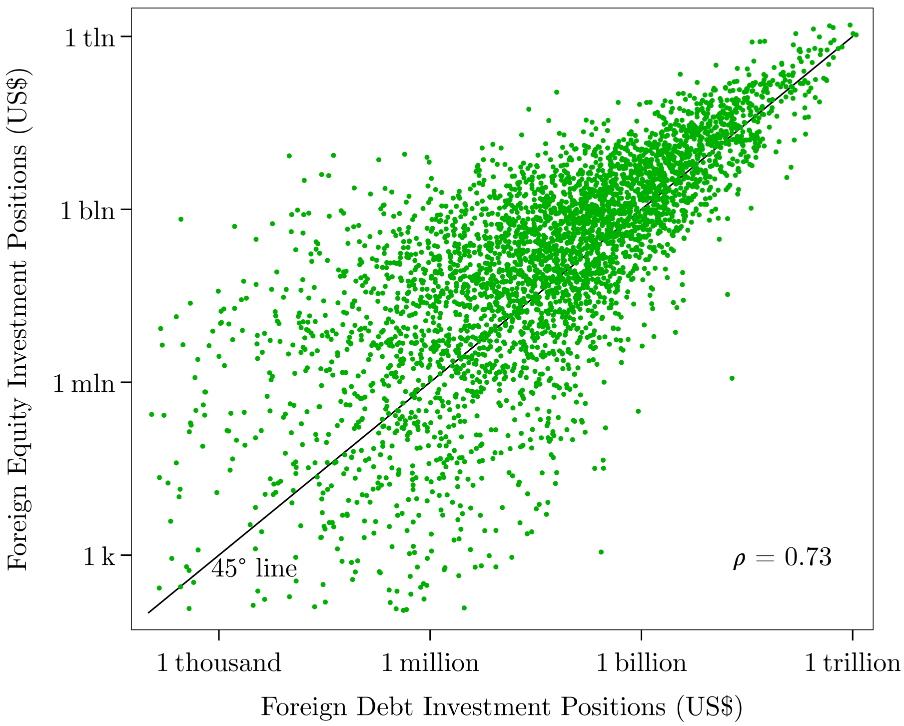

Figure Notes: This figure plots restated Foreign Equity Investment against restated Foreign Debt Investment. Each observation is a country pair and all data refer to the year 2017. The unit of measurement is US dollars at current prices. Log scale on both axes.

3.2.2 Distance Metrics

Informational advantage is captured, in our model, by the distances vector $\mathbf{d}_{ij}$. Empirically, this vector includes measures of cultural, geographic and linguistic distance.[24] We also consider religious distance as a historical determinant of cultural 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

[24]These variables are typically interpreted as capturing information frictions in the literature on the determinants of cross-border financial holdings (Portes et al., 2001). To further buttress the case that these variables capture such information frictions, we explored empirically their effect on the Social Connectedness Index, which is based on Facebook data (Bailey et al., 2021). We found that cultural, linguistic and geographic barriers bear an economically and statistically significant relationship with social connectedness. These results are available upon request, and a more complete analysis of the relationship between these indicators and the extent of information linkages is left for future research.

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 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.

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). These measures are constructed using historical trees. 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-Indo-European 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).[25] 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 $\mathbf{d}$. Its effect on capital positions can be interpreted more broadly as that of information frictions arising from cultural differences, to the extent that these are not fully captured by *Cultural Distance*.

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. As we will see, in our empirical analysis, we use religious distance as an instrument for *Cultural Distance*. That is, we assume that the only way more distant religious histories affects barriers to global capital allocation is through their contemporary effects on differences in values, norms and attitudes - including different attitudes towards religion and morale, which are captured in our measure of *Cultural Distance* based on the World Values Survey.[26]

[25]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.

[26]For the empirical analysis, all the measures of distance - geographic, cultural, linguistic and religious - were re-scaled to the $[0, 1]$ interval so that their respective effects can be compared to each other..

3.2.3 Control Variables

We use a variety of additional bilateral measures as control variables. Among them are several related to geography - *Border Contiguity*, *Latitudinal Distance* and *Longitudinal Distance*. We also consider variables called *Colonial Relationship* - capturing whether two countries in a pair were ever in a colonizer-colonized relationship, and *Common Colonizer*, denoting whether the two countries in a pair ever had a common colonizer.[27] In addition, we construct a bilateral dummy variable – *Common Legal Origin* - that captures whether i and j's legal systems come from the same legal tradition, based on the taxonomy of La Porta, Lopez-de Silanes, and Shleifer (2008).

We obtain the control dummy variable *Currency Peg* (which captures the presence of a de-jure fixed exchange rates arrangement) from the dataset of foreign exchange regimes of Harms and Knaze (2021). We use data points from year 2017. The variable *Currency Peg* is a dummy that evaluates to one if i and j have the same official currency or in the presence of a currency peg, either direct or indirect (such as two currencies being pegged to the same currencies). We also obtained, from the World Bank's International Center for the Settlement of Investment Disputes (ICSID), data on the presence of bilateral investment treaties, which we code as the dummy variable *Investment Treaty*.[28] In addition, we control for the presence of a *Tax Treaty*, using a dummy variable from Petkova, Stasio, and Zagler (2019).

To control for trade policy, we obtain data on regional trade agreements (RTAs) and their member countries from the WTO websites. We construct bilateral dummy variables representing joint memberships in *Customs Union*, *Free Trade Agreements*, and *Economic Integration Agreements* as of 2017. Finally, we control for a measure of *Trade Costs*, because trade costs can induce changes in international investment. For instance, high trade costs can spur FDI in an effort to "jump" tariffs. Or, on the contrary, there may be complementarities between trade in capital and trade in goods: the return to investment in a foreign country may be lower if exporting from the destination is costly, or if the investment requires paying tariffs to import capital goods into the destination country. The source of the trade cost data is the ESCAP-World Bank Trade Cost Database (2020), as initially developed in Novy (2013). This paper derives time-varying bilateral trade costs from a gravity model, which is solved analytically so that trade costs can be inferred using observed trade data. The ESCAP-World Bank Trade Cost Database[29] updates these calculations periodically, and estimates of trade costs are now available for a wide set of country pairs over the 1995-2018 period. We use the "undirected" trade cost measure – i.e. the geometric average of the wedge on import and export – for consistency (our explanatory variables are all undirected) and in order to avoid dropping too many observations.

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

[27]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.

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

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

Table 1: Summary Statistics

Panel A: Directed (Dependent) Variables

	Observations	Mean	StDev	Min	Max
Foreign Assets (US$ mln)	2,789	17,620	96,265	0	1,940,000
Foreign Equity Assets (US$ mln)	2,805	11,970	70,655	0	1,470,000
Foreign Debt Assets (US$ mln)	3,511	4,495	28,262	0	488,408

Panel B: Undirected (Independent) Variables

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

bilateral level, there are 69 countries, therefore $69 \times 69 = 4,761$ directed country pairs-observations (including diagonal i-to-i pairs) or 2,346 undirected country pairs. Table 1 displays summary statistics for the bilateral data.[30]

3.4 Estimating β : the Empirical Gravity Equation

Having already calibrated σ, we have β and δ left to calibrate. β is the vector of semi-elasticities of the precision of the investors' prior with respect to distances. We obtain β econometrically by estimating a

[30]The country-level sample is a subset of the bilateral sample. Five countries drop out due to lack of 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.

gravity regression.

On the left-hand side, we put bilateral restated asset positions data from the IMF, which we call $\hat{a}_{ij}$. This data (which originates from a survey) contains measurement error and is measured in nominal dollars. In our model, asset positions are measured in units of consumption in the current period (i.e. in PPP dollars). Assuming that capital flows are observed with a multiplicative error term that is independent of the distance vector ($\mathbf{d}_{ij}$) and letting p_j be the PPP adjustment factor for country j (not modeled explicitly until Section 7), we can write:

$$\hat{a}_{ij} \;=\; p_j \cdot a_{ij} \cdot \exp\left(\varepsilon_{ij}\right) \qquad \text{with} \qquad \varepsilon_{ij} \perp \mathbf{d}_{ij} \tag{3.4}$$

we can then re-write the gravity equation (2.29) as the following fixed effects linear regression model for the log of foreign investment:

$$\log \hat{a}_{ij} \;=\; \alpha_i + \gamma_j + \mathbf{d}_{ij}'\beta + \varepsilon_{ij} \tag{3.5}$$

where α_i is a country of origin fixed effect, γ_j is a country of destination fixed effect and

$$\alpha_i \;\stackrel{\text{def}}{=}\; \log\left(\tau_i \kappa_i y_i\right) \qquad \text{and} \qquad \gamma_j \;\stackrel{\text{def}}{=}\; \log\left[\theta_j\left(\lambda_j + \xi_j\right) p_j y_j\right] - \log\left(\delta M_j\right) \tag{3.6}$$

Fixed effects also absorb additional country of origin (i) and country of destination (j) factors or measurement error that are not explicitly modeled.

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 (*Foreign Assets*).[31] To capture $\mathbf{d}_{ij}$, we propose a parsimonious specification based on three measures of distance: *Geographic Distance, Cultural Distance* and *Linguistic Distance.*

Because the vector of distances $\mathbf{d}_{ij}$ 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.

4 Econometric Analysis

In this section, we estimate the parameter vector β, 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.

[31] 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 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

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

Table Notes: This table reports OLS estimates of a linear regression of a linear regression of the log of the variable listed on the top row (*Foreign Assets*, *Foreign Equity Assets*, *Foreign Debt Assets*) on the variables in the leftmost column, using data from 2017. Each observation is a directed country pair. All regressions include origin country (i) fixed effects and destination country (j) fixed effects. Additional controls in columns 4-6 are *Border Contiguity, 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. $^{*}p < .05$; $^{**}p < .01$

4.1 Least Squares Analysis

We begin by performing an OLS regression of the log of foreign investment (debt, equity or total) on the three distance measures, 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 an increase of one standard deviation 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 increase of one standard deviation in geographic distance (0.237 units) is associated with a 66.9% decrease in Foreign Assets, an increase of one standard deviation in cultural distance (0.162 units) is associated with a 49.1% decrease in Foreign Assets, while an increase of one standard deviation 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 geographic variables (border contiguity, 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, investment treaty, tax treaty and trade costs). The coefficient estimates on cultural, linguistic 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.[32]

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:

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

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. In order to avoid using a highly-inefficient estimator (as a consequence of the high degree of heteroskedasticity present in the residuals of this equation), we weigh observations by the inverse of the geometric mean of the GDPs of countries i and j (un-weighted estimates, which have larger standard errors, are shown in Appendix 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%).

[32]The estimates on the distance variables are also robust to directly including a measure of goods trade flows on the right-hand side of the specification (estimates are available upon request). The magnitudes of the semi-elasticities become somewhat smaller, due to the collinearity between trade and distance, but the distance measures remain statistically significant at the 1% level after the inclusion of goods trade. Trade in goods and foreign asset holdings are simultaneously determined, however, so we exclude goods trade from our baseline specification due to endogeneity concerns.

Table 3: Pseudo-Poisson Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable:	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-3.658**	-3.177**	-4.249**	-2.649**	-2.312**	-3.039**
	(0.356)	(0.401)	(0.453)	(0.366)	(0.433)	(0.412)
Geographic Distance	-3.056**	-2.965**	-2.701**	-4.317**	-5.181**	-2.368**
	(0.214)	(0.226)	(0.336)	(0.757)	(0.886)	(0.685)
Linguistic Distance	-1.456**	-1.995**	-1.303**	-0.384	-1.101**	0.212
	(0.296)	(0.246)	(0.333)	(0.295)	(0.341)	(0.340)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	2,754	2,770	3,459	2,754	2,770	3,459

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, 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. $^{*}p < .05$; $^{**}p < .01$

Table 3 displays the resulting estimates. In general, we find that the standardized magnitude of Poisson estimates on geographic and linguistic distances are slightly smaller than the corresponding OLS estimates, but that the magnitude of most effects is commensurate with that obtained under OLS. 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%. Broadly speaking, a consideration of the extensive margin does not greatly affect our basic finding that geographic, linguistic and cultural barriers exert quantitatively meaningful and statistically significant negative effects on foreign asset holdings.

4.3 Instrumental Variables Regressions

A challenge in estimating the effect of cultural distance on bilateral investment positions is the possibility of 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.[33] In that case, the OLS

[33] For obvious reasons, reverse causality is not an issue for geographic distance. Linguistic distance is also treated as exogenous in our empirical analysis, as it resulted from a long-term historical process that took place almost entirely in

TABLE 4: FIRST-STAGE REGRESSIONS

	(1)	(2)
	Cultural Distance	Cultural Distance
Religious Distance	0.341**	0.305**
	(0.030)	(0.028)
Geographic Distance	0.097**	0.048
	(0.020)	(0.047)
Linguistic Distance	0.173**	0.138**
	(0.035)	(0.031)
Control Variables	No	Yes
Observations	2,209	2,181
R-squared	0.672	0.734
Within R-squared	0.229	0.373
Kleibergen-Paap Wald F statistic	129.450	115.972
Cragg-Donald Wald F statistic	250.065	217.209
Stock & Yogo Critical Value (r=10%)	16.38	16.38

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, 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. $^*p < .05$; $^{**}p < .01$

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

pre-modern times and is unlikely to have been influenced by contemporary investment decisions.

Table 5: Instrumental Variables Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable in logs:	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-5.858**	-5.730**	-4.742*	-5.452**	-5.249**	-3.571
	(1.386)	(1.433)	(2.111)	(1.589)	(1.631)	(3.117)
Geographic Distance	-4.484**	-4.694**	-3.072**	-4.707**	-4.934**	-2.567*
	(0.373)	(0.389)	(0.462)	(0.992)	(0.970)	(1.054)
Linguistic Distance	-2.861**	-3.332**	-1.227	-1.796**	-2.230**	-0.007
	(0.548)	(0.582)	(1.050)	(0.599)	(0.614)	(1.292)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	2,209	2,181	1,320	2,181	2,153	1,297
Within R-squared	0.235	0.233	0.103	0.320	0.332	0.171

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, 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. $^{*}p < .05$; $^{**}p < .01$

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 instrument is 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.[34]

[34]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

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 a one standard deviation increase 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

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. To make the exposition simple, we take our model to the data assuming that the observed country-level data reflects the non-stochastic steady state – that is, $\zeta_{it} = 0$ and $R_{it} = \tau_i r_i$ in the cross section of the data that we observe (corresponding to the year 2017).[35]

5.1 Model Solution and Identification

We calibrate the distance semi-elasticities (β) using the 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).[36]

The only other parameter to calibrate is δ: we select its value to perfectly match the cross-country means of $\log k_i$ and $\log r_i$ (it's straightforward to show that, by matching one we match the other). Armed with empirical estimates for β and having calibrated σ and δ, we now solve the model.

Capital being the only moving factor, to solve the model means to find the country-level total asset stocks $\mathbf{s}$, the network of portfolio shares $\mathbf{\Pi}$ and (by extension) the vector of capital stocks $\mathbf{k}$. 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

of the instrumental variables is uncorrelated with error in measurement of the instrumented (endogenous) regressor.

[35]Alternatively, we can extract the shocks ζ_{it} and recover expected output. Because $R_{it} \equiv \zeta_{it}\mathbb{E}(R_{it})$, the shock can be recovered by dividing the marginal product of capital from PWT/World Bank in 2017 by its time series average (country-by-country). We would then have to distinguish, in our empirical and counterfactual analysis, between expected returns and realized returns to capital, and between expected and realized GDP, adding significant complexity to the exposition. We have implemented this alternative mapping of the model: because ζ_{it} has mean one, the resulting empirical findings are very close to those of the baseline model. They are available upon request.

[36]In Section 7, we examine the sensitivity of the counterfactual analysis to the use of alternative estimates of β, finding that such alternatives deliver broadly similar results to those in the benchmark exercise.

one single term $\hat{\omega}_i$:

$$y_i \quad = \quad \hat{\omega}_i \, k_i^{\kappa_i} \tag{5.1}$$

where

$$\hat{\omega}_i \quad \stackrel{\text{def}}{=} \quad \omega_i \, x_i^{\xi_i} \, \ell_i^{\lambda_i} \tag{5.2}$$

First, we compute country-level savings (s_i) from (observed) output y_i using equation (2.14). Second, we compute the matrix of portfolio shares $\mathbf{\Pi}$, given the income shares ($\kappa_i, \lambda_i, \xi_i$), output ($y_i$), taxes ($\tau_i$) and ($\varphi_{ij}$) using equation (2.27). $\mathbf{k}$ is then obtained as $\frac{1}{\delta}\mathbf{\Pi s}$. The residual model component that remains to be identified is $\hat{\omega}_i$: this is obtained from equation (5.1).

5.2 Model Fit

To evaluate the model's empirical performance, we want to compare untargeted data moments generated by the model against their empirical counterparts. 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 variants of our model that act as benchmarks in evaluating model fit. They are both identical to the baseline model, except for asset demand – i.e., the portfolio shares π_{ij} – which we assume to be an exogenously-determined function. In the first of these two benchmarks, the "frictionless" model, 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's (gross) capital income (see Lemma 2). In the second benchmark model – the "residuals" model – we go to the opposite extreme, and use the gravity regression residuals as additional frictions of undetermined origin. This allows us to perfectly fit the observed portfolio shares (after imputing missing values). Let the $\hat{\pi}_{ij}$ be the empirical (i, j) portfolio share implied by the IMF data.[37]

$$\hat{\pi}_{ij} \;=\; \frac{\hat{a}_{ij}}{\sum_{\iota=1}^{n} \hat{a}_{\iota j}} \tag{5.3}$$

To estimate it, we fill missing values of the bilateral investment data using the fitted values of equation (3.5). The resulting portfolio shares for the two benchmark models are then defined as:

$$\pi_{ij}^{\text{FL}} \;=\; \frac{\kappa_i \, y_i}{\sum_{\iota=1}^{n} \kappa_\iota \, y_\iota} \qquad\qquad \pi_{ij}^{\text{Res}} \;=\; \frac{\mathcal{E}_{ij} \, \kappa_i \, y_i}{\sum_{\iota=1}^{n} \mathcal{E}_{ij} \, \kappa_\iota \, y_\iota} \tag{5.4}$$

where $\mathcal{E}_{ij} \;=\; \hat{\pi}_{ij} / \pi_{ij}^{\text{FL}}$. We start evaluating our model by looking at how well it can fit the empirical portfolio shares ($\hat{\pi}_{ij}$), which are by construction identical to the portfolio shares of the residuals model $\left(\pi_{ij}^{\text{Res}}\right)$. In Figure 2, we compare the portfolio shares from the baseline model and the residuals model to

[37]By plugging equation (3.4) into equation (5.3), it is easily verified that any PPP adjustment at the country of origin level leaves portfolio shares unchanged.

Figure 2: Model Fit: Portfolio Shares (Targeted)

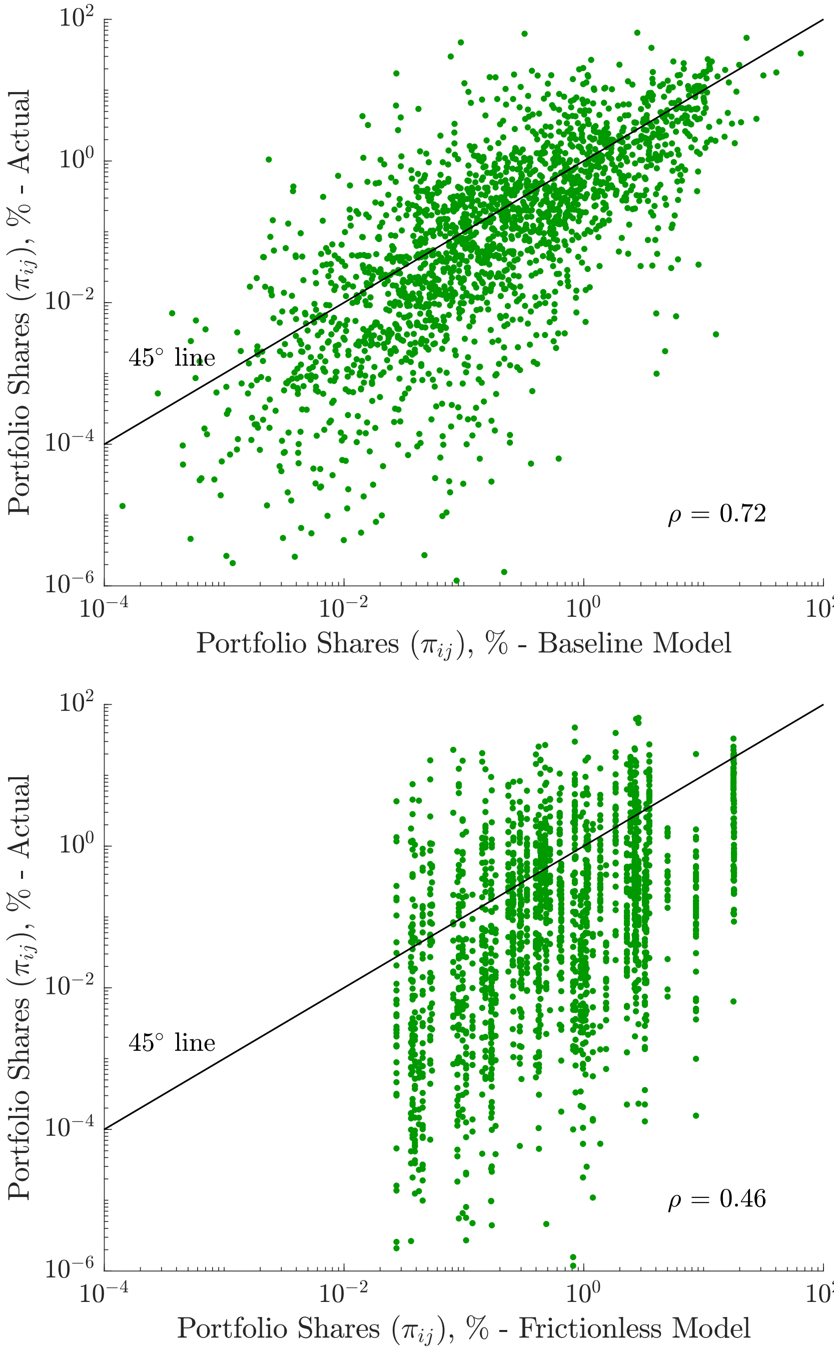

Figure Notes: the figure above plots the model-implied portfolio shares (π_{ij}), in percentage, against the actual ones, computed using IMF restated data. Every dot is a country pair. Country pairs where the IMF data was missing and had to be imputed are excluded. The model portfolio shares of the top panel are from the baseline, while those from the bottom panel are from the benchmark "frictionless" model.

Table 6: Model Fit: Untargeted Moments

Variable	Statistic	Data	Model: Baseline	Model: Frictionless	Model: Residuals
Return on Capital $\log(r_i)$	Mean	-2.281		- Targeted (δ) -	
	Standard Deviation	0.465	0.578	0.000	0.834
	Correlation w/Data	1.000	0.604	0.000	0.454
Capital/Employee $\log(k_i/\ell_i)$	Mean	12.270		- Targeted (δ) -	
	Standard Deviation	1.062	1.189	0.761	1.326
	Correlation w/Data	1.000	0.917	0.922	0.826
Home Bias $\log \pi_{ii} - \log \frac{k_i}{K}$	Mean	3.729	4.084	0.000	3.708
	Standard Deviation	1.241	1.085	0.000	1.022
	Correlation w/Data	1.000	0.870	0.000	0.732

the empirical ones (respectively, in the upper and lower panel). In producing this Figure, we take care of excluding country pairs whose dollar investment figure (a_{ij}) had to be imputed, as these observations might artificially inflate the fit of the baseline model.

The upper panel shows that the baseline model can match the empirical portfolio shares with a correlation (ρ) of 0.72. As this level of fit was obtained by only very few explanatory variables, we judge this to be a good fit. Because β is obtained by fitting bilateral asset positions, we consider this data moment "targeted."

By comparing the fit of the baseline model with that of the frictionless model, we can get a clear idea of how important policy and information frictions are in obtaining a good fit. Looking at the lower panel, we can clearly see that the fit of the frictionless model is significantly worse ($\rho = .46$). The fit of the frictionless model indicates two things: 1) destination country size (the only force shaping the frictionless portfolios) is clearly important to match the empirical portfolio shares;[38]; 2) market size is also insufficient to explain country portfolios. Policy and information frictions play an equally important role. The lower panel of Figure 2, which shows the fit of the frictionless model, displays a patter made of vertical lines. This pattern is entirely expected: by Proposition 2, a frictionless model will produce portfolio shares that are symmetric across origin countries (each origin country j allocates savings identically). For this reason, we can infer that each "vertical line" corresponds to a specific destination country i. The bilateral information frictions, crucially, allow us to break this symmetry and thus to fit the country portfolios to a much more satisfactory degree.

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),

[38]This is consistent with the findings of Portes and Rey (2005).

capital per employee (k_i/ℓ_i) and home bias, which we define (following Lau, Ng, and Zhang, 2010) as

$$\text{Home Bias}_i \quad \stackrel{\text{def}}{=} \quad \log \pi_{ii} - \log \frac{k_i}{K} \tag{5.5}$$

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. Rates of return on capital are 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. To compute Home Bias, we use the estimates of Lau, Ng, and Zhang (2010) of the percentage of local funds' holdings in domestic securities as the estimate for π_{ii}, and Penn World Tables' estimates of k_i/K.[39]

Overall, the baseline model comes closest to matching the data. As implied by the theorem in section 2, the Frictionless model does not produce any variation in rates of return. The Residuals model, on the other hand, overshoots the variance displayed by the empirical data. The baseline model comes close to matching the dispersion in returns. In addition, its empirical rates of return correlate more closely with the data than those from the Residuals model.

Similar results obtain for capital stock/employee. This data moment is redundant with respect to the first, in the sense that if we can perfectly match capital stocks, by construction we also match perfectly the rates of returns.[40] We nonetheless display it to make the point that, in terms of model fit, it is more informative to think about rates of return than capital stocks.

As implied by our theory, the Frictionless model does not generate any home bias, while both the Baseline and the Residuals model produce a large home bias. Given that our gravity equation loads negatively on measures of cultural and geographic distance, the fact that our model predicts some degree of home bias is not entirely surprising. What is unexpected is that our model is capable to match not only the overall level of home bias, but the specific value for each individual country with striking accuracy. Home bias in our model matches the data in both average magnitude (4.08 vs. 3.73) and cross-sectional dispersion (1.09 vs. 1.24) and the data-model correlation is 0.87. As shown in Figure 3, the only country for which our model's predicted value differs significantly from the empirical value is Ireland: this is easily explained by Ireland's role as a tax haven.[41] Because the frictionless model fails to generate any home bias at all, we are sure that the ability of our model to match home bias (as well as the cross section of

[39] Lau, Ng, and Zhang (2010) produce their own estimates of home bias using stock market capitalizations to proxy for k_i/K. These estimates are however not suitable for our analysis, because market caps dramatically overestimate the capital stock share of countries with well-developed stock markets (the US market cap share is 44%, nearly three times its capital stock share, which is 17%). Due to this conceptual difference, it is mathematically impossible for our model to exactly match LNZ's home bias figures for the US and China: we have verified that, to do so, our model would have to generate domestic investment shares above 100% for these two countries. Nonetheless, we have compared our Home Bias figures against the raw home bias figures from LNZ for robustness, and – still – we have found a very strong positive correlation ($\rho = 0.63$).

[40] The reason is that for both statistics, the difference between the model moment and the data moment lies in the capital stock variable (k_i). In the data, k_i is measured via PWT. In the model, k_i is endogenously determined.

[41] If exclude Ireland the correlation is 0.92.

Figure 3: Model Fit - Home Bias (Untargeted)

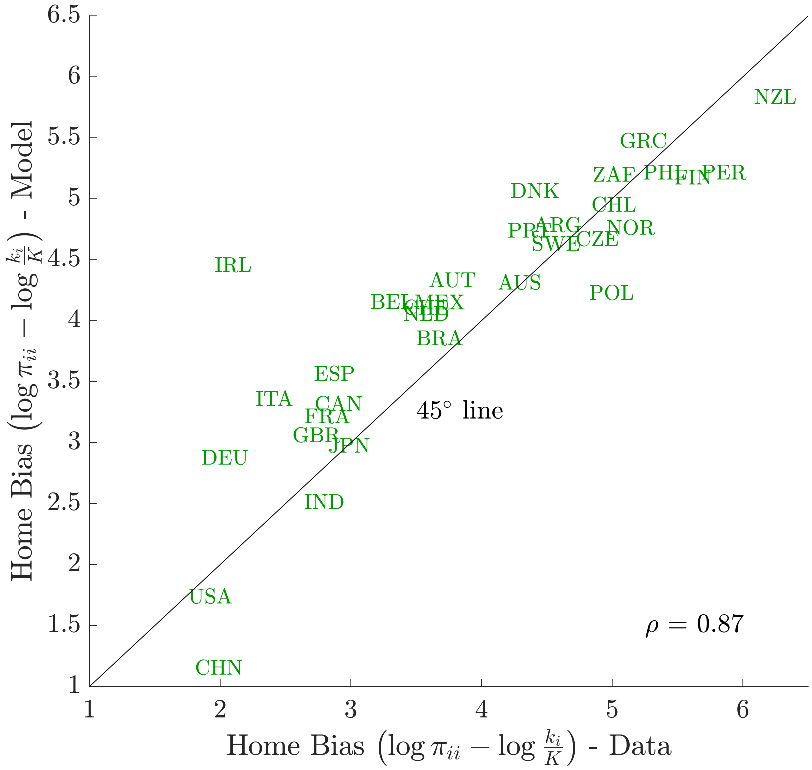

Figure Notes: This figure plots the model-implied home bias, against the empirical counterpart, which is computed by combining data from Lau et al. (2010) with the Penn World Table. Each observation is a country.

rates of returns) is exclusively due to the parsimonious set of frictions that we have introduced in it.

As for the other statistics, moving from the baseline to the residuals model does not seem to improve the fit of the model. This implies that, even if we introduced additional frictions in our model to better fit the empirical gravity equation, this would likely come at the expense of a worse fit in terms of untargeted country-level moments. In other words, the country-level data (coming mostly from the Penn-World Table) appears to be inconsistent, at least to some degree, with the bilateral asset positions (whose original source is the IMF's CDIS and CPIS databases).

A plausible explanation for why the baseline model outperforms the residuals model in matching untargeted moments is the large measurement error that is likely to exist in the bilateral investment data. First, there is the bias introduced by tax havens, which might not have been perfectly removed by the nationality re-statement procedures. Even absent that, CDIS and CPIS data (the "S" stands for survey) notoriously contain significant amounts of noise and missing observations. It is therefore likely that, when we perfectly fit the bilateral portfolio shares, we are implicitly trying to match noise, and this results in a worse fit of the untargeted country-level moments. This is akin to what happens when time series econometricians over-fit forecasting models, which end up under-performing out of sample.

For this reason, we shall refrain from doing counterfactuals on the residuals model. While we *could*

Figure 4: Country Heterogeneity in Returns to Capital

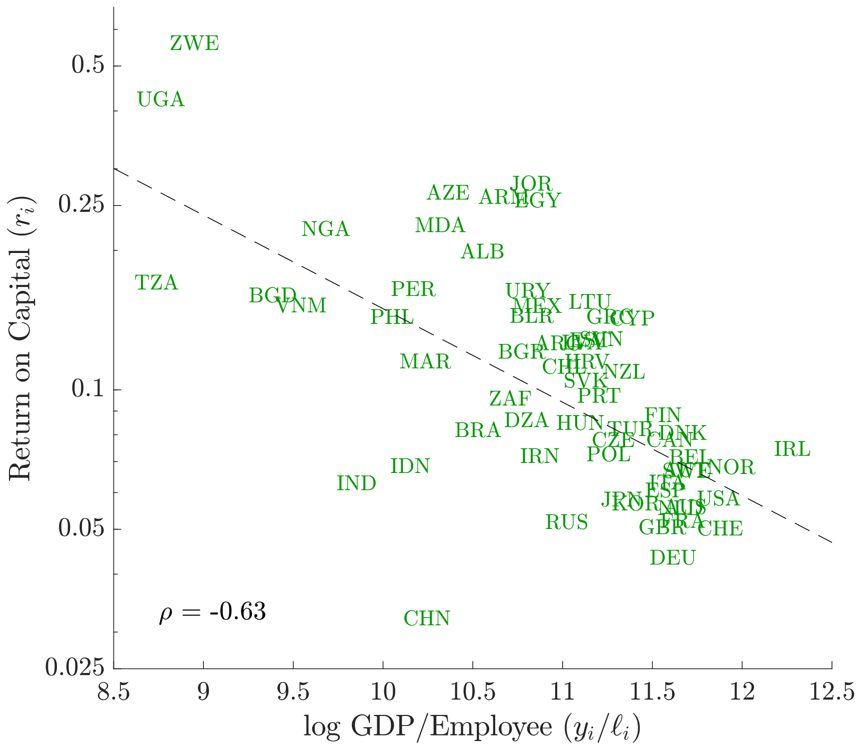

Figure Notes: This figure plots the model-implied rate of return on capital, against the log of GDP per employee (lower panel). Each observation is a country and the data are for 2017.

use the implicit wedges $\mathcal{E}_{ij}$ as measures of distortions, it is unclear what can be learnt from that exercise, as it would impossible for us to tell how much measurement error is contained in these implicit wedges.

5.3 Rates of Return Heterogeneity

In addition to matching data moments well, our model replicates some 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 economic development. In Figure 4, 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 unimpeded, 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 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

FIGURE 5: RATES OF RETURN AND HOME BIAS

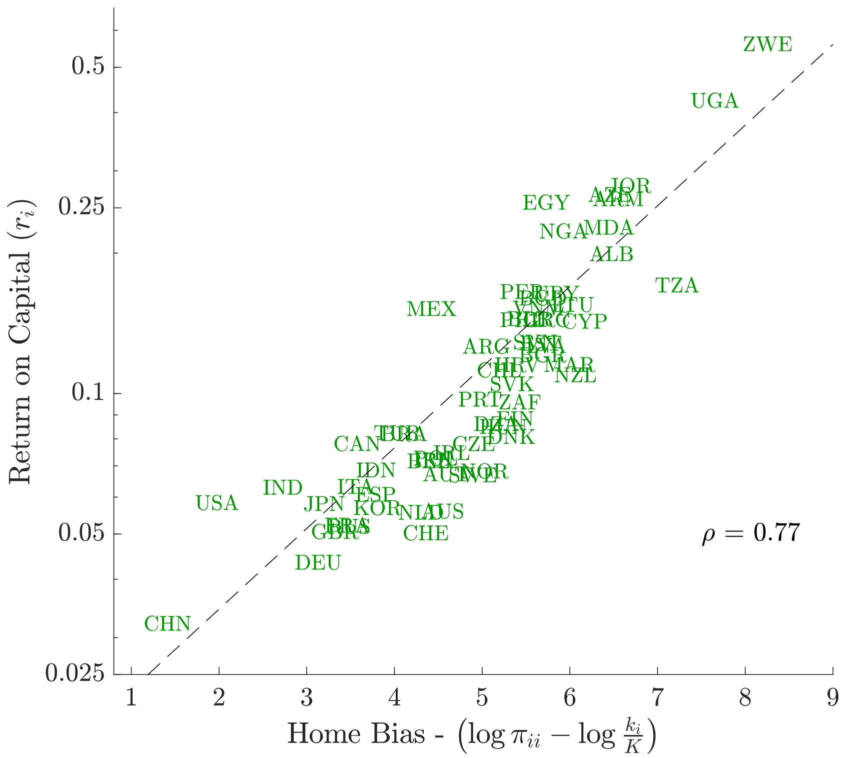

FIGURE NOTES: This figure plots the model-implied rate of return on capital, against a measure of home bias - the log difference of the shares of country i investment in country i portfolio and in the world portfolio $\left(\log \pi_{ii} - \log \frac{k_i}{K}\right)$. Each observation is a country and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

countries, thus shedding light on Lucas's puzzle.[42]

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 5.5) and plot it against the model-implied return to capital (r_i) in Figure 5. As visible from the graph, the two correlate strongly and positively ($\rho = 0.77$).

[42]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.

5.5 Discussion of Model Fit

Why does the model fit the data so well, given that the gravity regressions feature a within-R^2 of 0.25-0.30? The answer is along the following lines: while distances are defined bilaterally, they actually incorporate a significant amount of country-level variation. Some countries are more central (in the network of cultural and geographic distances) and others are more remote. Countries that are informationally opaque (because they have low centrality in the network of distances) display systematically higher rates of return to capital: these returns can be seen as reflective of network centrality.

Crucially, the i-variation and j-variation that exists in $\mathbf{d}_{ij}$ is not used in the regressions of Section 4, because it is netted out by fixed effects. This explains in part why, *within* destination country and *within* origin country, $\mathbf{d}_{ij}$ explain less than 30% of the variance in $\log a_{ij}$: country-level variation is not being exploited for identification, because there are too many confounding variables at the country level to reliably estimate β, some of them suggested by the model itself (see equation 3.6). These confounders are controlled for by including country of origin and country of destination fixed-effects. Nonetheless, in the economic model, this variation still very much affects country portfolios. Indeed, the fact that we are not using country-level variation to estimate the semi-elasticities β does not mean that this country-level variation does not impact capital allocation and rates of return to capital when we take the model to the data. The same insight can explain why the distance metrics, which are undirected by construction, can produce asymmetric effects (i.e. cause some countries to receive much less capital than they would otherwise): the asymmetry results from country-level (as opposed to pair-level) variation. Finally, this observation also accounts for why bilateral distances (not only country-level factors) can cause large capital misallocation and deadweight losses.[43] This is the subject to which we now turn.

6 Counterfactual Analysis

6.1 Capital Allocation Efficiency

In this section we perform a counterfactual analysis. We ask: if we could exogenously change the set of barriers affecting international investment, and let market forces reallocate capital, how would the cross-country distribution of capital and output change? What would be the efficiency gains?

Two motivations underlie this exercise. First, it can give us a better sense of the economic importance of the investment barriers we included in our model. Second, the findings in this section have non-trivial implications for international tax policy coordination, since tax rates interact with information frictions: if set optimally, they can potentially un-do the effect of informational advantage.

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 τ to a uniform positive value.[44] To remove information frictions, we make the investor prior precision φ_{ij} invariant to the distances $\mathbf{d}_{ij}$ (i.e. we set $\beta = 0$). The hypothetical policy intervention in

[43]For a contribution highlighting the importance of country-level factors for global capital allocation, see Gourinchas and Jeanne (2013).

[44]It is easy to see from equation (2.22) that the portfolio shares are unaffected by the particular choice of τ.

TABLE 7: COUNTERFACTUALS (2017)

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Information Barriers*	*Policy Barriers*
Welfare Statistics	(1)	(2)	(3)	(4)
World GDP (PPP$ trillions)	103.3	109.8	103.1	108.3
World GDP, % Difference from Zero-Gravity	-5.9%	0.0%	-6.1%	-1.3%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	+77.0%	0.0%	+55.4%	+39.0%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	+24.4%	0.0%	+11.9%	+19.3%

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

this case is to equip investors from country j with identical priors for all potential destination countries i, so that investors no longer have informational advantages. 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 equilibrium which is distorted by both information and policy barriers. In column (2), we present the *zero-gravity* equilibrium, from which all distortions have been removed ($\tau_i = 1, \beta = \mathbf{0}$). 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 ($\beta = \mathbf{0}$) while policy 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 information frictions have the largest effect in terms of capital allocation efficiency. When all policy frictions alone are removed (but information frictions are maintained), GDP is 6.1% lower than in the Zero-Gravity scenario. Tax policy coordination (understood as a convergence in the rate of taxation across countries - broadly construed to include both taxes and risk of expropriation) does not seem to improve worldwide capital allocation. This confirms our previous suggestion that policy and information frictions can (and do) interact. When information frictions alone are removed (but policy frictions are maintained), the world GDP loss is 1.3%*,* which is still a 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 How Much Capital Misallocation Can the Model Explain?

Using equation (3), in combination with the rates of return to capital that we constructed (for validation) using Penn World Tables and World Bank Data, we can obtain a model-free estimate of the deadweight loss from cross-country misallocation.[45] By comparing this model-free estimate to the deadweight loss that we computed in Table 7, we can gain a sense of the importance of the frictions that we *did* include in our model, relative to the frictions that we do *not* observe.

Using the model-free approach, we obtain an estimate, for the deadweight loss, of 6.6% of World GDP.

[45] To compute the formula we used, as output weights, the geometric average of the GDPs in the observed equilibrium (which are the same as those from the Penn World Tables) and those in the zero-gravity counterfactual.

Figure 6: Distribution of Capital and Output per Employee

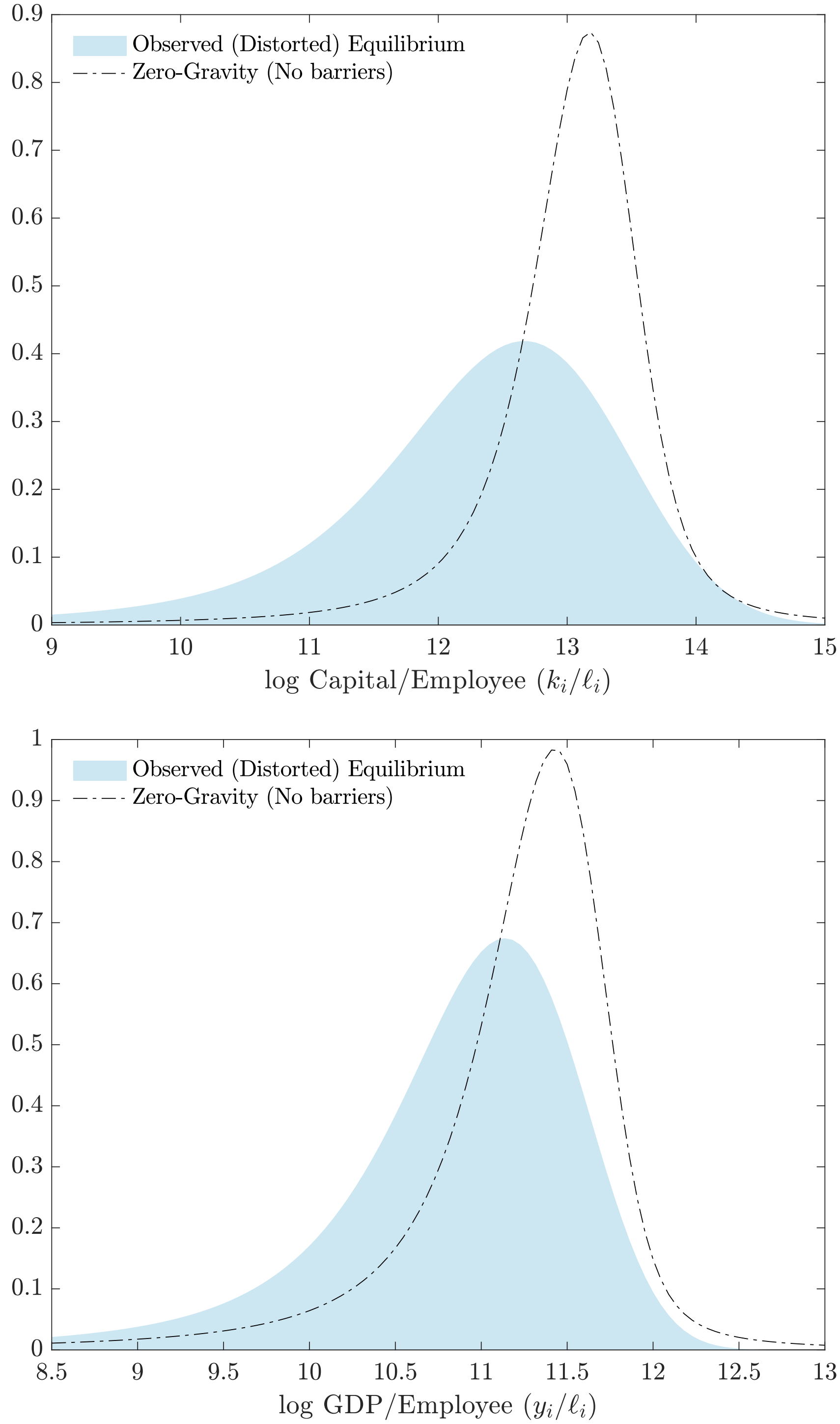

Figure Notes: This figure fits the probability density function of a *stable* distribution (a 4-parameter family of distributions with flexible skewness and fat tails) to country-level capital stock per employee (upper panel) and GDP per employee (bottom panel). In each panel, the lighter area is the distribution in the observed, distorted equilibrium. The dotted black line is the distribution in a counterfactual scenario in which all barriers (information and policy) have been removed.

Figure 7: Capital Reallocation Gains by Country

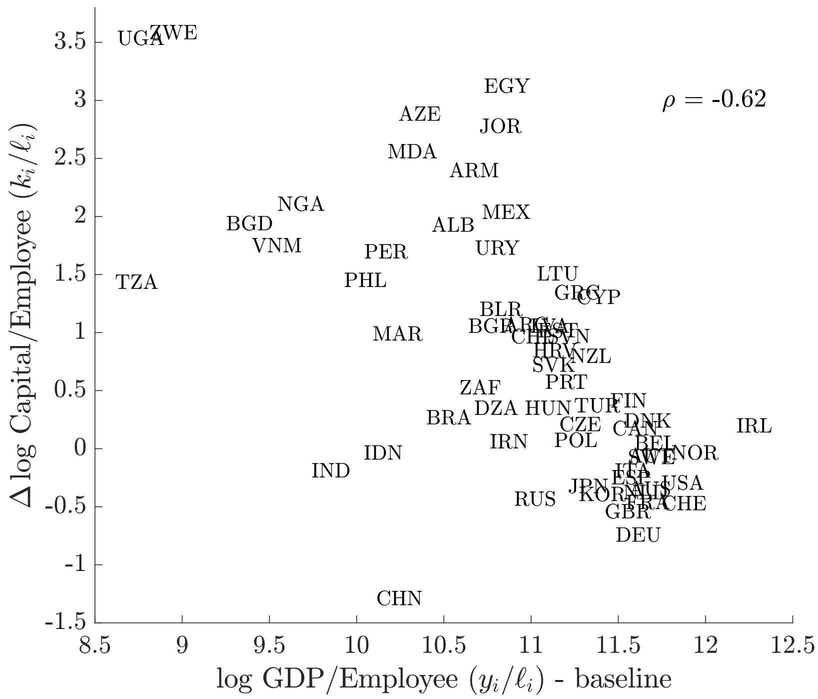

Figure Notes: This figure displays the baseline level of log output per capita (horizontal axis), against the log change in capital stock per employee (left axis) following the removal of all measured barriers to global capital allocation. Each observation is a country, and the data are from 2017.

Because this is only slightly higher than our model-implied deadweight loss (5.9%), we conclude that our parsimonious set of frictions can account for a large share of the capital misallocation that is likely to exist, based on measured rates of return. This is the flip-side of the fact that our model produces a realistic degree of dispersion in rates of return to capital, as we have shown previously in Table 6.

6.3 Capital and Income Inequality

While the overall effect of these three distortions on allocative efficiency and World GDP appears 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 to creating long-term cross-country inequality.

Figure 6 illustrates the effect of removing policy and information barriers 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 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 7 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 the poorest see capital per employee increase by an order of magnitude, and income per employee double.

6.4 Net Positions

Finally, we consider a comparison of net foreign asset positions under the observed equilibrium and the zero-gravity equilibrium ($\beta = 0$ 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.

So far, in our model, capital flows have been measured 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 the available data (that of Lane and Milesi-Ferretti, 2018), 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. As estimates for the discount rate and the depreciation rate (respectively), we use 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 $\iota \in (i, j)$ is:

$$a_{ij}^{(\iota)} = \frac{\tau_i r_i a_{ij}}{r_j + D} \tag{6.1}$$

The international investment position of country j is then:

$$\text{IIP}_j = \sum_{i \neq j} \left(a_{ij}^{(j)} - a_{ji}^{(j)} \right) \tag{6.2}$$

Figure 8: Net Asset Positions and Development

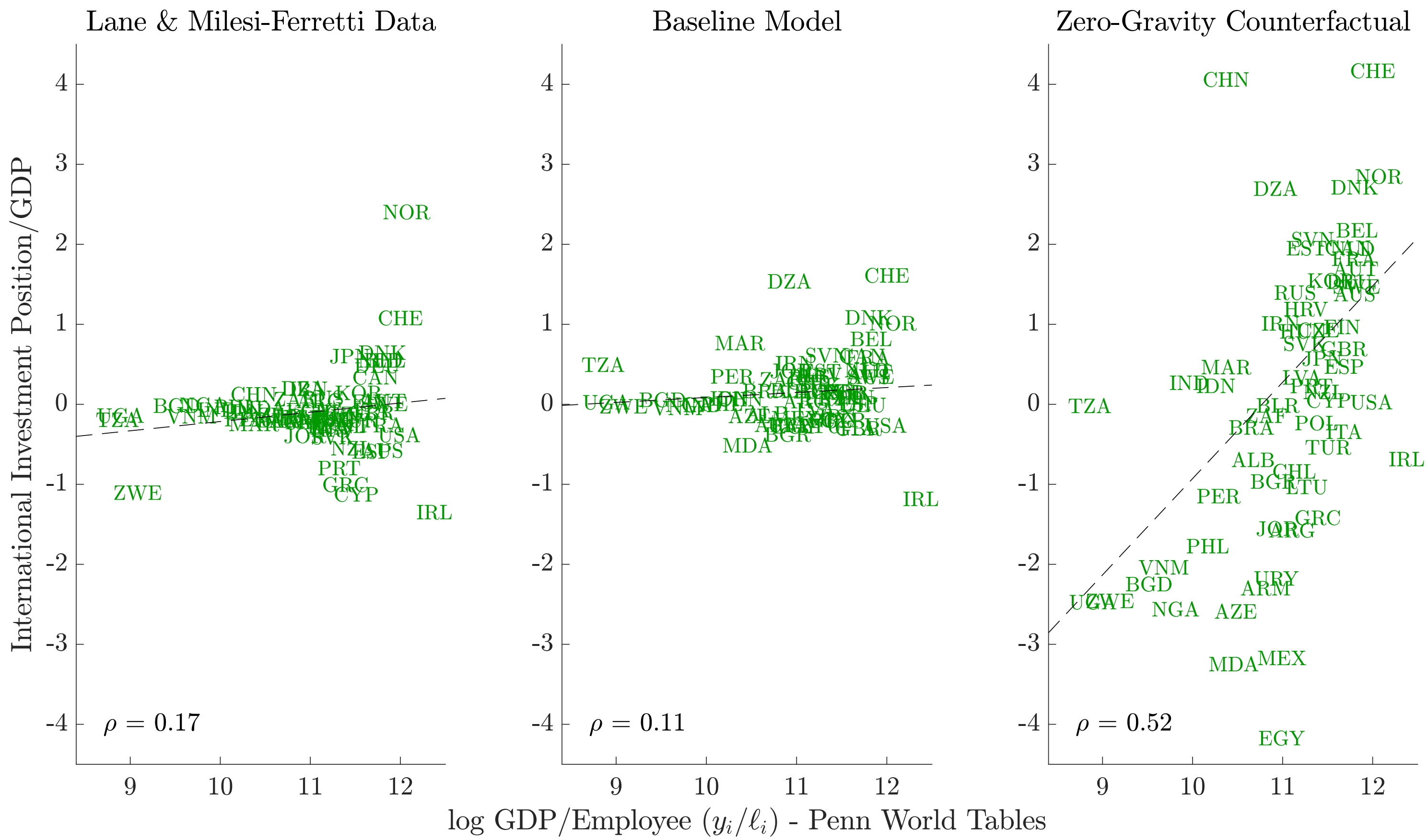

Figure Notes: the figure above plots the model-implied International Investment Position (IIP) as a share of GDP (y_i), against the log of GDP per employee. The left panel plots IIP/GDP as measured by Lane and Milesi-Ferretti (2018)'s database. The middle panel shows the model-implied IIP/GDP in observed distorted equilibrium, while the right panel plots IIP/GDP in the Zero-Gravity counterfactual, in which all barriers are removed.

We use 2017 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), divided by PPP GDP.

A notable feature of our model is that it generates persistent (steady-state) global imbalances. Figure 8 displays scatterplots of the resulting net foreign assets against log GDP per employee. Under the observed equilibrium, there are large deviations in net investment positions (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 – induced by investment taxes as well as information frictions – 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.[46]

7 Extensions and Robustness Checks

7.1 Trade Frictions

In our baseline model, we have assumed away frictions in trade of goods across countries: all countries produced a homogeneous, perfectly-tradable good. We now relax this assumption, by combining our international investment model of Section 2 with a model of trade where each country i produces a differentiated final good i (Armington, 1969), where $i \in \{1, 2, , \ldots, n\}$. The price of the good produced by each country i, denoted by p_i, is affected by trade barriers - such as tariffs - as well as other frictions in the goods market. The representative consumer's demand over all countries' goods has constant elasticity of substitution (CES), with elasticity η. 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.[47]

To make this model extension tractable, we shall focus on the special case without *ex post* productivity shocks (otherwise the shocks would affect the price of the final good). That is, $d_{it} = 0$ and $R_{it} = \tau_i r_i$ in every period t.

The price of a unit of physical capital might also differ across countries. As pointed out by Caselli and Feyrer (2007) and Monge-Naranjo et al. (2019), the Penn World Tables contain PPP adjustment factors for the capital stock, whose cross-country variation points to the presence of additional frictions to trade in capital that are captured by neither our tax measure nor information frictions. To let the price of physical capital vary across countries, we assume that the destination country levies an additional wedge

[46] These findings are consistent with those in Portes, Rey, and Oh (2001), although ours is the first paper to document them in the context of a structural model.

[47] This assumption can be micro-founded as follows: all final goods are identical, except for an origin country i-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 i-characteristic, drawn from an extreme value type 1 distribution.

on capital, equal to a fraction $\left(1 - 1/p_i^k\right)$ of all units of capital invested in destination country i. This additional tax is levied at the time when capital is purchased[48]. We measure p_i^k using PPP adjustment factors for capital from the Penn World Tables. From the point of view of the investors, the rate of return on capital (gross of the capital income tax τ_i) is equal to a statistic that CF call PMPKL ("price and natural resources-adjusted marginal product of capital") and MSS call VMPK (Value Marginal Product of Capital):

$$\text{PMPKL}_i \;\equiv\; \text{VMPK}_i \;=\; \kappa_i \frac{p_i y_i}{p_i^k k_i} \tag{7.1}$$

This leads to the following updated equation for the portfolio shares

$$\pi_{ij} \;=\; \frac{\left(\tau_i \kappa_i \frac{p_i y_i}{p_i^k k_i}\right)^{\frac{\sigma}{1-\sigma}} \;\varphi_{ij}}{\sum\limits_{\iota=1}^{n} \left(\tau_i \kappa_i \frac{p_i y_i}{p_i^k k_i}\right)^{\frac{\sigma}{1-\sigma}} \;\varphi_{\iota j}} \tag{7.2}$$

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 all the required 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 η, 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:

$$p_i' y_i' \;=\; p_i y_i \cdot \left(\frac{y_i'}{y_i}\right)^{\frac{\eta-1}{\eta}} \tag{7.3}$$

where p_i' and y_i' represent the new price and quantity levels following an exogenous change in τ_i or β.

In Appendix C, Table C.1, we repeat our counterfactual analysis for the extended model with frictions to trade in goods across countries. To keep the analysis consistent with Section 6, we compute efficiency gains and losses in terms of PPP GDP (y_i).

We find that, with respect to our baseline findings, the percentage world GDP loss is higher in the presence of goods trade frictions (7.6% 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 deadweight loss, and both sets of frictions significantly affect income distribution.

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 the long-run steady-state).

[48] As opposed to τ_i, which is levied as a percentage of the capital income.

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 may affect our results.

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

$$\tau_{ij} \;=\; \tau_i^{\text{Tax}} \cdot \tau_i^{\text{PR}} \cdot \tau_{ij}^{\text{KC}} \tag{7.4}$$

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

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

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

To estimate τ_{ij}^{KC}, we consider the five inflow restrictions dummies for country i (1 for FDI, 2 for portfolio equity and 2 for debt) as well as the five outflow restrictions dummies for country i (1 for FDI, 2 for portfolio equity and 2 for debt). We model each restriction as a (shadow) tax on foreign investment. To be conservative in our analysis, we assume that these taxes take on large values. In particular, we assume that both dummies corresponding to FDI investment restrictions are equivalent to a tax of 50%, while each of the four dummy variables corresponding to FPI restrictions is equivalent to a tax of 25%. We first compute the total tax (compounding both i inflow restrictions and j outflow restrictions) at the asset class level (FDI, equity portfolio and debt), and then take the simple average across the three asset classes. Formally:

$$\tau_{ij}^{\text{KC}} \;=\; \frac{1}{3}\left[(1-50\%)^{N_{ij}^{\text{FDI}}} + (1-25\%)^{N_{ij}^{\text{Equity FPI}}} + (1-25\%)^{N_{ij}^{\text{Debt}}}\right] \tag{7.5}$$

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. We treat capital controls as an additional dimension of policy barriers, i.e. we eliminate these controls whenever the counterfactual entails a removal of policy frictions. The percentage world GDP losses under this scenario is comparable to that obtained in our baseline exercise (5.2% vs. 5.9%). The marginal effects of the information frictions are also very similar to those found in the baseline exercise (6.3% versus 6.1%). Not surprisingly, now that we consider an additional policy friction, the deadweight loss from policy barriers becomes higher (4.7% versus 1.3%).

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:

$$\bar{r}_{ij} \stackrel{\text{def}}{=} \text{FP}_{ij} \cdot r_i \tag{7.6}$$

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:

$$\pi_{ij} = \frac{(\tau_i \bar{r}_{ij})^{\frac{\sigma}{1-\sigma}} \varphi_{ij}}{\sum_{\iota=1}^{n} (\tau_\iota \bar{r}_{\iota j})^{\frac{\sigma}{1-\sigma}} \varphi_{\iota j}} \tag{7.7}$$

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

$$\text{FP}_{ij} = \frac{r_i^f}{r_j^f} \tag{7.8}$$

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 dataset does not cover all the country pairs in our sample, because 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 investors who invest in or from a country where the *de jure* currency is illiquid will hedge with the corresponding anchor currency. This is a 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. 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 Country-Heterogeneity in Fundamental Volatility

Thus far we have made the simplifying assumption that the shocks to capital returns (ζ_{it}) were equally volatile across countries. We now relax this assumption. We still assume that ζ_{it} is drawn from a log-normal distribution. However, we now assume that the parameters of the underlying normal are country-specific: $-\frac{1}{2}\log v_i$ for the mean and $\log v_i$ for the variance (the shocks thus still have expectation one, by construction). We also assume that investors now form beliefs not on $(\tau_i r_i)^{\frac{\sigma}{1-\sigma}}$, but on $\left(\tau_i r_i/\sqrt{v_i}\right)^{\frac{\sigma}{1-\sigma}}$, with a similar distributional assumption (Gamma).

Because agent z holds log sub-utility and chooses the country with the highest expected log return, the following amended expression holds for the portfolio shares:

$$\pi_{ij} = \frac{\left(\dfrac{\tau_i r_i}{\sqrt{v_i}}\right)^{\frac{\sigma}{1-\sigma}} \cdot \varphi_{ij}}{\sum_{\iota=1}^{n} \left(\dfrac{\tau_\iota r_\iota}{\sqrt{v_i}}\right)^{\frac{\sigma}{1-\sigma}} \cdot \varphi_{\iota j}} \tag{7.9}$$

To proxy the variance of the fundamental shocks ($\log v_i$), we download country equity volatility indices from FRED (the source data is from 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 country heterogeneity in fundamental volatility. As for the previous robustness exercises with 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 heterogeneity in fundamental volatility.

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 4), where we use international investment data (*Total Assets*) from different years (2013-2017). The 95% confidence interval is plotted together with the estimated coefficients (dotted line). The estimated coefficient for 2017 always falls within the confidence interval for every other year, and remains close to its central estimate for all three 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 (in a statistical significance sense).

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 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 β (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 β. We find that the steady-state GDP loss induced by capital misallocation, around 6%, is broadly unchanged under both alternative choices of β, 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 Conclusions

In this paper, we have presented a novel theory of international capital allocation: a multi-country dynamic general equilibrium model with policy and information frictions, populated by rationally-attentive investors. In our structural framework, taxation, expropriation and informational frictions distort individually rational portfolio decisions. They create large global efficiency losses and contribute significantly to cross-country inequality.

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). Our parsimonious implementation of the model - based on just a few explanatory variables - reproduces several features of international asset markets: 1) it explains a significant share of the observed variation in country portfolios; 2) it produces large, realistic cross-sectional variation in rates of return across countries, which correlates negatively with portfolio home bias and the level of economic development, and which translates into persistent capital misallocation; 3) it predicts, out of sample and with strong accuracy, the overall level and the cross-section of home bias across countries (where "out-of-sample" means that we have not fed into the model any direct information about domestic capital investment); 4) it produces steady-state capital account imbalances that, consistent with the Lucas puzzle, do not correlate negatively with the level of development, implying that capital fails to flow from rich to poor countries.

To quantify the influence of these factors on the international allocation of capital and their real impact, we performed a number of counterfactual exercises. We studied how World GDP and the cross-country distribution of capital and output per worker would change if the effects of 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 at least 5.9% lower than it would be if the effect of these barriers to global capital allocation could be neutralized. The effect is even higher (7.8% of World GDP) when frictions to international trade are also taken into account.

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 information and policy barriers would lead to substantial economic gains and reductions in cross-country inequality: it would cause capital to reallocate from richer countries, where the rate of return on capital is lower, to poorer countries, where the rate of return is higher. Thus, neutralizing informational biases benefits countries that happen to be farther from the center where most investors are located. This is consistent with our theory, in which rationally-inattentive investors have prior information about asset returns, whose precision is affected by geographic, linguistic and cultural distances: in the steady state of our model, these distances generate and perpetuate an advantage to capital market access for central countries, and a disadvantage for countries that are more peripheral in a geographic, cultural and linguistic sense.

While previous research has mostly emphasized diversification and hedging as crucial to understanding these patterns, our analysis suggests that informational and policy barriers also play an important role.

How to address such biases and inefficiencies in an effective and coordinated way remains an open area of inquiry, both theoretically and empirically.

Our results also have implications for global tax policy coordination. In the presence of information frictions, the simple harmonization of capital tax rates across countries fails to improve capital allocation efficiency, and could even worsen it. From a normative perspective, we find that a social planner aiming to maximize world GDP should impose a lower tax rate on capital in countries that are remote with respect to investors, in order to counterbalance the effect of information frictions.

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 structural multi-country 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. Informational and policy barriers are important determinants of cross-country portfolios, and have a major effect on capital allocation efficiency and income distribution, including hindering the flow of capital from richer to poorer societies.

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Online Appendix: Barriers to Global Capital Allocation

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A Proofs and Derivations

Proof to Proposition 1. By Proposition 1 in Caplin, Dean, and Leahy (2019), (2.19) solves the rational inattention logit problem if and only if condition (2.20) holds. We therefore need to show that the latter is satisfied by:

$$\pi_{ij}^0 = \frac{\varphi_{ij}}{\sum_{\iota=1}^{N} \varphi_{\iota j}} \tag{A.1}$$

We guess and later verify that every country is selected with positive probability. This implies that we can re-write condition (2.20) as:

$$\mathbb{E}_{\tilde{\mathbf{r}}}^{G_j} \frac{\tilde{r}_i^{\frac{\sigma}{1-\sigma}} \cdot \pi_{ij}^0}{\sum_{\iota=1}^{n} \tilde{r}_\iota^{\frac{\sigma}{1-\sigma}} \cdot \pi_{\iota j}^0} = \pi_{ij}^0 \tag{A.2}$$

Next, we note that if $\tilde{r}_i^{\frac{\sigma}{1-\sigma}}$ follows a Gamma (Γ) distribution, we can write its scale and shape parameters in terms of the mean and the variance. If the mean is μ_j and the precision is φ_{ij} we have:

$$\tilde{r}_i^{\frac{\sigma}{1-\sigma}} \overset{G_j}{\sim} \Gamma\left(\mu_j^2 \varphi_{ij}, \frac{1}{\mu_j \varphi_{ij}}\right) \tag{A.3}$$

Using the scaling property of the Gamma distribution:

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

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

$$\left[\frac{\tilde{r}_1^{\frac{\sigma}{1-\sigma}} \varphi_{1j}}{\sum_\iota \tilde{r}_\iota^{\frac{\sigma}{1-\sigma}} \varphi_{\iota j}}, \frac{\tilde{r}_2^{\frac{\sigma}{1-\sigma}} \varphi_{2j}}{\sum_\iota \tilde{r}_\iota^{\frac{\sigma}{1-\sigma}} \varphi_{\iota j}}, \dots, \frac{\tilde{r}_n^{\frac{\sigma}{1-\sigma}} \varphi_{nj}}{\sum_\iota \tilde{r}_\iota^{\frac{\sigma}{1-\sigma}} \varphi_{\iota j}}\right] \overset{G_j}{\sim} \text{Dirichlet}\left(\mu_j^2 \varphi_{1j}, \mu_j^2 \varphi_{2j}, \dots, \mu_j^2 \varphi_{nj}\right) \tag{A.5}$$

we can now verify whether (A.1) respects (A.2) by plugging it in, and solving the expectation on the left hand side as the mean of a Dirichlet-distributed variable:

$$\mathbb{E}_{\tilde{\mathbf{r}}}^{G_j} \frac{\tilde{r}_i^{\frac{\sigma}{1-\sigma}} \cdot \frac{\varphi_{ij}}{\sum_{\iota'=1}^{N} \varphi_{\iota' j}}}{\sum_{\iota=1}^{n} \tilde{r}_\iota^{\frac{\sigma}{1-\sigma}} \cdot \frac{\varphi_{\iota j}}{\sum_{\iota'=1}^{n} \varphi_{\iota' j}}} = \mathbb{E}_{\tilde{\mathbf{r}}}^{G_j} \frac{\tilde{r}_i^{\frac{\sigma}{1-\sigma}} \varphi_{ij}}{\sum_{\iota=1}^{n} \tilde{r}_\iota^{\frac{\sigma}{1-\sigma}} \varphi_{\iota j}} = \frac{\mu_j^2 \varphi_{ij}}{\sum_{\iota=1}^{n} \mu_j^2 \varphi_{\iota j}} = \frac{\varphi_{ij}}{\sum_{\iota=1}^{N} \varphi_{\iota j}} \tag{A.6}$$

Because $\varphi_{ij} > 0$ for all i, j (by assumption) it is thus verified that all countries 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 $\Delta\mathbf{k}$ such that $\sum_i \Delta k_i = 0$:

$$\Delta Y \;\approx\; \sum_{i=1}^{n} r_i \Delta k_i \tag{A.7}$$

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

$$k_i \;=\; r^{-\frac{1}{1-\kappa_i}} \left(\kappa_i \omega_i\right)^{\frac{1}{1-\kappa_i}} \ell_i \tag{A.8}$$

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 (2.17) and (2.22) jointly imply:

$$\delta k_i \;=\; \sum_j \frac{\left(\tau_i r_i\right)^{\frac{\sigma}{1-\sigma}} \; k_i \, \varphi_{ij} s_j}{\sum_{\iota=1}^{n} \left(\tau_\iota r_\iota\right)^{\frac{\sigma}{1-\sigma}} \; k_\iota \, \varphi_{\iota j}} \tag{A.9}$$

if we simplify out k_i and equalize the rates of return ($r_i = r$), this can equation reduces to (2.38).

Finally, to prove Corollary 2, notice that if φ_{ij} is constant over i, it can be simplified out. Then, equation 2.38 further reduces to τ_i being constant over i. □

Proof to Proposition 3. Consider a second-order Taylor approximation of the change in World GDP around an efficient $\mathbf{k}$:

$$\Delta Y \quad \approx \quad r \sum_{i=1}^{n} \Delta k_i - \frac{1}{2} \sum_{i=1}^{n} \left(1 - \kappa_i\right) \frac{r}{k_i} \left(\Delta k_i\right)^2 \tag{A.10}$$

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

$$\frac{\Delta Y}{Y} \;\approx\; -\frac{1}{2} \sum_{i=1}^{n} \left(1 - \kappa_i\right) \frac{r k_i}{Y} \left(\Delta \log k_i\right)^2 \tag{A.11}$$

We then use the following facts

$$\Delta \log r_i \;=\; -\left(1-\kappa_i\right)\Delta \log k_i \tag{A.12}$$

$$r_i k_i \;=\; \kappa_i y_i \tag{A.13}$$

to derive:

$$\begin{aligned} 0 \;&=\; \sum_{i=1}^{n} \Delta k_i \;=\; \sum_{i=1}^{n} \frac{r k_i}{1-\kappa_i} \cdot \Delta \log r_i \;=\; \sum_{i=1}^{n} \frac{\kappa_i}{1-\kappa_i} \cdot \frac{y_i}{Y} \cdot \Delta \log r_i \\ &=\; \frac{\sum_{i=1}^{n} \frac{\kappa_i y_i}{1-\kappa_i}}{Y} \cdot \mathbb{E}^{\mathcal{W}_i}\left(\Delta \log r_i\right) \;=\; \left[\mathbb{E}^{\mathcal{W}_i}\left(\Delta \log r_i\right)\right]^2 \end{aligned} \tag{A.14}$$

We finally plug equations (A.12) and (A.13) inside equation (A.11) to obtain:

$$\frac{\Delta Y}{Y} \;\approx\; -\frac{1}{2}\sum_{i=1}^{n} \frac{\kappa_i}{1-\kappa_i} \cdot \frac{y_i}{Y}\left(\Delta \log r_i\right)^2 \;=\; -\frac{1}{2} \cdot \frac{\sum_{i=1}^{n} \frac{\kappa_i y_i}{1-\kappa_i}}{Y} \cdot \mathbb{E}^{\mathcal{W}_i}\left(\Delta \log r_i\right)^2 \tag{A.15}$$

Equation (A.14) implies that the last expectation on the right hand side of A.15 is the $\mathcal{W}_i$-weighted variance of log-returns:

$$\frac{\Delta Y}{Y} \;=\; -\frac{1}{2} \cdot \frac{\sum_{i=1}^{n} \frac{\kappa_i y_i}{1-\kappa_i}}{Y} \cdot \mathbb{V}^{\mathcal{W}_i}\left(\log r_i\right) \;=\; -\frac{1}{2} \cdot \mathbb{E}^{y_i}\left(\frac{\kappa_i}{1-\kappa_i}\right) \cdot \mathbb{V}^{\mathcal{W}_i}\left(\log r_i\right) \tag{A.16}$$

$\square$

B Measuring Political Risk

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

$$\tau_i^{\text{PR}} = \tau_i^{\text{PR}}(\text{ICRG}_i) \tag{B.1}$$

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

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

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

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

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

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

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

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

with boundary condition

$$\tau_i^{\text{PR}}(\text{ICRG}_i)|_{\text{ICRG}_i=10} = 1 \tag{B.6}$$

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

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

AKV perform instrumental variable regressions using two different datasets in their analysis (IMF and KLSV). We use the β_{AKV} estimate using KLSV data that controls for the initial level of GDP per capita.

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 Heterogeneity in Country Volatility.

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

	Observed (All Barriers)	*Zero-Gravity (No Barriers)*	*Information Barriers*	*Policy Barriers*
Welfare Statistics	(1)	(2)	(3)	(4)
World GDP (US$ trillions)	103.3	111.8	103.4	110.2
World GDP, % Difference in GDP from Zero-Gravity	-7.6%	0.0%	-7.5%	-1.4%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	78.8%	0.0%	59.3%	33.8%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	30.4%	0.0%	19.0%	17.5%

Table C.2: Counterfactuals with Capital Controls (2017)

Welfare Statistics	*Observed (All Barriers)* (1)	*Zero-Gravity (No Barriers)* (2)	*Information Barriers* (3)	*Policy Barriers* (4)
World GDP (US$ trillions)	103.3	109.0	102.1	103.9
World GDP, % Difference in GDP from Zero-Gravity	-5.2%	0.0%	-6.3%	-4.7%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	63.5%	0.0%	47.8%	57.5%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	13.5%	0.0%	9.4%	27.3%

Table C.3: Counterfactuals with Currency Hedging Costs (2017)

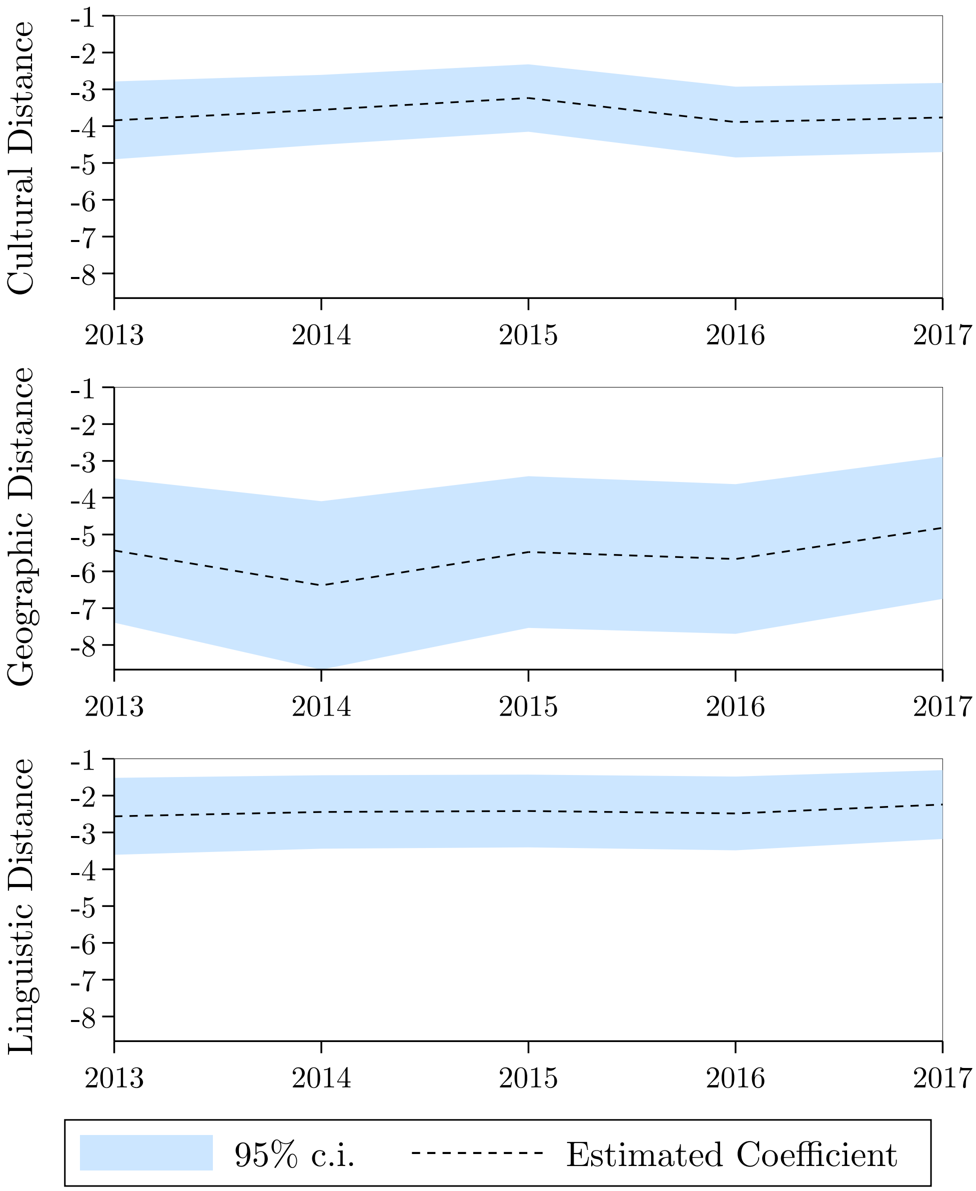
Welfare Statistics	*Observed (All Barriers)* (1)	*Zero-Gravity (No Barriers)* (2)	*Information Barriers* (3)	*Policy Barriers* (4)
World GDP (US$ trillions)	103.3	109.7	103.1	107.6
World GDP, % Difference in GDP from Zero-Gravity	-5.8%	0.0%	-6.0%	-1.9%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	73.2%	0.0%	51.8%	39.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	23.4%	0.0%	10.9%	19.4%

Table C.4: Counterfactuals with Volatility Heterogeneity (2017)

Welfare Statistics	*Observed (All Barriers)* (1)	*Zero-Gravity (No Barriers)* (2)	*Information Barriers* (3)	*Policy Barriers* (4)
World GDP (US$ trillions)	103.3	109.8	103.2	107.6
World GDP, % Difference in GDP from Zero-Gravity	-5.9%	0.0%	-6.0%	-2.0%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	73.0%	0.0%	51.5%	39.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	23.5%	0.0%	11.1%	19.5%

D Regression Coefficients Stability

Figure D.1: Coefficients Stability over Time



E Robustness check: alternative breakdown of foreign investment

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable in logs:	Assets	FDI	FPI	Assets	FDI	FPI
Cultural Distance	-4.174**	-3.537**	-3.826**	-3.554**	-2.785**	-3.722**
	(0.449)	(0.455)	(0.607)	(0.486)	(0.492)	(0.610)
Geographic Distance	-4.667**	-5.362**	-3.434**	-5.038**	-5.631**	-2.836*
	(0.321)	(0.344)	(0.400)	(0.984)	(0.977)	(1.271)
Linguistic Distance	-3.325**	-3.799**	-1.370	-2.288**	-2.559**	0.105
	(0.429)	(0.508)	(0.885)	(0.470)	(0.503)	(0.879)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	2,314	2,527	1,475	2,285	2,467	1,450
R-squared	0.772	0.722	0.814	0.797	0.754	0.834
Within R-squared	0.239	0.229	0.093	0.321	0.312	0.188

F Robustness check: residency-based foreign investment data

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

	(1)	(2)	(3)	(4)	(5)	(6)
Dep.variable in logs:	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-3.624**	-3.938**	-4.316**	-2.951**	-3.279**	-3.375**
	(0.417)	(0.477)	(0.406)	(0.447)	(0.500)	(0.439)
Geographic Distance	-4.598**	-4.860**	-3.070**	-4.830**	-5.398**	-4.038**
	(0.312)	(0.334)	(0.301)	(0.843)	(0.910)	(0.719)
Linguistic Distance	-3.410**	-3.965**	-0.990*	-2.338**	-2.879**	-0.713
	(0.427)	(0.495)	(0.480)	(0.457)	(0.497)	(0.483)
Control Variables	No	No	No	Yes	Yes	Yes
Observations	2,448	2,363	2,098	2,418	2,334	2,082
R-squared	0.763	0.741	0.769	0.795	0.777	0.794
Within R-squared	0.240	0.240	0.187	0.341	0.343	0.271

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 (β). Table G.2 uses OLS estimates, while Table G.1 uses Pseudo-Poisson regression estimates.

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

Welfare Statistics	*Observed (All Barriers)* (1)	*Zero-Gravity (No Barriers)* (2)	*Information Barriers* (3)	*Policy Barriers* (4)
World GDP (US$ trillions)	103.3	109.9	105.4	108.3
World GDP, % Difference in GDP from Zero-Gravity	-6.0%	0.0%	-4.1%	-1.5%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	101.5%	0.0%	58.4%	39.4%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	37.5%	0.0%	19.0%	16.3%

Table G.2: Counterfactuals using IV Estimates (2017)

Welfare Statistics	*Observed (All Barriers)* (1)	*Zero-Gravity (No Barriers)* (2)	*Information Barriers* (3)	*Policy Barriers* (4)
World GDP (US$ trillions)	103.3	109.7	103.0	108.2
World GDP, % Difference in GDP from Zero-Gravity	-5.8%	0.0%	-6.1%	-1.3%
St.Dev. of $\log(k_i/\ell_i)$, % Difference from Zero-Gravity	69.8%	0.0%	52.5%	37.2%
St.Dev. of $\log(y_i/\ell_i)$, % Difference from Zero-Gravity	19.8%	0.0%	9.2%	18.5%

H Unweighted Poisson regressions

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

Table H.1: Poisson Regressions

	(1)	(2)	(3)	(4)	(5)	(6)
	Assets	Equity	Debt	Assets	Equity	Debt
Cultural Distance	-2.295**	-1.827**	-2.922**	-1.765**	-1.181*	-2.261**
	(0.473)	(0.553)	(0.447)	(0.426)	(0.557)	(0.495)
Geographic Distance	-2.537**	-2.284**	-3.014**	-3.962**	-4.340**	-3.152**
	(0.245)	(0.254)	(0.318)	(0.670)	(0.674)	(1.060)
Linguistic Distance	-1.541**	-1.417**	-2.034**	-0.155	-0.444	-0.098
	(0.263)	(0.265)	(0.330)	(0.306)	(0.373)	(0.370)
Controls	No	No	No	Yes	Yes	Yes
Observations	2,789	2,805	3,511	2,754	2,770	3,459

I Alternative Micro-foundation for Gravity

In this appendix, we present an isomorphic model where the distances $\mathbf{d}_{ij}$ represent not information frictions but asset trade costs. This micro-foundation produces portfolio shares that are identical to those of our baseline model – i.e. these two models are, given our data, observationally equivalent (as in Gârleanu, Panageas, and Yu, 2020).

Assume now that investors have the "efficient" prior from equation (2.24) instead of that equation (2.23). Also, asset markets are subject to an additional distortion: investment is intermediated by an agent that collects a fee from investors. This fee depends on the distance between the origin and the destination country. The latter assumption stems from the plausible idea that asset trade costs are higher when origin and destination countries are at a greater distance from each other (perhaps because of travel, communication and translation costs). The fee is then rebated back to investors lump-sum. Specifically, if investor z chooses to invest in country i, they pay a multiplicative fee that depends on the vector of distances $\mathbf{d}_{ij}$:

$$1 - \psi_{ij} \ = \ \exp\left(\frac{1-\sigma}{\sigma} \cdot \mathbf{d}_{ij}'\beta + T_j\right) \tag{I.1}$$

so that the *ex post* return for an investor in country j is equal to:

$$R_{ijt} \ = \ \zeta_{it}\, \tau_i\, \psi_{ij}\, r_i \tag{I.2}$$

The term T_j is a proportional rebate that is equal for all investors from country j, and is determined in such a way that the investment intermediary of country j makes zero profits. Hence, the international investment fee does not directly affect the aggregate resource constraint: it distorts asset allocation, but it does not destroy capital.

It is easily verified that equilibrium portfolio shares are equal to

$$\pi_{ij} \ = \ \frac{(\tau_i r_i)^{\frac{\sigma}{1-\sigma}} \cdot k_i \cdot \exp\left(\mathbf{d}_{ij}'\beta\right)}{\sum_{\iota=1}^{n} \, (\tau_\iota r_\iota)^{\frac{\sigma}{1-\sigma}} \cdot k_i \cdot \exp\left(\mathbf{d}_{\iota j}'\beta\right)} \tag{I.3}$$

This is the same expression as the one obtained if we plug (2.23) into (2.22).