Barriers to Global Capital Allocation

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Abstract

International portfolios and heterogeneity in the rate of return to capital across countries are hard to reconcile with frictionless capital markets. In this paper, we develop a quantitative theory of international capital allocation: a multi-country dynamic general equilibrium model in which the entire network of cross-border investment is endogenously determined. The model features not only country heterogeneity in fundamental risk but also, crucially, a rich set of policy and information frictions that distort international capital flows. It embeds rationally-inattentive investors and produces closed-form solutions for international portfolios that follow a logit form. We take the model to the data using a parsimonious (yet easily extensible) set of frictions: capital income taxes, political risk, and measures of geographic, linguistic, and cultural distance between countries. Our framework accounts well for international portfolio patterns, the cross-section of home bias and rates of returns to capital, and other key features of international capital markets. Finally, we perform counterfactual exercises: in particular, we show that barriers to international investment reduce world output by about 6% and can account for nearly half of the observed cross-country inequality in capital per employee.

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

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1 Introduction

International capital flows have greatly increased in recent decades, but international investment patterns remain difficult to reconcile with frictionless capital markets (Maggiori, 2022; Du and Schreger, 2022). There is a dearth of capital flows from capital-abundant to capital-scarce economies, despite large and persistent capital-return differentials across countries (Lucas 1990; Monge-Naranjo, Sánchez, and Santaelulalia-Llopis 2019; David, Henriksen, and Simonovska 2014). International portfolios continue to display a high degree of home bias (French and Poterba, 1991; Coeurdacier and Rey, 2013). Moreover, we have good evidence that information frictions exert a strong influence on international portfolios, creating a gravity-like pattern, similar to that observed in international goods trade (Portes and Rey, 2005).

While these stylized facts have each been examined independently, there has been little attempt to understand how these phenomena are related, the extent to which they can be traced back to a common set of causes, or whether they can be unified under a single, coherent theoretical framework. Notwithstanding significant theoretical and empirical progress in international finance and macroeconomics1, a comprehensive work-horse model of international capital allocation, comparable to the gravity model in international trade (Eaton and Kortum, 2002), has yet to emerge.

Developing such a model is crucial both in order to reconcile these stylized facts as well as to study how international investment and production respond to changes in international investment frictions. Such a model should possess some key features: 1) it should be a multi-country general equilibrium model (i.e. it should map to the data on a country-by-country basis); 2) it should endogenously generate a realistic network of country-to-country bilateral investment positions (gross flows); 3) it should endogenize the rate of return on capital in each destination country; 4) it should accommodate a diverse range of policy and information frictions; 5) it should also provide a solid micro-foundation for information frictions as determinants of portfolio formation.

We micro-found information frictions at the core of our model, building on the previous literature on rational inattention in international finance (Van Nieuwerburgh and Veldkamp, 2009, 2010; Dziuda and Mondria, 2012). Investors based in different locations allocate their savings across destination countries via a rational-inattention logit demand system (Matějka and McKay, 2015; Pellegrino, 2023). Namely, investors do not know ex ante the risk-return profile of each destination country. We model this lack of knowledge using a prior distribution for risk-adjusted return to capital in every destination countries. Investors can obtain additional information about risk-adjusted returns by acquiring a signal. This signal is not restricted to having a specific probability distribution, and is obtained at a utility cost that is proportional to the informativeness of the signal. Different investors hold an informational advantage about assets located in specific destination countries (e.g. countries that are geographically close, as shown by Portes and Rey, 2005). Policy frictions are modeled as a tax (or shadow tax) on capital and are allowed to have an unpredictable component. Hence, our framework is general enough to allow for policy risk. Overall, this model, while quite general, is tractable and amenable to multiple extensions. It produces closed-form country portfolios that follow a logit functional form, and bilateral asset positions that follow a gravity-like equation.

1See for example recent work on exchange rates by Lustig and Richmond (2017, 2020); Gabaix and Maggiori (2015); Itskhoki and Mukhin (2021); Mukhin (2022).
The key insight and theoretical prediction of our model is that, in its steady-state equilibrium, a core-periphery structure will endogenously emerge in international capital markets. Country portfolios will be skewed towards central countries that are less affected by policy and information frictions. Because these countries are easily accessible to international investors, they display a low rate of return to capital. In contrast, peripheral countries, less easily accessible to international investors as the result of frictions, display a low capital stock and a high rate of return, which compensates investors for overcoming those barriers. In our framework, rates of return reflect not only risk premia, but also countries’ accessibility to international investors. This resulting global allocation of capital is, in general, suboptimal.

Next, we take the model to the data. While the model is sufficiently tractable and general to incorporate a multiplicity of barriers, we start from a parsimonious baseline specification with three frictions which we quantify explicitly: 1) country-specific capital income taxes (encompassing corporate income, dividends, and interest income taxes); 2) political risk (i.e., risk of expropriation); 3) measures of geographical, linguistic and cultural distances, whose impact of international portfolios can be estimated by running a classical gravity regression on bilateral investment data. For this econometric analysis we use IMF data on foreign direct and portfolio investment, recently restated from a residency to a nationality basis (Damgaard, Elkjaer, and Johannesen, 2019; Coppola, Maggiori, Neiman, and Schreger, 2020) to account for the presence of tax havens.

We obtain three sets of empirical results. First, we find that our baseline model produces realistic country portfolios and rates of return to capital. 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 predicted net asset positions correlate only weakly with income, consistent with the data and with Robert Lucas’s observation that there is a dearth of capital flows from rich to poor countries (Lucas, 1990). In addition, even though we estimate our gravity equation without using any data on domestic investment, our model predicts (out-of-sample) the degree of home bias of each origin country with high accuracy. Because home bias is entirely generated by geo-cultural distance, it can be viewed, through the lens of our model, as a direct implication of the gravity effect: domestic investment corresponds to the case where all distances are set to zero.

Second, we find that our three barriers exert a powerful influence on international asset positions. Geographic, cultural and linguistic distances generate a strong gravity effect on international portfolios that is quantitatively similar for different subcategories of foreign investment: equity vs. debt, foreign direct investment vs. foreign portfolio investment. Our measured elasticities condition on origin-country and destination-country fixed effects, are robust to the inclusion of an extremely large set of control variables, and remain quantitatively large irrespective of the estimation method (OLS, Poisson regression, and Instrumental Variables - IV)³.

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 alloca-

²The key difference with previous empirical gravity studies is that our gravity regression has a structural interpretation: it is used to recover model parameters - namely, the elasticity of the portfolio shares with respect to distances.

³The latter are used to ensure that our estimates of the effect of cultural distance are not amplified by reverse causality. Our IV approach relies on the fact that differences in religion between populations have an impact on contemporary measures of cultural distance. 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.
tion, World GDP is about 6% lower. 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 barriers would accrue to developing countries in Africa, Asia and Latin America, as the investment barriers in our model make these countries inaccessible to international investors.

We extend our basic model along several dimensions, by incorporating various additional frictions: barriers to goods trade; capital controls; currency hedging costs (to capture currency risk). None of these extensions materially affects our headline findings. We also perform a wide range of robustness checks.

To summarize our contribution: we provide a first quantitative multi-country model of international production and investment that embeds a rich set of policy and information barriers. Our model reconciles multiple stylized facts about the global allocation of capital and allows to study how the global economy reacts to changes in international investment frictions. We find that these barriers have important effects for the distribution of capital across countries, efficiency, and global inequality.

**Literature.** This paper contributes to several distinct literatures, including the literature on international macroeconomics with imperfect financial markets (see Maggiori, 2022; Du and Schreger, 2022, for a review) and the literature on gravity models in international finance. A recent contribution within this line of research is Lustig and Richmond (2020), showing that currency return factors obey a gravity structure - namely, currencies of countries which are more peripheral in a network of geographic, cultural and linguistic distances carry larger risk premia. Several earlier empirical papers documented that gravity regressions have strong explanatory power for bilateral international asset positions, including Ghosh and Wolf (1999), De Ménil (1999), Di Giovanni (2005), and Portes and Rey (2005), who provided an interpretation of these findings in terms of information costs. Martin and Rey (2004) provided a theoretical model to motivate these gravity regressions. Other related models are those by Sellin and Werner (1993) and Gârleanu, Panageas, and Yu (2020). An early contribution that combined both theory and data was Head and Ries (2008), who focused specifically on cross-border M&A.

Our contribution is distinct from this earlier literature because, for the first time, we embed gravity in international portfolios within a quantifiable multi-country dynamic general equilibrium model, where country output and the network of bilateral investment positions are endogenously determined in the steady-state equilibrium. Unlike previous empirical contributions, our gravity regressions are used to calibrate structural parameters of the model. This structural approach allows us to study how country-level capital and income respond to the removal of specific barriers to international investment.

In addition, our paper expands, in a new direction, the literature on rational inattention in macro-finance (Dasgupta and Mondria, 2018; Mackowiak, Matejka, Wiederholt et al., 2020). We use the rational inattention logit model (Matějka and McKay, 2015; Caplin, Dean, and Leahy, 2019; Pellegrino, 2023) to micro-found an international asset demand system (Koijen and Yogo, 2020; Jiang, Richmond, and Zhang, 2020). In line with previous theoretical work by Van Nieuwerburgh and Veldkamp (2009, 2010), in our model, rationally-inattentive investors choose not only how much to learn but also what assets to learn about. Such directed information acquisition implies that a home bias will persist even though, in theory, investors can perfectly learn expected returns. Our analysis is also 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.

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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-Tempered Stable specification, allowing us to derive a gravity equation.
More broadly, our research connects with spatial and dynamic models of trade and/or capital accumulation, including Liu and Ma (2021); Liu and Tsyvinski (2021); Redding (2016); Ravikumar, Santacreu, and Sposi (2019); Kleinman, Liu, and Redding (2022); Redding and Weinstein (2019); Antras and Helpman (2004); Antrás and Caballero (2009); Antrás and Yeaple (2014); Eaton, Kortum, Neiman, and Romalis (2016). We also contribute to a vast literature on open-economy financial macroeconomics analyzing the direction of international capital flows (De Ferra, Mitman, Romei et al., 2021; Maggiore, Neiman, and Schreger, 2020) Much of this literature focuses on issues of hedging, portfolio diversification, and currency risk (e.g. Itskhoki and Mukhin, 2021; Colacito and Croce, 2010; Itskhoki and Mukhin, 2022; Benigno, Fornaro, and Wolf, 2020; Hassan, Schreger, Schwedeler, and Tahoun, 2021). Recent work on international risk sharing and “flight to safety” includes, for instance, Kekre and Lenel (2021). In our baseline model, cross-border portfolio shares depend on two main drivers: a fundamental component, which captures the marginal productivity of capital as well as risk; and a distortionary component, which captures the effect of policy and information frictions. These two drivers can be further broken down these into four fundamental factors: 1) the physical return to capital; 2) risk and hedging (investors are less inclined to invest in countries with volatile productivity and more inclined to invest in countries that provide a better hedge against global shocks); 3) policy distortions, which may affect the mean as well as the dispersion of the perceived rate of return to capital; and 4) prior uncertainty (investors are more inclined to invest in countries about which they have more precise prior information). While in our baseline model we abstract from a role for money, in an extension of our framework we incorporate currency risk by modeling currency hedging cost directly, building on the observation that most international investors hedge currency risk (e.g., Sialm and Zhu, 2020).

We also build on previous work on natural resources and capital misallocation by Monge-Naranjo, Sánchez, and Sanitaeulalia-Llopis (2019), David, Henriksen, and Simonovska (2014) and earlier work by Caselli and Feyrer (2007). 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). Consistent with the more recent findings by Monge-Naranjo, Sánchez, and Sanitaeulalia-Llopis (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 studies 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 (Barro, Mankiw, and Martin, 1995), 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 geographic, institutional, historical and cultural determinants of international financial flows. The inclusion of cultural barriers in our model is motivated by earlier work of Papaioannou (2009). 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

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5The 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.
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), Aggarwal et al. (2012), 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).

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

2.1 Firms

In this section, we present a multi-country dynamic general equilibrium model with rationally-inattentive investors and imperfect capital mobility.

Time is discrete and indexed by $t$. There is a set of $n$ countries indexed by $i \in \{1, 2, \ldots, n\}$. Each country has a representative firm that acts competitively and produces a homogeneous, tradable good using a three-factor Cobb-Douglas production function. The assumption that the final good is perfectly tradable is relaxed in Subsection 7.2.

Total output is stochastic and equal to $y_{it} + d_{it}$. By definition, $y_{it}$ is the deterministic part, equal to

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

where $\omega_i$ is country $i$’s (expected) total factor productivity; $k_{it}$ is the input of reproducible capital; $\ell_{it}$ is the labor input; $x_{it}$ is the input of natural resources. $^6$ The parameters $\kappa_i$, $\lambda_i$ and $\xi_i$, 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:

$$\kappa_i + \lambda_i + \xi_i = 1 \quad (2.2)$$

d$_{it}$ is a mean-zero random component, proportional to $y_{it}$ as well as the capital share $\kappa_i$.$^7$

$$d_{it} = (\zeta_{it} - 1) \kappa_i y_{it} \quad (2.3)$$

$\zeta_{it}$ is a log-normally distributed shock to output with expectation equal to one. We construct the shock $\zeta_{it}$ as follows: its log can be decomposed as the sum of a country-level shock $z_{ct}^{c}$ and a global (country-invariant) shock $z_{wt}^{w}$. Both follow a Gaussian distribution:

$$\log \zeta_{it} \overset{\text{def}}{=} z_{ct}^{c} + z_{wt}^{w}, \quad z_{ct}^{c}, z_{wt}^{w} \sim N \quad (2.4)$$

We denote by $\Sigma_{ct}^{c}$ the variance of $z_{ct}^{c}$, $\Sigma_{wt}^{w}$ the variance of $z_{wt}^{w}$ and $\sigma_{ct}^{c} z_{wt}^{w}$ the covariance of $z_{ct}^{c}$ and $z_{wt}^{w}$. Therefore, each country’s output is allowed to co-vary with the global economic cycle to a different degree.

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 $\gamma$ units of capital to be used for production in the next period; $^8$ 3) taxed by government (not necessarily the domestic one) and converted into one unit of a public good.

The global resource constraint is thus:

$$\sum_{i=1}^{n} y_{it} = \sum_{i=1}^{n} \left( c_{it} + q_{it} + \frac{1}{\gamma} k_{it+1} \right) \quad (2.5)$$

$^6$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 after being utilized, so that all the capital available for next-period production must come at the expense of current-period consumption. We relax this assumption in Section 7.
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 the expected capital income:

$$\max_{\ell_{it}, \ell_{it} \cdot x_{it}} y_{it} - w_{it} \ell_{it} - m_{it} x_{it}$$

We assume that the shock $\zeta_{it}$ 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:

$$m_{it} = \xi_{i} \frac{y_{it}}{x_{it}}; \quad w_{it} = \lambda_{i} \frac{y_{it}}{\ell_{it}};$$

The capital income share is therefore equal to $\zeta_{it} \kappa_{i} y_{it}$. Because capital is a mobile factor, different shares of this income will accrue to investors from different countries. 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).

Each destination country $i$ exogenously imposes a (potentially random) tax rate equal to a share $(1 - \tau_{ijt})$ of the capital income accruing to agents located in origin country $j$. We assume that $\tau_{ijt}$ is log-normally distributed with mean $\mu_{ij}^{T}$ and logarithmic variance $\Sigma_{ij}^{T}$. To keep notation simple, we assume that $\tau_{ijt}$ is orthogonal to $\zeta_{it}$, although this can be easily relaxed.\(^9\)

All of the tax revenues in country $i$ go towards the production of the public good $q_{i}$. $\tau_{ijt}$ can be interpreted as a comprehensive measure that includes expropriation risk. A unit of capital invested in country $i$ yields, in expectation, a pre-tax return that is equal to the expected marginal product of capital in country $i$, which is defined as:

$$\text{EMPK}_{it} \overset{\text{def}}{=} \kappa_{i} \frac{y_{it}}{k_{it}}$$

We denote the net-of-tax return on a unit of capital invested in country $i$ by $\rho_{ijt}$, and it is equal to:

$$\rho_{ijt} \overset{\text{def}}{=} \tau_{ijt} \zeta_{it} \kappa_{i} \frac{y_{it}}{k_{it}}$$

### 2.2 Households

In each country $j$, a continuum of households $h \in [0, 1]$ is born every period $t$. Agents live for two periods. They are endowed with $\ell_{j}$ 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, and they make savings and asset allocation decisions. In the second period, the return on the capital saved at time $t$ is the old agents’ only source of income. Investors are atomistic, and invest their atom of capital in a single destination country $i$.

To keep the exposition simple, we assume that capital investment is lumpy: each atomistic investor $h$ in country $j$ invests their savings by buying claims to the return on the capital stock of one country $i$. This

\(^9\)The assumption that $\tau_{ijt}$ and $\zeta_{it}$ are lognormally-distributed can also be relaxed, by allowing for multiplicative Bernoulli jumps reflecting disaster risk. We consider this extension in Section 7.
assumption can be relaxed (with no consequences for our quantitative results) so that all investors $h$ in country $j$ invest in country $j$’s diversified portfolio. For example, in Subsection 7.5, we discuss how this can be obtained by introducing an additional class of agents that work as financial intermediaries.

International investment is subject to information and policy frictions. We model information frictions in cross-border investment using insights from the literature on rational inattention and flexible information acquisition (Sims, 2003; Matějka and McKay, 2015): agents make their asset allocation decisions using limited information about expected returns. Investors face both risk from the productivity shocks $\zeta_{it}$ and *epistemic uncertainty* about the distribution of the returns. That is, they do not know, ex-ante, the distribution of country returns, but they can learn it at a cost.

We make the following assumptions on investor behavior. First (in line with the previous literature) shocks to output $(\zeta_{it})$ and taxes $(\tau_{ijt}/\mu^j_t)$ are unpredictable and unlearnable; that is, investors cannot acquire any information that allows to predict $\zeta_{it}$ and $(\tau_{ijt}/\mu^j_t)$. Second, the $t + 1$ equilibrium expected returns, net of taxes, as well as their variances, are not known to investors at time $t$, when they make their asset allocation decisions. Furthermore, we assume that the agents form beliefs about a vector of expected net-of-tax log returns $r_{t+1}$, which we define as follows:

$$ r_{ijt} \overset{\text{def}}{=} \mathbb{E}_{\tau_{ijt}\zeta_{it}} (\log \rho_{it}) \quad (2.10) $$

To streamline notation, we define its exponential $R_{ijt}$:

$$ R_{ijt} \overset{\text{def}}{=} \exp (r_{ijt}) \quad (2.11) $$

We assume that agents form beliefs about $r_{jt+1}$ because, as we are about to show, this is a “sufficient statistic,” in the sense that all of the uncertainty about the agents’ lifetime utility is captured by $r_{jt+1}$. In other words, if the agents could perfectly learn $r_{jt+1}$, there would not be any value in learning about any other $t + 1$ object.\(^{10}\)

All households $h$ in country $j$ born at time $t$ are endowed with prior beliefs $G_j (r_{jt+1})$. At time $t$, when they are young, the agents can acquire a signal $\tilde{r}$ that is informative about $r_{t+1}$. Consistent with the literature on rational inattention, we assume that the agents’ information choice set is unrestricted: they can acquire any signal they wish - the signal is not restricted to have a specific distribution. That is, the households choose the joint distribution of $r_{t+1}$ and $\tilde{r}$, which we denote by $F (r_{jt+1}, \tilde{r})$. After observing the signal, they update their prior $G_j$ into a posterior $F (r_{jt+1}|\tilde{r})$. 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.

However, agents must exert effort in order to acquire the additional information, therefore incurring a disutility that is described using a cost function $I (F, G_j)$, which depends on the prior and the posterior distribution.

Using the posterior, the agents then select a country $i$ in which to invest $s_{ht}$, the amount of final good that is saved from their first period income. A household $h$, born in country $j$ at time $t$, solves the following

\(^{10}\)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.
constrained maximization problem:

\[ U_h \overset{\text{def}}{=} \max_{(c_{ht}, s_{ht}, t, F)} \left( 1 - \theta_j \right) \log c_{ht} + \theta_j \left[ \mathbb{E}_t^F \left( \log c_{ht+1} \right) - I(F, G_j) \right] + V_h(q_{jt}, q_{jt+1}) \]

subject to constraints:

\[
\begin{align*}
[t \text{ Budget Constraint}] : & \quad w_{jt} \ell_j + m_{jt}x_j = c_{ht} + s_{ht} \\
[t+1 \text{ Budget Constraint}] : & \quad c_{ht+1} = \rho_{ijt+1} \cdot \gamma s_{ht} \\
[\text{Bayes Rule Updating}] : & \quad \int_{\mathbb{R}^n} dF(r_{jt+1}, \tilde{r}) = G_j(r_{jt+1})
\end{align*}
\]

where \( c_{ht} \) is agent \( h \)'s consumption when they are young, \( c_{ht+1} \) is their consumption when they are old, and the patience parameter \( \theta_j \) is allowed to vary by country. \( V_h(q_{jt}, q_{jt+1}) \) is the expected utility value of the public good supplied by country \( j \) over the two periods. Because the public good enters the utility in a separable way, taxation does not distort saving (although it does distort asset allocation).

Following the literature on rational inattention (Sims, 2003; Matějka and McKay, 2015), we assume that the cost of information \( I_h(F, G_j) \) is proportional to the incremental information content of the signal acquired by \( h \), measured as the expected reduction in Shannon Entropy (H) between the posterior \( F \) and the prior \( G \):

\[
I(F, G_j) \overset{\text{def}}{=} \frac{1 - \eta}{\eta} \cdot \left[ H(G_j(r_{jt+1})) - \mathbb{E}_F H(F(r_{jt+1} | \tilde{r})) \right]
\]

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

### 2.3 The Consumption-Saving Decision

We begin by solving for the household’s consumption and saving decision. The Euler equation is:

\[
\mathbb{E}_t^F (\mathcal{M}_{ht+1} \rho_{ijt+1}) = 1
\]

where \( \mathcal{M}_{ht+1} \) is the stochastic discount factor, which takes on the usual formula:

\[
\mathcal{M}_{ht+1} \overset{\text{def}}{=} \gamma \cdot \frac{\theta_j}{1 - \theta_j} \cdot \frac{c_{ht}}{c_{ht+1}}
\]

Using the budget constraints for \( t \) and \( t + 1 \), we substitute \( s_{ht} \) inside the Euler equation. We thus find that, in equilibrium, all investors save a constant share \( \theta_j \) of their period 1 earnings:

\[
s_{ht} = s_{jt} = \theta_j (w_{jt} \ell_j + m_{jt}x_j) = \theta_j (\lambda_j + \xi_j) y_{jt} \quad \forall (j, t)
\]

### 2.4 Separability of the Household Problem

At first sight, the optimization problem in equation (2.12) appears intractable. However, it can be simplified and addressed with a few manipulations. First, we use the \( t + 1 \) budget constraint to write:

\[
\mathbb{E}_t^F (\log c_{ht+1}) = \log \theta_j + \log s_{ht} + \mathbb{E}_t^F (\log \rho_{ijt+1})
\]
Next, because the shocks $\zeta_{it}$ are unlearnable, we can use the law of iterated expectations to write:

$$E_t^F (\log \rho_{ijt+1}) = E_t^F (E_{r_{ijt+1}} \log \rho_{ijt+1}) = E_t^F (r_{ijt+1})$$  \hspace{1cm} (2.18)

Substituting (2.17) and (2.18), we can re-write the maximized utility from (2.12) in the simpler form:

$$U_h \overset{\text{def}}{=} \max_{c_{ht}, s_{ht}} \left[ (1 - \theta_j) \log c_{ht} + \theta_j \log s_{ht} \right] + \mathbb{E}_{F_t} \left[ \mathbb{E}_{\tau_{ijt}} \log \rho_{ijt+1} + 1 \right] + \text{constant}$$  \hspace{1cm} (2.19)

By restating problem (2.12) into (2.19), we have accomplished two things. First, we have verified (as previously conjectured) that $r_{ijt+1}$ is a sufficient statistic for the $t + 1$ utility, so that it makes sense for household $h$ to acquire a signal about $r_{jt+1}$. Second, we have separated the consumption/saving decision from the information acquisition/asset allocation decision. We already solved the first problem. The second now takes a familiar form with a known solution. Specifically, define $\pi_{ijt}$, the conditional probability that a generic investor from country $j$ invests in country $i$ at time $t$. Matějka and McKay (2015) show that the conditional probability of agent $h$ selecting country $i$ at time $t$ (where the conditioning is on $R_{ijt}$) – is given by:

$$\pi_{ijt} = \frac{R_{ijt}^{1 - \eta} \cdot \pi_{ijt}^0}{\sum_{i=1}^{n} R_{ijt}^{1 - \eta} \cdot \pi_{ijt}^0}$$  \hspace{1cm} (2.20)

$\pi_{ijt}^0$ is the corresponding unconditional probability, defined as follows

$$\pi_{ijt}^0 \overset{\text{def}}{=} \mathbb{E}_{G_j} (\pi_{ijt})$$  \hspace{1cm} (2.21)

This is a variation of the well-known multinomial logit model. An improvement in the information acquisition technology - that is, a higher value of the parameter $\eta$ - increases the elasticity of the portfolio shares $\pi_{ij}$ with respect to $R_{ijt}$. The intuition behind this result is that the easier it is for investors to acquire information about return fundamentals, the more these fundamentals will affect equilibrium portfolios. In the limit, where information becomes freely available ($\eta \to 1$), asset demand becomes infinitely elastic to return fundamentals and agents only invest in the country that offers the highest risk-adjusted, after-tax return. Conversely, when signals become prohibitively costly, investors’ demand for assets becomes completely inelastic, and agents simply invest in the country for which they have the most precise prior information.

### 2.5 International Capital Markets

Before proceeding to solve for country portfolios, we must define some additional notation. We define $a_{ijt}$ as the total claims to country $i$ capital by the investors of country $j$. Capital markets clearing implies the following two accounting relationships: 1) the supply of physical capital to country $i$ ($k_{it}$) equals the sum of all units of capital supplied from all countries $j$; 2) total claims by country $j$ towards all countries $i$ must equal country $j$’s total savings from the previous period:

$$k_{it} = \sum_{j=1}^{n} a_{ijt} \quad \text{and} \quad s_{jt-1} = \frac{1}{\gamma} \sum_{i=1}^{n} a_{ijt}$$  \hspace{1cm} (2.22)

We next describe how investors allocate their capital across different countries. Because investors are
atomistic, $\pi_{ijt}$ is not only the probability that household $h \in j$ invests in $i$, it is also the share of $j$–capital invested in country $i$ as a percentage of country $j$’s aggregate saving (the portfolio share) – formally:

$$\pi_{ijt} \equiv \frac{a_{ijt}}{\gamma s_{jt-1}}$$  \hspace{1cm} (2.23)

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

$$\begin{bmatrix}
  k_{1t} \\
  k_{2t} \\
  \vdots \\
  k_{nt}
\end{bmatrix} = \begin{bmatrix}
  \pi_{11,t} & \pi_{12,t} & \cdots & \pi_{n1,t} \\
  \pi_{21,t} & \pi_{22,t} & \cdots & \pi_{n2,t} \\
  \vdots & \vdots & \ddots & \vdots \\
  \pi_{n1,t} & \pi_{n2,t} & \cdots & \pi_{nn,t}
\end{bmatrix} \begin{bmatrix}
  s_{1,t-1} \\
  s_{2,t-1} \\
  \vdots \\
  s_{n,t-1}
\end{bmatrix}$$  \hspace{1cm} (2.24)

2.6 Calibrating the elasticity parameter $\eta$

The parameter $\eta \in (0, 1)$ governs the elasticity of substitution among different countries’ assets, and is therefore an important determinant of the representative investors’ portfolios.

We calibrate $\eta = 1/2$, based on the fact that, for a small open economy $i$, the elasticity of investment with respect to the expected return is equal to:

$$\frac{\partial \log a_{ijt}}{\partial \log EMPK_{it}} = \frac{\eta}{1 - \eta} \cdot (1 - \pi_{ij}) \approx \frac{\eta}{1 - \eta}$$  \hspace{1cm} (2.25)

we can compare $\frac{\eta}{1 - \eta}$ to empirical estimates of the demand elasticity with respect to returns.$^{11}$ $\eta = 1/2$ 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 $\frac{\eta}{1 - \eta} = 1$.\textsuperscript{12}

2.7 Prior Beliefs and Equilibrium Country Portfolios

In order to derive country portfolios, we need to make an assumption about investors’ prior beliefs. We start with some definitions. First, define the global portfolio share $\pi_{it}$:

$$\pi_{it} \overset{\text{def}}{=} \frac{k_{it}}{K_t}$$  \hspace{1cm} (2.26)

\textsuperscript{11}Because we have 62 countries in our dataset, this approximation will be reasonably accurate even in the presence of significant domestic investment.

\textsuperscript{12}Another reason to calibrate $\eta = 1/2$ is that $\eta$ is restricted to be between 0 and 1: from a Bayesian perspective, if we impose a uniform prior for $\eta$ over this interval, any estimate of $\eta$ should be shrunk towards the mid-point of the range.
Second, we define an important property of the investors’ prior, which we call Stationarity. The prior $G_j$ satisfies this property if $\pi_{ijt}^0$, the unconditional ($G_j$) expectation of the time $t$ portfolio shares equals the previous period’s global portfolio share $\pi_{it-1}$.

**Definition 1.** We say that the $j$-investors’ prior $G_j$ is (strictly) Stationary if:

$$\pi_{ijt}^0 \equiv \mathbb{E}^{G_j}(\pi_{ijt}) = \pi_{it-1} \quad (2.27)$$

Intuitively, this assumption imposes some form of rationality on the investors’ beliefs: at time $t$, before they receive any signal about the return vector $r_{it+1}$, they allocate their assets – in expectation – in the same way the previous generation of investors did. This makes sense because, at time $t$, investors can see the asset allocation of the previous generation.

This restriction on the agents’ prior is useful because it provides us with an efficient benchmark model. To be more specific, we can show (and we do in subsection 2.10) that, if the agents’ prior is stationary, the steady-state equilibrium of this model equalizes the risk-adjusted rate of return to capital among destination countries. In turn, this implies that, in absence of risk premia and distortions, the steady-state equilibrium delivers an efficient allocation of capital, in the sense that it maximizes world GDP. This is true even when information is not free ($\eta < 1$).

In order to model information frictions, we must deviate from this efficient benchmark. We do so by weakening condition (2.27) in the following way.

**Definition 2.** We say that the $j$-investors’ prior $G_j$ is Weakly Stationary if, for some time-invariant vector of constants, $(C_{ij1}, C_{ij2}, ..., C_{ijn})$:

$$\pi_{ijt}^0 \pi_{it-1} = C_{ij} \quad (2.28)$$

In what follows, we restrict our attention to weakly-stationary priors, as they produce closed-form solutions for steady-state country portfolios. The analytical results of Pellegrino (2023) imply that there exists a family of priors (called Tempered Stable distributions) that can be parametrized to satisfy this condition. Specifically, we assume that $j$-investors’ prior beliefs at $t-1$ are such that $R_{ijt}$ follows a Tempered Stable distribution with common mean and dispersion that is exponential in $\Sigma^G_{ij}$ (a destination country-specific dispersion parameter) and inversely proportional to $\pi_{it-1}$.

In Appendix B, we show that this prior satisfies:

$$\log \frac{\pi_{it-1}}{\pi_{ijt}^0} = \Sigma^G_{ij} \quad (2.29)$$

implying that the prior is weakly stationary. If $\Sigma^G_{ij} > \Sigma^G_{ij}$, $j$-investors are endowed with a less precise prior for $i$ assets than for $i$ assets.

Having specified the households’ prior beliefs, we can now derive the matrix of portfolio shares in closed form. We find that household optimization yields logit demand for international assets, as in Koijen and Yogo (2020).

**Proposition 1.** The equilibrium share of $j$ capital invested in destination country $i$ is:

$$\pi_{ijt} = \frac{(R_{it}/\Delta_{ij})k_{it-1}}{\sum_{i=1}^{n}(R_{it}/\Delta_{ij})k_{it-1}} \quad (2.30)$$

where $R_{it}$ is the risk-adjusted expected return to capital in country $i$, defined as follows:

$$\log R_{it} \equiv \log \text{EMP}_i - \left(\sigma_{iw}^z + \frac{1}{2} \Sigma^z_i \right) \quad (2.31)$$
and $\Delta_{ij}$ is the “return wedge”, defined as follows:

$$\log \Delta_{ij} \overset{\text{def}}{=} -\log \mu_{ij}^T + \frac{1}{2} \Sigma_{ij}^T + \Sigma_{ij}^G$$

(2.32)

Proof. Substitute equation (2.26) inside (2.29) and then (2.29) inside (2.20). Then use the fact that $R_{it} = R_{it} \exp \left( \log \mu_{ij}^T - \frac{1}{2} \Sigma_{ij}^T \right)$ and collect the terms for $\Delta_{ij}$. \hfill $\square$

Portfolio shares depend on two main drivers: 1) a fundamental component ($R_{it}$), which captures the marginal productivity of capital as well as risk; 2) a distortionary component $\Delta_{ij}$, which captures the effect of policy and information frictions.

These two drivers can be further broken down into four fundamental factors: 1) the physical return to capital, which is captured by the first term in parentheses inside equation (2.31); 2) risk and hedging, which is captured by the second term in parentheses: investors are less inclined to invest in countries with volatile productivity (high $\Sigma_z^T$) and more inclined to invest in countries that provide a better hedge against global TFP shocks (low $\sigma_{iz}$); 3) policy distortions ($\tau_{ij}$), which may affect the mean $\mu_{ij}^T$ as well as the dispersion $\Sigma_{ij}^T$ of the perceived rate of return to capital; 4) prior uncertainty $\Sigma_{ij}^G$: investors are more inclined to invest in countries about which they have more precise prior information.

An alternative way to see how the wedge $\Delta_{ij}$ distorts the perceived rate of return to capital is to re-write the term in parentheses from equation (2.30) as:

$$\log \left( \frac{R_{it}}{\Delta_{ij}} \right) = \log \left( \mu_{ij}^T \kappa_i y_{iit} - \frac{1}{2} \Sigma_z^T + \frac{1}{2} \Sigma_{ij}^T + \Sigma_{ij}^G \right)$$

(2.33)

The wedge distorts the perceived rate of return from investing from $i$ to $j$ in three ways. First, changes in the mean of the policy distortions $\mu_{ij}^T$ feed directly into the mean perceived return (first term in parentheses on the right). Second, policy distortions, to the extent that they are unpredictable, inflate the risk premium, via $\Sigma_{ij}^T$. Third, information frictions add a premium for prior uncertainty $\Sigma_{ij}^G$.

### 2.8 Global Capital Markets Clearing and Steady-State Equilibrium

To close the model, we find the vector of capital stocks $k$ that simultaneously clears the market for inputs and assets. First, define the following diagonal matrices:

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

(2.34)

Then, notice that the matrix of country shares $\Pi$ is a function of the $t-1$ vector capital stocks $(k_{t-1})$ and the rates of return, which are themselves a function of current period capital stocks $(k_t)$. Since $s = \Theta (\Lambda + \Xi) y$ and $y$ is a function of $k$, equation (2.24) can be re-written as:

$$k_t = \gamma \Pi \left( r(k_t), k_{t-1} \right) \cdot \Theta \cdot (\Lambda + \Xi) \cdot y(k_{t-1})$$

(2.35)

The steady-state market-clearing vector of equilibrium capital stocks $k^*$ is then determined as the fixed point of equation (2.35) by setting $k_t = k_{t-1}$. Notice that there is a trivial equilibrium at $k = 0$. When
we solve equation (2.35) 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:

\[
c_j = \sum_{i=1}^{n} \rho_i a_{ij} + (1 - \theta_j) (w_j \ell_j + m_j x_j)
\]

(2.36)
given that the total untaxed factor income in country \( j \) is given by:

\[
y_j - q_j = \rho_j k_j + w_j \ell_j + m_j x_j
\]

(2.37)

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

\[
c_j + q_j + s_j - y_j = \sum_{i=1}^{n} \rho_i a_{ij} - \theta_j (w_j \ell_j + m_j x_j) - \rho_j k_j + s_j = \sum_{i=1}^{n} \rho_i a_{ij} - \rho_j k_j
\]

(2.38)

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.

### 2.9 Steady-State Investment Positions and Gravity

We now proceed to derive steady-state bilateral investment positions \( a_{ij} \). Using the fact that country \( i \)’s gross capital income is, in expectation, \( E(\rho_i k_{it}) = [\Delta_{ij} \cdot \exp(\sigma_{iw} + \Sigma_i y_i)]^{-1} \kappa_i y_i \), equilibrium portfolio shares can be re-written as follows:

\[
\pi_{ij} = \frac{[\Delta_{ij} \cdot \exp(\sigma_{iw} + \frac{1}{2} \Sigma_i)]^{-1} \kappa_i y_i}{\sum_{i=1}^{n} [\Delta_{ij} \cdot \exp(\sigma_{iw} + \frac{1}{2} \Sigma_i)]^{-1} \kappa_i y_i}
\]

(2.39)

The denominator of equation (2.39) can be interpreted as the size of the global market for capital that is available to country \( j \) investors (adjusted for risk and frictions). We call it \( M_j \):

\[
M_j \overset{\text{def}}{=} \sum_{i=1}^{n} [\Delta_{ij} \cdot \exp(\sigma_{iw} + \frac{1}{2} \Sigma_i)]^{-1} \kappa_i y_i
\]

(2.40)

Multiplying both sides of equation (2.39) by \( s_j \) and using the fact that \( s_j = \theta_j (\lambda_j + \xi_j) y_j \), equation (2.39) can be re-written with the total asset position \( a_{ij} \) on the left-hand side. These gross asset positions obey a gravity-like equation:

\[
a_{ij} = \frac{\gamma \kappa_i}{\exp(\sigma_{iw} + \Sigma_i/2)} \cdot \theta_j \left( \frac{\lambda_j + \xi_j}{M_j} \right) \cdot \left( \frac{y_i \cdot y_j}{\Delta_{ij}} \right)
\]

(2.41)

In comparison to the classical gravity equation in trade (Eaton and Kortum, 2002), our gravity equation differs in that geographic distance is here replaced by the general wedge \( \Delta_{ij} \), which captures both policy and information frictions. Information frictions, in particular, have been previously shown by Portes, Rey, and Oh (2001) to produce gravity effects in international investment.
2.10 Theoretical Results on Steady-State Capital Allocation

In this subsection, we present a series of theoretical results that help 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:\textsuperscript{13}

$$Y_t \overset{\text{def}}{=} \sum_{i=1}^n y_{it}$$ (2.42)

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

**Definition 3** (Efficient Capital Allocation). We say that an allocation $k_t$ is efficient if it maximizes World GDP $Y_t$ given world capital $K_t \overset{\text{def}}{=} \sum_{i=1}^n k_{it}$, that is:

$$k_t \in \arg \max_{k'} Y_t (k') \quad \text{s.t.} \quad \sum_{i=1}^n k_{it}' = \sum_{i=1}^n k_{it}$$ (2.43)

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 are no bilateral distortions – that is, $\Delta_{ij} \equiv \Delta_i \times \Delta_j$ – then all origin countries $j$ hold identical portfolios of foreign assets ($\pi_{ijt}$ is independent of $j$).

**Proof.** This can be easily verified by substituting ($\Delta_{ij} \equiv \Delta_i \times \Delta_j$) inside equation (2.30). Then $\Delta_j$ simplifies out from the numerator and the denominator and the resulting expression for $\pi_{ijt}$ not depend on $j$. \hfill \Box

**Proposition 3.** In steady-state equilibrium, if there are no objective distortions – that is, $\Delta_{ij} = \Delta_j$ (does not depend on $i$) – risk-adjusted expected returns are equalized across countries: $R_i = R^* \forall i = 1, 2, \ldots, n$.

**Proof.** See Appendix A. \hfill \Box

One implication of Proposition 2 and 3 is that, in the absence of distortions, 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 that the effective absence of asset markets frictions translates in factor markets efficiency and vice versa.\textsuperscript{14}

**Theorem** (Dual Efficiency). Consider a steady-state equilibrium. The following three statements are equivalent (each is true if and only if the other two statements hold):

1. Capital is efficiently allocated
2. The expected MPK is equalized across countries ($\text{EMPK}_i = \text{EMPK}^*$ for $i = 1, 2, \ldots, n$)

\textsuperscript{13}The stochastic components $d_{it}$ have mean zero, so their sum becomes negligible as the number of countries becomes large.

\textsuperscript{14}This is not a re-statement of the First Welfare Theorem, because it is a statement about GDP, not welfare.
3. The wedges \( \Delta_{ij} \) satisfy the following condition:

\[
\sum_{j=1}^{n} \left[ \frac{\Delta_{ij} \cdot \exp \left( \frac{1}{2} \Sigma_i^2 + \sigma_i^2 \right)}{\sum_{i=1}^{n} \left[ \Delta_{ij} \cdot \exp \left( \frac{1}{2} \Sigma_i^2 + \sigma_i^2 \right) \right]} \right]^{-1} s_j = \mathcal{C} \quad \text{for } i = 1, 2, \ldots, n
\]

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

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

**Corollary 2.** Uniform risk premia \( (\sigma_i^2 + \Sigma_i^2/2 = \text{constant}) \) and frictions \( (\Delta_{ij} = \Delta) \) are jointly sufficient (but not necessary) for statements (1)-(3) to obtain.

**Proof.** Appendix A.

Intuitively, the condition outlined in equation (2.44) requires that taxes, risk and information frictions offset each other. This is important because it implies that it is possible, for a social planner, to attain the first-best allocation without necessarily having to necessarily alter risk/information. Consider for example the case with symmetric risk premia: a benevolent global planner can implement the efficient allocation by imposing lower capital taxes in countries that are more peripheral in the network informational distances, and that therefore find it harder to attract capital due to information frictions.

### 3 Data and Econometric Specification

#### 3.1 Measurement of the Wedges

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 gravity equation for international investment. We conclude the section by outlining our econometric strategy to estimate this gravity model.

In order to take our model to the data, we must be able to quantify the wedge \( \Delta_{ij} \). This wedge incorporates any friction (policy, information) affecting the international allocation of capital, and therefore can be broken down into several underlying terms. The set of frictions that we want our model to incorporate depend on the setting, and there is no set rule. By virtue of the generality of our model, we could include virtually any friction affecting the allocation of capital.

For our baseline empirical application, we must necessarily focus on a subset of the possible frictions. We choose a parsimonious specification, based on our reading of the previous literature, plausible exogeneity, and the broader relevance to our research question. We are not sold to a particular specification: in fact, in Section 7, we will try and introduce various additional or alternative wedges.

Specifically, we incorporate three types of wedge: one reflects capital taxation \( (\Delta_{ij}^{\text{Tax}}) \) the second reflects political risk \( (\Delta_{ij}^{\text{PR}}) \), the third reflects geo-cultural distance across countries \( (\Delta_{ij}^{\text{Dist}}) \), as in Lustig and Richmond (2020):

\[
\Delta_{ij} = \Delta_{ij}^{\text{Tax}} \times \Delta_{ij}^{\text{PR}} \times \Delta_{ij}^{\text{Dist}}
\]

We outline three broad strategies that can be used to calibrate the wedges. The first and most obvious strategy is direct measurement: if estimates of specific frictions (for example, taxes on capital) are available, all we need to do is to simply express \( \Delta_{ij} \) as a function of the measured wedges. A second
strategy is to use regression analysis. A third strategy is to recover the wedges directly from the data using wedge accounting.

We are able to use direct measurement for the capital taxation and political risk wedges ($\Delta^\text{Tax}_i$ and $\Delta^\text{PR}_i$); we then outline a regression strategy to recover $\Delta^\text{Dist}_{ij}$. While we do not employ a wedge accounting approach in the baseline empirical application, we use the wedge accounting version of the model as a convenient benchmark to evaluate the ability of our model in matching untargeted moments of the data (see subsection 5.2).

3.1.1 Tax Wedge

Our observable measures of taxation captures four factors: 1) corporate income taxes; 2) taxes on dividends; 3) taxes on interest income. This composite tax rate is constructed using the formula:

$$\Delta^\text{Tax}_i = \left[ \frac{4}{5} (1 - \text{CITR}_i) (1 - \text{DWTR}_i) + \frac{1}{5} (1 - \text{IWTR}_i) \right]^{-1}$$  (3.2)

CITR$_i$ 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. DWTR$_i$ and IWTR$_i$ 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).\textsuperscript{15}

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.

3.1.2 Political Risk Wedge

Our formula also includes $\Delta^\text{PR}_i$, a wedge that captures political risk. We measure this wedge by combining a composite measure produced by the International Country Risk Group (ICRG) with empirical estimates by 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 political risk. The ICRG index ranges from zero (extreme political risk) to ten (virtually no political risk).\textsuperscript{16}

We compute the wedge on political risk using the following equation:

$$\log \Delta^\text{PR}_i = \beta_{\text{PR}} (10 - \text{ICRG}_i)$$  (3.3)

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

\textsuperscript{15}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.

\textsuperscript{16}The political risk index is missing for a handful of countries, for which we input a political risk score of 5.
The third component of the return wedge reflects cultural and geographic distances among countries, which have been shown to generate “gravity” effects in currency markets Lustig and Richmond (2020) as well as in foreign direct and portfolio investment (Portes and Rey, 2005; Aggarwal, Kearney, and Lucey, 2012; Ahern, Daminelli, and Fracassi, 2015).

Portes, Rey, and Oh (2001) have shown that an important mechanism for this gravity effect is information frictions: investors are likely to know more about countries that are closer to them along geographic, linguistic, and cultural lines. For example, Spanish investors, before they do any specific research about investment opportunities, may have an informational advantage about the Portuguese market, relative to some other country with the same financial size as Portugal’s, but at larger geographic, linguistic, or cultural distances from them. While our framework allows for distances to affect international portfolios through information frictions (namely, through the prior dispersion $\Sigma_C^{ij}$), we do not claim that prior uncertainty is necessarily the only channel: distances may also affect portfolio shares through the other components of the wedge $\Delta_{ij}$. Our empirical framework is crafted to allow for flexibility over the mechanism. Our research question is not to econometrically identify this mechanism, as this has already been addressed by previous research.

We propose a parsimonious specification based on three measures of distance: Geographic Distance, Cultural Distance and Linguistic Distance. Thus, we assume that we can approximate the barriers to global capital movements as a log-linear function of the following measurable variables:

$$\log \Delta_{ij}^{Dist} = -(\text{GeoDist}_{ij} \cdot \beta_g + \text{CultDist}_{ij} \cdot \beta_c + \text{LingDist}_{ij} \cdot \beta_l) \quad (3.4)$$

These measures of bilateral distances are described in more detail in Section 3.2.2. In order to estimate the weights $\beta_g, \beta_c,$ and $\beta_l$, we estimate the gravity equation derived from the model. As discussed above, the model implies a gravity equation for bilateral asset holdings (equation (2.41)). 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 $(d_{ij})$ and letting $p_j$ be the PPP adjustment factor for country $j$ (not modeled explicitly until Section 7), we can write:

$$\hat{a}_{ij} = p_j \cdot a_{ij} \cdot \exp(\varepsilon_{ij}) \quad \text{with} \quad \varepsilon_{ij} \perp (\text{GeoDist}_{ij}, \text{CultDist}_{ij}, \text{LingDist}_{ij}) \quad (3.5)$$

Then, we can formulate the gravity equation (2.41) as the following fixed effects linear regression model for the log of bilateral asset holdings:

$$\log \hat{a}_{ij} = \alpha^o_i + \alpha^d_j + \text{GeoDist}_{ij} \cdot \beta_g + \text{CultDist}_{ij} \cdot \beta_c + \text{LingDist}_{ij} \cdot \beta_l + \varepsilon_{ij} \quad (3.6)$$

where, on the left-hand side, $\hat{a}_{ij}$ is bilateral restated asset positions from the IMF and, on the right-hand side, $\alpha^o_i$ is a country of origin fixed effect and $\alpha^d_j$ is a country of destination fixed effect:

$$\alpha^d_i \overset{\text{def}}{=} \log \left( \gamma \kappa_i y_i \right) - \sigma_{iw}^{i} - \frac{1}{2} \Sigma_{i}^{z} \quad \text{and} \quad \alpha^o_j \overset{\text{def}}{=} \log \left( s_j / M_j \right) \quad (3.7)$$

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

Equation (3.6) 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).\footnote{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).} Since the vector of distances 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.

3.2 Data

3.2.1 Dependent Variables: Restated Foreign Investment Data

We use 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 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.

For 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.\footnote{Coppola et al. (2020) combine all European Monetary Union countries into a single entity. We re-state the asset position}

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$^\circ$ line, indicating that they are similar in size and tend to track each other closely. This suggests that they might be driven by a similar set of underlying factors, an issue that our econometric analysis will clarify. Similar observations hold for the distinction between FDI and FPI, which are considered as alternative dependent variables in the Appendix.
3.2.2 Distance Metrics

Our empirical measures of distances include cultural, geographic and linguistic distance. We also consider religious distance as a historical determinant of cultural distance.

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 broadly similar across pairs. For each question, the measure consists of the Euclidian distance in answers between country pairs. Distances are then averaged over questions to obtain a summary index. Averages can be computed by question category, but here we use the average over all underlying 98 questions.

We 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 of EMU individual countries using the EMU reallocation matrices.
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).\footnote{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.} 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 include it as an additional measure of distance. 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.\footnote{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 Macroeconomic Data

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

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

The last ingredient is natural resources rents as a percent of GDP ($\xi_i$): this is obtained from the most recent version (2018) of the World Bank’s Wealth of Nations dataset.
3.2.4 Mechanism and Rationale for the Choice of Explanatory Variables

The right-hand-side variables in investment gravity regressions are typically interpreted as capturing policy and information frictions in the literature on the determinants of cross-border financial holdings (Portes and Rey, 2005). Many variables could be included on the explanatory side. The reasons for choosing taxes on capital, political risk, and three measures of distance (cultural, geographic and linguistic) are: 1) parsimony; 2) data availability - we want to retain as many countries as possible in our sample; 3) minimizing the likelihood of reverse causation - we prefer to use variables that are unlikely to be themselves affected by bilateral investment, or for which we have a defensible instrument.

It is worth noting that, in principle, we do not have to assume that taxes on capital and political risk only affect policy frictions, while geographic, cultural, and linguistic distance only affect information friction. On the contrary, our specification is general enough, both theoretically and empirically, to allow for government-induced barriers to affect information flows and, conversely, for bilateral distances to affect policy frictions. That said, it is plausible to assume that taxes and political risk can be mainly interpreted as policy frictions, while a large part of the effects of geographic, cultural and linguistic distances are likely to occur through their impact on informational barriers and biases.

To explore whether these variables do indeed capture information frictions, we looked at their effect on the Social Connectedness Index, which is based on Facebook data (Bailey, Gupta, Hillenbrand, Kuchler, Richmond, and Stroebel, 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. For the purpose of the analysis of this paper, all we need is that taxes, political risk and distances affect policy and information frictions, while we remain relatively agnostic about the decomposition and classification of the effects across the different observable variables.

3.2.5 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. 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). The variable Currency Peg is a dummy equal 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 use 2017 data. We also obtained, from the World Bank’s International Center for the Settlement of Investment Disputes (ICSID), data on bilateral investment treaties, which we code as the dummy variable Investment Treaty. In addition, we control for a Tax Treaty dummy, using data from Petkova, Stasio, and Zagler (2019).

21The 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.

Table 1: Summary Statistics

Panel A: Directed (Dependent) Variables

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

Panel B: Undirected (Independent) Variables

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

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, solved analytically so that trade costs can be inferred using observed trade data. The ESCAP-World Bank Trade Cost Database updates these
calculations periodically, and estimates of trade costs are now available for a wide set of country pairs over the 1995-2018 period.\textsuperscript{23} We use the “undirected” trade cost measure – i.e. the geometric average of the wedge on imports and exports – for consistency (our explanatory variables are all undirected) and in order to avoid losing 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 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.\textsuperscript{24}

### 4 Econometric Analysis

In this section, we estimate the parameter vector $\beta$, the effect of geographic and cultural distances on log foreign investment (three semi-elasticities). Our objective is both to provide a quantitative assessment of the statistical impact of cross-border investment frictions, and to retrieve structural parameters for the model of Section 2, for the counterfactual analysis to follow.

#### 4.1 Least Squares Analysis

We begin by performing an OLS regression of equation ((3.6)), 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: $\%\Delta FA_{ij} = e^{\beta x} \Delta x_{ij} - 1$. We find large effects of these barriers: an 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

\textsuperscript{23}https://www.unescap.org/resources/escap-world-bank-trade-cost-database

\textsuperscript{24}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.
Table 2: OLS Regressions

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

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

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 goal is to address the possibility that omitted variables bias affected our main coefficients of interest. 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
### Table 3: Pseudo-Poisson Regressions

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

**Table Notes:** This table reports Iteratively-Reweighted Least Squares (IRLS) estimates of a Pseudo-Poisson regression of the variables listed on the topmost row (Foreign Assets, Foreign Equity Assets, Foreign Debt Assets) on the variables in the leftmost column. Each observation is a directed country pair. All regressions include origin country (i) fixed effects and destination country (j) fixed effects. Additional controls in columns 4-6 are Border Contiguity, 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

variables does not fundamentally alter the inferences drawn from the more parsimonious specification.

### 4.2 Pseudo-Poisson Regressions

One shortcoming of the econometric model described by equation (3.6) 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 (3.6) as:

$$
\hat{a}_{ij} = \exp \left( \alpha_i^d + \alpha_j^o + \text{GeoDist} \cdot \beta_G + \text{CultDist}_i \cdot \beta_C + \text{LingDist}_i \cdot \beta_L + \varepsilon_{ij} \right)
$$

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

25The 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 4: First-Stage Regressions

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

**Table Notes:** This table reports Ordinary Least Squares (OLS) estimates of a linear regression of the variables listed on the topmost row on the variables in the leftmost column. These correspond to the first stage of the IV regressions (1) and (4) presented in Table 5. Each observation is an undirected country pair. All regressions include origin country ($i$) fixed effects and destination country ($j$) fixed effects. All regressions control for Geographic Distance. Additional controls in columns 3 and 4 are Border Contiguity, 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. $^*p < .05$; $^{**}p < .01$

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

Table 3 displays the resulting estimates. In general, we find that the standardized magnitude of Poisson 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
Table 5: Instrumental Variables Regressions

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

Table Notes: This table reports Instrumental Variable (IV) estimates of a linear regression of the log of the variable listed on the top row (Foreign Assets, Foreign Equity Assets, Foreign Debt Assets) on the variables in the leftmost column. Cultural Distance is the endogenous regressor and the excluded instrument is Religious Distance. Each observation is a directed country pair. All regressions include origin country (i) fixed effects and destination country (j) fixed effects. The additional controls in columns 4-6 are Border Contiguity, 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

geographic, linguistic and cultural barriers exert quantitatively meaningful and statistically significant negative effects on foreign asset holdings.

4.3 Instrumental Variables Regressions

While estimating causal effects of is not the main objective of our econometric analysis, we nonetheless worry about how the estimated coefficient on cultural distance could be affected by 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. In that case, the OLS estimates of the gravity equation (3.6) 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

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

26
instrumental variable. Other measures of historical relatedness, like Colonial Relationship, are used as controls rather than instruments out of concern about their excludability from the second stage.

Religious Distance, like linguistic distance, is constructed using a branching tree that traces the historical splits of different religious denominations. It is plausible that the contemporary effects of such splits on our dependent variable should operate (mainly or exclusively) through contemporary differences in values and beliefs (including, but not limited to, religious beliefs), measured by Cultural Distance.

Table 4 presents estimation results for the first-stage regressions. We present results for the parsimonious specification (column 1), and for the specification with additional controls (column 2). First stage regressions lead to interesting results. Consistent with findings in Spolaore and Wacziarg (2016), religious distances is positively and significantly correlated with cultural distance: the 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. The instrument comfortably passes several tests for weak instruments.

Table 5 presents results for the second stage. As before, there are six columns, corresponding to three dependent variables (log total foreign assets, log foreign equity investment, and log debt investment) and to whether we include additional controls or not. Cultural Distance is treated as endogenous. Compared to the OLS results of Table 2, we find that the magnitude of the effect of cultural distance rises. Take for instance the effect of cultural distance on log Foreign Assets (column 1). The effect of a one standard deviation increase in Cultural Distance was -49.1% under OLS, and it rises in magnitude to -61.3% under IV. Similar differences are seen across specifications. On the other hand, across specifications the standardized magnitude of the effect of geographic distance is roughly unchanged compared to OLS (in column 1, it is -65.4% versus -66.9% under OLS, for instance). Lastly, the effect of 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 total foreign assets, foreign equity assets and 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 (ζ_{it} = 1) – that is, we map PPP GDP in the year 2017 to y_{it}.

While our model allows for country-specific risk premia, we take our baseline model to the data assuming that countries are identical in their risk properties – i.e. they have identical variance of output shocks and covariance with global output. We do so for two reasons, related to exposition: 1) The focus of this paper is on the frictions. In the baseline version of our model, we examine whether policy and information frictions alone can account for salient facts about international capital allocation (without appealing to differences in risk). 2) In our counterfactual analysis, we focus on changes in country and world GDP, so this baseline model has the advantage that changes in GDP map directly to changes

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27Finding IV estimates on the instrumented variables that are larger in magnitude than OLS estimates is quite common in the literature, even in cases (like ours) where we expect reverse causality to bias OLS estimates away from zero. A common explanation is that IV estimation helps address attenuation bias coming from measurement error, if error in measurement of the instrumental variables is uncorrelated with error in measurement of the instrumented (endogenous) regressor.
Figure 2: Model Fit: Portfolio Shares (Targeted)

Figure Notes: the figure above plots the model-implied portfolio shares ($\pi_{ij}$), 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.
in welfare: counterfactuals have a straightforward welfare interpretation. In any case, we repeat all of our counterfactual analyses in a more general model in Section 7, where we calibrate country-level risk premia, finding results very similar to the baseline exercise.

5.1 Model Solution and Identification

We calibrate the distance semi-elasticities \((\beta)\) 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).

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

Capital being the only moving factor, solving the model means finding the country-level total asset stocks \(s\), the network of portfolio shares \(\Pi\), and (by extension) the vector of capital stocks \(k\). 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 one single term \(\tilde{\omega}_i\):

\[
y_i = \tilde{\omega}_i k_i^{\kappa_i} \tag{5.1}
\]

where

\[
\tilde{\omega}_i \overset{\text{def}}{=} \omega_i x_i \xi_i \lambda_i \tag{5.2}
\]

First, we compute country-level savings \((s_i)\) from (observed) output \(y_i\) using equation (2.16). Second, we compute the matrix of portfolio shares \(\Pi\), given the income shares \((\kappa_i, \lambda_i, \xi_i)\), output \((y_i)\) and the matrix of wedges \((\Delta_{ij})\) using equation (2.39). \(k\) is then obtained as \(\gamma \Pi s\). The last model component that remains to be identified is \(\tilde{\omega}_i\): 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 \(\pi_{ij}\) – 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”

\[\text{In Section 7, we examine the sensitivity of the counterfactual analysis to the use of alternative estimates of } \beta, \text{ finding that such alternatives deliver broadly similar results to those of the benchmark exercise.}\]
**Table 6: Model Fit: Untargeted Moments**

<table>
<thead>
<tr>
<th>Variable</th>
<th>Statistic</th>
<th>Data</th>
<th>Model: Baseline</th>
<th>Frictionless</th>
<th>Residuals</th>
</tr>
</thead>
<tbody>
<tr>
<td>Return to Capital</td>
<td>Mean</td>
<td>-2.281</td>
<td></td>
<td>(matched by calibrating $\gamma$)</td>
<td>0.578</td>
</tr>
<tr>
<td></td>
<td>Standard Deviation</td>
<td>0.465</td>
<td></td>
<td></td>
<td>0.000</td>
</tr>
<tr>
<td></td>
<td>Correlation w/Data</td>
<td>1.000</td>
<td></td>
<td></td>
<td>0.834</td>
</tr>
<tr>
<td>Capital/Employee</td>
<td>Mean</td>
<td>12.270</td>
<td></td>
<td>(matched by calibrating $\gamma$)</td>
<td>1.189</td>
</tr>
<tr>
<td>log ($k_i/\ell_i$)</td>
<td>Standard Deviation</td>
<td>1.062</td>
<td></td>
<td></td>
<td>0.761</td>
</tr>
<tr>
<td></td>
<td>Correlation w/Data</td>
<td>1.000</td>
<td></td>
<td></td>
<td>1.326</td>
</tr>
<tr>
<td>Home Bias</td>
<td>Mean</td>
<td>3.729</td>
<td></td>
<td></td>
<td>4.084</td>
</tr>
<tr>
<td>log $\pi_{ii} - \log \frac{K_i}{R}$</td>
<td>Standard Deviation</td>
<td>1.241</td>
<td></td>
<td></td>
<td>1.085</td>
</tr>
<tr>
<td></td>
<td>Correlation w/Data</td>
<td>1.000</td>
<td></td>
<td></td>
<td>1.022</td>
</tr>
</tbody>
</table>

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:

$$\hat{\pi}_{ij} = \frac{\hat{a}_{ij}}{\sum_{i=1}^{n} \hat{a}_{ij}} \quad (5.3)$$

To estimate it, we fill missing values of the bilateral investment data using the fitted values of equation (3.6). The resulting portfolio shares for the two benchmark models are then defined as:

$$\pi_{ij}^{FL} = \frac{\kappa_i y_i}{\sum_{i=1}^{n} \kappa_i y_i} \quad \pi_{ij}^{Res} = \frac{\mathcal{E}_{ij} \kappa_i y_i}{\sum_{i=1}^{n} \mathcal{E}_{ij} \kappa_i y_i} \quad (5.4)$$

where $\mathcal{E}_{ij} = \hat{\pi}_{ij}/\pi_{ij}^{FL}$. We begin the evaluation of 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 ($\pi_{ij}^{Res}$). In Figure 2, we compare the portfolio shares from the baseline model to 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 ($\rho$) of 0.72. As this level of fit was obtained by only very few explanatory variables, we judge this to be a good fit. Since $\beta$ is obtained by fitting bilateral asset positions, we consider this data moment to be 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,

---

29 By plugging equation (3.5) into equation (5.3), it is easily verified that any PPP adjustment at the country of origin level leaves portfolio shares unchanged.
we can clearly see that the fit of the frictionless model is significantly worse ($\rho = 0.46$). 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; $^{30}$ 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 pattern 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 much more satisfactorily.

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: physical rates of return on capital ($\text{EMPK}_i$), capital stock per employee ($k_i/\ell_i$) and home bias, which we define (following Lau, Ng, and Zhang, 2010) as

$$\text{Home Bias}_i \overset{\text{def}}{=} \log \pi_{ii} - \log \frac{k_i}{K} \quad (5.5)$$

Our sources for the “Data” column are as follows. Rates of return on capital are computed using the

$^{30}$This is consistent with the findings of Portes and Rey (2005).
methodology of 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 $\pi_{ii}$, and Penn World Tables’ estimates of $k_i/K$.\footnote{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 ($\rho = .63$).}

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 the rates of returns perfectly.\footnote{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.} 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.\footnote{If we exclude Ireland the correlation rises to 0.92.} Because the frictionless model fails to generate any home bias at all, we can be certain that the ability of our model to match home bias (as well as the cross section of rates of returns) is exclusively due to the parsimonious set of frictions that it contains. Coeurdacier and Rey (2013) suggest an alternative measure of home bias for equities:

$$
\text{Home Bias}_{\text{Alt}} \overset{\text{def}}{=} 1 - \frac{1 - \pi_{ii}}{1 - k_i/K} \quad (5.6)
$$

We were able to obtain this measure from their paper, but is only available for ten of the countries in our sample. In Appendix J we compute our model-equivalent measure and show that it also capable of matching their measure of home bias remarkably well ($\rho = .68$).

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, country-level data (coming mostly from the Penn-World Tables) appears to be inconsistent, at least to some degree, with 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 un-targeted moments is measurement error in bilateral investment data. While we use nationality-based restated investment positions, this correction may be imperfect. In addition, 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 noisy variables, and this results in a worse fit of the untargeted country-level moments. For this reason, we refrain from doing counterfactuals on the residuals model.

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 & Volosovych, 2008) about the paucity of such flows in the data. In our model, these return differentials are produced by our measured wedges. Consequently, these barriers help explain the absence of large movements of capital towards developing countries, shedding light on the Lucas puzzle.\textsuperscript{34}

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 ($\rho = 0.77$).

\textsuperscript{34}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 baseline model, returns to capital are higher in emerging markets due to frictions. We re-introduce risk premia in 7.1.
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 as follows. 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. Thus, these returns can be seen as reflective of network centrality.

Crucially, the $i$-variation and $j$-variation that exists in our various measures of distance 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, distances 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 $\beta$, some of them suggested by the model itself (see equation 3.7). 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, we are not using country-level variation to estimate the semi-elasticities $\beta$, but this country-level variation does 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. 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. 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 the efficiency gains be?

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 interesting implications for international tax policy coordination, since tax rates interact with information frictions: if set optimally, they can potentially undo the effect of informational advantage.

Our counterfactuals consist of removing or activating, within our model, any of the wedges. To remove a wedge we change the (previously estimated) matrix of wedges to a uniform positive value. To the extent that the wedges (in particular those related to distance) reflect information frictions, the hypothetical policy intervention in this case would be 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’ 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 (frictionless) 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: Counterfactuals (2017)

<table>
<thead>
<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (PPP$ trillions)</td>
<td>103.3</td>
<td>109.8</td>
<td>109.4</td>
<td>108.1</td>
<td>103.1</td>
</tr>
<tr>
<td>World GDP, % Difference from Frictionless</td>
<td>-5.9%</td>
<td>0.0%</td>
<td>-0.3%</td>
<td>-1.6%</td>
<td>-6.1%</td>
</tr>
<tr>
<td>St.Dev. of log($k_i/\ell_i$), % Difference from Frictionless</td>
<td>+77.0%</td>
<td>0.0%</td>
<td>+12.2%</td>
<td>+28.4%</td>
<td>+55.4%</td>
</tr>
<tr>
<td>St.Dev. of log($y_i/\ell_i$), % Difference from Frictionless</td>
<td>+24.4%</td>
<td>0.0%</td>
<td>+5.7%</td>
<td>+13.6%</td>
<td>+11.9%</td>
</tr>
</tbody>
</table>

Table Notes: This table presents welfare statistics for four counterfactuals of the model described in Section 2. Each of columns (2)-(5) is a counterfactual, and the rows represent different welfare statistics of interest. Observed is the equilibrium allocation with all measured barriers. Frictionless is the counterfactual in which all barriers (taxes, political risk, and geo-cultural distance) have been removed. Columns (3)-(5) illustrate two additional counterfactuals from which only the corresponding distortion is in place. ($k_i/\ell_i$) is the capital stock per employee, while ($y_i/\ell_i$) is output (GDP) per employee. Actual World PPP$ GDP (including countries not in the model) in 2017 was $121 trillion.
Figure Notes: This figure fits the probability density function of a stable distribution (a 4-parameter family of distributions with flexible skewness and fat tails) to country-level capital stock per employee (upper panel) and GDP per employee (bottom panel). In each panel, the lighter area is the distribution in the observed, distorted equilibrium. The dotted black line is the distribution in a counterfactual scenario in which all wedges have been removed.
Table 7 presents the main results from the counterfactual analysis. In column (1), we present the observed equilibrium which is distorted by geo-cultural distance, taxes, and political risk. In column (2), we present the Frictionless equilibrium, from which all distortions have been removed ($\Delta_{ij} = 1 \forall i, j$). In column (3), we consider a counterfactual equilibrium (Taxes Only) where distortions from both political risk and geo-cultural distance are eliminated ($\Delta_{ij}^{\text{Dist}} = \Delta_{ij}^{\text{PR}} = 1 \forall i, j$) while distortions from taxes remain in place. In column (4), we consider a counterfactual equilibrium (Political Risk Only) where distortions from taxes and geo-cultural distance are eliminated ($\Delta_{ij}^{\text{Dist}} = \Delta_{ij}^{\text{Tax}} = 1 \forall i, j$) while distortions from political risk remain in place. In column (5), we consider a counterfactual equilibrium (Geo-cultural Distances Only) where distortions from taxes and political risk are eliminated ($\Delta_{ij}^{\text{Tax}} = \Delta_{ij}^{\text{PR}} = 1 \forall i, j$) while distortions from geo-cultural distance 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 Frictionless counterfactual (column 2). We find that distortions from geo-cultural distance have the largest effect in terms of capital allocation efficiency. When both distortions from taxes and political risk are removed (but distortions from geo-cultural distance are maintained), GDP is 6.1% lower than in the Frictionless 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 distortions from taxes and political risk can (and do) interact with distortions from geo-cultural distance. When distortions from geo-cultural distance and taxes are removed (but distortions from political risk are maintained), the world GDP loss is 1.6%, 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 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 Frictionless 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 distortions from Geo-cultural Distance alone are maintained, dispersion in log capital per employee is 55.4% higher than in the Frictionless benchmark. The dispersion of log output per employee is 11.9% higher. Finally, we find that by only maintaining investment taxes (political risk), dispersion in log capital per employee is 12.2% (28.4%) higher compared to the Frictionless benchmark, while dispersion in log output per employee is 5.7% (13.6%) higher. In other words, distortions from investment taxes, political risk, and geo-cultural distance all significantly contribute to creating long-term cross-country inequality.

Figure 6 illustrates the effect of removing distortions from taxes, political risk, and geo-cultural distance 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
What explains this reduction in inequality? When capital distortions are removed, capital tends to be reallocated to countries that have higher rates of returns on capital under 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 Frictionless world (vertical axis). As can be seen from the graph, there are significant winners and losers – albeit on average most countries experience an increase in capital and output per capita. The strong negative correlation between 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. Some of the poorest countries see capital per employee increase by an order of magnitude, and income per employee double.

6.3 Net Positions

Finally, we consider a comparison of net foreign asset positions under the observed equilibrium and the Frictionless 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 \( (a_{ij} \cdot E MK_i / \Delta_i^{Tax}) \) 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 DR, 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:

\[
a_{ij}^{(\iota)} = \frac{a_{ij} \cdot E MK_i / \Delta_i^{Tax}}{EMK_i / \Delta_i^{Tax} + 4.5\%}
\] (6.1)

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

\[
IIP_j = \sum_{i \neq j} \left( a_{ij}^{(j)} - a_{ji}^{(j)} \right)
\] (6.2)

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. Both in our theoretical framework and in our counterfactual analysis, we do not differentiate between Foreign Portfolio Investments (FPI) and Foreign Direct Investment (FDI) but focus on overall net foreign asset positions, for two reasons. The first reason is that, as discussed earlier, available measures of FPI and FDI are highly correlated with each other and do not seem to capture qualitatively and quantitatively features which are different enough to justify a separate analytical treatment. The second reason is that a country’s net foreign asset position is given not only by the sum of FPI and FDI but also by Reserves and Other (mostly, bank loans), which would require a separate analytical and empirical treatment if they were to be disaggregated in the counterfactual analysis. By focusing on net foreign asset positions, we can avoid such conceptual and empirical complications.

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 (middle panel). 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 (right 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 Frictionless equilibrium, capital indeed flows from rich to poor countries. The presence of distortions from taxes, political risk, and geo-cultural distance 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, political risk, and geo-cultural distances – imposes quantitatively important output losses for the majority of countries, and in general for World GDP, and can potentially account for a significant share of the observed cross-country dispersion in capital/employee.\(^{35}\)

\(^{35}\) These findings are consistent with those in Portes and Rey (2005), although ours is the first paper to document them in the context of a structural model.
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 Frictionless counterfactual, in which all barriers are removed.
7 Extensions and Robustness Checks

7.1 Re-Introducing Country Risk Premia

In order to focus on the role of barriers and to give a straightforward welfare interpretation to our counterfactuals, thus far we have worked with a model where countries are identical in terms of their risk properties. We now present our findings from using the more general model, where we re-introduce the risk premia, and show that these results are substantially unchanged.

To proxy the variance of the rates of return, we download country equity volatility indices from FRED (the original source is from Bloomberg). For the few (emerging) countries for which this is unavailable, we use the CBOE Emerging Markets ETF Volatility Index. A problem with using these volatility indices is that they are annualized, while we are working with an overlapping generations model, where the relevant time horizon might be longer than one year.

We therefore assume that the return variance used by the investor is equal to the annualized variance, scaled by a fixed factor (which reflects the investment horizon in years), which we calibrate to maximize the fit of the model EMPK with the empirical EMPK. Using this procedure, we obtain an investment duration of 11 years and 3 weeks.

We find that the model augmented with risk premia matches the data marginally better than the model without risk premia (the correlation of the model EMPK with the empirical EMPK increases from 0.60 to 0.61).

In Appendix D, Table D.1 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 five scenarios being considered. Our results are virtually unchanged when we account for heterogeneity in fundamental volatility.

7.2 Adding Frictions in Goods Trade

In our baseline model, we have assumed away frictions in trade of goods across countries, so that the law of one price holds for capital and final output, and thus one can be converted into the other at a fixed rate that is common across all countries ($\gamma$). However, in the data, countries differ in the relative price of physical capital with respect of PPP-adjusted output as a consequence of frictions in goods trade (Monge-Naranjo et al., 2019).

We model these frictions in goods trade in a tractable way. We assume that, in addition to the final good firms, there is a representative, perfectly-competitive intermediate good firm that can convert every unit of final good invested into exactly $p^y_i/p^k_i$ units of capital, so that $p^k_i/p^y_i$ is the relative price of capital in units of final good in country $i$.

We measure $p^k_i/p^y_i$ using PPP adjustment factors for capital from the Penn World Tables. Because now the real price of capital varies across countries, from the point of view of the international investors, the relevant measure of return to capital is no longer EMPK, but a statistic which Monge-Naranjo, Sánchez, and Santaellalia-Llopis (2019) call VMPK (Value Marginal Product of Capital):

$$VMPK_i = \kappa_i \frac{p^y_i y_i}{p^k_i k_i}$$

(7.1)

As can be easily seen from the formula above, this statistic is proportional to EMPK, and inversely-proportional to the real price of capital in the destination country. Intuitively, unlike EMPK, this statistic
allows for cross-country variation in the real cost of installing one unit of capital. While world GDP maximization requires the equalization of EMPK in the baseline model (without goods trade frictions), this version requires equalization of VMPK (see Monge-Naranjo et al., 2019).

This modification leads to the following updated equation for the risk-adjusted expected return $R_{it}$:

$$\log R_{it} \overset{\text{def}}{=} \log \left( \frac{p_{it}^y y_{it}}{p_{it}^k k_{it}} \right) - \left( \sigma_{it}^2 + \frac{1}{2} \sum^z_i \right) \quad (7.2)$$

Define $\tilde{k}_{it}$, the capital stock of country $i$ priced in units of consumption:

$$\tilde{k}_{it} = \frac{p^k_i}{p^y_i} k_{it} \quad (7.3)$$

For an efficient benchmark steady state (i.e. equalization of VMPK), we must modify the investor’s prior so that it is now proportional to $\tilde{k}_{it}$ (as opposed to $k_{it}$). The definition of the portfolio shares must be updated as follows:

$$\pi_{ijt} \overset{\text{def}}{=} \frac{p^k_{it}}{p^y_{it}} \frac{a_{ijt}}{\gamma s_{jt-1}} \quad (7.4)$$

This is because $a_{ijt}$ is in units of country $i$ capital. Consequently, we must amend equation 2.24 as follows:

$$\begin{bmatrix} k_{1t} \\ k_{2t} \\ \vdots \\ k_{nt} \end{bmatrix} = \gamma \begin{bmatrix} p_{11t}^{y} p_{1t}^{k} \\ 0 \\ p_{21t}^{y}/p_{2t}^{k} \\ \vdots \\ 0 \end{bmatrix} \begin{bmatrix} \pi_{11t} \\ \pi_{12t} \\ \vdots \\ \pi_{n1t} \end{bmatrix} \begin{bmatrix} \gamma p_{1t}^{y/k} \\ \gamma p_{2t}^{y/k} \\ \vdots \\ \gamma p_{nt}^{y/k} \end{bmatrix} \begin{bmatrix} s_{1,t-1} \\ s_{2,t-1} \\ \vdots \\ s_{n,t-1} \end{bmatrix} \quad (7.5)$$

In Appendix D, Table D.2, we repeat our counterfactual analysis for the extended model with frictions to trade in goods across countries. What we find is that the model with goods trade frictions yields exactly the same counterfactual calculations as the baseline model.

This result might seem counterintuitive, in light of the fact that the previous literature found that world GDP losses from capital immobility depend on whether EMPK or VMPK are used as the sufficient statistic for the GDP losses.

Our finding makes intuitive sense, however, when we remember three facts. First, the key distinction between this model and the previous one (where physical goods trade is undistorted) is that static maximization of world GDP requires the equalization not of physical marginal productivities of capital across countries (EMPK), but of PMPKL/VMPK. Therefore, when we remove all investment distortions, the model without goods trade frictions equalizes EMPK across countries, while the model with trade frictions equalizes VMPK. Second, when we introduce investment frictions, the World GDP losses depend on the resulting variance in EMPK/VMPK. The third, crucial fact is that, in our model, we measure wedges directly, as opposed to inferring them from cross-country variation in EMPK/VMPK as sufficient statistics for the GDP losses. While in PWT data these two statistics are not perfectly correlated, our measured wedges are the same, regardless of whether we include frictions in goods trade or not. The consequence of our direct measurement approach is that measured wedges generate the same variation in EMPK in the model without goods trade friction as they do in VMPK, in the model with trade frictions. Another way to say this is that the resulting EMPK from the model without goods trade frictions and VMPK from the model with good trade frictions are perfectly correlated. The natural consequence is that the resulting GDP losses are identical. This is again, a consequence of the fact that we are measuring
the wedges directly.

In sum, our direct measurement of the wedges implies that our model-implied counterfactuals are robust to the introduction of goods trade frictions.

### 7.3 Adding Capital Controls

One type of barrier that we have deliberately omitted from our model is capital controls. 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). Nonetheless, capital controls are enacted in order to affect capital flows. Therefore, we next want to verify whether their effect interacts with that of our baseline wedges.

We can easily model the effect of capital controls by adding a wedge:

$$\Delta_{ij} = \Delta_{i}^{\text{Tax}} \times \Delta_{ij}^{\text{PR}} \times \Delta_{ij}^{\text{Dist}} \times \Delta_{ij}^{\text{KC}}$$  \hspace{1cm} (7.6)

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

Turning to the empirical implementation, we measure the degree of 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 $\Delta_{ij}^{\text{KC}}$, we consider the five inflow restrictions dummies for country $i$ as well as the five outflow restrictions dummies for country $j$ (1 for FDI, 2 for portfolio equity and 2 for debt). We measure $\Delta_{ij}^{\text{KC}}$ as one minus the simple average of all 10 dummies. Formally:

$$\Delta_{ij}^{\text{KC}} = \left(1 - \frac{N_{i}^{\text{in}} + N_{j}^{\text{out}}}{10}\right)^{-1}$$  \hspace{1cm} (7.7)

where $N_{i}^{\text{in}}$ is the sum of the inflow restrictions for country $i$ and $N_{j}^{\text{out}}$. This makes $\Delta_{ij}^{\text{KC}}$ equal to one by construction when all possible restrictions are absent, and equal to infinity when all possible restrictions are present.

In Appendix D, Table D.3 we repeat our counterfactual analysis for the extended model with capital controls. We treat capital controls as an additional dimension of taxation, i.e. we eliminate these controls whenever the counterfactual entails a removal of the capital taxes. The percentage world GDP losses under this scenario is comparable to that obtained in our baseline exercise (6.6% vs. 5.9%). The marginal
effects of distortions from geo-cultural distance are also very similar to those found in the baseline exercise (6.2% versus 6.1%). Not surprisingly, now that we consider distortions from taxes and capital control, the deadweight loss becomes higher (1.0% versus 0.3%).

7.4 Currency Risk 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 wedge to our model:

$$
\Delta_{ij} = \Delta_{i}^{\text{Tax}} \times \Delta_{i}^{\text{PR}} \times \Delta_{ij}^{\text{Dist}} \times \Delta_{ij}^{\text{Ccy}}
$$

(7.8)

$\Delta_{ij}^{\text{Ccy}}$ is a wedge that we empirically measure as the forward premium for the $(i, j)$ currency pair. To keep consistency with subsection 7.1, we use the 10-year forward premium. 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 $\Delta_{ij}^{\text{Ccy}}$ as the foreign investment return, adjusted for currency risk.

We obtain forward premia from the Covered Interest Parity dataset of Du and Schreger (2022). 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 without 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 (2022). 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 D, Table D.4 we repeat our counterfactual analysis for the extended model with currency hedging costs. Currency hedging costs remain in place throughout the five scenarios. The world GDP loss and inequality effects that we find according to this extended model are essentially unchanged compared

\[36\text{We also verified that the same results hold by using a forward premium over a different maturity.}\]
to the baseline, and the marginal effect of geo-cultural distance, taxes, and political risk remains very close to the baseline level.

7.5 Diversification and More General Asset Demand Specifications

In the baseline model, for simplicity, we focused on the scenario where all investors choose a single asset. We will now relax this assumption, allowing investors to diversify their asset holdings and making the asset demand system more general.

For example, we can assume that the savings of all households \( h \) in country \( j \) are invested in a mutual fund, also referred to as \( j \). The fund earns a total income at time \( t \) equal to \( \sum_{i=1}^{n} \rho_{it} \pi_{igt} s_{jt-1} \). All investors \( h \), at time \( t - 1 \), serve as stock-pickers for the fund, each investing an equal, atomistic share of the fund’s assets. As compensation, they receive additional shares in the fund: specifically, each household \( h \) receives (at time \( t \)) a share of the period \( t \) income of the fund proportional to \( R_{ht} s_{jt-1} \), where \( R_{ht} \) is the level of \( R_{it} \) for the country selected by household \( h \). This arrangement encourages households to gather information about investments, as more successful stock-pickers receive a larger share of the fund’s dividends.

The above model produces the exact same country portfolios and capital allocation as our baseline model. The only difference is that investors now share the fundamental risk (\( \zeta_{it} \)) and the unpredictable component of \( \tau_{igt} \) and thus all investors \( h \) in country \( j \) hold identical shares (of different size) of country \( j \)’s portfolio. Furthermore, it is not necessary for the households and stock-pickers to overlap – we can achieve the same country portfolios by creating a separate class of agents (professional stock-pickers) with (near-)zero mass that is incentivized in the same manner.

This approach can be further developed to deliver a more general demand system, by modifying the definition of vector \( r_{it} \) (which the investor learns about, and which determines their share of fund \( j \)’s dividends) to be a more general function of asset fundamentals:

\[
r_{it} = \Upsilon (\text{EMPK}_i, \Sigma^z_i, \sigma^z_{iw}, \mu^T_i, \Sigma^T_i)
\]

Investors can now assign flexible weights to expected returns, covariances, taxes, and so on. Different choices for the function \( \Upsilon \) would result in alternative asset demand systems and, consequently, alternative configurations of the global allocation of capital.

7.6 Coefficients Stability

How stable are the coefficient estimates on Cultural Distance, Linguistic Distance and Geographic Distance over time? Appendix E, Figure E.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.

7.7 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 F, Table F.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 we do not include additional controls (columns 2 and 3) or whether we include them (columns 5 and 6). Linguistic Distance is negatively associated with FDI but not FPI (in a statistical significance sense).

7.8 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 G, Table G.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.

7.9 Sensitivity Analysis on Coefficient Estimates

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

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

7.10 Sovereign Flows

One possible critique of our study is its reliance on bilateral portfolio investment data from the International Monetary Fund (IMF), which is known to encompass sovereign (government) flows. These flows may be driven by different motivations than private investors’ flows, potentially explaining the unexpected reverse flow towards wealthy countries. Government or sovereign capital flows can be motivated by factors such as reducing risks from private flows, strengthening political alliances, or providing development aid.

Here, we address these concerns by outlining how our research methodology and the data sources we use mitigate any doubts about the validity of our findings.

Firstly, our study incorporates both equity and debt flows in the gravity regressions. To address the concern about including sovereign debt flows, we emphasize that our findings remain consistent across various specifications using equity flows, debt flows, or a mix of both. This consistency indicates that the frictions we examine are robust and not solely driven by the presence of sovereign debt flows in the gravity regressions.

Secondly, it is important to note that we use gravity regressions only to obtain the parameter vector $\beta$. For our counterfactual analyses, we apply these model parameters without directly incorporating the IMF bilateral portfolio investment data.

Since the potential impact of sovereign debt flows on our results could only stem from biasing our estimates of the gravity regression coefficients, and these coefficients do not appear to be particularly sensitive to the
type of investment (if anything, they seem to be larger when we exclude debt flows), we can confidently conclude that the inclusion of sovereign flows in the IMF data is not spuriously generating any of our findings.

7.11 Relaxing the Assumption of Full Depreciation

We finally show how to modify our model by relaxing the assumption that capital fully depreciates across generations. For this alternative model, we assume instead that $\delta$ is the rate of depreciation of reproducible capital. Capital – after being used for production in period $t$ – depreciates by a rate $\delta \in (0, 1)$ and is inherited (together with natural resources) by young agents. These young agents will be able to re-invest it for production in the next period.

The $t+1$ budget constraint must therefore be amended as follows:

$$c_{ht} + s_{ht} = w_j \ell_j + m_j x_j + (1 - \delta) s_{jt-1}$$  \hspace{1cm} (7.10)

And the agent’s optimal saving decision is now:

$$s_{jt} = \theta_j [w_j \ell_j + m_j x_j + (1 - \delta) s_{jt-1}]$$  \hspace{1cm} (7.11)

In the steady state, it must be that:

$$s_{jt} = \theta_j \cdot \frac{w_j \ell_j + m_j x_j}{1 - \theta_j (1 - \delta)}$$  \hspace{1cm} (7.12)

the rest of the model is virtually unchanged. Results for this alternative model are available upon request.

8 Conclusions

We presented a new theory of international capital allocation: a multi-country dynamic general equilibrium model with policy and information frictions, populated by rationally-inattentive investors. In our structural framework, these frictions distort individually-rational portfolio allocations.

We showed that a parsimonious implementation of the model - based on just a few explanatory variables - reproduces several key 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 the degree of home bias and the level of economic development, translating into persistent capital misallocation; 3) it predicts, out of sample and with high accuracy, the overall level and the cross-section of home bias across countries (where “out-of-sample” means that we have not used any direct information about domestic capital investment); 4) it produces steady-state capital account imbalances that do not correlate negatively with the level of development, implying that capital fails to flow from rich to poor countries as much as it should ((Lucas, 1990)).

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 these barriers have a sizable impact on the distribution of capital across countries, with implications for efficiency: world GDP is about 6% lower than it would be if the effect of these barriers to global capital allocation could be neutralized. The effect is identical when frictions to international trade are also taken into account.
This misallocation 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 (or offsetting) of geo-cultural distances, taxes, and political risk by a social planner would lead to substantial economic gains and reductions in cross-country inequality: it would lead 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, removing these barriers to the international flow of capital benefits countries that are otherwise “peripheral” - i.e. countries that, because of these barriers, are less accessible to most investors. In sum, these barriers generate and perpetuate an advantage, in terms of capital market access, for “central” countries, and a disadvantage for countries that are farther from where most investors are geographically and culturally located.

While diversification and hedging have generally been viewed as crucial for understanding these patterns, our analysis suggests that information and policy barriers also play an important role. How to address these inefficiency in an effective and coordinated way remains an open area of inquiry.

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 and empirical progress in modeling international asset markets within 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, Bob 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.

References


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A Proofs and Derivations

**Proof to Proposition 3.** If \( \Delta_{ij} = \Delta_j \), we can plug equation (2.30) inside the steady-state version of equation (2.24) to obtain:

\[
\gamma_k = R_k k \sum_{j=1}^{n} \frac{s_j}{\sum_{i=1}^{n} R_i k_i}
\]

rearranging we obtain the following expression for \( R_i \), which does not depend on \( i \):

\[
R_i = \frac{\gamma \sum_{i=1}^{n} R_i k_i}{\sum_{j=1}^{n} s_j} = R^*
\]

**Proof to Theorem (Dual Efficiency) and Corollary.** We start by showing that a necessary and sufficient condition for World GDP maximization is that the rates of returns on capital are equalized across countries. To show necessity, consider the first-order Taylor approximation for the change in \( Y \) following a change \( \Delta k \) such that \( \sum_i \Delta k_i = 0 \):

\[
\Delta Y \approx \sum_{i=1}^{n} \text{EMPK}_i \cdot \Delta k_i
\]

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

\[
k_i = (\text{EMPK}^*)^{-\frac{1}{1-\kappa_i}} (\kappa_i \omega_i)^{1-\kappa_i} \ell_i
\]

This implies that \( K \) and \( Y \) are also strictly-decreasing functions of \( \text{EMPK}^* \). As a consequence, it is not possible to vary \( \text{EMPK}^* \) 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 (2.24) and (??) jointly imply:

\[
\gamma k_i = \sum_{j=1}^{n} \frac{[\Delta_{ij} \cdot \exp \left( \frac{1}{2} \Sigma_i^z + \sigma_{iw}^2 \right) \cdot \text{EMPK}_i \cdot k_is_j]}{\sum_{i=1}^{n} [\Delta_{ij} \cdot \exp \left( \frac{1}{2} \Sigma_i^z + \sigma_{iw}^2 \right) \cdot \text{EMPK}_i \cdot k_i]}
\]

if we simplify out \( k_i \) and equalize the rates of return (\( \text{EMPK}_i = \text{EMPK}^* \)), this equation reduces to (2.44).

Finally, to prove Corollary 2, notice that if \( \exp \left( \frac{1}{2} \Sigma_i^z + \sigma_{iw}^2 \right) \) is constant over \( i \), it can be simplified out. Then, equation (2.44) further reduces to \( \Delta_{ij} \) being constant over \( i \).
B Prior Specification

Following Pellegrino (2023), we assume that the investors’ priors belong to a family of probability models known as Tweedie Distributions, which are indexed by their expectation, a dispersion parameter and a “power index” $p$. This family includes several well-known distributions, such as the Gaussian and the Poisson. Pellegrino (2023) shows that a closed-form solution to the RI-logit problem of Matějka and McKay (2015) obtains for Tweedie-family priors with power index $p \geq 2$; this subset is known as Tempered Stable (TS) distributions. They have $\mathbb{R}_+$ for domain, and include the Gamma and the Inverse Gaussian, along as their special cases (Exponential, Chi-squared, Erlang, etc...).

We assume that, according to $G_j$, $R_{ijt}$ follows a multivariate TS distribution, with common mean $\mu_j$ and power index $p$ and dispersion parameter that is inversely proportional to $\pi_{it-1}$. This prior captures a realistic feature of international financial markets: investors have more precise prior beliefs about countries that are larger and more financially developed (as measured by their share of the world capital stock).

Our specification for the agent’s prior perturbs this efficient specification by introducing bilateral heterogeneity in the precision of the prior information, in the form of a destination country-specific dispersion parameter $\Sigma^{G}_{ij}$. Specifically, we assume that:

$$R_{ijt+1} \overset{G_j}{\sim} \text{Tw}_p \left( \mu_j^G, \frac{\exp \Sigma^G_{ij}}{\pi_{it-1}} \right) \quad p \geq 2, \ \mu_j \geq 0 \quad (B.1)$$

Then, Proposition 1 of Pellegrino (2023) implies that:

$$\pi^0_{ijt} = \frac{\pi_{it-1} / \exp \Sigma^G_{ij}}{\sum_{i=1}^n \pi_{it-1} / \exp \Sigma^G_{ij}} \quad (B.2)$$

which directly implies equation (2.29).
C Measuring Political Risk

We model the political risk wedge $\Delta_i^{PR}$ as a function of the ICRG index:

$$\Delta_i^{PR} = \Delta^{PR}(ICRG_i) \quad (C.1)$$

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

$$\frac{\partial \log \sum_{j \neq i} a_{ij}}{\partial \log \Delta_i^{PR}} = -\frac{\eta}{1 - \eta} \sum_{j \neq i} \frac{a_{ij}}{k_i} (1 - \pi_{ij}) \approx -\frac{\eta}{1 - \eta} \quad (C.2)$$

Alfaro, Kalemli-Ozcan and Volosovych (2008, AKV) regress capital inflows per capita on ICRG. From AKV’s regression and summary statistics tables, we can compute:

$$\frac{d \log \sum_{j \neq i} a_{ij}}{d ICRG_i} = \beta^{PR} \overset{\text{def}}{=} \left[ \frac{d \left( \sum_{j \neq i} a_{ij}/Population_i \right)}{d ICRG_i} \right] \cdot \left[ \frac{\sum_{j \neq i} a_{ij}}{Population_i} \right]^{-1} \quad (C.3)$$

where ICRG$_i$ is ICRG’s measure of political risk for country $i$ (higher scores indicate lower political risk); 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 table of summary statistics. From the chain rule:

$$\frac{d \log k_i}{d ICRG_i} = \frac{\partial \log k_i}{\partial \log \Delta_i^{PR}} \cdot \frac{\partial \log \Delta_i^{PR}}{d ICRG_i} \quad (C.4)$$

Combining the two equations above, and assuming that $\Delta_i^{PR} = 1$ when ICRG$_i = 10$ (implying the expropriation risk is zero for a country with the maximum ICRG score) we then have the following trivial ODE for $\Delta_i^{PR}$:

$$\frac{d \log \Delta_i^{PR}}{d ICRG_i} = -\frac{1 - \eta}{\eta} \cdot \beta^{PR} \quad (C.5)$$

with boundary condition

$$\Delta_i^{PR}(ICRG_i)|_{ICRG_i=10} = 1 \quad (C.6)$$

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

$$\log \Delta_i^{PR} = \beta^{PR} (10 - ICRG_i) \quad (C.7)$$

AKV perform instrumental variable regressions using two different datasets in their analysis (IMF and KLSV). We use the $\beta^{PR}$ estimate using KLSV data that controls for the initial level of GDP per capita.
D 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 D.1: Counterfactuals with Risk Premia (2017)**

<table>
<thead>
<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (PPP$ trillions)</td>
<td>103.3</td>
<td>109.3</td>
<td>109.2</td>
<td>106.8</td>
<td>103.2</td>
</tr>
<tr>
<td>World GDP, % Difference from Frictionless</td>
<td>-5.4%</td>
<td>0.0%</td>
<td>-0.0%</td>
<td>-2.3%</td>
<td>-5.6%</td>
</tr>
<tr>
<td>St.Dev. of log (k_{i}/\ell_{i}), % Difference from Frictionless</td>
<td>+71.5%</td>
<td>0.0%</td>
<td>+12.1%</td>
<td>+27.8%</td>
<td>+49.9%</td>
</tr>
<tr>
<td>St.Dev. of log (y_{i}/\ell_{i}), % Difference from Frictionless</td>
<td>+24.6%</td>
<td>0.0%</td>
<td>+5.8%</td>
<td>+13.8%</td>
<td>+12.0%</td>
</tr>
<tr>
<td>Welfare Statistics</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
</tr>
<tr>
<td>-------------------------------------------</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
<td>-----</td>
</tr>
<tr>
<td>World GDP (PPP$ trillions)</td>
<td>103.3</td>
<td>109.8</td>
<td>109.4</td>
<td>108.1</td>
<td>103.1</td>
</tr>
<tr>
<td>World GDP, % Difference from Frictionless</td>
<td>-5.9%</td>
<td>0.0%</td>
<td>-0.3%</td>
<td>-1.6%</td>
<td>-6.1%</td>
</tr>
<tr>
<td>St.Dev. of log ($k_i/\ell_i$), % Difference from Frictionless</td>
<td>+77.0%</td>
<td>0.0%</td>
<td>+12.2%</td>
<td>+28.4%</td>
<td>+55.4%</td>
</tr>
<tr>
<td>St.Dev. of log ($y_i/\ell_i$), % Difference from Frictionless</td>
<td>+24.4%</td>
<td>0.0%</td>
<td>+5.7%</td>
<td>+13.6%</td>
<td>+11.9%</td>
</tr>
</tbody>
</table>
Table D.3: Counterfactuals with Capital Controls (2017)

<table>
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<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (PPP$ trillions)</td>
<td>103.3</td>
<td>110.6</td>
<td>109.5</td>
<td>109.1</td>
<td>103.8</td>
</tr>
<tr>
<td>World GDP, % Difference from Frictionless</td>
<td>-6.6%</td>
<td>0.0%</td>
<td>-1.0%</td>
<td>-1.4%</td>
<td>-6.2%</td>
</tr>
<tr>
<td>St.Dev. of log (k_i/ℓ_i), % Difference from Frictionless</td>
<td>+65.2%</td>
<td>0.0%</td>
<td>+0.5%</td>
<td>+25.9%</td>
<td>+44.6%</td>
</tr>
<tr>
<td>St.Dev. of log (y_i/ℓ_i), % Difference from Frictionless</td>
<td>+14.6%</td>
<td>0.0%</td>
<td>-6.8%</td>
<td>+12.7%</td>
<td>+7.3%</td>
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</table>
Table D.4: Counterfactuals with Currency Hedging Costs (2017)

<table>
<thead>
<tr>
<th>Welfare Statistics</th>
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<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (PPP$ trillions)</td>
<td>103.3</td>
<td>109.8</td>
<td>109.5</td>
<td>107.6</td>
<td>103.1</td>
</tr>
<tr>
<td>World GDP, % Difference from Frictionless</td>
<td>-5.9%</td>
<td>0.0%</td>
<td>-0.3%</td>
<td>-2.0%</td>
<td>-6.1%</td>
</tr>
<tr>
<td>St.Dev. of log ($k_i/\ell_i$), % Difference from Frictionless</td>
<td>+74.1%</td>
<td>0.0%</td>
<td>+12.1%</td>
<td>+28.8%</td>
<td>+52.6%</td>
</tr>
<tr>
<td>St.Dev. of log ($y_i/\ell_i$), % Difference from Frictionless</td>
<td>+23.6%</td>
<td>0.0%</td>
<td>+5.7%</td>
<td>+13.8%</td>
<td>+11.1%</td>
</tr>
</tbody>
</table>
E Regression Coefficients Stability

Figure E.1: Coefficients Stability over Time

- Cultural Distance
- Geographic Distance
- Linguistic Distance

95% c.i. Estimated Coefficient
### Table F.1: OLS Regressions using FDI/FPI breakdown instead of Equity/Debt

<table>
<thead>
<tr>
<th>Dep. variable in logs:</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultural Distance</td>
<td>Assets</td>
<td>FDI</td>
<td>FPI</td>
<td>Assets</td>
<td>FDI</td>
<td>FPI</td>
</tr>
<tr>
<td></td>
<td>(0.449)</td>
<td>(0.455)</td>
<td>(0.607)</td>
<td>(0.486)</td>
<td>(0.492)</td>
<td>(0.610)</td>
</tr>
<tr>
<td>Geographic Distance</td>
<td>-4.667**</td>
<td>-5.362**</td>
<td>-3.434**</td>
<td>-5.038**</td>
<td>-5.631**</td>
<td>-2.836*</td>
</tr>
<tr>
<td></td>
<td>(0.321)</td>
<td>(0.344)</td>
<td>(0.400)</td>
<td>(0.984)</td>
<td>(0.977)</td>
<td>(1.271)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-3.325**</td>
<td>-3.799**</td>
<td>-1.370</td>
<td>-2.288**</td>
<td>-2.559**</td>
<td>0.105</td>
</tr>
<tr>
<td></td>
<td>(0.429)</td>
<td>(0.508)</td>
<td>(0.885)</td>
<td>(0.470)</td>
<td>(0.503)</td>
<td>(0.879)</td>
</tr>
<tr>
<td>Control Variables</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,314</td>
<td>2,527</td>
<td>1,475</td>
<td>2,285</td>
<td>2,467</td>
<td>1,450</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.772</td>
<td>0.722</td>
<td>0.814</td>
<td>0.797</td>
<td>0.754</td>
<td>0.834</td>
</tr>
<tr>
<td>Within R-squared</td>
<td>0.239</td>
<td>0.229</td>
<td>0.093</td>
<td>0.321</td>
<td>0.312</td>
<td>0.188</td>
</tr>
</tbody>
</table>
### G Robustness check: residency-based foreign investment data

#### Table G.1: OLS Regressions using un-restated data

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

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

<table>
<thead>
<tr>
<th>Welfare Statistics</th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
</tr>
</thead>
<tbody>
<tr>
<td>World GDP (PPP$ trillions)</td>
<td>103.3</td>
<td>109.9</td>
<td>109.7</td>
<td>107.7</td>
<td>105.4</td>
</tr>
<tr>
<td>World GDP, % Difference from Frictionless</td>
<td>-6.0%</td>
<td>0.0%</td>
<td>-0.2%</td>
<td>-2.0%</td>
<td>-4.1%</td>
</tr>
<tr>
<td>St.Dev. of log ($k_i/\ell_i$), % Difference from Frictionless</td>
<td>+101.5%</td>
<td>0.0%</td>
<td>+4.7%</td>
<td>+34.7%</td>
<td>+58.4%</td>
</tr>
<tr>
<td>St.Dev. of log ($y_i/\ell_i$), % Difference from Frictionless</td>
<td>+37.5%</td>
<td>0.0%</td>
<td>+0.6%</td>
<td>+15.0%</td>
<td>+19.0%</td>
</tr>
<tr>
<td>Welfare Statistics</td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td></td>
</tr>
<tr>
<td>----------------------------------------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td>------</td>
<td></td>
</tr>
<tr>
<td>World GDP (US$ trillions)</td>
<td>103.3</td>
<td>109.7</td>
<td>109.3</td>
<td>108.0</td>
<td></td>
</tr>
<tr>
<td>World GDP, % Difference in GDP from Frictionless</td>
<td>-5.8%</td>
<td>0.0%</td>
<td>-0.3%</td>
<td>-1.5%</td>
<td></td>
</tr>
<tr>
<td>St.Dev. of log $(k_i/\ell_i)$, % Difference from Frictionless</td>
<td>+69.8%</td>
<td>0.0%</td>
<td>+11.7%</td>
<td>+26.9%</td>
<td></td>
</tr>
<tr>
<td>St.Dev. of log $(y_i/\ell_i)$, % Difference from Frictionless</td>
<td>+19.8%</td>
<td>0.0%</td>
<td>+5.5%</td>
<td>+12.9%</td>
<td></td>
</tr>
</tbody>
</table>
I Unweighted Poisson regressions

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

Table I.1: Poisson Regressions

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
<th>(6)</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cultural Distance</td>
<td>-2.295**</td>
<td>-1.827**</td>
<td>-2.922**</td>
<td>-1.765**</td>
<td>-1.181*</td>
<td>-2.261**</td>
</tr>
<tr>
<td></td>
<td>(0.473)</td>
<td>(0.553)</td>
<td>(0.447)</td>
<td>(0.426)</td>
<td>(0.557)</td>
<td>(0.495)</td>
</tr>
<tr>
<td></td>
<td>(0.245)</td>
<td>(0.254)</td>
<td>(0.318)</td>
<td>(0.670)</td>
<td>(0.674)</td>
<td>(1.060)</td>
</tr>
<tr>
<td>Linguistic Distance</td>
<td>-1.541**</td>
<td>-1.417**</td>
<td>-2.034**</td>
<td>-0.155</td>
<td>-0.444</td>
<td>-0.098</td>
</tr>
<tr>
<td></td>
<td>(0.263)</td>
<td>(0.265)</td>
<td>(0.330)</td>
<td>(0.306)</td>
<td>(0.373)</td>
<td>(0.370)</td>
</tr>
<tr>
<td>Controls</td>
<td>No</td>
<td>No</td>
<td>No</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>Observations</td>
<td>2,789</td>
<td>2,805</td>
<td>3,511</td>
<td>2,754</td>
<td>2,770</td>
<td>3,459</td>
</tr>
</tbody>
</table>
J Alternative Measure of Home Bias

In this appendix, we plot the measure of equity home bias from Coeurdacier and Rey (2013) against its model-implied counterpart.

Figure J.1: Model Fit - Home Bias (Alternative Measure)

Figure Notes: This figure plots the model-implied home bias, computed according to Coeurdacier and Rey (2013)’s formula, against its empirical counterpart, which is taken directly from CR’s paper. Each observation is a country.