Gravity in FX R^2:
Understanding the Factor Structure in Exchange Rates

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Abstract

We relate the risk characteristics of currencies to measures of physical, cultural, and institutional distance. The currencies of countries which are more distant from other countries are more exposed to systematic currency risk because of a gravity effect in the factor structure of bilateral exchange rates: When a currency appreciates against a basket of all other currencies, its bilateral exchange rate appreciates more against the currencies of distant countries. As a result, currencies of peripheral countries are more exposed to the systematic variation than currencies of central countries. Trade network centrality is the best predictor of a currency's overall exposure to systematic risk.

Keywords: Exchange Rates, Factor Models, Gravity Equation, Home Bias, Trade Network, Centrality

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Exchange rates appear to be disconnected from macroeconomic quantities: macro variables cannot reliably forecast changes in spot exchange rates (Meese and Rogoff, 1983) and exchange rates are only weakly correlated with macro variables (Backus and Smith, 1993; Kollmann, 1995). However, bilateral exchange rates do co-vary strongly: common FX factors explain a large share of the variation in bilateral exchange rates (see Verdelhan, 2015). We show that this systematic variation in exchange rates is largely explained by measures of distance between countries.

Currencies of countries which are more distant from other countries — physically, culturally, and institutionally — are more exposed to systematic risk. This is due to a gravity effect in the factor structure of bilateral exchange rates: When a currency systematically appreciates against a basket of other currencies, it appreciates more against currencies of distant countries than currencies of close countries. For example, when the dollar appreciates against a basket of developed market currencies, on average, it appreciates more versus the Australian dollar than the Canadian dollar. This implies that peripheral countries, which are distant from most other countries, have exchange rates that are more exposed to systematic risk than central countries. Trade network centrality is the best predictor of overall exposure to systematic risk in FX markets.

We measure exposure to systematic currency variation in a way that is analogous to measuring market betas of stocks. For example, starting from a basket of exchange rates with respect to the dollar, we construct dollar base factor as the average appreciation of the dollar versus the basket. This dollar base factor measures the systematic variation in dollar based exchange rates — similar to the return on the equity market. To measure individual currencies' exposure to systematic dollar variation, we regress changes in bilateral exchanges rates on the dollar base factor. We call these regression coefficients base factor loadings. Exposure to base factor variation explains a substantial amount of the time series variation in bilateral exchange rates: for the average currency pair in our sample the base factor regression has an R^2 of 47%. We show that distance is a key determinant of the cross-sectional variation in exposure to the base factors, as measured by the base factor loadings. To visualize this distance effect, Figure (1) plots the loadings on the US dollar base factor. Physical distance to the U.S. clearly has a large impact on the dollar loadings. The farther a country is from the US, the higher its currency's loading on the dollar base factor. We refer to this as the gravity effect in factor structure in exchange rates.

Our measures of distance include not only physical distance, but also shared language, legal origin, shared border, colonial linkages and resource similarity. The average loading for

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Figure 1: Loadings on USD Factor
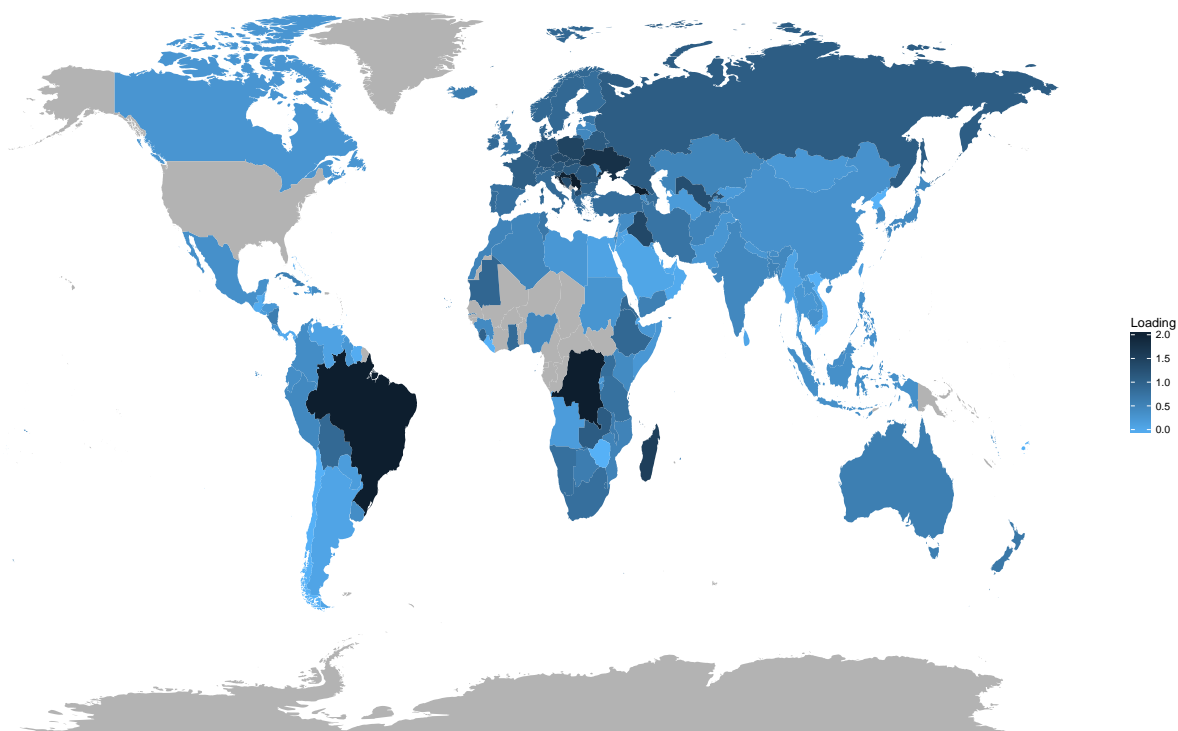
Map of φ^* from the regression $\Delta s = \alpha_{i,j} + \varphi^* \Delta base_t^{\$} + e$. $\Delta base_t^{\$}$ is the average appreciation of the US dollar at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 for 162 countries from Global Financial Data.

a given base currency is one. Doubling the distance between a country and the base country increases the loading by 15% for an average country. A shared language lowers the loading between 11 and 15%. In the case of U.S. based exchange rates, the loading on the dollar factor decreases by 50% when the other country uses English as one of its main languages. Shared border lowers the loading by another 8 to 14%, while colonial linkages lower the loadings by up to 32%. Natural resource similarity further lowers the loadings.[1] As a result, the covariation structure of exchange rates is determined to a large extent by reasonably exogenous initial conditions.

To the extent that distance proxies for trade costs, our results support the notion that trade costs are central to understanding exchange rates. Obstfeld and Rogoff (2000) argue that costs of international trade can account for most of the outstanding puzzles in international trade. Recently, Eaton, Kortum, and Neiman (2016) conduct the following experiment: they remove trade frictions in a calibrated version of the Eaton, Kortum, Neiman, and Romalis (2016) model of international trade. Interestingly, this experiment eliminates many of the standard international finance puzzles, including the Backus and Smith (1993) exchange rate disconnect. Our paper provides empirical evidence that trade costs are a robust determinant of exchange rate covariation, as predicted by standard theory.

All of these distance variables help to explain the intensity of trade flows between countries. One of the most robust empirical findings in international trade is the gravity equation's success in accounting for trade flows (Tinbergen, 1962): the size of trade flows between two countries is inversely proportional to the distance between two countries (see Anderson and van Wincoop, 2004; Costinot, 2014; Head and Mayer, 2014, for recent surveys). The elasticity of trade flows with respect to distance is large and remarkably stable over time (Leamer and Levinsohn, 1995). Economists have long understood proximity to be a source of comparative advantage in international trade, even though standard theories of international trade do not create a direct role for distance (see Chaney, 2013, for a recent survey of the limited role of distance in modern trade theory).[2] Interestingly, we also find that the gravity effect in the factor structure in exchange rates is robust to controlling for trade intensity and financial flows.

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[1]The distance effect is not driven by emerging market currencies. When we exclude emerging market currencies, the distance effect increases from 15 to 25%. Shared legal origin further lowers the loadings by 31% among this subset of developed countries. The gravity variables account for about 1/4 of all the variation in the loadings.

[2]In a standard model, shipping costs that increase log-linearly in distance do give rise to a gravity equation indirectly. If shipping costs were the sole driver, then the distance effect should have decreased over time, but there is no evidence of this.

In a complete markets model, the change in the spot exchange rate measures the difference between the foreign and domestic state prices; spot exchange rates only need to adjust if the foreign and domestic state prices diverge. Thus, the sensitivity of spot exchange rate changes to the common factor is governed by the differences in the exposures of the SDFs to common or global shocks. Our findings imply that the loadings of a country's pricing kernel on common sources of risk must differ more for distant country pairs than for close country pairs.[3] This distance pattern in the common risk factor loadings generates larger currency loadings on the base factor for the exchange rates of distant country pairs. Additionally, for peripheral countries that are on average distant, this model generates a higher a higher variance of the currency base factor and high average R^2s in the factor regressions. We confirm a strong, negative relation between the average R^2 of a country's currency, its average distance from other countries, and its centrality in the global trade network.

An additional implication of our gravity-based factor model of exchange rates is that peripheral countries that are distant from most other countries have a lot of non-diversifiable risk built into their nominal exchange rates. As a result, the average R^2 in factor regressions will be high for these base currencies. This is exactly what we find: distant countries have high average R^2 in exchange rate factor regressions, while central countries tend to have low R^2.

There is a large literature in international finance on common or global risk factors, mostly focused on equities. This literature includes world arbitrage pricing theory, developed by Adler and Dumas (1983); Solnik (1983); a world consumption-capital asset pricing model (CAPM), Wheatley (1988); a world CAPM, Harvey (1991); world latent factor models, Campbell and Hamao (1992); Bekaert and Hodrick (1992); Harvey, Solnik, and Zhou (2002); world multi-loading models, Ferson and Harvey (1993); and more recently work on time-varying capital market integration by Bekaert and Harvey (1995); Bekaert, Hodrick, and Zhang (2009). We contribute by identifying distance as the key determinant of a bilateral exchange rate's loadings on these global risk factors. There is an emerging literature on exchange rates that imputes a central role to global risk factors (see Backus, Foresi, and Telmer, 2001; Lustig, Roussanov, and Verdelhan, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012; Hassan, 2013; Ready, Roussanov, and Ward, 2013; Richmond, 2015).

While we largely understand the determinants of stock return loadings (e.g. financial leverage or growth options), much less is known about the determinants of currency loadings

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[3]This is consistent with the stylized trade facts: countries with stronger trade linkages have more correlated business cycles (see Frankel and Rose, 1998).

with respect to global risk factors. Currency loadings determine a currency's risk characteristics and returns (Lustig and Verdelhan, 2007; Lustig, Roussanov, and Verdelhan, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012; Lettau, Maggiori, and Weber, 2014). Recently, Hassan (2013), Ready, Roussanov, and Ward (2013) and Richmond (2015) develop theories that shed light on the origins of currency loadings. Hassan (2013) points out that larger countries' currencies will tend to appreciate in response to adverse global shocks and hence offer a hedge. In an equilibrium model of international trade, Ready, Roussanov, and Ward (2013) distinguish between commodity exporters and final goods producers. In their model, the real exchange rate of commodity exporters depreciates in response to an adverse global shock. Richmond (2015) shows how the global trade network generates common global risk, which central countries are more exposed to. This causes central countries' currencies to appreciate in bad global states, which drives down their interest rates and currency risk premia. We find that currencies of countries that are distant from the U.S. have a high loading with respect to the dollar factor and hence add more systematic risk to a U.S. investor's well-diversified portfolio of long positions in foreign currency.

Our findings have interesting portfolio implications. Equities and other assets of distant countries that are most appealing to, say, a U.S. investor from a diversification perspective will tend to impute more non-diversifiable currency risk to her portfolio. These findings may shed additional light on the home bias puzzle in equities (see Lewis, 1999, for a survey). There exists some empirical work on the relation between distance and relative price variability. In a seminal paper, Engel and Rogers (1996) find that the distance between cities in the U.S. and Canada is the main determinant of relative price variability across cities, but they document a large U.S.-Canada border effect (see also Parsley and Wei, 2001, for more recent evidence). Our findings attribute the covariation in relative prices in various countries to distance between the base country and the other countries. To the best of our knowledge, extant models do not directly address the effect of distance on real exchange rate covariation. Presumably, part of the distance effects could be rationalized in standard, neo-classical models with shipping costs that increase loglinearly in distance.

The rest of this paper is organized as follows. Section (1) describes a complete markets model of exchange rate covariation. Section (2) documents the factor structure in bilateral exchange rates and its relation to measures of distance. Section (3) tests the gravity model of exchange rate co-variation. Section (4) presents a calibrated long-run risks model using our gravity model. Section (5) checks the robustness of our findings. Section (6) concludes.

1 A Simple Theory of Exchange Rate Covariation

1.1 Complete Market Models of Exchange Rates

We begin by presenting simple model of exchange rate covariation, which motivates our empirical measure. The starting point for our analysis is a class of flexible, affine models of interest rates and exchange rates. This extends earlier work by Backus, Foresi, and Telmer (2001), Hodrick and Vassalou (2002), Brennan and Xia (2006), Leippold and Wu (2007), Lustig, Roussanov, and Verdelhan (2011) and Sarno, Schneider, and Wagner (2012). Specifically, we adopt a version of the model developed by Lustig, Roussanov, and Verdelhan (2011); Verdelhan (2015).

Single-Factor SDF Model

There are N countries, one of which we classify as the home country. All foreign country values are denoted with $*$. There is no time variation in factor loadings in the model. The real log SDF m_{t+1}^* in the foreign countries is given by:

$$-m_{t+1}^* = \alpha + \chi \sigma^{*,2} + \xi^* \left(\sigma^g\right)^2 + \tau^* \sigma^* u_{t+1}^* + \kappa^* \sigma^g u_{t+1}^g,$$

where u_{t+1}^* are local shocks and u_{t+1}^g is a common shock that originates in the home country, all of which are zero mean and variance 1. To give content to the notion that u^g originates in the home country, we impose that $0 \leq \kappa^* \leq 1$. To keep the analysis simple, we have also abstracted from time-variation in the σ's. The assumption that that the common shock originates in the base country is only to simplify exposition. This single common shock model is a simplified version of a richer model with K common shocks, which we present in Section (1.1). In that model, we do not constrain where the shock originates and all results carry through. A version of our model with heteroskedasticity nests commonly used structural models such as the long run risks model pioneered by Colacito and Croce (2011); Bansal and Shaliastovich (2013) in FX.

By no arbitrage, when markets are complete, the change in the log exchange rate in foreign currency per unit of home currency is given by:

$$\Delta s_{t+1} = m_{t+1} - m_{t+1}^*$$
$$= (\alpha^* - \alpha) + (\xi^* - \xi)\left(\sigma^g\right)^2 + \left(\chi^* \sigma^{*,2} - \chi \sigma^2\right) + \left(\tau^* \sigma^* u_{t+1}^* - \tau \sigma u_{t+1}\right) + (\kappa^* - 1)\sigma^g u_{t+1}^g$$

The expected excess return on foreign currency is given by: $E_t[rx_{t+1}] + \frac{1}{2}Var_t[\Delta s_{t+1}] =$

$\tau\sigma^2 + (1 - \kappa^*)\sigma^{g,2}$. This model produces a factor structure in bilateral exchange rates, driven by the common factor u_{t+1}^g. We define the base factor for the home currency as the equal-weighted average of the log changes in bilateral exchange rates:

$$\Delta base_{t+1} \;=\; \frac{1}{N}\sum_{j=1}^{N}\Delta s_{t+1}$$

$$=\; (\overline{\alpha^*} - \alpha) + (\overline{\xi^*} - \xi)(\sigma^g)^2 + (\overline{\chi^*\sigma^{*,2}} - \chi\sigma^2) + (\overline{\tau\sigma^* u_{t+1}^*} - \tau\sigma u_{t+1}) + (\overline{\kappa^*} - 1)\sigma^g u_{t+1}^g$$

The base factor measures the systematic variation in the home country's currency versus all foreign currencies. For large N, we have the following simple expression for currency i's base factor, which only depends on the base-country-specific shock and common shock:

$$\lim_{N\to\infty}\Delta base_{t+1} = (\overline{\alpha^*} - \alpha) + (\overline{\xi^*} - \xi)(\sigma^g)^2 + (\overline{\chi^*\sigma^{*,2}} - \chi\sigma^2) - \tau\sigma u_{t+1} + (\overline{\kappa^*} - 1)\sigma^g u_{g,t+1}$$

In this model, different bilateral exchange rates will have different exposures to the base factor generated by different values of κ^*. The slope coefficient φ^* in a projection of the bilateral exchange rate changes, Δs, on the base factor, $\Delta base$, governs how much systematic risk the bilateral exchange rate is exposed to. This coefficient is determined the SDFs' loadings on the common shocks: all else equal, the lower it is, the higher the slope coefficient φ^*.

Proposition 1. *The variance of the base factor, the covariance of the exchange rate with the base factor, the loadings on the base factor and the R^2 are given by, respectively:*

$$Var\left(\lim_{N\to\infty}\Delta base_{t+1}\right) = \tau^2\sigma^2 + (\overline{\kappa^*} - 1)^2(\sigma^g)^2$$

$$Cov\left(\Delta s_{t+1}, \lim_{N\to\infty}\Delta base_{t+1}\right) = \tau^2\sigma^2 + (\kappa^* - 1)(\overline{\kappa^*} - 1)(\sigma^g)^2$$

$$\varphi^* = \frac{Cov\left(\Delta s_{t+1}, \lim_{N\to\infty}\Delta base_{t+1}\right)}{Var\left(\lim_{N\to\infty}\Delta base_{t+1}\right)} = \frac{\tau^2\sigma^2 + (\kappa^* - 1)(\overline{\kappa^*} - 1)(\sigma^g)^2}{\tau^2\sigma^2 + (\overline{\kappa^*} - 1)^2(\sigma^g)^2},$$

$$R^2 = \frac{\varphi^{*,2}\,Var\left(\lim_{N\to\infty}\Delta base_{t+1}\right)}{Var(\Delta s_{t+1})} = \frac{\left[\tau^2\sigma^2 + (\kappa^* - 1)(\overline{\kappa^*} - 1)(\sigma^g)^2\right]^2}{\left[\tau^2(\sigma^2 + \sigma^{*,2}) + (\kappa^* - 1)^2(\sigma^g)^2\right]\left[\tau^2\sigma^2 + (\overline{\kappa^*} - 1)^2(\sigma^g)^2\right]}.$$

The slope coefficient φ^* does not depend on the idiosyncratic volatility of the SDF. The only source of cross-sectional variation is κ^*. The slope coefficient is monotonically decreasing in κ^*, hence, it is a natural measure of exposure to the common shock. A country with average exposure has a loading of one; less (more) than average exposure translates into a loading larger (smaller) than one.

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We hypothesize that the common shock exposure, κ^*, decreases monotonically in distance from the foreign country, $*$, to the home country.

Assumption 1. *The common shock exposure is always largest in the base country $0 < \kappa^* \leq 1$, and κ^* decreases monotonically in distance from $*$ to the home country.*

In the context of gravity models of trade and financial flows, this assumption is intuitive. When countries trade more or have more bilateral financial flows, their pricing kernels will be more exposed to the same common shock. Distance governs the correlation of the pricing kernel: as the distance to $*$ declines and κ^* increases, the covariance of the pricing kernels at home and abroad increases.

Armed with Assumption 1, we can start to interpret these results. First, the variance of the base factor $\text{Var}\left(\lim_{N\to\infty}\Delta base_{t+1}\right)$ is higher in 'peripheral' countries that are more distant from other countries. These are countries with larger $|\overline{\kappa^*} - 1|$ is larger. $|\overline{\kappa^*} - 1|$ is an inverse measure of network centrality for the home country; 'network closeness' is defined as the inverse of the average distance. An increase in the variance of the base factor in turn increases the average R^2 in the factor regressions.

Second, we interpret the loading, φ^*. The only source of cross-sectional variation is κ^*, the exposure to the common shock. The country-specific shock does not matter for the loadings on the base factor. Since the home country loads more than average on the common factor, then $\varphi^* \geq 0$ is always positive since we imposed that $\kappa^* < 1$. Given our assumptions, φ^* are bounded by:

$$\left[\frac{\tau^2\sigma^2}{\tau^2\sigma^2 + (\overline{\kappa^*} - 1)^2 (\sigma^g)^2}, \frac{\tau^2\sigma^2 - (\overline{\kappa^*} - 1)(\sigma^g)^2}{\tau^2\sigma^2 + (\overline{\kappa^*} - 1)^2 (\sigma^g)^2}\right].$$

The lower bound is attained when $\kappa^* = 1$. This is the case of perfect risk sharing when commodity baskets and preferences are identical. The upper bound is attained when $\kappa^* = 0$. This is the case of no exposure to common risks. In addition, φ^* increases as κ^* decreases, or equivalently, as distance increases. As κ^* drops below $\overline{\kappa^*}$, φ increases above one. In a trade context, this implies that lower trade intensity goes together with higher exposures to the base factor.

Finally, we can interpret the R^2. While the bilateral R^2 is not in general monotonic in κ^*, it is decreasing in the average loading $\overline{\kappa^*}$. This shows that as the loading on the common factor of the average foreign country decreases from 1, the R^2 for the average foreign country will increase. With Assumption 1, this tells us that countries which are on average distant from other countries will on average have high R^2 in our base factor regressions.

In Section (3), we test the prediction of the model that distance has a significant effect on the currency factor structure.

Long-Run Risk Interpretation

Our factor model nests the long run risks model pioneered in FX by Colacito and Croce (2011); Bansal and Shaliastovich (2013). We specify the consumption growth process the home country and the foreign country, as:

$$\Delta c_{t+1} = \mu + x_t^g + \sigma \eta_{t+1}, \tag{1}$$

$$\Delta c_{t+1}^* = \mu + \kappa^* x_t^g + \sigma^* \eta_{t+1}^*, \tag{2}$$

$$x_{t+1}^g = \rho_x x_t^g + \varphi_e \sigma e_{t+1}^g, \tag{3}$$

where $(\eta_t, \eta_t^*, e_t^g,)$ are i.i.d. mean-zero, variance-one innovations. As in Colacito and Croce (2011), country-level consumption growth contains a common low-frequency component x_t^g which originates in the home country, and impacts foreign consumption growth as well. This specification confronts the Brandt, Cochrane, and Santa-Clara (2006) puzzle: complete market models can only reconcile the low volatility of exchange rate changes Δs with the high volatility of m if m and m^* are highly correlated. Colacito and Croce (2011) impute a high degree of correlation to the SDFs through the persistent component of consumption growth x_t^g. We adopt their approach. To simplify the analysis, we abstract from a country-specific persistent consumption growth component, because these would not affect the loadings of bilateral exchange rates on the common base factor. In the context of this model, it is w.l.o.g. to have a single common factor in consumption growth when studying the loadings of exchange rates on the common factor, because only the covariation with the home country matters.

We use the following notation: $\theta = (1-\alpha)/(1-\rho)$ and $\psi = 1/\rho$, where α is the risk aversion and ψ is the intertemporal elasticity of substitution. β is the time discount factor. With Epstein-Zin preferences, the log SDF in country k is a function of log consumption changes and the log total wealth return:

$$m_{t+1} = \frac{1-\alpha}{1-\rho} \log \beta - \frac{1-\alpha}{1-\rho} \rho \Delta c_{t+1} + \left(\frac{1-\alpha}{1-\rho} - 1 \right) r_{t+1}^A.$$

By no arbitrage, when markets are complete, the change in the log exchange rate is given

by:

$$\Delta s_{t+1} = m_{t+1} - m_{t+1}^* = -\frac{1-\alpha}{1-\rho}\rho(\Delta c_{t+1} - \Delta c_{t+1}^*) + \left(\frac{\rho-\alpha}{1-\rho}\right)(r_{t+1}^A - r_{t+1}^{*,A}).$$

We define the log price-consumption ratio z_t as $p_t - c_t$. We now have a log-linear approximation of the return on wealth: $r_{t+1}^A = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta c_{t+1}$, where $\kappa_1 = exp(p-c)/(1+exp(p-c))$ and $\kappa_0 = \log(1+exp(p-c))-(p-c)\kappa_1$. In the Section (A.1), we show that the log price-consumption ratio z_t is linear in the state variable x_t^g: $z_t = A_0 + \kappa^* \frac{1-\rho}{1-\kappa_1\rho_x} x_t^g$. To simplify the notation, we use the following shorthand: $\sigma^g = \frac{(\alpha-\rho)\kappa_1}{1-\kappa_1\rho_x}\varphi_e\sigma$. The innovation to the exchange rate is given by

$$\Delta s_{t+1} - E_t[\Delta s_{t+1}] = \alpha(\sigma^* \eta_{t+1}^* - \sigma\eta_{t+1}) + (\kappa^* - 1)\sigma^g e_{t+1}^g$$

Exchange rates respond to the local temporary consumption shocks in the home country, the foreign shocks, as well as the common shocks to the persistent component: The base factor (without dropping the foreign currency) for currency i is simply given by:

$$\Delta base_{t+1} - E_t[\Delta base_{t+1}] = \frac{1}{N}\sum_{j=1}^{N}(\Delta s_{t+1} - E_t[\Delta s_{t+1}])$$

$$= \alpha(\overline{\sigma^* \eta_{t+1}^*} - \overline{\sigma\eta_{t+1}}) + (\overline{\kappa^*} - 1)\sigma^g e_{t+1}^g$$

For large N, we have the following simple expression for currency i's base factor, which only depends on the base-country-specific and the common shock:

$$\lim_{N\to\infty} \Delta base_{t+1} - E_t[\Delta base_{t+1}] = -\alpha\sigma\eta_{t+1} + (\overline{\kappa^*} - 1)\sigma^g e_{t+1}^g.$$

Proposition 2. *The variance of the base factor, the covariance of the exchange rate with the base factor and the loadings on the base factor are given by, respectively:*

$$Var_t\left(\lim_{N\to\infty}\Delta base_{t+1}\right) = \alpha^2\sigma^2 + (\overline{\kappa^*} - 1)^2(\sigma^g)^2$$

$$Cov_t\left(\Delta s_{t+1}, \lim_{N\to\infty}\Delta base_{t+1}\right) = \alpha^2\sigma^2 + (\kappa^* - 1)(\overline{\kappa^*} - 1)(\sigma^g)^2$$

$$\varphi_t^* = \frac{Cov_t\left(\Delta s_{t+1}, \lim_{N\to\infty}\Delta base_{t+1}\right)}{Var_t\left(\lim_{N\to\infty}\Delta base_{t+1}\right)} = \frac{\alpha^2\sigma^2 + (\kappa^* - 1)(\overline{\kappa^*} - 1)(\sigma^g)^2}{\alpha^2\sigma^2 + (\overline{\kappa^*} - 1)^2(\sigma^g)^2},$$

$$R^2 = \frac{\varphi^{*,2}Var\left(\lim_{N\to\infty}\Delta base_{t+1}\right)}{Var(\Delta s_{t+1})} = \frac{\left[\alpha^2\sigma^2 + (\kappa^* - 1)(\overline{\kappa^*} - 1)(\sigma^g)^2\right]^2}{\left[\alpha^2(\sigma^2 + \sigma^{*,2}) + (\kappa^* - 1)^2(\sigma^g)^2\right]\left[\alpha^2\sigma^2 + (\overline{\kappa^*} - 1)^2(\sigma^g)^2\right]}.$$

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where $(\sigma^g)^2 = \left(\frac{(\alpha-\rho)\kappa_1}{1-\kappa_1\rho_x}\varphi_e\right)^2 \sigma^2$.

Multi-Factor SDF Model

A richer model would allow for multiple common factors. Most of the analysis carries through. The log SDF, m_{t+1}^* in each country is given by:

$$-m_{t+1}^* = \alpha^* + \chi^*\sigma^{*,2} + \sum_{k=1}^{K}\xi_k^*\left(\sigma_k^g\right)^2 + \tau^*\sigma^*u_{t+1}^* + \sum_{k=1}^{K}\kappa_k^*\sigma_k^g u_{k,t+1}^g,$$

where u_{t+1} are local shocks and $u_{k,t+1}^g$ are common global shocks, all of which are zero mean and variance 1. Exchange rates changes are

$$\Delta s_{t+1} = m_{t+1} - m_{t+1}^*$$

$$= (\alpha^* - \alpha) + \sum_{k=1}^{K}(\xi_k^* - \xi_k)\left(\sigma_k^g\right)^2 + \tau^*\sigma^*u_{t+1}^* - \tau\sigma u_{t+1} + \sum_{k=1}^{K}(\kappa_k^* - \kappa_k)\sigma_k^g u_{k,t+1}^g$$

For large N, we have the following simple expression for currency i's base factor:

$$\lim_{N\to\infty}\Delta base_{t+1} = \quad (\overline{\alpha^*} - \alpha) + \sum_{k=1}^{K}(\overline{\xi_k^*} - \xi_k)\left(\sigma_k^g\right)^2 - \tau\sigma u_{t+1} + \sum_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)\sigma_k^g u_{k,t+1}^g \quad (4)$$

Proposition 3. *The variance of the base factor, the covariance of the exchange rate with the base factor and the loadings on the base factor are given by, respectively:*

$$Var\left(\lim_{N\to\infty}\Delta base_{t+1}\right) = \tau^2\sigma^2 + \sum_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)^2\left(\sigma_k^g\right)^2$$

$$Cov\left(\Delta s_{t+1}, \lim_{N\to\infty}\Delta base_{t+1}\right) = \tau^2\sigma^2 + \sum_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)(\kappa_k^* - \kappa_k)\left(\sigma_k^g\right)^2$$

$$\varphi^* = \frac{Cov\left(\Delta s_{t+1}, \lim_{N\to\infty}\Delta base_{t+1}\right)}{Var\left(\lim_{N\to\infty}\Delta base_{t+1}\right)} = \frac{\tau^2\sigma^2 + \sum\limits_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)(\kappa_k^* - \kappa_k)\left(\sigma_k^g\right)^2}{\tau^2\sigma^2 + \sum\limits_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)^2\left(\sigma_k^g\right)^2}$$

The base factor loading φ^* varies due to differences in loadings on the K common factors. The term $\sum\limits_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)(\kappa_k^* - \kappa_k)\left(\sigma_k^g\right)^2$ measures this difference. For each factor k, we distinguish two cases. First, when $\overline{\kappa_k^*} < \kappa_k$, the factor k is relatively important for home country. We refer to these as the home country's 'own factors'. In this case, the base factor loading φ^*

increases if the factor is less important for j ($\kappa_k^* < \kappa_k$). Second, when $\overline{\kappa_k^*} > \kappa_k$ the factor is less importantthe home country. In this case, the base factor loading φ^* increases if the factor is more important for the foreign country ($\kappa_k^* > \kappa_k$).

Finally, it is easy to check that he expected excess return on a long position in the basket of foreign currencies is given by: $E_t[rx_{t+1}] + \frac{1}{2}Var_t[\Delta base_{t+1}] = \tau\sigma^2 - \sum_{k=1}^{K}\kappa_k(\overline{\kappa_k^*} - \kappa_k)(\sigma_k^g)^2$.

Assumption 2. *The weighted difference in factor exposures $\sum_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)(\kappa_k^* - \kappa_k)(\sigma_k^g)^2$ increases monotonically in log distance from $*$ to home.*

When the foreign and home countries are more distant from each other, it is natural to assume that the foreign country is less exposed to the home country's 'own factors' ($\overline{\kappa_k^*} < \kappa_k$, case 1) and $*$ is more exposed to the other factors ($\kappa_k^* > \kappa_k$, case 2). Assumption 2 implies that $\text{Var}\left(\lim_{N\to\infty}\Delta base_{t+1}\right) = \tau^2\sigma_i^2 + \sum_{k=1}^{K}(\overline{\kappa_k^*} - \kappa_k)^2(\sigma_k^g)^2$ is larger for peripheral countries that are farther from the average country. Countries that are distant from each other have different factor loadings — more so for factors that are important for countries' base factor variation ($\overline{\kappa_k^*} \ll \kappa_k$). Given Assumption 2 , the exchange rate loadings on the base factor also increase with distance.

2 The Factor Structure in Exchange Rates

We now turn to empirically measuring the base factor loadings and their determinants. We start by describing the data. Next, we document the empirical properties of the base factors and their relation to systematic currency risk. Finally, we show how measures of distance between countries can explain the variation in systematic currency risk.

2.1 Data Description

We obtain daily FX data from Global Financial Data (GFD) for 162 countries from January 1, 1973 until December 31, 2014. All FX data is with respect to the US dollar and is converted to end-of-month. CPI data used to calculate real exchange rate changes is monthly from GFD. Our main results restrict the sample to 24 developed and 23 emerging countries as classified by MSCI in August 2015. In Section (5) we present robustness tests on the full and developed samples. We provide additional details of the sample construction in Appendix B.

Most gravity data is available from Head, Mayer, and Ries (2010) and Mayer and Zignago (2011). Distance is the population weighted average between large cities in each country pair

(Mayer and Zignago (2011)). Common language is 1 if a language is spoken by over 9% of the population in both countries (Mayer and Zignago (2011)). Common legal origins is from Porta, Lopez-de Silanes, and Shleifer (2007), linguistic similarity from Desmet, Ortuno-Ortin, and Wacziarg (2012), and genetic distance from Spolaore and Wacziarg (2009). The data on pegs is from Shambaugh (2004). The peg classification is based upon bilateral exchange rate volatility being less than 2% in two consecutive years. For full sample tests, the peg dummy is 1 if either currency was pegged to the other or both currencies were pegged to the same currency at any point in the sample. For the 5-year rolling tests, the peg dummy is 1 if either currency was pegged to the other or they were pegged same currency at any point in the prior 6 years.

Trade data is from United Nations COMTRADE and The Center for International data. Bilateral asset holdings are from the IMF Coordinated Portfolio investment survey. GDP data are from the World Bank's World Development Indiactors. Finally, we construct a measure of natural resource similarity between two countries. To do this, we obtain and clean the list of natural resources by country from the CIA world factbook. Using the list of natural resources, we construct vectors of dummy variables — 1 if a country has the resource, 0 otherwise. Natural resource similarity between two countries is the cosine similarity of the vectors of resource dummy variables.

2.2   Estimation

Base factor loadings are estimated for all base currencies in the sample against all other currencies following the procedure in Verdelhan (2015). Specifically, base factor loadings, $\varphi_{i,j}^*$, are estimated from the regression

$$\Delta s_{i,j,t} = \alpha_{i,j} + \varphi_{i,j}^* \Delta base_{i,t} + u_{i,j,t} \ , \tag{5}$$

where $s_{i,j,t}$ is the time t exchange rate in units of currency j per unit of currency i and $\Delta base_{i,t}$ is the average appreciation of the currency i against all other currencies at time t. Starting with US based spot rates, we convert all rates to a specific base currency i. To avoid a mechanical relation between exchange rate changes and base factors, we calculate a separate base factor for each currency j, which omit that currency. For example, we construct the US dollar factor, $\Delta base_{\$,t} = \frac{1}{N-1} \sum_{k \neq j} \Delta s_{\$j,t}$, by averaging the change in the exchange rate across all bilateral exchange rates against the USD. When we study the relation between the USD/GBP bilateral exchange rate, $\Delta s_{\$,\pounds,t}$, and the USD base factor, we drop the USD/GBP bilateral exchange rate from the construction of the base factor.

Conditional base factor loadings, $\varphi_{i,j,t}^*$, are estimated using 60 month rolling windows. The regression must have 48 months of available data for the conditional base factor loading to be estimated. Monthly rolling factor loadings are averaged to generate yearly observations.

The base factors are closely related to the first principal component of bilateral exchange rate changes. To show this, we compute the first principal component of the bilateral exchange rates $\Delta s_{i,j,t}$ for each base currency i. For example, instead of the dollar base factor, we could use the first principal component of all bilateral exchange rates against the dollar[4]. Table (B3) in Section (B.4) reports the correlations of the 1st principal component and the base factor by base currency. For most currencies, the first principal component is essentially the base factor. The only exception is Singapore with a correlation of 0.86. As a result, we simply proceed by analyzing the base factors.

The objective of our paper is to explain the base factor loadings, $\varphi_{i,j}^*$. The base factor loadings impact numerous important quantities in foreign exchange markets. Consider the R^2 of the regression in Equation (5):

$$R_{i,j}^2 = \frac{\left(\widehat{\varphi}_{i,j}^*\right)^2 \sum_t \left(\Delta base_{i,t} - \overline{\Delta base_i}\right)^2}{\sum_t \left(\Delta s_{i,j,t} - \overline{\Delta s_{i,j}}\right)^2} . \tag{6}$$

This is a measure of the amount of systematic currency risk faced by a domestic investor in the base country who takes long positions in foreign currency. All else equal, countries j with a larger loading on the base factor will tend to have a higher R^2. In addition, base countries i with more volatile base factors tend to have higher average R^2. Table (1) presents a decomposition of exchange rate variance for each base country[5]. The first column reports the average variance of the bilateral exchange rates. The second column reports the average, across currencies j, of the variance explained by the base factor (the numerator of Equation (6)). The third column reports the idiosyncratic variance of the bilateral exchange rates. The numbers in the first column are the sum of the numbers in the second and third column. All three columns are multiplied $\times 100$. The fourth column reports average R^2.

There is large amount of variation in the variances explained by the base factors, reported in the first column. The average explained variance is 0.68 for developed countries and 3.37 for emerging market countries. In some countries, a high explained variance reflects the

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[4]To compare base factors and 1st principal components, it is necessary to construct a different sample because a balanced panel is needed. For this comparison only, all observations from countries which join the euro are dropped, except for Germany. The German exchange rate becomes the Euro starting in 1999. Using this sample, base factors and 1st principal components are calculated for each potential base currency.

[5]Table (B4) reports the same results for real exchange rates, computed using the ratio of the countries' CPIs.

Table 1: Variance Decomposition of Bilateral Exchange Rates by Base Currency

	FX Var	Base Var	Id. Var	R^2 Mean		FX Var	Base Var	Id. Var	R^2 Mean
Developed Countries					**Emerging Countries**				
Australia	2.81	0.95	1.86	0.50	Brazil	12.57	11.05	1.52	0.89
Austria	3.20	0.64	2.55	0.31	Chile	10.75	9.06	1.69	0.82
Belgium	3.29	0.67	2.63	0.32	China	2.81	1.07	1.74	0.53
Canada	2.31	0.42	1.89	0.33	Colombia	2.48	0.67	1.81	0.45
Denmark	2.31	0.52	1.78	0.29	Czech Republic	6.22	4.40	1.82	0.76
Euro Area	1.11	0.48	0.64	0.41	Egypt	3.71	2.01	1.69	0.66
Finland	3.24	0.51	2.74	0.31	Greece	3.14	0.67	2.47	0.39
France	3.24	0.61	2.63	0.29	Hungary	3.08	1.32	1.76	0.58
Germany	3.32	0.70	2.62	0.33	India	2.36	0.44	1.92	0.34
Hong Kong	2.29	0.41	1.88	0.30	Indonesia	6.03	4.33	1.70	0.78
Ireland	3.23	0.53	2.70	0.29	Korea	3.23	1.32	1.91	0.56
Israel	4.17	2.48	1.70	0.69	Malaysia	2.30	0.40	1.90	0.30
Italy	3.28	0.55	2.73	0.33	Mexico	8.19	6.42	1.77	0.81
Japan	2.94	1.04	1.90	0.51	Peru	16.29	14.71	1.57	0.88
Netherlands	3.30	0.68	2.62	0.32	Philippines	2.94	1.04	1.90	0.52
New Zealand	2.87	0.96	1.91	0.50	Poland	6.36	4.60	1.76	0.77
Norway	2.31	0.46	1.85	0.28	Qatar	2.22	0.46	1.76	0.32
Portugal	3.26	0.55	2.71	0.29	Russian Federation	8.76	7.80	0.96	0.87
Singapore	2.11	0.22	1.89	0.17	South Africa	3.31	1.40	1.91	0.58
Spain	3.40	0.65	2.75	0.37	Taiwan	2.31	0.43	1.87	0.32
Sweden	2.41	0.54	1.86	0.34	Thailand	2.66	0.78	1.89	0.45
Switzerland	2.59	0.77	1.82	0.42	Turkey	4.47	2.78	1.69	0.72
United Kingdom	2.45	0.55	1.90	0.37	United Arab Emirates	2.21	0.44	1.77	0.31
United States	2.25	0.41	1.84	0.30					
All	2.83	0.68	2.15	0.36	All	5.15	3.37	1.77	0.59

Summary statistics of data from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi_{i,j}^* \Delta base_{i,t} + e_{i,j,t}$ for each possible base currency i. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Base Var, FX Var, and Id Var are cross-sectional means for each base currency. Base Var is the variance attributed to the base factor, FX Var is the total variance, and Id Var is the remaining idiosyncratic variance. R^2 mean is the cross-sectional mean of the R^2 for each base currency. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI.

effects of high and volatile inflation episodes — the explained variances for Brazil, Peru and Israel are respectively 11.05, 14.71 and 2.48.

But the composition of the variances are different as well. The average R^2 is 0.36 for developed countries' currencies, compared to an average R^2 of 0.59 for emerging market currencies. This reflects the fact that the ratio of the explained variance to exchange rate variance is higher for the latter than the former. To clearly visualize the mapping from location to R^2 in currency markets, Figure (2) plots the average R^2 on a map. Countries that are distant from most other countries have a high average R^2. These peripheral countries have a high average R^2 because they are distant from most other countries. Conversely, central countries have low average R^2 due to being close to most other countries.

Figure (3) shows this relation. The first panel plots average R-squared versus average distance to all other countries. The second panel uses a measure of average distance which is the first principal component of bilateral gravity variables. The third panel uses a measure of countries' position in the global trade network from (Richmond, 2015). Even within the group of developed currencies, countries that are central in the global trade network tend to have low R^2: the R^2 of Belgium, Singapore, and Hong Kong are 0.32, 0.17, and 0.30, respectively. Countries in the periphery of the global trade network tend to have high R^2s: the R^2 is 0.50 for Australia and New Zealand.

Figure 2: Average R^2 by Base Factor
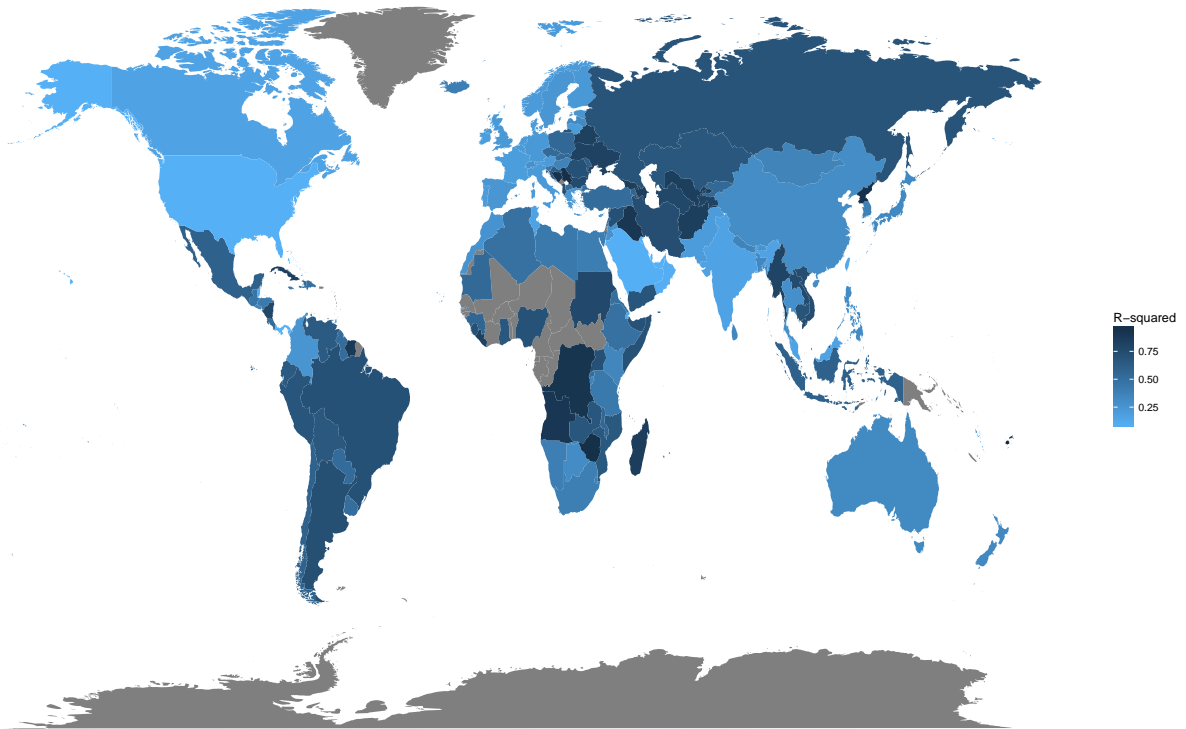
Map of cross-sectional average R-squared from the regression $\Delta s_t = \alpha + \varphi^* \Delta base_t + e_t$ for each possible base currency. $\Delta base_t$ is the average appreciation of the US dollar at time t relative to all available currencies, excluding the bilateral exchange rate on the r.h.s. from the basket. Spot rates are monthly from January 1973 until December 2014 for 162 countries from Global Financial Data.

Figure 3: Average R-Squared vs Measures of Average Distance

Plots of average R-squared versus measures of average distance and trade network centrality. R-squared values, $R^2_{i,j}$, are from regressions $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi^*_{i,j}\Delta base_{i,t} + e_{i,j,t}$. $E[R^2_{i,j}]$ is the cross-sectional average R-squared for each i. For each currency j, $\Delta base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Average distance is measured in km for each country to all other countries in the sample. Gravity PC is the first principal component of bilateral distance, shared language, shared legal origins, shared colonial origins, resource similarity, and shared border. Trade centrality is alpha centrality of a network with bilateral trade intensity as weights as in (Richmond, 2015). Trade centrality ranking is the time series average ranking where rankings are normalized to the maximum number of countries in the sample. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI.

3   The Gravity Effect in the Factor Structure

In the previous section, we established that variation in base factor loadings drives important differences in the properties of exchange rates. In this section, we show that variation in base factor loadings can largely be understood as a function of measures of distance between countries.

3.1   Summary Statistics

We begin by summarizing the key variables in our dataset. Table (2) reports summary statistics for all of the variables in our main sample. There are a total of 2,070 base coun-

try/foreign country combinations. There is a lot of variation in the loadings across currencies. The average loadings are close to one. The average standard deviation of the loadings across countries for a given base currency is 0.33. Similarly, there is a lot of variation in the R^2. The average R^2 is 0.47 while the cross-sectional standard deviation is 0.29. The average distance between a base currency and its counterparts is 8.62 (in logs) or 5541 km. On average, 13% (4%) of the countries share a language (border) with the base currency. The average resource similarity with the base currency is 0.24. 2% share the same colonizer with the base currency. 28% of the currencies have been pegged to the base currency or have shared a peg with the base currency to another currency at any point in the sample.

Table 2: Full Sample Summary Statistics

	N	Mean	Median	Sd	Min	Max
Loading	2,070	0.95	1.00	0.33	-0.15	2.95
Loading (Real)	1,640	0.93	0.99	0.33	-0.16	3.25
R-squared	2,070	0.47	0.46	0.29	0.00	0.98
R-squared (Real)	1,640	0.47	0.45	0.29	0.00	0.99
Log Dist	2,070	8.62	9.00	0.93	5.08	9.88
Common Language	2,070	0.13	0.00	0.34	0.00	1.00
Shared Border	2,070	0.04	0.00	0.20	0.00	1.00
Resource Similarity	2,070	0.24	0.23	0.17	0.00	0.82
Linguistic Proximity	957	1.06	0.22	2.23	0.00	15.00
Genetic Distance	1,023	0.72	0.78	0.52	0.00	2.67
Colonial Linkage	2,070	0.02	0.00	0.14	0.00	1.00
Peg Dummy	2,070	0.28	0.00	0.45	0.00	1.00

Summary statistics of the factor loadings and gravity data. Factor loadings, $\varphi_{i,j}^*$, are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi_{i,j}^* \Delta base_{i,t} + e_{i,j,t}$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI.

Table (B2) reports summary statistics for the rolling sample. In the rolling sample, only 12% of the currencies are pegged to or share a peg with the base currency. In the 5-year rolling samples, the peg dummy is 1 if either currency was pegged to other or they were pegged same currency at any point in the 6 years prior.

3.2   Understanding the variation in the loadings

To explain the variation in base factors loadings, we regress the full sample loadings, $\varphi_{i,j}^*$, on various exogenous measures of the economic distance between i and j. We include physical distance, shared language, shared legal origin, share border, colonial link, resource similarity, genetic distance and linguistic similarity. All of the regressions indicate that an increase in the economic distance between i and j increases $\varphi_{i,j}^*$, the sensitivity of the bilateral exchange rate to the base factor.

The dependent variable in our model is estimated. This does not bias the estimates, but may introduce heteroskedasticity into the residuals (Lewis and Linzer, 2005). Additional correlation in the residuals arises due to the interdependent nature of exchange rates. Therefore, in all tables we report standard errors correcting for heteoroskedasticity (White, 1980), clustering on base factor or foreign country (Cameron, Gelbach, and Miller, 2011), or clustering on country pairs (Aronow, Samii, and Assenova, 2015) — depending on the specification. Additional details are in B.3.

Table (3) reports the results for MSCI developed and emerging countries. In this sample, physical distance, shared language, colonial linkages and resource similarity all have robust effects on the loading. The average loading for a given base factor is one, while the cross-sectional standard deviation is 0.42 (0.23) for developed (emerging market) countries. A one standard deviation in log distance (the equivalent of approx. 8,500 km) increases the loading by about 0.13. This number is robust across different specifications, except the no peg specification. Shared language lowers the loading by about 0.11. Shared border lowers the loading by 0.13. Colonial linkages lower the loadings by up to 0.23. Resource similarity also lowers the loadings. Legal origin, linguistic proximity, and genetic distances, do not have a statistically significant effect on the currency loadings. This specification accounts for 1/4 of all the variation in the loadings. Given the measurement error in these loadings, this is a remarkably high number.

Specifications (1), (2) and (3) do not control for pegs. For completeness, specification (4) introduces a peg dummy. The peg dummy is one if the currencies were ever pegged to each other or the same currency at any point in the sample. Controlling explicitly for pegs mitigates most of these 'economic distance' effects. This is not surprising. We have already established in the previous section that the decision to peg is driven the same largely determined by the same exogenous 'economic distance' variables. The broader claim that economic distance determines currency covariation (with or without currency pegs) is still valid. Note that resource similarity is no longer significant in specification (4). That is not

Table 3: Full Sample Regressions with Nominal Loadings

	All (1)	All (2)	All (3)	All (4)	No Pegs
Log Distance	0.156***	0.162***	0.141***	0.116***	0.083**
	(4.376)	(3.635)	(3.737)	(3.923)	(2.202)
Shared Language			−0.110***	−0.088**	−0.123***
			(−3.149)	(−2.568)	(−2.845)
Shared Legal		−0.039	−0.005	0.013	0.028
		(−1.180)	(−0.187)	(0.513)	(0.857)
Shared Border		−0.084*	−0.130***	−0.083*	−0.114
		(−1.799)	(−3.285)	(−1.740)	(−1.229)
Colonial Link		−0.078	−0.234**	−0.210**	−0.310***
		(−1.209)	(−2.297)	(−2.089)	(−3.758)
Resource Similarity		−0.172**	−0.146**	−0.097	−0.081
		(−2.095)	(−2.294)	(−1.272)	(−0.813)
Linguistic Proximity		−0.002			
		(−0.411)			
Genetic Distance		−0.053			
		(−1.386)			
Peg Dummy				−0.239***	
				(−3.901)	
R^2	0.189	0.212	0.230	0.322	0.095
Num. obs.	2070	903	2070	2070	1498

surprising, given that resource similarity was a major determinant of the decision to peg. If a currency has been pegged to the base currency, or if they both have been pegged to the same currency in our sample, this lowers the loadings by another 0.25. This effect is not entirely mechanical: the peg dummy is one if the currencies were pegged at any point during the sample.

Finally, specification (5) excludes all currencies that were pegged at some point in the 1973-2014 sample. This reduces the number of country pairs from 2,070 to 1,498. The R^2 drops from 23.0% to 9.5%. However, distance, language, and colonial link effects are statistically significant at the 5% level. We will use rolling sample regressions in order to have a more targeted control for currency pegs below.

In Table (B5), we compare the nominal loadings to the real loadings. The real loadings are computed by running the same regression of real exchange rate changes on the real base factor. Specifications (1) and (2) report results without a peg dummy for nominal and real loadings respectively. Specifications (3) and (4) report the same regression with a peg dummy. Both pairs of regressions are on matched samples. In both cases, the magnitude and significance of the regression coefficients are similar. This is consistent with Mussa (1986)'s observation that real exchange rates largely track nominal ones.

3.3   Marginal Propensity to Peg and Rolling Sample Estimates

Exchange rate regimes are endogenous. The decision to peg is largely governed by distance between the countries and other measures of economic distance. To show this, Table (4) reports the estimation results for a logit model similar to Tenreyro (2007). The dependent variable is a peg dummy which measures whether two currencies were ever pegged to each other or to the same currency. Because the peg dummy is symmetric and the gravity data is symmetric, the models are only estimated on unique pairs of countries.

Distance, resource similarity, genetic distance, and common legal origins are significant determinants of whether currencies are pegged. Distance reduces the likelihood of a peg. In specification (3), a one unit increase in log distance from its mean (8.73 to 9.73 in logs or 6,186km to 16,815km) decreases the peg probability by approximately 5%. An increase in resource similarly from its mean of .19 to .29 increases the peg probability by 2% in specification (3). Finally, having common legal origins increases the peg probability by 7% in specification (2).

To control for the effect of pegs in a targeted way, we use the rolling estimates of the base loadings. Table (5) reports the results of regressions of base factor loadings computed over

Table 4: Marginal Propensity to Peg in Full Sample

	(1)	(2)	(3)
Log Distance	−0.061***	−0.072**	−0.045**
	(−3.319)	(−2.411)	(−2.111)
Shared Language			0.059
			(1.452)
Shared Legal		0.068**	0.049*
		(2.131)	(1.915)
Shared Border		0.070	0.119*
		(1.088)	(1.935)
Colonial Link		−0.015	−0.004
		(−0.260)	(−0.078)
Resource Similarity		0.309**	0.226**
		(2.345)	(2.288)
Linguistic Proximity		−0.002	
		(−0.282)	
Genetic Distance		0.057**	
		(2.069)	
Num. obs.	12699	7652	12403

Logit models of peg dummy on gravity data. Peg dummy measures whether countries were ever pegged to each other or to the same currency during the sample. A currency pair is considered pegged if the bilateral exchange rate volatility is less than 2% in 2 consecutive years (Shambaugh (2004)). The table reports marginal effects at the mean. Data is yearly from 1973 until 2014 for the 162 countries in the Global Financial Data dataset. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

60-month rolling windows on time fixed effects and the gravity variables. The peg dummy is now defined differently; it is one only if the currencies were pegged to each other or to the same currency at any point in the prior 72 months. Overall, the r-squareds in the rolling regressions are substantially lower, presumably because the loading estimates are noisier.

As before, the peg dummy in the fourth specification mitigates some of these economic distance effects, because these same effects ultimately determine the likelihood of a peg. Specification (4) controls for pegs while (1)-(3) do not. Overall, the size of the coefficients in specification (4) are somewhat smaller than those in specification (3). The distance coefficient is still around 0.14 in specification (4). The shared language effect is -0.10. The effects of a shared border is around -0.11. The effect of a colonial linkage has decreased from -0.28 to -0.2, while the effect of resource similarity is roughly constant. A one standard deviation increase in resource similarity reduces the loading by 0.04. Specification (5) excludes the pegs altogether. Reassuringly, the magnitudes of these slope coefficients does not differ significantly between specification (4) and specification (5).

Interestingly, when the shared language is English, the effects are much larger. For example, when we only consider the USD factor, the loading decreases by 0.53 when the other country has English as one of its major languages (see Table (B6) in the Section (B.4)).

Finally, Table (B7) checks the results of the nominal against the real base factor loadings in the rolling sample regressions. The samples are matched on the available of CPI data. In the real specifications (1)-(3), some of the coefficients are smaller in absolute value. In particular, colonial linkages are no longer statistically significant. However, the distance is even stronger. The r-squareds in the real specifications are slightly lower than in the nominal specifications.

Our results also hold for real exchange rates, echoing Mussa (1986); Flood and Rose (1995)'s observation that real exchange rates largely track the nominal ones, even if the nominal exchange rate is fixed. The sensitivity of changes in the real exchange rate to the base factor is governed by the same economic forces, and the coefficients have similar magnitudes. The only exception is the effect of colonial linkages. Engel (1999) attributes most of the variation in U.S. real exchange rates to the relative prices of tradeables. Based on extrapolation of Engel (1999)'s decomposition, our findings imply that the relative prices of tradeables in countries that are economically distant, and hence trade less, will be more sensitive to the common factor. Conversely, the factor structure in relative prices will be weaker in countries that are close and trade more intensely. In product-level data, there

Table 5: Rolling Sample Regressions with Nominal Factor loadings

	All (1)	All (2)	All (3)	All (4)	No Pegs
Log Distance	0.155***	0.163***	0.138***	0.119***	0.121***
	(4.298)	(3.807)	(3.443)	(3.410)	(3.259)
Shared Language			−0.122***	−0.096***	−0.107***
			(−3.096)	(−3.142)	(−3.038)
Shared Legal		−0.041	−0.019	−0.033	−0.032
		(−1.064)	(−0.623)	(−1.295)	(−1.197)
Shared Border		−0.055	−0.126**	−0.076	−0.113**
		(−1.069)	(−2.548)	(−1.638)	(−2.556)
Colonial Link		−0.144**	−0.281***	−0.200***	−0.225***
		(−2.276)	(−3.367)	(−4.581)	(−3.724)
Resource Similarity		−0.198**	−0.166***	−0.151**	−0.165**
		(−2.475)	(−2.599)	(−2.454)	(−2.229)
Linguistic Proximity		−0.003			
		(−0.580)			
Genetic Distance		−0.037			
		(−1.275)			
Peg Dummy				−0.472***	
				(−8.710)	
Within R^2	0.086	0.114	0.114	0.185	0.086
Num. obs.	61130	27021	61130	58298	53532

Regressions $\varphi^*_{i,j,t} = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j,t}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi^*_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \varphi^*_{i,j,t} \Delta base_{i,\tau} + e_{i,j,\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

is evidence that producer-currency pricing (price stickiness) may account for some of these effects[6] (see, e.g., Nakamura and Steinsson, 2008; Gopinath and Rigobon, 2008). Recent evidence suggests that these effects are not entirely due to price stickiness. Burstein and Jaimovich (2009) find evidence in U.S-Canadian product-level data that active pricing-to-market, i.e. changes in the mark-ups contingent on the location of the sale, accounts for a lot of the variation in the relative prices of tradeables. Interestingly, we even find similar effects of distance on real exchange rate co-variation within the Euro zone.

3.4 R^2

Table (6) reports the results of a regression of the R^2 in the base factor regressions on the same explanatory variables. As expected, distance increases the R^2s: distant currencies are subject to more systematic risk. A 1 log point increase in distance increased the adjusted R^2 by about 0.06. Shared legal origin, colonial linkages and resource similarity further lower these loadings.

3.5 Average R^2 by Base Currency

Table (7) reports the results of a regression of the average R^2 for each country on measures of average distance of that country from others. These regressions corresond to Figure (3). As expected, countries which are on-average more distant from other countries have bilateral exchange rates which are more exposed to systematic risk.

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[6]In these models, flexible exchange rates are a good substitute for flexible prices and facilitate the adjustment to country-specific shocks. (For an equilibrium model, see Obstfeld and Rogoff, 1995)

Table 6: Rolling Sample Regressions with Nominal Factor R-Squared

	All (1)	All (2)	All (3)	All (4)	No Pegs
Log Distance	0.066***	0.106***	0.060***	0.052***	0.049***
	(4.235)	(4.351)	(3.630)	(3.815)	(3.512)
Shared Language			−0.039***	−0.026**	−0.032***
			(−2.648)	(−2.514)	(−2.659)
Shared Legal		−0.047*	−0.015	−0.021*	−0.021*
		(−1.936)	(−1.084)	(−1.825)	(−1.909)
Shared Border		0.023	−0.040**	−0.020	−0.021
		(0.611)	(−1.995)	(−1.318)	(−1.481)
Colonial Link		0.043**	−0.117***	−0.085***	−0.085***
		(2.132)	(−2.950)	(−3.572)	(−3.275)
Resource Similarity		−0.083	−0.063***	−0.053**	−0.061**
		(−1.503)	(−2.704)	(−2.221)	(−2.199)
Linguistic Proximity		0.007**			
		(1.964)			
Genetic Distance		−0.034			
		(−1.255)			
Peg Dummy				−0.199***	
				(−6.956)	
Within R^2	0.041	0.088	0.052	0.084	0.032
Num. obs.	61106	27016	61106	58274	53532

Regressions $\varphi_{i,j,t}^* = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi_{i,j,t}^*$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \varphi_{i,j,t}^* \Delta base_{i,\tau} + e_{i,j,\tau}$ with $\tau = t - 59 \dots t$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Real exchange rate changes include relative differences in inflation. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table 7: Regressions of Average RSquared on Measures of Average Distance

	(1)	(2)	(3)	(4)	(5)
Intercept	0.476***	0.477***	0.695***	0.670***	0.671***
	(16.415)	(16.372)	(11.410)	(10.631)	(10.448)
Average log Distance	0.069**			0.039	
	(2.354)			(1.408)	
Average of Gravity PC		0.149**			0.072
		(2.266)			(1.140)
Centrality Ranking			−0.426***	−0.376***	−0.378***
			(−3.988)	(−3.372)	(−3.315)
Adj. R^2	0.094	0.086	0.253	0.270	0.258
Num. obs.	45	45	45	45	45

Regressions $E[R_{i,j}^2] = \alpha + \kappa H_i + e_i$ of average R-squared on measures of average distance and trade network centrality. R-squared values, $R_{i,j}^2$, are from regressions $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi_{i,j}^* \Delta base_{i,t} + e_{i,j,t}$. $E[R_{i,j}^2]$ is the cross-sectional average R-squared for each i. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Average distance is measured in km for each country to all other countries in the sample. Gravity PC is the first principal component of bilateral distance, shared language, shared legal origins, shared colonial origins, resource similarity, and shared border. Trade centrality is alpha centrality of a network with bilateral trade intensity as weights as in (Richmond, 2015). Trade centrality ranking is the time series average ranking where rankings are normalized to the maximum number of countries in the sample. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

4 Calibrated LRR Model

As illustrated in Section (1.1), the base factor loadings provide a measure of exposure to common shocks. To demonstrate how the base factor loadings relate to the structural parameters of a long run risk model, we calibrate the single factor model in Section (1.1). Our calibration follows Colacito and Croce (2011), with the specific parameters given in Table (8).

Table 8: Parameters of Calibrated LRR Model

|	
β	.998
α	4.25
ψ	2
ρ	$1/\psi$
μ_c	0.0016
σ_c	0.0068
ϕ_e	.048
σ_x	$\phi_e \times \sigma_c$
ρ_x	.987

We begin by limiting ourselves to base factor loadings with respect to the British pound and calibrating the κ^* to match the cross-section of these base factor loadings. The results are illustrated in Figure (4) which plots the loadings on the persistent, common component of consumption growth versus distance from the UK. Clearly, there is a strong negative relation between the implied κ^* values and distance. The specific relation is given by:

$$\kappa^* = 1.46 - 0.11 \times \log \text{distance}$$

The fact that the implied κ^* have a negative relation with distance is a direct consequence of the negative monotonic relation between base factor loadings and κ^* in Proposition (2) and that the base factor loadings are increasing in distance. As explained in Section (1.1), this result is intuitive: If countries are closer to each other it is plausible that they will be more exposed to similar risks thank countries which are more distant from each other. This calibration illustrates how the base factor loadings provide a new way to measure exposure to shocks in international asset pricing models. The key insight is that the base factor loadings isolate exposure to common shocks.

To better understand quantitatively how exposure to long-run risk relates to measures of distance, we perform the same calibration for each developed base country. That is, we fix the loading on the persistent component of consumption growth to 1 for the base country and

Figure 4: Inferred Loadings on U.K. Consumption in LRR Model
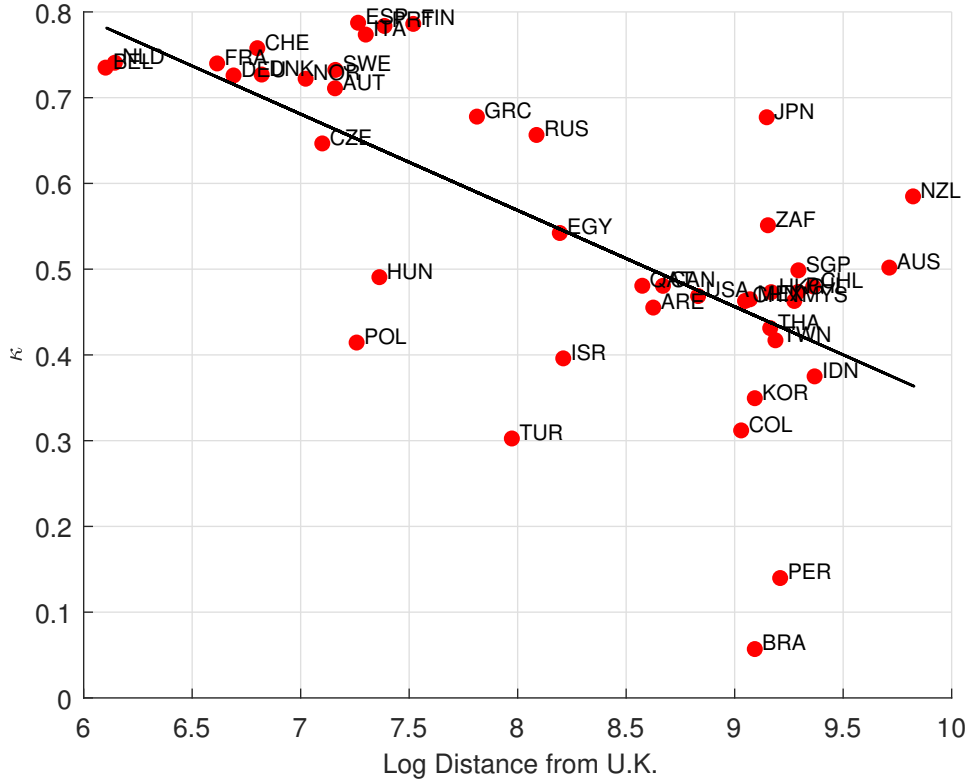
Inferred exposure to long-run risk shocks (κ) versus measures of distance from the UK. κ are calibrated to match base factor loadings in a long-run risk model with heterogeneous exposure to global factors. The base country is limited to be the UK. Base factor loadings, $\varphi_{i,j}^*$, are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi_{i,j}^* \Delta base_{i,t} + e_{i,j,t}$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed countries, as classified by MSCI.

calibrate the cross-section of kappas to the cross-section of betas for each foreign country. We then regress these κ^* values on gravity variables. The results are in Table (9). These regressions include a base country fixed effect to control for the fact that we fix the base country $\kappa = 1$. As in the UK only calibration, the calibrated κ^* are in general decreasing in distance. These results provide additional moments for international models of exchange rate determination to target and provide additional insight into the fundamental source of hetereogeneity in exposure to global risk.

Table 9: Regressions of Calibrated Kappa Values on Gravity Variables (MSCI Developed Countries)

	All (1)	All (2)	All (3)	No Pegs
Log Distance	-0.188^{***}	-0.181^{***}	-0.126^{***}	-0.145^{***}
	(-7.010)	(-6.930)	(-4.792)	(-4.253)
Shared Language		0.101	0.107	-0.090^{*}
		(1.451)	(1.526)	(-1.709)
Shared Legal		0.122^{*}	0.073	0.301^{***}
		(1.816)	(1.301)	(4.186)
Shared Border		-0.037	-0.051	
		(-0.506)	(-0.810)	
Colonial Link		0.165^{**}		
		(2.341)		
Resource Similarity		0.039	0.040	0.035
		(0.447)	(0.455)	(0.398)
Peg Dummy			0.219^{***}	
			(3.210)	
Within Adj. R^2	0.422	0.519	0.580	0.322
Num. obs.	506	506	506	334

Regressions $\kappa^*_{i,j} = \delta + \varphi G_{i,j} + e_{i,j}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. $\kappa^*_{i,j}$ are calibrated to match base factor loadings in a long-run risk model with heterogeneous exposure to global factors. Base factor loadings, $\varphi^*_{i,j}$, are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi^*_{i,j} \Delta base_{i,t} + e_{i,j,t}$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed countries, as classified by MSCI. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

5 Robustness

5.1 Developed Currencies

Table (B8) considers only the subset of developed countries, using the MSCI designation of developed countries. In this subsample, the distance effect is even stronger. In specifications (1)-(3), the effect of log distance on the loading is around 0.23, compared to 0.14. Some of the other variables are no longer enter significantly. Shared legal origin lowers the loading by more than 0.3 when pegs are removed. These variables jointly account for about 1/3 of the variation in the loadings.

5.2 All Currencies

Table (B9) presents results using data for all 162 countries in our sample. When we expand beyond the subset of MSCI developed and emerging countries, all gravity effects remain significant, but the coefficients are mitigated. A log point increase in distance increases the base factor loading by 3 bps, compared to 14 bps in the developed and emerging subset.

5.3 Trade and GDP

Table (B10) presents results controlling for bilateral imports plus exports to GDP of the foreign country and for the GDP share of the base country. Column (1) presents results only controlling for bilateral exports and imports normalized by foreign country's GDP. More trade between the foreign country and the base country, relative to the foreign country's GDP, lowers the base factor loading. Surprisingly, the R-squared in this regression is only 3%, despite the fact that gravity variables explain trade intensities quite well. Column (3) includes a control for the size of the base country. Column (4) includes both trade to GDP and GDP shares.

5.4 Financial Asset Holdings

Table (B11) presents results controlling for various forms of bilateral asset holdings as reported by the IMF Coordinated Portfolio Investment Survey. Asset holdings are measured as total assets held by each foreign country in the base country and are normalized by GDP or total assets held. The results echo those of the trade regressions – asset holdings do lower

base factor loadings, but the amount of variance that is explained by the asset holdings is small compared to that of the gravity variables.

5.5 Fixed Effects

Table (B12) presents results with different fixed effects. Column (1) is without any fixed effects, column (2) has year fixed effects, column (2) has base-country year fixed effects, and column (4) has base-coutry year and year fixed effects. The key takeaway is that the different fixed effects do not affect the qualitative of quantitve implications of our gravity model.

5.6 Persistence

It could be the case that the increase in global financial integration has lowered the explanatory power of gravity variables on base factor loadings over time. To examine this, Figure (B1) plots 15-year rolling sample R-squared values. Interestingly, the R-squared has remained remarkably stable for both the developed country subset and the 47 developed and emerging country subset.

5.7 Currency Unions

This section presents regressions for just the euro subset. Base factors are constructed only using real data on the subset of euro area countries. The results are from 1999-2014. Table (B13) reports the results. Even in this Euro subset, the real exchange rate co-variation is consistent with the gravity effects we have documented. In a univariate regression of the loadings on log distance, the slope coefficient is 0.13, similar to the effects we have documented in the full sample. Siimlarly, the coefficient on shared language is -0.29.

6 Conclusion

When Fed chairman Bernanke signaled an end to large-scale asset purchases in May 2013, some emerging market currencies subsequently depreciated by more than 25% against the USD, while other currencies did not depreciate at all (Nechio et al., 2014). What governs the differential response of currencies to a monetary policy shock, or any other shocks, in the U.S.? Are these mostly due to differences in policies and economic conditions across countries? Our paper shows that the differential response of currencies to these types of

shocks are determined to a large extent by initial conditions that are completely outside of the control of monetary and fiscal policy.

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A Model Appendix

A.1 Long Run Risks Model

We first use a log-linear approximation of the wealth return. We then assume that the price-consumption ratio is linear in the state variables. Finally, we check this conjecture and compute the corresponding coefficients by using the log-linear Euler equation.

Let us look again at the Campbell-Shiller decomposition. Start from $1 = (R_{t+1}^A)^{-1} R_{t+1}^A = (R_{t+1}^A)^{-1}(P_{t+1} + C_{t+1})/P_t$. Multiply both sides by the price-consumption ratio P_t/C_t:

$$\frac{P_t}{C_t} = (R_{t+1}^A)^{-1}(1 + \frac{P_{t+1}}{C_{t+1}})\frac{C_{t+1}}{C_t}.$$

Taking logs leads to:

$$p_t - c_t = -r_{t+1}^A + \Delta c_{t+1} + \log(1 + e^{p_{t+1} - c_{t+1}}).$$

A first-order Taylor approximation of the last term around the mean price-consumption ratio P/C gives:

$$
\begin{aligned}
p_t - c_t &= -r_{t+1}^A + \Delta c_{t+1} + \log(1 + \frac{P}{C}) + \frac{P/C}{1 + P/C}(p_{t+1} - c_{t+1} - (p - c)), \\
&\simeq -r_{t+1}^A + \Delta c_{t+1} + \kappa_0 + \kappa_1(p_{t+1} - c_{t+1}),
\end{aligned}
$$

where $\kappa_1 = exp(p - c)/(1 + exp(p - c))$ and $\kappa_0 = \log(1 + exp(p - c)) - (p - c)\kappa_1$. Define the log price-consumption ratio z_t as $p_t - c_t$. We now have a log-linear approximation of the return on wealth:

$$r_{t+1}^A = \kappa_0 + \kappa_1 z_{t+1} - z_t + \Delta c_{t+1}.$$

Guess and verify that the log price-consumption ratio z_t is linear in the state variables $x_{i,t}^g$

$$z_t = A_0 + A_1 x_t^g$$

Assume joint conditional normality of consumption growth, x, and the variance of consumption growth. Verify the conjecture above from the Euler equation:

$$E_t[e^{m_{t+1}^* + r_{t+1}^A}] = 1 \Leftrightarrow E_t\left[m_{t+1}^*\right] + E_t\left[r_{t+1}^A\right] + \frac{1}{2}Var_t\left[m_{t+1}^*\right] + \frac{1}{2}Var_t\left[r_{t+1}^A\right] + Cov_t\left[m_{t+1}^*, r_{t+1}^A\right] = 0$$

With Epstein-Zin preferences, we have shown that the log SDF is a function of log consumption changes and the log total wealth return:

$$m^*_{t+1} = \frac{1-\alpha}{1-\rho} \log \varphi - \frac{1-\alpha}{1-\rho} \rho \Delta c^*_{t+1} + \left(\frac{1-\alpha}{1-\rho} - 1 \right) r^{*,A}_{t+1}.$$

Substituting in the expression for the log total wealth return r^A into the log SDF, we compute innovations, and the conditional mean and variance of the log SDF:

$$m^*_{t+1} - E_t \left[m^*_{t+1} \right] = -\lambda^*_{m,\eta} \sigma^* \eta^*_{t+1} - \lambda^*_{m,e} \sigma e^g_{t+1}$$

$$E_t \left[m^*_{t+1} \right] = m_0 + [-\frac{1-\alpha}{1-\rho} \rho \kappa^* + \frac{\rho - \alpha}{1-\rho}(\kappa^* + A^*_1(\kappa_1 \rho_x - 1))] x^g_t$$

$$Var_t \left[m^*_{t+1} \right] = \left((\lambda^*_{m,\eta})^2 \sigma^2 + (\lambda^*_{m,e})^2 \sigma^2 \right)$$

where $\lambda^*_{m,\eta} = \alpha$, $\lambda^*_{m,e} = \frac{\alpha-\rho}{1-\rho} B^*$, and $B^* = \kappa_1 A^*_1 \varphi_e$.

Likewise, using the Campbell-Shiller approximation of r^A, we compute innovations in the consumption claim return, and its conditional mean and variance:

$$r^{*,A}_{t+1} - E_t \left[r^{*,A}_{t+1} \right] = \sigma^* \eta^*_{t+1} + B^* \sigma e^g_{t+1}$$

$$E_t \left[r^{*,A}_{t+1} \right] = r_0 + [\kappa^* + A^*_1(\kappa_1 \rho_x - 1)] x^g_t$$

$$Var_t \left[r^{*,A}_{t+1} \right] = (\sigma^{*,2} + \sigma^2 B^{*,2}).$$

The conditional covariance between the log consumption return and the log SDF is given by the conditional expectation of the product of their innovations:

$$Cov_t \left[m^*_{t+1}, r^{*,A}_{t+1} \right] = \left(-\sigma^{*,2} \lambda^*_{m,\eta} - \sigma^2 \lambda^*_{m,e} B^* \right)$$

Using the method of undetermined coefficients , we can solve for the constants:

$$A^*_1 = \kappa^* \frac{1-\rho}{1-\kappa_1 \rho_x},$$

$$A^*_0 = \frac{1}{\theta(1-\kappa_1)} \times \left[\theta(\kappa_0 + \mu + \log \beta - \rho \mu) + \frac{1}{2} \sigma^{*,2}(1 + \lambda^{*,2}_{m,\eta} - 2\lambda^*_{m,\eta}) + \frac{1}{2} \sigma^2 (B^{*,2} + \lambda^{*,2}_{m,e} - 2\lambda^*_{m,e}) \right].$$

The log price-consumption ratio z_t is linear in the state variable x^g_t: $z^*_t = A^*_0 + \kappa^* \frac{1-\rho}{1-\kappa_1 \rho_x} x^g_t$. We use A^*_1 to denote the loading on the state variable: $A^*_1 = \kappa^* \frac{1-\rho}{1-\kappa_1 \rho_x}$. Using the expression for the innovation to the log SDF $m^*_{t+1} - E_t \left[m^*_{t+1} \right]$, we can back out the innovation to the equilibrium exchange rate as:

$$\Delta s_{t+1} - E_t[\Delta s_{t+1}] = \lambda^*_{m,\eta} \sigma^* \eta^*_{t+1} + \lambda^*_{m,e} \sigma e^g_{t+1} - \lambda_{m,\eta} \sigma \eta_{t+1} - \lambda_{m,e} \sigma e^g_{t+1},$$

where $\lambda^*_{m,\eta} = \alpha$, $\lambda^*_{m,e} = \frac{\alpha-\rho}{1-\rho}B^*$, and $B^* = \kappa_1 A^*_1 \varphi_e$; $\lambda_{m,\eta} = \alpha$, $\lambda_{m,e} = \frac{\alpha-\rho}{1-\rho}B$, and $B = \kappa_1 A_1 \varphi_e$. This expression in turn can be simplified as

$$\Delta s_{t+1} - E_t[\Delta s_{t+1}] = \alpha(\sigma^* \eta^*_{t+1} - \sigma\eta_{t+1}) + \frac{\alpha-\rho}{1-\rho}\kappa_1 \varphi_e \left((\kappa^* - 1)\frac{1-\rho}{1-\kappa_1\rho_x}\right)\sigma e^g_{t+1}.$$

A.2 Statistical Factor Models of Exchange Rates

We consider a simple, statistical (latent) factor model for exchange rate variation. There are multiple latent factors driving exchange rate variation:

$$\Delta s_{i,j,t} = \alpha_{i,j} + \gamma'_{i,j} \boldsymbol{f}_t + u_{i,j,t} , \tag{7}$$

where $s_{i,j,t}$ denotes the time t log exchange rate in units of currency j per unit of currency i and $\boldsymbol{f}_t$ denotes a $K \times 1$ vector of orthogonal factors. An increase in $s_{i,j,t}$ implies an appreciation of currency i relative to currency j. Collecting terms, we can write this factor model in vector notation: $\Delta \boldsymbol{s}_{i,t} = \boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_i \boldsymbol{f}_t + \boldsymbol{u}_{i,t}$, where $\boldsymbol{\Gamma}_i$ is the $N \times K$ matrix of loadings. The variance-covariance matrix of exchange rates is $\boldsymbol{\Gamma}_i \boldsymbol{\Gamma}'_i + \boldsymbol{\Sigma}_{e,i}$. From triangular arbitrage, we know that $\Delta s_{i,j,t} - \Delta s_{i,k,t} = \Delta s_{k,j,t}$. That implies the following restriction on the loadings: $\gamma'_{i,j} - \gamma'_{i,k} = \gamma'_{k,j}$. Triangular arbitrage implies that the matrix of loadings satisfy the following restrictions : $\boldsymbol{e}'_j \boldsymbol{\Gamma}_i - \boldsymbol{e}'_k \boldsymbol{\Gamma}_i = \boldsymbol{e}'_j \boldsymbol{\Gamma}_k$, and the disturbances satisfy the following restrictions: $\boldsymbol{e}'_j \boldsymbol{u}_i - \boldsymbol{e}'_k \boldsymbol{u}_i = \boldsymbol{e}'_j \boldsymbol{u}_k$, where $\boldsymbol{e}'_j$ is an $N \times 1$ vector of zero with a one in the j-th position. Hence, the variance-covariance matrix is singular.

The latent factors can include global FX factors such as the dollar factor and the carry trade factors. Our setup also allows for N local factors in $\boldsymbol{f}_t$, i.e. factors that are specific to country i and only affects bilateral exchange rates between i and some other country j, but have no effect on other bilateral exchange rates that do not involve i. These are fixed effects for home country and time. Factor i is local to country i if and only if $\gamma'_{i,j}(i) = \gamma'_{i,k}(i)$, implying that $\gamma'_{k,j}(i) = 0$ for all k, j. Complete market models give rise to local factors if their SDFs are subject to country-specific shocks.

Each base factor is a different linear combination of the underlying factors $base_{i,t} = \boldsymbol{\delta}'_i \boldsymbol{f}_t$, given by

$$\Delta base_{i,t} = \frac{1}{N-1}\sum_{k\neq j}\Delta s_{i,k,t} = \frac{1}{N-1}\sum_{k\neq j}\gamma'_{i,k}\boldsymbol{f}_t + \frac{1}{N-1}\sum_{k\neq j}u_{i,k,t}.$$

As $N \to \infty$, the L.L.N. implies that last term converges to zero. The base factor eliminates idiosyncratic noise. We construct the base factor for country k, which is a different linear

combination of the underlying factors:

$$\Delta base_{k,t} = \frac{1}{N-1}\sum_{j\neq k}\Delta s_{k,j,t} = \frac{1}{N-1}\sum_{j\neq k}\left(\boldsymbol{\gamma}'_{i,j} - \boldsymbol{\gamma}'_{i,k}\right)\boldsymbol{f}_t + \frac{1}{N-1}\sum_{j\neq k}u_{i,k,t}.$$

Note that the local i-factor will drop out from the base factor. That follows immediately from the restriction on the factor loadings. Since this is a different linear combination, each country's loadings on the new base factor will differ as well. Why examine different base currencies? We cannot identify the $N \times K$ coefficients from only $N-1$ different independent loadings with respect to one base factor. Hence, we exploit the entire cross-section. If there are N local factors, then each base currency adds novel information.

Simple Example with Two Factors   To build some intuition, we consider a simple example with two exchange rate factors:

$$\Delta s_{i,j,t} = \alpha_{i,j} + \boldsymbol{\gamma}_{i,j}(1)f_{t,1} + \boldsymbol{\gamma}_{i,j}(2)f_{t,2} + u_{i,j,t} \ . \tag{8}$$

We construct the base factor,

$$\Delta base_{i,t} = \frac{1}{N-1}\sum_{k\neq j}\Delta s_{i,k,t} = \frac{1}{N-1}\sum_{k\neq j}\left(\boldsymbol{\gamma}_{i,k}(1)f_{t,1} + \boldsymbol{\gamma}_{i,k}(2)f_{t,2}\right) + \frac{1}{N-1}\sum_{k\neq j}u_{i,k,t}$$

As $N \to \infty$, the L.L.N. implies that last term converges to zero. The base factor eliminates idiosyncratic noise.

In our paper, the object of interest is the slope coefficient in a projection of the exchange rate changes on the base factor. For large N, this slope coefficient is given by:

$$\varphi^*_{i,j} = \frac{\boldsymbol{\gamma}_{i,j}(1)\sum_{k\neq j}\boldsymbol{\gamma}_{i,k}(1)\sigma^2_f(1) + \boldsymbol{\gamma}_{i,j}(2)\sum_{k\neq j}\boldsymbol{\gamma}_{i,k}(2)\sigma^2_f(2)}{\frac{1}{N-1}\left(\sum_{k\neq j}\boldsymbol{\gamma}_{i,k}(1)\right)^2\sigma^2_f(1) + \frac{1}{N-1}\left(\sum_{k\neq j}\boldsymbol{\gamma}_{i,k}(2)\right)^2\sigma^2_f(2)}, \tag{9}$$

where we have used the orthogonality of the factors. The slope coefficient only depends on the currency factor loadings and the volatility of the factors. When we switch to a new base country, the change in spot exchange rates are given by:

$$\Delta s_{kjt} = (\alpha_{i,j} - \alpha_{i,k}) + \left(\boldsymbol{\gamma}_{i,j}(1) - \boldsymbol{\gamma}_{i,k}(1)\right)f_{t,1} + (\gamma_{i,j}(2) - \gamma_{i,k}(2))f_{t,2} + u_{i,j,t} - u_{i,k,t}. \tag{10}$$

We construct the base factor for country k, which is a different linear combination of the underlying factors:

$$\Delta base_{k,t} = \frac{1}{N-1}\sum_{j\neq k}\left((\gamma_{i,j}(1) - \gamma_{i,k}(1))f_{t,1} + (\gamma_{i,j}(2) - \gamma_{i,k}(2))f_{t,2}\right) + \frac{1}{N-1}\sum_{j\neq k}(u_{i,j,t} - u_{i,k,t})$$

As $N \to \infty$, the L.L.N. implies that last term converges to zero. The new slope factor in a projection of the exchange rate changes on the base factor is given by:

$$
\begin{aligned}
\varphi_{k,j}^* &= \frac{\left(\boldsymbol{\gamma}_{i,j}(1) - \boldsymbol{\gamma}_{i,k}(1)\right) \sum_{l \neq j} \left(\boldsymbol{\gamma}_{i,l}(1) - \boldsymbol{\gamma}_{i,k}(1)\right) \sigma_f^2(1)}{\frac{1}{N-1}\left(\sum_{k \neq j}(\boldsymbol{\gamma}_{i,j}(1) - \boldsymbol{\gamma}_{i,k}(1))\right)^2 \sigma_f^2(1) + \frac{1}{N-1}\left(\sum_{k \neq j}(\boldsymbol{\gamma}_{i,j}(1) - \boldsymbol{\gamma}_{i,k}(2))\right)^2 \sigma_f^2(2)} \\
&+ \frac{\left(\boldsymbol{\gamma}_{i,j}(2) - \boldsymbol{\gamma}_{i,k}(2)\right) \sum_{l \neq j} \left(\boldsymbol{\gamma}_{i,l}(2) - \boldsymbol{\gamma}_{i,k}(2)\right) \sigma_f^2(2)}{\frac{1}{N-1}\left(\sum_{k \neq j}(\boldsymbol{\gamma}_{i,j}(1) - \boldsymbol{\gamma}_{i,k}(1))\right)^2 \sigma_f^2(1) + \frac{1}{N-1}\left(\sum_{k \neq j}(\boldsymbol{\gamma}_{i,j}(1) - \boldsymbol{\gamma}_{i,k}(2))\right)^2 \sigma_f^2(2)}
\end{aligned}
$$

In general, there is no simple mapping from one set of base factor loadings to another, because the new base factor is a different linear combination of the fundamental exchange rate factors. However, suppose that the first factor is country i's local factor. Then k's base factor is not exposed to i's local factor:

$$
\Delta base_{k,t} = \frac{1}{N-1} \sum_{j \neq k} \Delta s_{k,j,t} = \frac{1}{N-1} \sum_{j \neq k} (\gamma_{i,j}(2) - \gamma_{i,k}(2)) f_{t,2} + \frac{1}{N-1} \sum_{j \neq k} u_{i,k,t}
$$

and the loadings only measure covariance with the second factor:

$$
\varphi_{k,j}^* = \left(\boldsymbol{\gamma}_{i,j}(2) - \boldsymbol{\gamma}_{i,k}(2)\right) \frac{\sum_{l \neq j}\left(\boldsymbol{\gamma}_{i,l}(2) - \boldsymbol{\gamma}_{i,k}(2)\right)}{\frac{1}{N-1}\left(\sum_{l \neq j}\left(\boldsymbol{\gamma}_{i,l}(2) - \boldsymbol{\gamma}_{i,k}(2)\right)\right)^2}
$$

Hence, local factors to country i are eliminated when we switch base factor.

Simple Example with Single Factor Suppose that there is a single latent factor (e.g. the dollar factor) driving all of the currency variation; we can easily derive the loadings for any bilateral exchange rate. Suppose we switch to a new base currency k. Theloadings on base factor i are given by:

$$
\varphi_{i,j}^* = \gamma_{i,j} \frac{\sum_{k \neq j} \gamma_{i,k}}{\frac{1}{N-1}\left(\sum_{k \neq j} \gamma_{i,k}\right)^2}
$$

The loadings on base factor k are given by:

$$
\varphi_{k,j}^* = \gamma_{i,j} \frac{\sum_{l \neq j}\left(\gamma_{i,l} - \gamma_{i,k}\right)}{\frac{1}{N-1}\left(\sum_{l \neq j}(\gamma_{i,l} - \gamma_{i,k})\right)^2} - \gamma_{i,k} \frac{\sum_{l \neq j}\left(\gamma_{i,l} - \gamma_{i,k}\right)}{\frac{1}{N-1}\left(\sum_{l \neq j}(\gamma_{i,l} - \gamma_{i,k})\right)^2},
$$

which is an affine transformation of the $\varphi_{i,j}^*$. There is no additional information from switching to a different base currency in a single factor world. Essentially, the same single factor

model applies for base currency k:

$$\Delta s_{kjt} = (\alpha_{i,j} - \alpha_{i,k}) + (\gamma_{i,j} - \gamma_{i,k}) f_t + u_{i,j,t} - u_{i,k,t}. \tag{11}$$

In this single factor world, we only really need to analyze one base currency. The new slope coefficients $\gamma_{k,j} = (\gamma_{i,j} - \gamma_{i,k})$ can be backed out from the other ones. A single factor specification counterfactually implies that the bilateral exchange rate for equidistant countries from the base country (e.g. the U.S.) does not load on the (dollar) factor.

B Data Appendix

B.1 FX and CPI Data

Spot rates in foreign currency per US dollar are from Global Financial Data (GFD). The sample is daily from January 1, 1973 to December, 31 2014 for 162 countries: Afghanistan, Albania, Algeria, Angola, Argentina, Armenia, Aruba, Australia, Austria, Azerbaijan, Bahamas, Bahrain, Bangladesh, Barbados, Belarus, Belgium, Belize, Bermuda, Bhutan, Bolivia, Bosnia and Herzegovina, Botswana, Brazil, Brunei Darussalam, Bulgaria, Burundi, Cabo Verde, Cambodia, Canada, Cayman Islands, Chile, China, Colombia, Comoros, Congo, Costa Rica, Croatia, Cuba, Cyprus, Czech Republic, Denmark, Djibouti, Dominican Republic, Ecuador, Egypt, El Salvador, Eritrea, Estonia, Ethiopia, Europe, Fiji, Finland, France, Gambia, Georgia, Germany, Ghana, Greece, Guatemala, Guinea, Guyana, Haiti, Honduras, Hong Kong, Hungary, Iceland, India, Indonesia, Iran, Iraq, Ireland, Israel, Italy, Jamaica, Japan, Jordan, Kazakhstan, Kenya, Korea, Kuwait, Kyrgyzstan, Lao People's Democratic Republic, Latvia, Lebanon, Lesotho, Liberia, Libya, Lithuania, Luxembourg, Macao, Macedonia, Madagascar, Malawi, Malaysia, Maldives, Malta, Mauritania, Mauritius, Mexico, Moldova, Mongolia, Morocco, Mozambique, Myanmar, Namibia, Nepal, Netherlands, New Zealand, Nicaragua, Nigeria, Norway, Oman, Pakistan, Panama, Paraguay, Peru, Philippines, Poland, Portugal, Qatar, Romania, Russian Federation, Rwanda, Samoa, Sao Tome and Principe, Saudi Arabia, Serbia, Seychelles, Sierra Leone, Singapore, Slovakia, Slovenia, Somalia, South Africa, Spain, Sri Lanka, Sudan, Suriname, Swaziland, Sweden, Switzerland, Syrian Arab Republic, Taiwan, Tajikistan, Tanzania, Thailand, Trinidad and Tobago, Tunisia, Turkey, Turkmenistan, Uganda, Ukraine, United Arab Emirates, United Kingdom, Uruguay, Uzbekistan, Vanuatu, Venezuela, Viet Nam, Yemen, Zambia, and Zimbabwe.

Spot rates for countries which adopt the euro are omitted after the adoption date. The

euro series starts on January 1, 1999. End-of-month series are constructed from the daily data.

CPI data is from GFD and is used to calculate real exchange rate changes. For countries which only provide quarterly CPI data, we interpolate a monthly series. CPI observations where month-over-month continuously compounded inflation is greater than 50% are omitted. We also omit Armenia, Ukraine, Herzegovina, Serbia, Nicaragua, Peru, and Brazil from the CPI data due to hyperinflation episodes.

Country classifications (developed, emerging, and frontier) are from MSCI [7] as of August 2015.

B.2 Gravity Data

Below is a description and source for each of the gravity variables in our dataset.

Distance — Population weighted average distance in kilometers between large cities' of each country pair (Mayer and Zignago (2011)).

Shared Language — Common language is 1 if a language is spoken by over 9% of the population in both countries (Mayer and Zignago (2011)).

Shared Legal — Dummy variable from a classification of countries' legal origins. See Porta, Lopez-de Silanes, and Shleifer (2007) for a description and discussion.

Colonial Link — A dummy variable which is 1 if countries have shared a common colonizer after 1945. See Mayer and Zignago (2011).

Resource similarity — We obtain a list of natural resources by country from the CIA world factbok[8]. Using this list, we construct vectors of dummy variables — 1 if a country has the resource, 0 otherwise. Natural resource similarity between two countries is the cosine similarity of the vectors of resource dummy variables.

Linguistic similarity — Population weighted measure of linguistic proximity based upon language trees. A higher value implies that the average language spoken within the two countries diverged more recently. Data is from Desmet, Ortuno-Ortin, and Wacziarg (2012).

Genetic distance — Weighted genetic distance between population subgroups within country pairs. Genetic distance is calculated off of differences in allele frequency. A higher value implies that the population within the two countries diverged genetically at a more recent date. The data is from Spolaore and Wacziarg (2009).

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[7]Available at https://www.msci.com/market-classification
[8]Available at https://www.cia.gov/library/publications/the-world-factbook/fields/2111.html

Peg Dummy — A currency is considered pegged if the bilateral exchange rate volatility is less than 2% in two consecutive years. The peg dummy is 1 if either currency was pegged to the other or both currencies were pegged to the same currency at any point in the sample. For the 5-year rolling samples, the peg dummy is 1 if either currency was pegged to other or they were pegged same currency at any point in the prior 6 years. The data on pegs is from Shambaugh (2004).

B.3   Calculation of Standard Errors

The triangular arbitrage condition for exchange rates requires careful calculation of standard errors in our regressions. Consider the general factor model in Equation (7):

$$\Delta s_{i,j,t} = \alpha_{i,j} + \gamma'_{i,j} \boldsymbol{f}_t + e_{i,j,t}. \tag{12}$$

From triangular arbitrage, $\Delta s_{i,k} = \Delta s_{i,j} - \Delta s_{k,j}$, which implies $\gamma_{i,k} = \gamma_{i,j} - \gamma_{k,j}$. This relation is true for any factors $\boldsymbol{f}$, including base factors, which are a linear combination of the underlying factors. This implies that *base* factor loadings may be correlated if they contain the same base or foreign country. As a result, there may be correlation in the errors in our primary regression specifications:

$$\varphi^*_{i,j} = \delta + \lambda G_{i,j} + e_{i,j}.$$

We accommodate for this by using dyadic clustering as in Cameron and Miller (2014) and Aronow, Samii, and Assenova (2015). The latter paper uses the multi-way clustering algorithm of Cameron, Gelbach, and Miller (2011), which we apply in this paper. These standard errors allow for arbitrary correlation when an observation contains the same country — whether base or foreign. Specifically, we assume that

$$E\left[e_{i,j} e_{i',j'} | G_{i,j}, G_{i',j'}\right] = 0 \text{ unless } i = i' \text{ or } j = j' \text{ or } i = j' \text{ or } j = i'.$$

Table (B1) illustrates the importance of correctly estimating the standard errors. Columns 1 and 2 only cluster on base country or foreign country respectively. Column 3 clusters on both base country and foreign country. All three of these columns have smaller standard error estimates than column 4 which uses dyadic clustering. Clustering on base country and foreign country (column 3) produces standard errors that are closest to the dyadic clustering, consistent with the findings of Cameron and Miller (2014).

Table B1: Rolling Sample Regressions with Nominal Factor loadings (MSCI Developed and Emerging Subset) Comparing Different Variance Estimates

	Base Cluster	Foreign Cluster	Both Cluster	Dyad Cluster
Log Distance	0.139***	0.139***	0.139***	0.139***
	(6.189)	(6.537)	(4.656)	(3.499)
Shared Language	−0.120***	−0.120***	−0.120***	−0.120***
	(−3.904)	(−4.634)	(−3.434)	(−3.025)
Shared Legal	−0.020	−0.020	−0.020	−0.020
	(−0.986)	(−0.927)	(−0.816)	(−0.659)
Shared Border	−0.126***	−0.126***	−0.126***	−0.126**
	(−3.052)	(−3.425)	(−3.065)	(−2.546)
Colonial Link	−0.278***	−0.278***	−0.278***	−0.278***
	(−4.862)	(−5.279)	(−4.284)	(−3.320)
Resource Similarity	−0.165***	−0.165***	−0.165***	−0.165***
	(−3.373)	(−3.950)	(−3.219)	(−2.605)
Within R^2	0.114	0.114	0.114	0.114
Num. obs.	61130	61130	61130	61130

Regressions $\varphi^*_{i,j,t} = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi^*_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \varphi^*_{i,j,t}\Delta base_{i,\tau} + e_{i,j,\tau}$ with $\tau = t - 59 \dots t$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Standard errors clustered on base country, foreign country, or both using Cameron, Gelbach, and Miller (2011)). Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

B.4 Additional Tables and Figures

Table B2: Rolling Sample Summary Statistics

	N	Mean	Median	Sd	Min	Max
Loading	61,260	0.92	0.98	0.48	-4.17	4.84
Loading (Real)	47,613	0.92	0.97	0.44	-3.13	5.78
R-squared	61,236	0.48	0.49	0.30	0.00	1.00
R-squared (Real)	47,613	0.47	0.49	0.28	0.00	1.00
Log Dist	86,715	8.62	9.00	0.93	5.08	9.88
Common Language	86,715	0.13	0.00	0.34	0.00	1.00
Shared Border	86,715	0.04	0.00	0.20	0.00	1.00
Resource Similarity	86,715	0.24	0.23	0.17	0.00	0.82
Linguistic Proximity	40,184	1.06	0.22	2.23	0.00	15.00
Genetic Distance	42,956	0.72	0.78	0.52	0.00	2.67
Colonial Linkage	86,715	0.02	0.00	0.14	0.00	1.00
Peg Dummy	83,160	0.12	0.00	0.33	0.00	1.00

Summary statistics of the factor loadings and gravity data. Factor loadings, $\varphi^*_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \varphi^*_{i,j,t}\Delta base_{i,\tau} + e_{i,j,\tau}$ with $\tau = t - 59\ldots t$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI.

Table B3: Correlation of 1st Principal Components and Base Factors by Country

Base	Correlation
Australia	-1.00
Brazil	1.00
Canada	0.99
Chile	1.00
China	0.99
Colombia	1.00
Czech Republic	1.00
Denmark	0.99
Egypt	-1.00
Germany	0.99
Hong Kong	0.99
Hungary	1.00
India	0.99
Indonesia	-1.00
Israel	1.00
Japan	1.00
Korea	1.00
Malaysia	-0.99
Mexico	-1.00
New Zealand	1.00
Norway	0.99
Peru	-0.98
Philippines	-0.99
Poland	1.00
Qatar	-0.99
Russian Federation	-1.00
Singapore	0.86
South Africa	1.00
Sweden	0.99
Switzerland	1.00
Taiwan	0.95
Thailand	1.00
Turkey	1.00
United Arab Emirates	0.99
United Kingdom	0.99
United States	-0.99

For each base currency i, the 1st p.c. of all bilateral exchange rate changes $\Delta s_{i,j,t}$ is computed. The base factor $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are from Global Financial for 24 developed and 23 emerging countries, as classified by MSCI.

Table B4: Variance Decomposition of Real Bilateral Exchange Rates by Base Currency

	Base Var	FX Var	Id Var	R^2 Mean	Load Sd		Base Var	FX Var	Id Var	R^2 Mean	Load Sd
Developed Countries						**Emerging Countries**					
Australia	1.02	3.29	2.26	0.49	0.15	Chile	18.07	19.99	1.92	0.87	0.04
Austria	0.61	3.86	3.25	0.27	0.63	China	1.54	3.46	1.92	0.58	0.19
Belgium	0.62	3.98	3.36	0.27	0.60	Colombia	0.79	3.02	2.23	0.46	0.34
Canada	0.46	2.78	2.32	0.32	0.31	Czech Republic	5.02	7.24	2.22	0.77	0.07
Denmark	0.51	2.74	2.23	0.26	0.51	Egypt	2.63	4.87	2.24	0.68	0.07
Finland	0.48	3.96	3.48	0.28	0.33	Greece	0.86	4.01	3.15	0.45	0.16
France	0.55	3.93	3.38	0.25	0.60	Hungary	1.62	3.58	1.96	0.60	0.18
Germany	0.66	4.02	3.36	0.29	0.59	India	0.72	3.07	2.35	0.41	0.14
Hong Kong	0.54	2.85	2.31	0.35	0.30	Indonesia	5.03	6.95	1.92	0.79	0.05
Ireland	0.49	3.94	3.45	0.26	0.52	Korea	1.50	3.80	2.30	0.56	0.12
Israel	6.43	8.59	2.15	0.81	0.13	Malaysia	0.50	2.82	2.32	0.31	0.32
Italy	0.51	3.98	3.47	0.30	0.34	Mexico	8.26	10.35	2.09	0.83	0.12
Japan	1.08	3.41	2.33	0.49	0.15	Philippines	1.27	3.59	2.32	0.53	0.15
Netherlands	0.61	3.98	3.37	0.27	0.61	Poland	11.33	13.33	2.00	0.86	0.19
New Zealand	1.01	3.36	2.34	0.49	0.12	Russian Federation	17.77	18.71	0.94	0.94	0.05
Norway	0.43	2.72	2.30	0.24	0.39	Taiwan	0.64	2.93	2.29	0.38	0.34
Portugal	0.68	4.17	3.49	0.36	0.32	Thailand	0.91	3.23	2.31	0.46	0.22
Singapore	0.31	2.62	2.31	0.21	0.49	Turkey	4.30	6.11	1.81	0.77	0.09
Spain	0.61	4.12	3.50	0.35	0.23						
Sweden	0.51	2.82	2.31	0.32	0.31						
Switzerland	0.74	3.01	2.27	0.39	0.35						
United Kingdom	0.54	2.88	2.34	0.35	0.20						
United States	0.46	2.74	2.28	0.31	0.45						
All	0.86	3.64	2.78	0.34	0.41	All	4.60	6.73	2.13	0.62	0.18

Summary statistics of data from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi_{i,j}^* \Delta base_{i,t} + e_{i,j,t}$ for each possible base currency i. $\Delta s_{i,j,t}$ is the log real change in the bilateral exchange rate calculated by substracting differences in log inflation. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Base Var, FX Var, and Id Var are cross-sectional means for each base currency. Base Var is the variance attributed to the base factor, FX Var is the total variance, and Id Var is the remaining idiosyncratic variance. R^2 mean is the cross-sectional mean of the R^2 for each base currency. Load Sd is the standard deviation of the loadings $\varphi_{i,j}^*$ for each base currency i. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI.

Table B5: Full Sample Regressions with Nominal and Real Base Factor loadings

	Nominal (1)	Real (1)	Nominal (2)	Real (2)
Log Distance	0.159***	0.139***	0.130***	0.112***
	(4.382)	(4.188)	(4.692)	(4.611)
Shared Language	−0.130***	−0.143***	−0.111***	−0.126***
	(−3.051)	(−4.023)	(−2.842)	(−3.947)
Shared Legal	−0.025	−0.041	−0.007	−0.025
	(−0.921)	(−1.432)	(−0.239)	(−0.802)
Shared Border	−0.092**	−0.121**	−0.032	−0.065
	(−2.418)	(−2.577)	(−0.782)	(−1.252)
Colonial Link	−0.038	0.017	−0.048	0.008
	(−0.848)	(0.271)	(−0.841)	(0.097)
Resource Similarity	−0.084	−0.070	−0.046	−0.035
	(−1.463)	(−1.424)	(−0.572)	(−0.522)
Peg Dummy			−0.239***	−0.222***
			(−3.919)	(−4.111)
R^2	0.286	0.243	0.376	0.320
Num. obs.	1640	1640	1640	1640

Regressions $\varphi^*_{i,j} = \delta + \lambda G_{i,j} + e_{i,j}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi^*_{i,j}$, are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \varphi^*_{i,j}\Delta base_{i,t} + e_{i,j,t}$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Real exchange rate changes include relative differences in inflation. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B6: Rolling Sample Regressions with Nominal Factor loadings (US Base Factor Only)

	All (1)	All (2)	All (3)	No Pegs
Log Distance	-0.095	-0.188	0.030	-0.008
	(-0.416)	(-1.000)	(0.329)	(-0.059)
Shared Language		-0.523^{***}	-0.516^{***}	-0.737^{***}
		(-2.978)	(-4.292)	(-4.075)
Shared Legal		0.020	0.027	0.191
		(0.095)	(0.224)	(0.949)
Resource Similarity		-0.136	-0.025	-0.015
		(-0.315)	(-0.086)	(-0.044)
Peg Dummy			-0.866^{***}	
			(-7.849)	
Within R^2	0.003	0.120	0.345	0.204
Num. obs.	1500	1500	1462	1146

Regressions $\varphi_{\$,j,t}^{base} = \alpha_{\$,j} + \kappa_t + \varphi G_{\$,j} + e_{\$,j}$ of base factor loadings on gravity variables. $G_{\$,j}$ is a set of gravity variables. Base factor loadings, $\varphi_{\$,j,t}^{base}$, are from 60-month rolling regressions $\Delta s_{\$,j,\tau} = \alpha_{\$,j} + \varphi_{\$,j,t}^{base} base_{\$,\tau} + e_{\$,j,\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{\$,t}$ is the average appreciation of of the US dollar at time t relative to all available currencies, excluding currency j. Spot rates are from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Standard errors are clustered on foreign country using Cameron, Gelbach, and Miller (2011)). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B7: Rolling Sample Regressions with Nominal and Real Base Factor loadings

	Nominal (1)	Real (1)	Nominal (2)	Real (2)
Log Distance	0.171***	0.154***	0.151***	0.136***
	(4.357)	(4.357)	(4.639)	(4.723)
Shared Language	−0.157***	−0.163***	−0.126***	−0.134***
	(−3.364)	(−3.635)	(−3.357)	(−3.686)
Shared Legal	−0.023	−0.035	−0.037	−0.046
	(−0.708)	(−1.037)	(−1.214)	(−1.455)
Shared Border	−0.080	−0.084*	−0.023	−0.032
	(−1.542)	(−1.758)	(−0.543)	(−0.853)
Colonial Link	−0.110**	−0.094**	−0.084**	−0.077**
	(−2.198)	(−2.077)	(−2.391)	(−2.464)
Resource Similarity	−0.100**	−0.100*	−0.090	−0.093
	(−2.072)	(−1.859)	(−1.424)	(−1.465)
Peg Dummy			−0.445***	−0.412***
			(−9.405)	(−9.228)
Within Adj. R^2	0.160	0.156	0.226	0.217
Num. obs.	47493	47493	45002	45002

Regressions $\varphi^*_{i,j,t} = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi^*_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \varphi^*_{i,j,t} \Delta base_{i,\tau} + e_{i,j,\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Real exchange rate changes include relative differences in inflation. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B8: Rolling Sample Regressions with Nominal Factor loadings (MSCI Developed Countries)

	All (1)	All (2)	All (3)	All (4)	No Pegs
Log Distance	0.222***	0.233***	0.222***	0.172***	0.176***
	(5.139)	(4.729)	(5.495)	(5.700)	(5.655)
Shared Language			−0.115	−0.101	−0.047
			(−1.048)	(−1.192)	(−0.557)
Shared Legal		−0.231*	−0.231*	−0.233**	−0.292***
		(−1.877)	(−1.952)	(−2.437)	(−2.833)
Shared Border		0.074*	−0.007	0.022	0.014
		(1.818)	(−0.066)	(0.297)	(0.217)
Colonial Link		−0.076	−0.267***	−0.316***	−0.316***
		(−0.782)	(−3.091)	(−4.376)	(−3.937)
Resource Similarity		−0.126	−0.048	−0.083	−0.090
		(−0.953)	(−0.337)	(−0.632)	(−0.664)
Linguistic Proximity		−0.010			
		(−1.220)			
Genetic Distance		−0.109			
		(−1.121)			
Peg Dummy				−0.418***	
				(−5.327)	
Within R^2	0.239	0.309	0.327	0.382	0.260
Num. obs.	13840	5757	13840	13840	12160

Regressions $\varphi^*_{i,j,t} = \alpha_{i,j} + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi^*_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \varphi^*_{i,j,t} \Delta base_{i,\tau} + e_{i,j,\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 24 developed countries, as classified by MSCI. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B9: Rolling Sample Regressions with Nominal Factor loadings

	All (1)	All (2)	All (3)	All (4)	No Pegs
Log Distance	0.047***	0.028	0.033**	0.030**	0.033**
	(3.894)	(1.543)	(2.476)	(2.047)	(2.134)
Shared Language			−0.074***	−0.063***	−0.061***
			(−3.415)	(−3.727)	(−3.582)
Shared Legal		−0.038**	−0.025**	−0.018*	−0.023*
		(−2.284)	(−2.041)	(−1.655)	(−1.774)
Shared Border		−0.082**	−0.093***	−0.067***	−0.073**
		(−2.444)	(−3.111)	(−2.643)	(−2.547)
Resource Similarity		−0.094*	−0.042	−0.051	−0.075**
		(−1.856)	(−1.011)	(−1.456)	(−1.976)
Linguistic Proximity		−0.009**			
		(−2.430)			
Genetic Distance		−0.004			
		(−0.145)			
Peg Dummy				−0.343***	
				(−8.361)	
Within R^2	0.002	0.002	0.004	0.026	0.003
Num. obs.	664507	239311	645845	565960	481296

Regressions $\varphi^*_{i,j,t} = \alpha_{i,j} + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi^*_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \varphi^*_{i,j,t}\Delta base_{i,\tau} + e_{i,j,\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{i,t}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are monthly from January 1973 until December 2014 from Global Financial Data for 162 countries. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B10: Rolling Sample Regressions controlling for Trade and GDP (MSCI Developed and Emerging Subset)

	All (1)	All (2)	All (3)	No Pegs
Log Distance		0.140***	0.144***	0.122***
		(3.325)	(3.415)	(3.187)
Shared Language		−0.107***	−0.106***	−0.100***
		(−2.879)	(−2.843)	(−2.942)
Shared Legal		−0.030	−0.031	−0.030
		(−1.015)	(−1.014)	(−1.122)
Shared Border		−0.102*	−0.091	−0.105**
		(−1.832)	(−1.519)	(−2.030)
Colonial Link		−0.293***	−0.275***	−0.219***
		(−3.205)	(−2.916)	(−3.499)
Resource Similarity		−0.191***	−0.204***	−0.185**
		(−3.055)	(−3.115)	(−2.417)
Trade/GDP (Foreign)	−2.111***	−0.721***	−0.897**	−0.838**
	(−3.750)	(−2.688)	(−2.245)	(−2.082)
log GDP Share (Base)			0.012	0.018
			(1.413)	(1.257)
Within R^2	0.024	0.124	0.130	0.094
Num. obs.	54884	54884	54338	49946

Regressions $\gamma_{ijt}^{base} = \alpha + \kappa_t + \beta G_{ij} + e_{ij}$ of base factor loadings on gravity variables. G_{ij} is a set of gravity variables. Base factor loadings, γ_{ijt}^{base}, are from 60-month rolling regressions $\Delta s_{ij\tau} = \alpha + \gamma_{ijt}^{base} base_{i\tau} + e_{ij\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{it}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Real exchange rate changes include relative differences in inflation. Standard errors clustered on base country and foreign country using Cameron, Gelbach, and Miller (2011)). t-statistics in parentheses. * p<0.10, ** p<0.01, *** p<0.01.

Table B11: Rolling Sample Regressions with Bilateral Asset Holdings (MSCI Developed and Emerging Subset)

|	All (1)	All (2)	All (3)	All (4)	All (5)	No Pegs	No Pegs
Log Distance			0.138***	0.127***	0.130***	0.122***	0.121***
			(3.443)	(3.865)	(4.050)	(3.766)	(3.678)
Shared Language			−0.122***	−0.086**	−0.102***	−0.068***	−0.067**
			(−3.096)	(−2.447)	(−2.814)	(−2.792)	(−2.559)
Shared Legal			−0.019	−0.041	−0.040	−0.053	−0.053
			(−0.623)	(−0.938)	(−0.956)	(−1.344)	(−1.424)
Shared Border			−0.126**	−0.082	−0.078	−0.067	−0.060
			(−2.548)	(−1.014)	(−0.909)	(−1.250)	(−1.173)
Colonial Link			−0.281***	−0.355***	−0.320***	−0.237***	−0.221***
			(−3.367)	(−3.097)	(−2.881)	(−3.876)	(−3.502)
Resource Similarity			−0.166***	−0.116**	−0.096**	−0.091	−0.094
			(−2.599)	(−2.416)	(−2.192)	(−1.346)	(−1.376)
Assets to GDP (Foreign)	−0.497			−0.091		0.301	
	(−1.312)			(−0.300)		(1.534)	
Assets to GDP (Base)	−0.902***			−0.495**		−0.278	
	(−3.012)			(−2.407)		(−0.844)	
Assets to Total (Base)		−0.446			0.757		2.186
		(−0.173)			(0.373)		(1.185)
Assets to Total (Foreign)		−3.765***			−1.475		−2.402
		(−3.291)			(−0.776)		(−1.266)
Within R^2	0.010	0.001	0.114	0.120	0.117	0.095	0.091
Num. obs.	14522	16446	61130	14522	16316	13892	15016

Regressions $\gamma_{ijt}^{base} = \alpha + \kappa_t + \varphi G_{ij} + e_{ij}$ of base factor loadings on gravity variables. G_{ij} is a set of gravity variables. Base factor loadings, γ_{ijt}^{base}, are from 60-month rolling regressions $\Delta s_{ij\tau} = \alpha + \gamma_{ijt}^{base} base_{i\tau} + e_{ij\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{it}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B12: Rolling Sample Regressions with Nominal Factor Loadings GFD Data (MSCI Developed and Emerging Subset) Comparing FEs

	None	Year	Base-Year	Base-Year/Year
Log Distance	0.119***	0.119***	0.147***	0.147***
	(3.421)	(3.410)	(4.425)	(4.434)
Shared Language	−0.095***	−0.096***	−0.084**	−0.085**
	(−3.082)	(−3.142)	(−2.387)	(−2.427)
Shared Legal	−0.033	−0.033	−0.030	−0.030
	(−1.305)	(−1.295)	(−1.177)	(−1.160)
Shared Border	−0.076*	−0.076	−0.044	−0.044
	(−1.653)	(−1.638)	(−0.970)	(−0.965)
Colonial Link	−0.202***	−0.200***	−0.174***	−0.174***
	(−4.564)	(−4.581)	(−2.967)	(−2.991)
Resource Similarity	−0.152**	−0.151**	−0.164**	−0.164**
	(−2.465)	(−2.454)	(−2.430)	(−2.418)
Peg Dummy	−0.471***	−0.472***	−0.494***	−0.494***
	(−8.696)	(−8.710)	(−8.255)	(−8.183)
Within R^2	0.186	0.185	0.198	0.198
Num. obs.	58298	58298	58298	58298

Regressions $\gamma_{ijt}^{base} = \alpha + \kappa_t + \beta G_{ij} + e_{ij}$ of base factor loadings on gravity variables. G_{ij} is a set of gravity variables. Base factor loadings, γ_{ijt}^{base}, are from 60-month rolling regressions $\Delta s_{ij\tau} = \alpha + \gamma_{ijt}^{base} base_{i\tau} + e_{ij\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{it}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Real exchange rate changes include relative differences in inflation. Standard errors clustered on base country and foreign country using Cameron, Gelbach, and Miller (2011)). t-statistics in parentheses. * p<0.10, ** p<0.01, *** p<0.01.

Figure B1: 15-year rolling sample R-squareds of base factor loadings on gravity variables
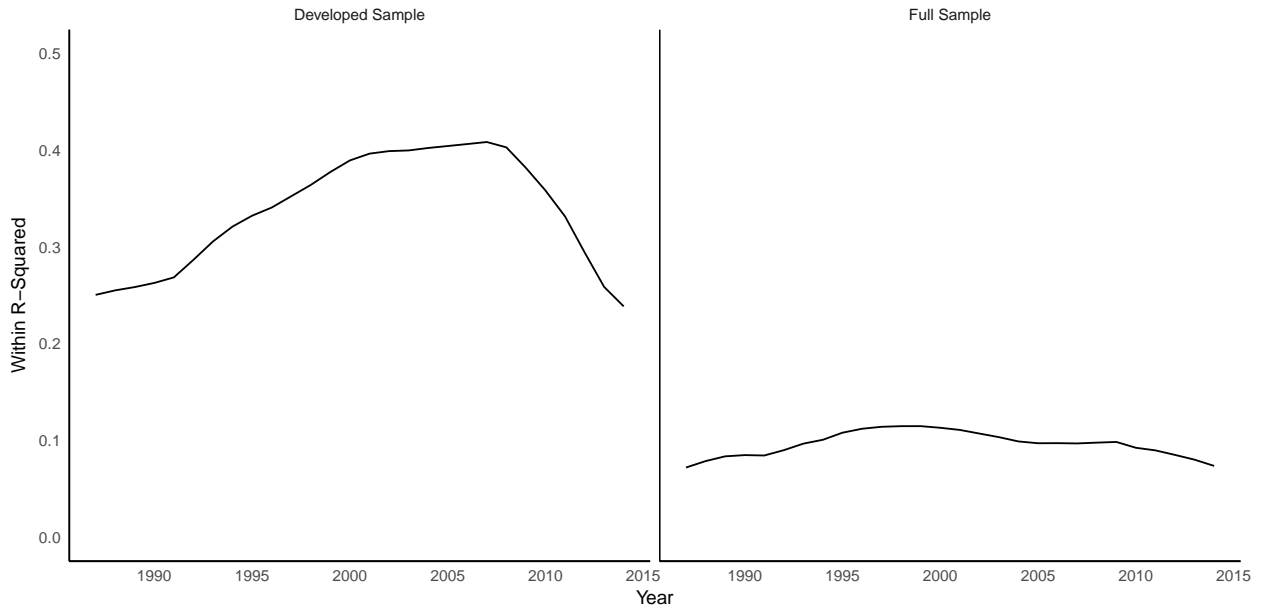
Plots of 15-year rolling sample R-squared from regressions $\gamma_{ijt}^{base} = \alpha + \kappa_t + \varphi G_{ij} + e_{ij}$ of base factor loadings on gravity variables. G_{ij} is a set of gravity variables. Base factor loadings, γ_{ijt}^{base}, are from 60-month rolling regressions $\Delta s_{ij\tau} = \alpha + \gamma_{ijt}^{base} base_{i\tau} + e_{ij\tau}$ with $\tau = t - 59 \ldots t$. For each currency j, $base_{it}$ is the average appreciation of currency i at time t relative to all available currencies, excluding currency j. Spot rates are from Global Financial Data for 24 developed and 23 emerging countries, as classified by MSCI. Standard errors are clustered on country dyads using Aronow, Samii, and Assenova (2015). t-statistics in parentheses. t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.

Table B13: Euro Subsample Real Base Factor loadings vs Gravity

	Model 1	Model 2
Log Distance	0.130***	0.100**
	(3.425)	(2.156)
Shared Legal		0.025
		(0.538)
Shared Border		-0.022
		(-0.219)
Shared Language		-0.294***
		(-4.003)
Adj. R^2	0.036	0.050
Num. obs.	306	306

Regressions $\varphi_{i,j}^* = \delta + \lambda G_{i,j} + e_{i,j}$ of real base factor loadings on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor loadings, $\varphi_{i,j}^*$, are from the regression $\Delta s_{i,j,t} = \alpha + \varphi_{i,j}^* \Delta base_{i,t} + e_{i,j,t}$. For each currency j, $base_{i,t}$ is the average real appreciation of currency i at time t relative to all available currencies, excluding currency j. Real spot rate changes are from Barclays and Reuters for 18 Euro area countries from 1999 through 2013. Robust t-statistics in parentheses. * p<0.10, ** p<0.05, *** p<0.01.