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Essays Concerning the Fundamental Determinants of International Asset Prices

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by

Robert Jamison Richmond

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Abstract of the Dissertation

Essays Concerning the Fundamental Determinants of International Asset Prices

by

Robert Jamison Richmond

Doctor of Philosophy in Management

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Professor Mikhail Chernov, Chair

In the first chapter of this dissertation, I uncover an economic source of exposure to global risk that drives international asset prices. Countries which are more central in the global trade network have lower interest rates and currency risk premia. As a result, an investment strategy that is long in currencies of peripheral countries and short in currencies of central countries explains unconditional carry trade returns. To explain these findings, I present a general equilibrium model where central countries' consumption growth is more exposed to global consumption growth shocks. This causes the currencies of central countries to appreciate in bad times, resulting in lower interest rates and currency risk premia. In the data, central countries' consumption growth is more correlated with world consumption growth than peripheral countries', further validating the proposed mechanism.

In the second chapter of this dissertation (with Hanno Lustig), we show that measures of distance explain exchange rate covariation. Exchange rates strongly co-vary across currencies against a base currency (e.g., the dollar). We uncover a gravity equation in the factor structure: The key determinant of a currency's exchange rate (e.g., the CHF/USD) beta on the common base factor (e.g., the dollar factor) is the distance between this country (e.g., Switzerland) and the base country (e.g., the U.S.): the farther the country, the larger the

beta. Shared language, legal origin, shared border, resource similarity and colonial linkages significantly lower the betas. On average, the exchange rates of peripheral countries tend to have high R^2s in factor regressions, while central countries have low R^2s. If the pricing kernel loadings on global risk factors are more similar for country pairs that are closer, a no-arbitrage model of interest rates and exchange rates replicates this distance-dependent factor structure.

The dissertation of Robert Jamison Richmond is approved.

Andrew Granger Atkeson

Andrea Lynn Eisfeldt

Barney P Hartman-Glaser

Mikhail Chernov, Committee Chair

University of California, Los Angeles

2016

To Mom, Dad,

Ali, Mandy, Krissy,

and all of my friends.

Thank you for making this all

possible and enjoyable.

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Vita

2007-2011	B.S. Applied Mathematics, University of Colorado, Boulder, Colorado, *Magna Cum Laude*
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CHAPTER 1

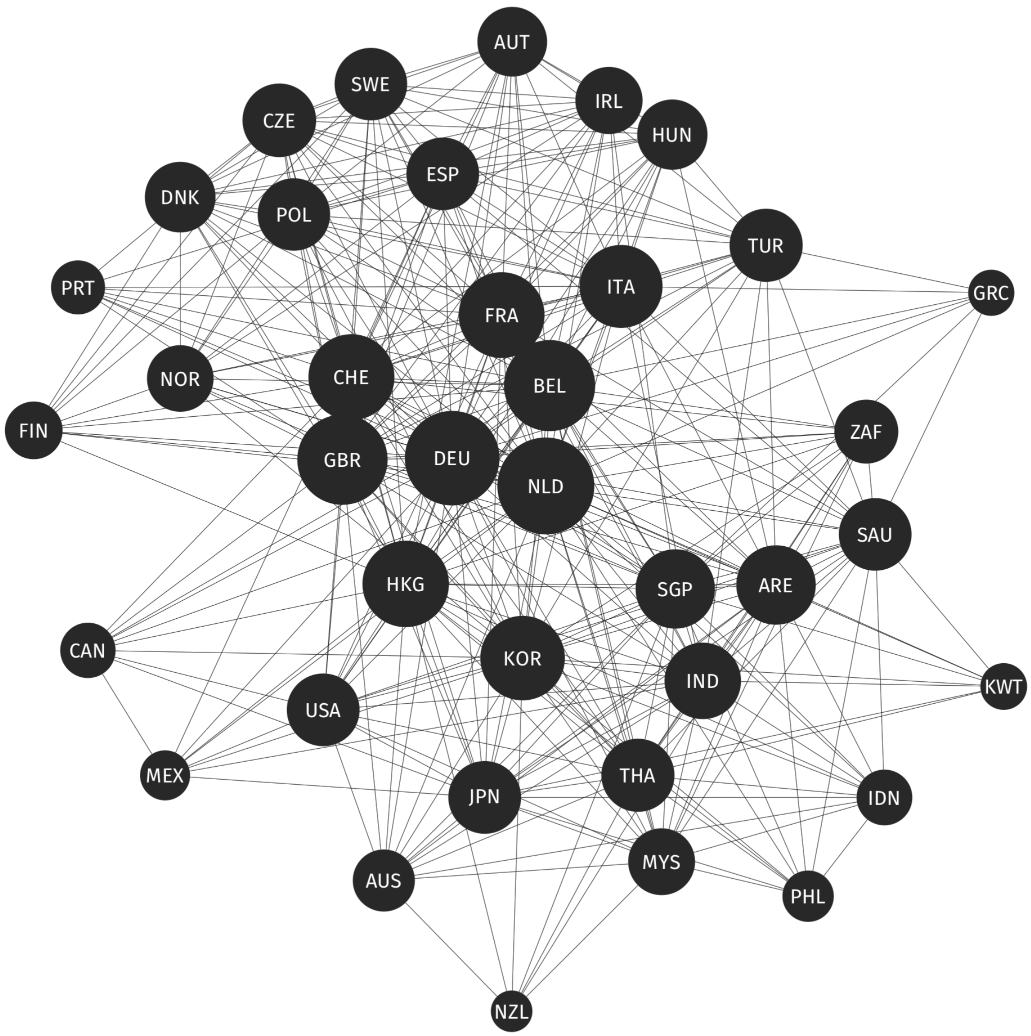
Trade Network Centrality and Currency Risk Premia

Carry trade investors who went long in currencies with high average interest rates, by borrowing in currencies with low average interest rates, obtained an annualized Sharpe ratio of 0.43 between 1995 and 2013. This Sharpe ratio is similar to those found in U.S. equity markets and is surprising given the strategy's simple, unconditional nature. Although the returns to carry trade strategies are well studied, less is known about their economic origins. In this paper, I show that differences in interest rates that drive currency returns are explained by countries' trade network centrality — a measure of their importance in the global trade network. By connecting returns to economic quantities, I shed light on the fundamental origins of exposure to risk that drives international asset prices.

To make the connection between returns and quantities, I begin with the simple observation that countries share and are exposed to risk through trade links. These trade links form a global trade network, which is depicted for 2013 in Figure (1.1). Each circle represents a country and each line represents a trade link. Trade links are measured using pair-wise total trade normalized by pair-wise total GDP and only the top half are displayed. The position and size of each circle corresponds to the country's *overall* importance in the trade network — its trade network centrality. Countries are more central if they have many strong links to countries that are themselves central. For example, global trade hubs, such as Singapore and Hong Kong, are central. In contrast, countries which only trade a small amount with a few partners, such as New Zealand, are peripheral. These cross-sectional differences in trade network centrality turn out to be a significant determinant of countries' unconditional interest rates and currency risk premia.

Figure (1.2) illustrates the relation between centrality, interest rates, and currency risk

Figure 1.1: World Trade Network in 2013



Country links are measured by bilateral trade intensity — pair-wise total trade normalized by pair-wise total GDP. Links are drawn if bilateral trade intensity is greater than the cross sectional median. Circle size and position corresponds to alpha centrality calculated on the adjacency matrix of bilateral trade intensities. Trade data are reported exports from the IMF Direction of Trade Statistics GDP data from the World Bank, both in dollars.

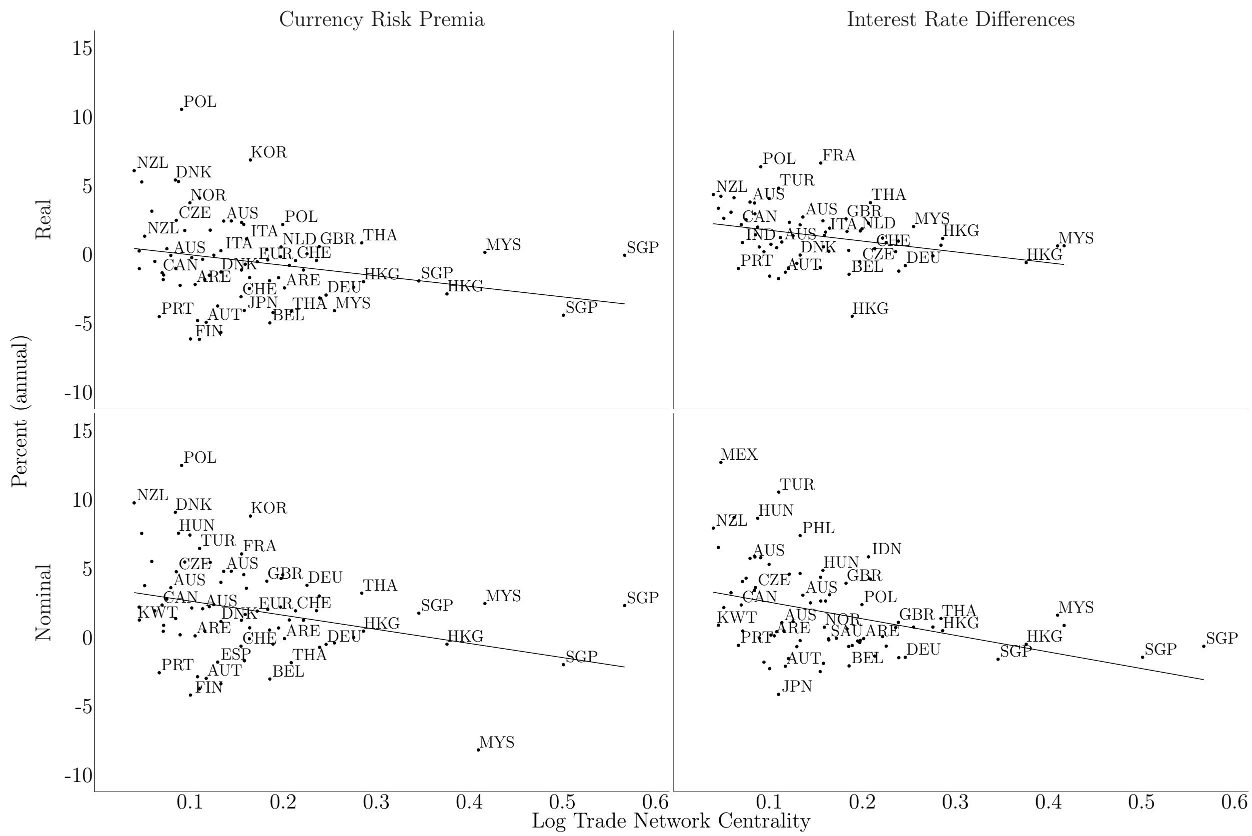
premia. To focus on unconditional variation, I plot 10-year averages of interest rate differentials and risk premia for a U.S. investor versus 10-year averages of trade network centrality. Central countries, such as Singapore, have low average interest rates and currency risk premia. On the contrary, peripheral countries, such as New Zealand, have high average interest rates and currency risk premia. In general, interest rates and currency risk premia are decreasing in trade network centrality. These patterns hold for both nominal and real risk premia and interest rate differentials[1] A U.S. investor who went long in a portfolio of peripheral countries' currencies and short in a portfolio of central countries' currencies from 1984 through 2013 received an annualized Sharpe ratio of 0.50 — similar to that of the unconditional carry trade.

Why do central countries have lower interest rates and currency risk premia? To answer this question, I present a tractable, multi-country model which shows that the currencies of central countries are a good hedge against global consumption risk. Households in each country consume a non-tradable good and a bundle of tradable goods produced in a global production network. The production network gives rise to global risk that drives differences in interest rates and currency risk premia. Central countries are more important in the production network than peripheral countries because more of global output relies on their goods as intermediates. Therefore, production shocks in the center of the network affect global output more than production shocks in the periphery. Importantly, bad shocks to tradables output coincide with bad shocks to non-tradables output. This causes central countries' consumption bundles to be more exposed to bad shocks to global output.

Countries' differential exposure to global shocks imputes variation in their real exchange rates. This is because real exchange rates are simply the relative price of countries' consumption bundles. When a country receives a bad shock, the price of its non-tradables increases relative to tradables, which increases the overall price of its bundle. In particular, when central countries receive a bad shock, global marginal utility is high. In these high marginal utility states, the relative price of central countries' consumption bundle increases, causing

[1]For real values, inflation expectations are lagged year-over-year inflation as in Atkeson and Ohanian (2001). The patterns are very similar using ex-post realized inflation.

Figure 1.2: Risk Premia and Interest Rate Differentals versus Centrality



Decade long averages of annualized risk premia rx and annualized 1-month interest rate differences (measured using covered interest rate parity with forward spreads $f-s$) versus trade network centrality for 39 countries. For real values, inflation expectations are lagged year-over-year inflation as in Atkeson and Ohanian (2001). For each country, monthly observations are averaged into 3 blocks (1984-1992, 1993-2002, 2003-2013). Centrality is Katz (1953) centrality centrality of an adjacency matrix of bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Trade data are annual reported exports from the IMF Direction of Trade Statistics and annual GDP data are from the World Bank, both in dollars. Foreign exchange data are monthly from Barclay's and Reuter's.

their currency to appreciate. As a result, central countries' currencies appreciate in high marginal utility states and are a good hedge against global consumption risk. This results in central countries having low interest rates and currency risk premia.

To test the model, I construct an empirical counterpart of the model's centrality measure using observed trade data. As predicted, a 1 standard deviation increase in a country's centrality lowers its annualized currency risk premia by 0.9% and its interest rate differential by 1.6%, relative to the U.S. This is a large effect given that the cross-sectional standard deviation of average risk premia and interest rate differentials are 3.5% and 5.3% respectively. I control for two alternative explanations. First, countries may have low risk premia and interest rates because they are large (Hassan, 2013). Although countries' GDP share does have a significant impact on their interest rates, controlling for GDP share does not change the economic or statistical significance of trade network centrality. Second, countries may rely heavily on trade causing them to be highly exposed to global shocks. This mechanism could also result in lower interest rates and currency risk premia. Interestingly, countries' trade-to-GDP ratio does not impact interest rates or currency risk premia when controlling for centrality. This suggests that a country's importance for global trade, rather than the importance of trade for the country, is a key determinant of interest rates and currency risk premia.

As an additional test, I sort currencies into portfolios. Sorting into portfolios reduces idiosyncratic currency risks (Fama and MacBeth, 1973; Lustig and Verdelhan, 2007) and focuses on variation associated with countries' trade network centrality. When sorted on trade network centrality, interest rates and currency risk premia are increasing from the portfolio of central countries to the portfolio of peripheral countries. Furthermore, countries' consumption growth covariances with world consumption growth are decreasing from the central to peripheral portfolios. Both findings are consistent with the model's implications.

Using the portfolio sorts, I compare the returns of a centrality based risk factor, PMC, to an unconditional carry trade risk factor, $UHML^{FX}$. PMC is long peripheral countries' currencies and short central countries' currencies, while $UHML^{FX}$ is long high average interest currencies and short low average interest rate currencies. In a regression of $UHML^{FX}$

on PMC there is no unexplained excess return and $UHML^{FX}$ moves almost one-for-one with PMC. This finding provides an economic explanation of the assymetric exposure to global risk that is necessary for the carry trade (Lustig, Roussanov, and Verdelhan, 2011).

More broadly, my results link fundamental quantities to international asset prices by contributing to three active areas of research: networks, exchange rate determination, and international risk sharing. I make these contributions theoretically by embedding the non-tradables friction of Backus and Smith (1993) within a multi-country version of the network model of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012)[2]. The latter work shows how production networks can give rise to aggregate economic fluctuations. In my model, differences in exposure to such aggregate fluctuations leads to variation in real exchange rates.

The variation in real exchange rates implied by my model is consistent with Burstein, Eichenbaum, and Rebelo (2006) and Betts and Kehoe (2008). Both papers show that variation in the relative price of non-tradables to tradables is important for movement in real exchange rates. Additional variation in real exchange rates arises due to relative prices of tradable goods across countries, as noted in Engel (1999). A survey of the connection between prices and exchange rates can be found in Burstein and Gopinath (2014).

Research on the relation between exchange rates and interest rates began with tests of the uncovered interest parity (UIP) condition by Bilson (1978) and Fama (1984). Hassan and Mano (2013) decomposes the returns to various currency strategies and shows how they are related. Lustig and Verdelhan (2007) were the first to sort currencies into portfolios on interest rates and to show that U.S. consumption growth risk exposure explains this cross-section of currency returns. Work by Bekaert (1996), Bansal (1997), Backus, Foresi, and Telmer (2001), and Lustig, Roussanov, and Verdelhan (2011) provides restrictions on models that are necessary to explain deviations from UIP. My work helps to understand the economic source of these deviations, both theoretically and empirically.

[2]As an implication of their model, Ahern (2012) shows that firms which are in central industries earn higher equity returns because they are more exposed to market risk.

Additionally, my paper is related to work on global risk, market integration, and international asset pricing models. Solnik (1974) presents an international CAPM model. Following this work, Harvey (1991) and Dumas and Solnik (1993) examine the global price of risk and stock and FX markets, respectively. Bekaert and Harvey (1995) examine the time variation in global market capital market integration and show how this varition impacts expected returns across countries. Ferson and Harvey (1993) show how predictability in equity markets is related to global economic risks. Maggiori (2011) presents a model which explains why financially developed countries' currencies become reserve currencies.

My results on consumption covariances relate to work on international risk sharing such as Stockman and Tesar (1990), Obstfeld (1994), Lewis (1995), and Tesar (1995). In particular, the last paper presents the cross-section of consumption growth covariances that I show is related to trade network centrality. Colacito and Croce (2011) show that correlation in long-run consumption risk can resolve disconnects between economic fundamentals and asset prices.

Most closely related to my paper are papers that also study unconditional currency returns using country asymmetries. Ready, Roussanov, and Ward (2013) solve and empirically test a model where countries that produce commodity goods are distinct from countries that produce final goods. In their model, currencies of commodity producing countries depreciate in bad times, increasing their currency risk premia. Hassan (2013) shows that currencies of larger countries hedge investors against a greater proportion of consumption risk and therefore have lower currency risk premia and interest rates.

Theoretical explanations of conditional currency returns include Alvarez, Atkeson, and Kehoe (2009), Verdelhan (2010), Bansal and Shaliastovich (2012), and Gabaix and Maggiori (2014). Della Corte, Riddiough, and Sarno (2013) empirically test the last paper and show that external imbalances explain a large proportion of the cross-section of currency returns. Lettau, Maggiori, and Weber (2014) show that the cross-section of currency returns can be priced by a model of downside risk.

This paper is organized as follows. In Section (1.1) I develop a theoretical model that motivates the link between centrality, interest rates, and currency risk premia. In Section (1.2), I construct an empirical measure of centrality and test the model's predictions. I conclude in Section (2.5). Section (1.4) contains derivations and proofs for the model. Section (1.5) contains details on the empirical results and robustness checks.

1.1 Model with Network-Based Production

In this section, I present a multi-country model with network-based production. The model shows that countries that are central in the global trade network have lower interest rates and currency risk premia due to higher exposure to common consumption growth risk.

1.1.1 Model Environment

The economy consists of N countries indexed $i = 1, \ldots, N$. Each country has a representative household, a production sector for a unique tradable good, and a production sector for non-tradable goods. Tradable goods are used as intermediates for production of other tradable goods and for consumption. There are three time periods, $t = 0, 1, 2$. Time 0 is a planning period. At $t = 1, 2$ each country realizes a pair of shocks denoted Z_{it} and Y_{it}. At $t = 1, 2$ each representative household is endowed with one unit of labor which it supplies to the domestic production sectors. The shocks are summarized by $\xi_t = \{(Z_{it}, Y_{it})\}_{i=1}^{N}$. At time $t = 1$, there is no risk and shocks are normalized to 1. At time $t = 2$, shocks have i.i.d. distributions across countries. The distributions of the shocks are

$$z_{i1} = \log(Z_{i1}) = 0, \tag{1.1}$$

$$y_{i1} = \log(Y_{i1}) = 0, \tag{1.2}$$

$$z_{i2} = \log(Z_{i2}) \overset{i.i.d}{\sim} G_z, \tag{1.3}$$

$$y_{i2} = \log(Y_{i2}) \overset{i.i.d}{\sim} G_y \text{ for all } i. \tag{1.4}$$

The representative household in country i ranks consumption according to

$$\log\left(\overline{C}_{i1}(\xi_1)\right) + \beta E\left[\log\left(\overline{C}_{i2}(\xi_2)\right)\right], \tag{1.5}$$

where $\beta \in (0,1)$ is the subjective discount factor and $\overline{C}_{it}(\xi_t)$ is the time t consumption aggregator over tradable and non-tradable goods given by

$$\overline{C}_{it}(\xi_t) = (N_{it}(\xi_t))^{\theta}\left(\prod_{j=1}^{N}(C_{ijt}(\xi_t))^{\frac{1}{N}}\right)^{1-\theta}. \tag{1.6}$$

For each country i at time t, $C_{ijt}(\xi_t)$ is its consumption of country j's unique tradable good and $N_{it}(\xi_t)$ is its non-tradable endowment. The parameter $\theta \in (0,1)$ measures the preference weighting between non-tradable and tradable goods. To emphasize trade network position as the only source of country hetereogeneity, all countries have symmetric preferences and each tradable goods has equal weight $\frac{1-\theta}{N}$.

All goods are non-storable. The domestic production sectors distribute any profits to their country's representative household. Output at times $t = 1, 2$ in country i's non-tradable sector is

$$N_{it}(\xi_t) = (Z_{it})^{\rho}\left(L_{it}^{N}(\xi_t)\right)^{\rho}(Y_{it})^{1-\rho}, \tag{1.7}$$

where $L_{it}^{N}(\xi_t)$ is the labor supplied to non-tradables production and $\rho \in (0,1]$ is a weighting parameter between the shocks. When $\rho < 1$ non-tradables endowments depend on both shocks, Z_{it} and Y_{it}. When $\rho = 1$, non-tradables endowments are only a function of the shocks Z_{it}. The shocks Z_{it} are the same shocks that impact domestic tradables output specified next. Therefore, low realizations of non-tradables coincide with negative productivity shocks in the domestic tradeables sector. In a standard calibration, Stockman and Tesar (1995) find a correlation of 0.46 between shocks to traded and non-traded sectors within countries.

Each country produces its unique tradable good in a domestic production sector using other countries' tradable goods as intermediates. The structure of this production network is determined by production weights w_{ij}. These production weights are the key source of assymetries across countries that determines their trade network centrality and the resulting variation in international asset prices. Specifically, output at $t = 1, 2$ of country i's tradable good is

$$\overline{X}_{it}(\xi_t) = (Z_{it})^{\alpha} \left(L_{it}^{T}(\xi_t)\right)^{\alpha} \prod_{j=1}^{N} (X_{ijt}(\xi_t))^{(1-\alpha)w_{ij}}, \tag{1.8}$$

where $X_{ijt}(\xi_t)$ is the amount of country j tradables used as an intermediate in country i's tradables production, Z_{it} is the idiosyncratic shock in country i, and $L_{it}^{T}(\xi_t)$ is labor supplied to the tradables sector in country i. The parameter $\alpha \in (0, 1)$ measures the elasticity of output with respect to labor. The intermediate production weights, $w_{ij} \geq 0$, measure the importance of other countries' tradable goods for country i's output. A larger w_{ij} implies that more of country j's tradable good is needed to produce a unit of country i's tradable goods. I assume $\sum_{j=1}^{N} w_{ij} = 1$ for all i so that tradables output has constant returns to scale.

Output of country i tradables must equal the total amount used as intermediates in the production of other tradables plus the total amount consumed. Additionally, total labor supplied to the non-tradables and tradables sector in each country must equal each representative household's endowment. Therefore, the market clearing conditions are

$$\overline{X}_{it}(\xi_t) = \sum_{j=1}^{N} X_{jit}(\xi_t) + \sum_{j=1}^{N} C_{jit}(\xi_t) \quad \forall\ i, \tag{1.9}$$

$$1 = L_{it}^{N}(\xi_t) + L_{it}^{T}(\xi_t) \qquad \forall\ i. \tag{1.10}$$

Financial markets are complete — at time 0, the representative households and firms trade a complete set of Arrow-Debreu claims for non-tradable goods at price $P_{it}^{N}(\xi_t)$, tradable goods at price $P_{it}^{T}(\xi_t)$, and to provide labor at wage $\Omega_{it}(\xi_t)$. This implies that the time 0 budget constraint for country i's representative household is given by

$$\begin{aligned} & P_{i1}^{N}(\xi_1) N_{i1}(\xi_1) + \sum_{j=1}^{N} P_{j1}(\xi_1) C_{ij1}(\xi_1) + \\ & \int_{\xi_2} \left(P_{i2}^{N}(\xi_2) N_{i2}(\xi_2) + \sum_{j=1}^{N} P_{j2}(\xi_2) C_{ij2}(\xi_2) \right) d\xi_2 \\ \leq\ & \Omega_{i1}(\xi_1) + \Pi_{i1}^{N}(\xi_1) + \Pi_{i1}^{T}(\xi_1) + \int_{\xi_2} \left(\Omega_{i2}(\xi_2) + \Pi_{i2}^{N}(\xi_2) + \Pi_{i2}^{T}(\xi_2)\right) d\xi_2, \end{aligned} \tag{1.11}$$

where $\Pi_{it}^N(\xi_t)$ and $\Pi_{it}^T(\xi_t)$ are the time 0 state-contingent value of profits from the domestic non-tradables and tradables production sectors, respectively. Profits in the non-tradables and tradables sectors are

$$\Pi_{it}^N(\xi_t) = P_{it}^N(\xi_t)N_{it}(\xi_t) - \Omega_{it}(\xi_t)L_{it}^N(\xi_t) \ , \tag{1.12}$$

$$\Pi_{it}^T(\xi_t) = P_{it}^T(\xi_t)\overline{X}_{it}(\xi_t) - \Omega_{it}(\xi_t)L_{it}^T(\xi_t) - \sum_{j=1}^{N} P_{jt}^T(\xi_t)X_{ijt}(\xi_t). \tag{1.13}$$

The equilibrium definition is as follows.

Definition 1. *An Arrow-Debreu competitive equilibrium consists of non-tradable goods prices $\{P_{it}^N(\xi_t)\}_{i=1...N}$, tradable goods prices $\{P_{it}^T(\xi_t)\}_{i=1...N}$, wages $\{\Omega_{it}(\xi_t)\}_{i=1...N}$, non-tradable labor input $\{L_{it}^N(\xi_t)\}_{i=1...N}$, tradable labor input $\{L_{it}^T(\xi_t)\}_{i=1...N}$, tradable goods inputs $\{X_{ijt}(\xi_t)\}_{i,j=1...N}$, and tradable goods consumptions $\{C_{ijt}(\xi_t)\}_{i,j=1...N}$ for each ξ_t, such that households maximize Equation (1.5) subject to Equation (1.11), non-tradables firms maximize Equation (1.12), tradables firms maximize Equation (1.13), tradable goods markets clear, Equation (1.9), and labor markets clear, Equation (1.10), for all i.*

1.1.2 Social Planner Solution

Instead of solving directly for the competitive equilibrium, I exploit the second welfare theorem and solve a social planner's problem. Specifically, the competitive equilibrium can be supported as the solution to a social planner's problem with some Pareto weights for each representative household (Negishi, 1960). This is possible because financial markets are complete — agents trade a complete set of state contingent claims. I assume that lump sum transfers occur before trading such that all Pareto weights are equal to 1. Details of the solution in this section can be found in Section (1.4).

Because preferences are time-separable and goods are non-storable, the solution to the planner problem can be found by solving a simple static problem for each shock realization. For notational simplicity, I omit dependence on ξ_t going forward. The social planner's objective is

$$\underset{\substack{\{C_{ijt},\ X_{ijt}\}_{i,j=1\dots N}\\ \{L^N_{it},\ L^T_{it}\}_{i=1\dots N}}}{\text{maximize}} \qquad \sum_{i=1}^{N}\Big(\log\left(\overline{C}_{i1}\right)+\beta E\big[\log\left(\overline{C}_{i2}\right)\big]\Big) \tag{1.14}$$

$$\text{subject to} \qquad \overline{C}_{it}=\left((Z_{it})^{\rho}\left(L^N_{it}\right)^{\rho}(Y_{it})^{1-\rho}\right)^{\theta}\left(\prod_{j=1}^{N}(C_{ijt})^{\frac{1}{N}}\right)^{1-\theta} \tag{1.15}$$

$$(Z_{it})^{\alpha}\left(L^T_{it}\right)^{\alpha}\prod_{j=1}^{N}(X_{ijt})^{(1-\alpha)w_{ij}}=\sum_{j=1}^{N}X_{jit}+\sum_{j=1}^{N}C_{jit} \tag{1.16}$$

$$1=L^N_{it}+L^T_{it} \qquad \forall\ i,t. \tag{1.17}$$

Equation (1.15) is household i's consumption basket with its non-tradables endowment substituted in — non-tradable goods must be consumed domestically. Equation (1.16) is the market clearing condition with output replaced by the tradables production function. Equation (1.17) is the market clearing condition for labor in each country. In each period t and for each possible realization of shocks, the planner chooses intermediate usages of tradables $\{X_{ijt}\}_{i,j=1,\dots,N}$, tradables final consumptions $\{C_{ijt}\}_{i,j=1,\dots,N}$, and labor supplies $\{L^N_{it}\ ,\ L^T_{it}\}_{i=1\dots N}$. These quantities imply total tradable goods outputs $\{\overline{X}_{it}\}_{i=1,\dots,N}$ and consumption baskets $\{\overline{C}_{it}\}_{i=1,\dots,N}$.

To solve the model, I assign Lagrange multipliers Ψ_{it} to each resource constraint in Equation (1.16) and G_{it} to each labor market constraint in Equation (1.17). The Lagrange multipliers Ψ_{it} measure the shadow price of each country's tradable good. First order conditions with respect to C_{jit} and X_{jit} give

$$C_{jit}=\frac{(1-\theta)}{N\Psi_{it}}, \tag{1.18}$$

$$X_{jit}=\frac{\Psi_{jt}\overline{X}_{jt}(1-\alpha)w_{ji}}{\Psi_{it}}. \tag{1.19}$$

Rearranging Equation (1.19) shows how the production weights, w_{ji}, are related to expenditure shares:

$$X_{jit}=\frac{\Psi_{jt}\overline{X}_{jt}(1-\alpha)w_{ji}}{\Psi_{it}} \implies \frac{\Psi_{it}X_{jit}}{\Psi_{jt}\overline{X}_{jt}}=(1-\alpha)w_{ji}. \tag{1.20}$$

Country j's production expenditure on country i's tradable goods, normalized by the value of j's output, is proportional to the production weights w_{ji}. Combining the first order conditions with the resource constraint, Equation (1.16), implies

$$\begin{aligned}\overline{x}_t &= (\boldsymbol{I} - (1-\alpha)W)^{-1} (\alpha z_t + a) \\ &= \left(\boldsymbol{I} + (1-\alpha)W + (1-\alpha)^2 W^2 + (1-\alpha)^3 W^3 + \ldots\right) (\alpha z_t + a), \end{aligned} \tag{1.21}$$

where $\overline{x}_t = \left[\log(\overline{X}_{1t}), \ldots, \log(\overline{X}_{Nt})\right]'$ is the vector of log tradable outputs, $z_t = [\log(Z_{1t}), \ldots, \log(Z_{Nt})]'$ is the vector of log shocks, $W = [w_{ij}]$ is the matrix of production weights, and the constant vector a is defined in Section (1.4). Throughout the paper, I define $\mathbf{1}$ as the vector of ones of and $\boldsymbol{I}$ as the identity matrix — both are assumed to be of the appropriate dimension. The second equality follows from expanding the inverse as a series.

Equation (1.21) shows that tradables output is the result of propagation of shocks due to the interdependent nature of production. The way that shocks propagate through the production network is determined by the matrix of production weights W. Equilibrium output is the result of direct and indirect effects of the network's structure. A shock to the output of one country impacts production of all countries that rely on its goods as intermediates and, in turn, the countries that rely on those. The decay of this propagation is governed by the value of $1-\alpha$, where higher values imply that shocks propagate further due to more reliance on intermediates in production. With Cobb-Douglas production technology, propagation only occurs downstream because price changes exactly offset the output impact of production shocks (Shea, 2002). With more general production technology, shocks could propagate via importing relationships. Therefore, in the empirical tests I examine whether shocks propagate upstream, downstream, or in both directions.

Given tradables output of each country in Equation (1.21), log consumption baskets are

$$\overline{c}_t = \theta\left(\rho z_t + (1-\rho) y_t\right) + \frac{(1-\theta)\alpha}{N} \left(z_t'(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}\right) + d, \tag{1.22}$$

where $y_t = [\log(Y_{1t}), \ldots, \log(Y_{Nt})]'$ is the vector of log shocks, $\overline{c}_t = \left[\log(\overline{C}_{1t}), \ldots, \log(\overline{C}_{Nt})\right]'$

is the vector of log consumptions, and d is a vector of constants defined in Section (1.4).

The term $(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}$ in Equation (1.22) is known as Katz centrality in the network literature (Katz, 1953; Bonacich and Lloyd, 2001). For a symmetric adjacency matrix, $W = W'$, Katz centrality is equivalent to Eigenvector centrality (Bonacich and Lloyd, 2001). Throughout the remainder of the paper, I refer to this measure as trade network centrality or simply centrality. Centrality measures a country's importance in the production network and is the key quantity in the model.

Country i's centrality, v_i, is just the i'th element of the centrality vector, which I define as v:

$$v_i = \left[(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}\right]_i . \tag{1.23}$$

With this definition, log consumption at time t for country i is

$$\begin{aligned}\bar{c}_{it} &= \theta\left(\rho z_{it} + (1-\rho)y_{it}\right) + \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} v_j z_{jt}\right) + d_i \\ &= \theta\left(\rho z_{it} + (1-\rho)y_{it}\right) + F_t + d_i, \end{aligned} \tag{1.24}$$

where the second equality is just a definition of F_t. Each country's consumption depends on two components. The first component in Equation (1.24), $\theta\left(\rho z_{it} + (1-\rho)y_{it}\right)$, is country i's non-tradable endowment. The second component is a centrality weighted sum of all production shocks in the economy given by

$$F_t = \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} v_j z_{jt}\right). \tag{1.25}$$

Importantly, this second component is symmetric across countries. It can be interpreted as the common risk factor in global consumption growth (Lustig, Roussanov, and Verdelhan, 2011). Shocks to central countries impact the common component more than shocks to peripheral countries. This can be seen simply because central countries have larger values of v_i in the sum. Economically, a shock in the center of the network will have large effects on aggregate consumption because global output relies more on central country goods as intermediates. Because shocks to non-tradables endowments are positively correlated with shocks to tradables production, central countries' consumption growth is more exposed to common consumption growth shocks. This is the key mechanism in the model.

To formally show that the consumption of central countries' is more exposed to common consumption shocks, I calculate average global consumption growth

$$\begin{aligned}\widehat{\Delta \overline{c}_2} &= \frac{1}{N}\sum_{j=1}^{N}\Delta \overline{c}_{j2} \\ &= \left(\frac{1}{N}\sum_{j=1}^{N}\left(\theta\rho + v_j\alpha(1-\theta)\right)z_{j2}\right) + \left(\frac{\theta(1-\rho)}{N}\sum_{j=1}^{N}y_{j2}\right),\end{aligned} \tag{1.26}$$

where changes in log consumption between period 1 and 2 are given by $\Delta \overline{c}_{i2}$ for $i = 1, \dots, N$. There are no time 1 shocks in consumption growth terms because $z_{i1} = y_{i1} = 0$ for all i. I define σ_z^2 as the variance of z_{i2} for all i. In the following proposition, I show that central country consumption growth covaries more with global average consumption growth.

Proposition 1. *For two countries i and j*

$$\text{Cov}(\Delta \overline{c}_{i2}, \widehat{\Delta \overline{c}_2}) - \text{Cov}(\Delta \overline{c}_{j2}, \widehat{\Delta \overline{c}_2}) = \frac{\sigma_z^2}{N}\theta\rho\alpha(1-\theta)(v_i - v_j). \tag{1.27}$$

Therefore, $v_i > v_j$ implies $\text{Cov}(\Delta \overline{c}_{it}, \widehat{\Delta \overline{c}_2}) > \text{Cov}(\Delta \overline{c}_{jt}, \widehat{\Delta \overline{c}_2})$.

The mechanism that drives Proposition (1) also impacts asset prices and exchange rates. For each country, assets that pay off in units of the local consumption baskets are priced by the intertemporal marginal rate of substitution (IMRS) of the country's representative household. I use M_{i2} to denote the IMRS of country i's representative household between time 1 and time 2. Country i's log IMRS is given by

$$\begin{aligned}m_{i2} &= \delta + \overline{c}_{i1} - \overline{c}_{i2} \\ &= \delta - \theta\left(\rho z_{i2} + (1-\rho)y_{i2}\right) - \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N}v_j z_{j2}\right),\end{aligned} \tag{1.28}$$

where I have used $\delta = \log(\beta)$ and $z_{i1} = y_{i1} = 0$.

Exchange rates are simply the relative price of countries' consumption baskets. Therefore, given complete financial markets, exchange rate changes are the ratio of the countries' IMRS:

$$M_{i2}\frac{Q_{ij1}}{Q_{ij2}} = M_{j2} \implies \Delta q_{ij2} = m_{i2} - m_{j2}, \tag{1.29}$$

where Q_{ijt} denotes the time t exchange rate in units of currency j per unit of currency i and lowercase letters denote logs. This expression shows that country i's currency appreciates relative to country j's when it has higher marginal utility growth. Equivalently, country i's currency appreciates when the relative price of its consumption basket increases. For example, if the U.S. receives a negative consumption shock that increases the price of its consumption basket relative to Mexico's, the Dollar will appreciate relative to the Peso.

The time 1 log interest rate in country i is $rf_{i1} = -\log E\left[M_{i2}\right]$, which implies that the log interest rate differential between country j and country i at time 1 is

$$rf_{j1} - rf_{i1} = \log E\left[M_{i2}\right] - \log E\left[M_{j2}\right]. \tag{1.30}$$

Foreign currency investors receive the interest differential over their home country and lose any appreciation of the home currency. Combining Equation (1.29) and Equation (1.30) gives the log risk premium to going long in currency j for a country i investor:

$$\begin{aligned} E\left[rx_{ij2}\right] &= rf_{j1} - rf_{i1} - E\left[\Delta q_{ij2}\right] \\ &= \left(\log E\left[M_{i2}\right] - \log E\left[M_{j2}\right]\right) - \left(E\left[m_{i2}\right] - E\left[m_{j2}\right]\right). \end{aligned} \tag{1.31}$$

For intuition, consider the case where the production shocks are log-normally distributed: $z_{i2} \overset{i.i.d}{\sim} \mathcal{N}(\mu_z, \sigma_z^2)$. In this case, risk premia and interest rate differentials have a particularly simple form:

$$\mathrm{E}\left[rx_{ij2}\right] = rf_{j1} - rf_{i1} = \sigma_z^2 \frac{\theta(1-\theta)\alpha\rho}{N}\left(v_i - v_j\right). \tag{1.32}$$

This equation shows that central countries have lower currency risk premia and interest rates.

When country i is more central than country j, i.e. $v_i > v_j$, the currency risk premium for a country i investor going long in the currency of country j is positive and equal to the interest rate differential. This is a result of central countries being more exposed to common shocks to consumption growth, as shown in Proposition (1). On average, bad global shocks — which originate in the center of the network — increase central country marginal utility more. Higher marginal utility in bad times causes central country currencies to appreciate in bad times, making them a good consumption hedge and lowering their risk premia. Interest rates are also lower in central countries due to higher consumption growth variance.

The intuition from the normal case generalizes to any i.i.d. distribution of shocks z_{i2} in Equation (1.3) and i.i.d distribution of shocks y_{i2} in Equation (1.4). This is important because of work such as Chernov, Graveline, and Zviadadze (2012) and Brunnermeier, Nagel, and Pedersen (2008) showing that currency investment strategies exhibit significant negative skewness. By incorporating higher order moments into the distribution of z_{i2}, such as skewness (Barro, 2006), currency risk premia will reflect these higher order moments. Exploiting the convexity of cumulant generating functions gives the following general proposition (the proof is in Section (1.4)).

Proposition 2. *For any two countries with $v_i > v_j$, the* log *currency risk premium for going long in currency j from country i and* log *interest rate differential satisfy*

$$\mathrm{E}\left[rx_{ij2}\right] = rf_{j1} - rf_{i1} > 0.$$

This proposition is the key takeaway from the model. Central countries have lower interest rates and lower currency risk premia than peripheral countries because their exchange rate tends to appreciate in high marginal utility states.

1.2 Data, Empirical Centrality, and Currency Strategies

In this section, I test the predictions of Proposition (1) and Proposition (2):

1. Central country consumption growth covaries more with global consumption growth.

2. Countries that are central in the global trade network have low currency risk premia and low interest rates.

1.2.1 Data Sources

Daily spot and forward rates are from Barclay's and Reuter's[3]. The sample period is 1984 to 2013. A list of the 39 countries and the dates of data availability is in Table (1.6). I use one-month forward rates and convert daily observations to end-of-month series. All exchange rates are with respect to the U.S. Dollar. Consumer price indices used to calculate inflation are monthly from Barclay's and Reuter's. Data for Australia and New Zealand are only available quarterly, therefore I use interpolated monthly values.

I use q_{it} and f_{it} to denote the log spot and forward exchange rates in units of currency i per U.S. dollar. r_{it} is the 1-month log interest rate. Country indices are omitted anytime a value is with respect the U.S. Assuming that covered interest parity holds[4], forward spreads are equal to the interest rate differential: $f_{it} - q_{it} \approx r_{it} - r_t$. I calculate log risk premia for a U.S. investor going long in country i as

$$rx_{it+1} = r_{it} - r_t - \Delta q_{it+1} \approx f_{it} - q_{it+1}. \tag{1.33}$$

An investor who goes long in currency i at time t and divests at time $t+1$ receives the interest rate differential, less the appreciation of the home currency. All forward spreads and risk premia are annualized. I calculate real interest rate differentials from forward spreads by substracting expected inflation differentials. Expected inflation is calculated as lagged year-over-year change in log price indices following Atkeson and Ohanian (2001).

Bilateral trade data are from the International Monetary Fund's Direction of Trade Statistics. Data are annual from 1973 through 2013, covering 173 reporting countries. I use

[3]The data can be obtained through Datastream

[4]See Akram, Rime, and Sarno (2008) for evidence that covered interest parity tyically holds at frequencies higher than daily. Due to large deviations from covered interest parity, some observations are omitted as specified in Section (1.5). Removing these observations has almost no impact on the results.

reported exports for each country, which are in current U.S. dollars "free on board." Current U.S. dollar GDP and population data are from the World Bank's World Development Indicators.

Real consumption data are from the Penn World Tables 7.1 (Heston, Summers, and Aten, 2002). The data consists of real per capita GDP and consumption in international prices for 189 countries from 1950 to 2010.

For all datasets, I limit the sample to the 39 countries which foreign exchange data are available. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. For robustness, I present results without using the euro aggregate in Table (1.9), results calculating centrality with all 173 countries in the trade data in Table (1.10), results omitting pegged currencies in Table (1.11), and results on a developed country subset in Table (1.12).

1.2.2 Empirical Trade Network Centrality

To determine each country's position in the trade network, I construct a measure of the strength of trade ties between country pairs. I define bilateral trade intensity as

$$\widetilde{w}_{ijt} = \widetilde{w}_{jit} = \frac{\widetilde{X}_{ijt} + \widetilde{X}_{jit}}{\widetilde{Y}_{it} + \widetilde{Y}_{jt}}, \tag{1.34}$$

where $\widetilde{X}_{ijt}$ is the dollar value of exports from country i to country j at time t (equivalently the imports by j from i), and $\widetilde{Y}_{it}$ is the dollar GDP of country i at time t. Bilateral trade intensity measures the total trade between two countries, normalized by their total GDP. This measure is also used in work by Frankel and Rose (1998) on currency unions. In my case, it is motivated by the relation in Equation (1.20) of the model. I use a symmetric variant to remain agnostic about the direction that shocks propagate through the trade network. In the model, due to Cobb-Douglas production technology, shocks only propagate downstream from exporters to importers. In reality, a bad shock to an importing country is likely to impact the countries which it imports from — due to lower demend. Therefore, I focus on the symmetric case, but also present results using normalized export weights, $\widetilde{w}_{ijt} = \frac{\widetilde{X}_{ijt}}{\widetilde{Y}_{it}+\widetilde{Y}_{jt}}$, and normalized import weights, $\widetilde{w}_{ijt} = \frac{\widetilde{X}_{jit}}{\widetilde{Y}_{it}+\widetilde{Y}_{jt}}$ in Table (1.7). The results are robust to the different specifications.

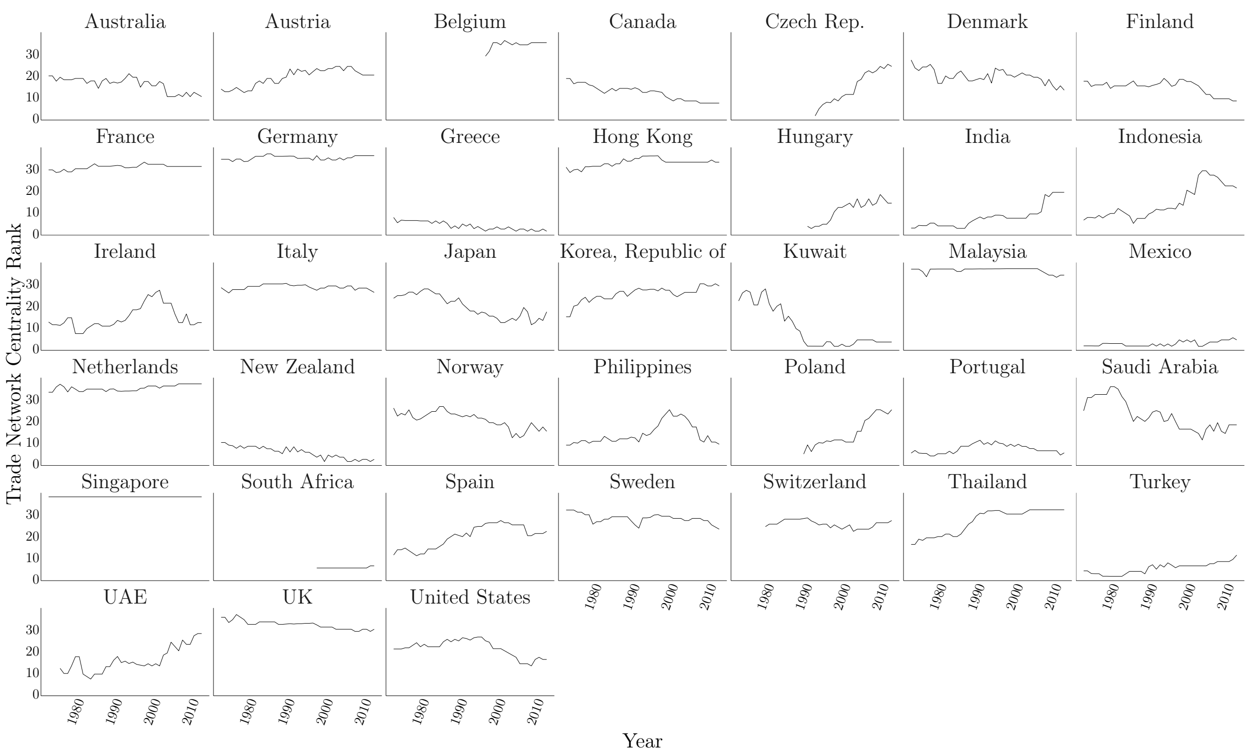
For each year, I construct an adjacency matrix, denoted $\widetilde{W}_t$, consisting of the bilateral trade intensities. Using the adjacency matrix, I calculate centrality for all countries each year as in Equation (1.23)[5]. To understand what trade network centrality is measuring, it helps to examine the weights in Equation (1.34). Trade links are stronger if bilateral trade represents a large proportion of countries' pair-wise total GDP. For example, New Zealand and Australia trade a significant amount of their total GDP with each other, which leads to a large bilateral trade intensity for these two countries. That said, they do not trade a significant proportion of pair-wise GDP with many other countries, such as the U.S. and Canada. Therefore, the weights with these larger countries will be smaller. In contrast, countries like the Netherlands and Singapore are home to some of the largest ports in the world and are hubs for European, Asian, and global trade. On average, these countries will have high bilateral trade intensities with most countries in the world. It is important to remember that for each country, weights are calculated for all other countries in the sample. The centrality measure takes into account the global position of a country by considering a country to be central if it has strong trade links with countries that are themselves central.

Figure (1.3) shows the time series of centrality rankings. As predicted, Asian trade hubs such as Hong Kong and Singapore are the most central, while countries such as New Zealand are peripheral. Interestingly, despite an exponential increase in the level of global trade from 1973 to 2013, countries' relative centralities are a highly persistent. This persistence is why trade network centrality explains unconditional properties of countries, such as average interest rates and average currency risk premia.

I begin by testing Proposition (2), where I show that central countries' currency risk pre-

[5] I use $1-\alpha = 1$. Varying $1-\alpha$ has almost no effect on the ranking of countries' centralities. For example, the minimum rank correlation (across years) of centralities calculated with $1-\alpha = 1$ and $1-\alpha = 0.1$ is 0.99.

Figure 1.3: Time Series of Centrality Ranking by Country



Rankings of countries' centrality in the global trade network by year. Centrality is centrality of an adjacency matrix of yearly bilateral trade intensities — pair-wise total trade divided by total GDP. Rankings are normalized each year to between 1 and 39 (maximum number of countries in the sample). Trade data are annual reported exports from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. Data are annual from 1973 to 2013.

mia and interest rates are lower than peripheral countries'. Table (1.1) presents regressions of forward spreads and risk premia on standardized trade network centrality. A one standard deviation increase in trade network centrality lowers forward spreads by 1.6% and currency risk premia by 0.9%, consistent with Proposition (2). The magnitude of these effects are large given that the cross-sectional standard deviation of countries' average risk premia and forward spreads are 3.2% and 4.9% respectively.

I also present specifications with various controls in Table (1.1). First, central countries may be larger on average. Therefore, following Hassan (2013), I control for country size using countries' GDP shares. GDP share is a significant determinant of forward spreads and risk premia — a one standard deviation increase in GDP share lowers forward spreads by 0.9% and risk premia by 0.4%. That said, the centrality coefficient is effectively unchanged and the magnitude of the centrality effect is much larger than that of GDP share. Next, I control for a countries' total trade normalized by its GDP — a measure of the importance of trade for a country. This is in contrast to centrality, which measures a country's importance for global trade. As an example, a country could have large trade to GDP because it trades a significant amount of its GDP with one country, but it will not typically be central. Consistent with the prediction that trade network centrality is what matters for risk premia and interest rates, controlling for trade to GDP does not impact the magnitude of the centrality coefficients.

Although country level interest rates and risk premia are important, the returns to the carry trade are a result of heterogeneous exposure to a global risk factor. To test this, I use portfolio sorts in the next section.

1.2.3 Carry Trade Risk Factors

Following Lustig and Verdelhan (2007) and Lustig, Roussanov, and Verdelhan (2011), I sort currencies into portfolios. Portfolio sorts eliminate the idiosyncratic component of currency returns and uncover the common — undiversifiable — component of currency risk associated with the sorting variable. Sorting on forward spreads generates the standard cross-section of carry trade returns, while the innovation in this paper is sorting on trade network centrality.

Table 1.1: Explanatory Regressions for Risk Premia and Forward Spreads

	rx	rx	rx	$f-s$	$f-s$	$f-s$
Centrality	-0.861^{**}	-0.886^{***}	-0.978^{*}	-1.580^{**}	-1.641^{***}	-1.742^{**}
	(-2.465)	(-2.612)	(-1.958)	(-2.449)	(-2.667)	(-2.458)
GDP Share		-0.362^{*}			-0.901^{**}	
		(-1.784)			(-2.047)	
Trade to GDP			0.142			0.195
			(0.326)			(0.336)
R^2	0.454	0.455	0.454	0.108	0.132	0.109
Num. obs.	655	655	655	664	664	664

Regressions of log risk premia rx_t and forward spreads $f_t - s_t$ on standardized GDP share, standardized trade to GDP, and standardized trade network centrality, v_{it}. All specifications include time fixed effects. Excess returns and forward spreads are yearly averages of annualized observations. Centrality is Katz (1953) centrality of an adjacency matrix of yearly bilateral trade intensities pair-wise total trade divided by total GDP. GDP share is the fraction of world GDP for each country, where world GDP is the total GDP of all available countries in the sample for that year. Trade data are annual reported exports from the IMF Direction of Trade Statistics and annual GDP data are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Foreign exchange data are monthly from Barclay's and Reuter's for 39 countries from 1/1984 to 12/2013. Observations are omitted after a country secedes its currency to the euro. Standard errors are clustered by country using Cameron, Gelbach, and Miller (2011). t-statistics in parentheses. ***, **, and * denote significance at the 1%, 5%, and 10% levels.

Table (1.2) reports the results. In each month t, currencies are sorted into 4 portfolios using three sorting variables: prior year trade network centrality, current forward spreads, and average forward spreads from 1984 to 1995. All sorting variables are observable at time t, making these sorts implementable trading strategies. Portfolios are rebalanced monthly, although trade network centralities are observed yearly and unconditional forward spreads are constant. Standard errors are calculated by bootstrapping 10,000 samples.

Panel A presents portfolios sorted on trade network centrality. Interest rates are monotonically increasing from the portfolio of peripheral countries to portfolio of central countries, producing an average spread in interest rates of 541 basis points. On average, peripheral country currencies depreciate by 80 basis points, while central country currencies appreciate by 161 basis points. Therefore, the 541 basis point interest rate differential translates to a 301 basis point spread in log excess returns. Central countries also have lower real interest rates. As with nominal interest rates, real interest rate differentials are monotonically increasing from central to peripheral portfolios with a spread between central and peripheral portfolios of 218 basis points. The annualized Sharpe ratio of a long peripheral, short central country portfolio is 0.50.

Panel A also presents evidence for Proposition (1), where I show that consumption growth covariances are increasing in centrality. To obtain a measure of consumption covariances, I regress each countries' per capita log consumption growth on world consumption growth using 20-year rolling windows

$$\Delta\widetilde{c}_{i\tau} = \alpha_{it} + \beta_{it}\Delta\widetilde{c}_{W\tau} + \epsilon_{i\tau} \quad \tau = t-19,\dots,t. \tag{1.35}$$

Real per capita consumption is from the Penn World Table. I calculate log world per capita consumption, $\widetilde{c}_{Wt}$, by omitting each country i. The average consumption growth β is increasing from 0.13 for the portfolio of peripheral countries to 0.82 for the portfolio of central countries[6]. This finding shows that consumption growth in central countries is

[6]Standard errors for consumption growth betas are computed using a 20-year block bootstrap given that they are estimated using a rolling sample.

more correlated with world consumption growth. This is consistent with Proposition (1) and helps to explain the heterogeneity in consumption growth covariances found in papers such as Tesar (1995).

As a benchmark for the portfolio sorts on trade network centrality, in Panels B and C of Table (1.2) I sort currencies into portfolios on forward spreads. In Panel B, I sort on current forward spreads, which represent returns to the carry trade. In Panel C, I sort on average forward spreads, which represent unconditional returns to the carry trade. For the unconditional sorts, I use the average forward spread in the first half of the sample (1984-1995 to remain consistent with Lustig, Roussanov, and Verdelhan (2011)). Both sorts on current forward spreads and average forward spreads produce monotonic cross sections of currency risk premia. Neither currencies with currently high interest rates, nor currencies with on-average high interest rates, depreciate enough to offset the interest rate differential with the U.S.

To compare the returns of the three cross-sections in Table (1.2), I construct long-short risk factors (Lustig, Roussanov, and Verdelhan, 2011) for each sorting variable. I refer to the excess returns to the long-short trade network centrality strategy as PMC — peripheral minus central. The long-short risk factor from sorts on current forward spreads in Panel B is referred to as HML^{FX} — high minus low forward spread. Finally, the long-short risk factor from sorts in Panel C is referred to as $UHML^{FX}$ — unconditional HML^{FX}. Because the set of currently high interest rate currencies includes currencies with on-average high interest rates, the returns to HML^{FX} subsume the returns to $UHML^{FX}$. Importantly, HML^{FX} and $UHML^{FX}$ can be interpreted as risk factors in the sense that currencies with similar interest rates co-move.

Table (1.3) presents annualized summaries of the three risk factors. The first 3 columns are for all available data, while the last two columns match the sample period of PMC and HML^{FX} to $UHML^{FX}$. HML^{FX} has the highest annual return of 5.65% and a Sharpe ratio of 0.68. PMC and $UHML^{FX}$ have similar return profiles, although the Sharpe ratio of PMC is higher, due to lower volatility. Over the matched period, $UHML^{FX}$ (4.36%) makes up over half of the returns to HML^{FX} (7.22%). All strategies exhibit crash risk, with

Table 1.2: Portfolios Sorted on Centrality and Forward Spreads

	Panel A: Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.08	1.13	1.19	1.36	-0.28
Forward Spread: $f_t - s_t$					
mean	5.42	1.66	1.42	0.01	5.41
std	1.23	0.56	0.60	0.51	1.24
se	0.23	0.10	0.11	0.09	0.23
Risk Premia: rx_t					
mean	4.62	2.84	2.59	1.62	3.01
std	7.53	9.10	8.80	6.05	5.95
se	1.38	1.66	1.62	1.10	1.10
Sharpe ratio					
mean	0.61	0.31	0.29	0.27	0.50
se	0.21	0.19	0.19	0.19	0.20
Real Interest Differential: $r_{it} - r_t$					
mean	2.73	1.10	0.95	0.55	2.18
std	0.52	0.58	0.57	0.57	0.62
se	0.10	0.11	0.11	0.11	0.11
Consumption Growth Coefficient: β_i					
mean	0.13	0.52	0.54	0.85	-0.72
se	0.23	0.05	0.07	0.08	0.30
	Panel B: Unconditional Forward Spread				
	Low	2	3	High	UHML^{FX}
Average Forward Spread (1984-1995)					
mean	-1.54	1.51	3.95	6.12	7.67
Forward Spread: $f_t - s_t$					
mean	-1.71	0.03	0.53	3.93	5.63
se	0.10	0.08	0.10	0.10	0.09
Risk Premia: rx_t					
mean	-1.25	0.03	0.77	3.11	4.36
std	6.12	6.69	9.22	12.05	10.16
se	1.44	1.57	2.17	2.82	2.39
Sharpe ratio					
mean	-0.20	0.00	0.08	0.26	0.43
se	0.24	0.24	0.24	0.24	0.25
	Panel C: Current Forward Spread				
	Low	2	3	High	HML^{FX}
Previous forward spread: $f_{t-1} - s_{t-1}$					
mean	-1.87	0.20	2.33	8.61	10.48
Forward Spread: $f_t - s_t$					
mean	-1.67	0.25	2.33	8.25	9.92
se	0.09	0.08	0.09	0.27	0.28
std	0.50	0.44	0.49	1.46	1.56
Risk Premia: rx_t					
mean	-1.01	1.80	3.99	4.63	5.65
se	1.28	1.28	1.48	1.86	1.51
std	7.11	7.05	8.10	10.16	8.32
Sharpe ratio					
mean	-0.14	0.26	0.49	0.46	0.68
se	0.18	0.19	0.19	0.19	0.20

Summary statistics of portfolios sorted on trade network alpha centrality v_{it}, current log forward spreads $f_t - s_t$, and average log forward spreads from 1/1984 to 12/1995. Each month t currencies are ranked on one of the 3 criteria and placed into 4 portfolios with equal weights. The last column is the difference between the high portfolio and the low portfolio. Log risk premia are $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Real interest rate differentials are forward spreads less the expected inflation differential. Expected inflation is lagged year-over-year change in log CPI. Centrality v_{it} is Katz (1953) centrality of an adjacency matrix of yearly bilateral trade intensities — pair-wise total trade divided by total GDP. Mean, SD, and Sharpe ratios are annualized. Standard errors are from bootstrapping 10,000 samples. Trade data are annual reported exports from the IMF Direction of Trade Statistics and annual output data are GDP from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

negative skewness and large maximum drawdowns. Interestingly, PMC appears to be less exposed to this risk, with a maximum drawdown of 15% compared to 25% for HML^{FX} and 33% for $UHML^{FX}$. This is related to the findings of Bekaert and Panayotov (2015), who show that some carry trades exhibit less skewness than others.

Table 1.3: Summary Statistics of Currency Risk Factors

	PMC	HML^{FX}	$UHML^{FX}$	PMC (2)	HML^{FX} (2)
Mean	3.01	5.65	4.36	3.40	7.22
SD	5.95	8.32	10.16	5.77	8.27
Sharpe Ratio	0.50	0.68	0.43	0.59	0.87
Skewness	− 0.06	− 0.05	− 0.08	− 0.07	− 0.05
Excess Kurtosis	− 0.30	− 0.61	0.18	− 0.01	− 0.58
Maximum Drawdown	0.15	0.25	0.33	0.12	0.20
N	348	359	216	216	216

Risk factors are constructed from excess returns of currencies sorted into 4 portfolios. PMC is from sorts of currencies on prior year trade network alpha centrality and goes long peripheral countries and short central countries. HML^{FX} is from sorts of currencies on currently observable log forward spreads $f_t - s_t$ and goes long high interest rate currencies and short low interest rate currencies. $UHML^{FX}$ is from sorts of currencies on average log forward spreads from 1/1984 to 12/1995 and goes long high average interest rate currencies and short low average interest rate currencies. Summaries for $UHML^{FX}$ are from 1/1996 to 12/2013. Summaries for PMC (2) and HML^{FX} (2) are also are calculated from 1996 to 2013 for comparison to $UHML^{FX}$. All portfolios are rebalanced monthly and moments are annualized. All moments are annualized. Mean and standard deviation are reported in percentage points. Centrality is alpha centrality of an adjacency matrix of yearly bilateral trade intensities — pair-wise total trade divided by total GDP. Trade data are annual reported exports from the IMF Direction of Trade Statistics and GDP from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

1.2.4 Cross-Sectional Asset Pricing Tests

I next show that the returns to PMC can be used to explain the unconditional returns to the currency carry trade. If PMC can be used to explain the returns to the unconditional carry trade, it should co-move with and subsume the excess returns to $UHML^{FX}$. To test this hypothesis, I regress the benchmark risk factors, HML^{FX} and $UHML^{FX}$, on the centrality risk factor PMC

$$(U)HML_t^{FX} = \alpha + \beta PMC_t + \epsilon_t. \tag{1.36}$$

The results are presented in Table (1.4). PMC is highly correlated with $UHML^{FX}$, with a statistically significant β of 1.3. The unexplained excess returns, α, are statistically insignificant and are only 4 basis points annually. PMC is correlated with HML^{FX}, but an unexplained excess return still exist. Because HML^{FX} is constructed using conditional data in current forward spreads, while trade network centrality is and unconditional property of countries, this finding is not surprising.

Table 1.4: Explanatory Regressions for Benchmark Risk Factors

	HML^{FX}	$UHML^{FX}$
α	4.345***	0.038
	(2.979)	(0.021)
β	0.588***	1.270***
	(5.678)	(9.905)
Adj. R^2	0.179	0.517
Num. obs.	348	216

The regression specification is $fac_t = \alpha + \beta PMC_t + \epsilon_t$. fac_t is either HML_t^{FX} or $UHML_t^{FX}$ which are conditional and unconditional carry trade factors. HML_t^{FX} is long currently high forward spread countries and short currently low forward spread countries. $UHML_t^{FX}$ is from a sort on average forward spreads between 1/1984 and 12/1995 - long high forward spread, short low forward spread. PMC_t is long peripheral countries and short central countries. Centrality is calculated as alpha centrality for 39 developed and developing countries using bilateral trade intensity — pair-wise total trade divided by total GDP — as adjacency matrix weights. All factors are from sorts into 4 portfolios. Trade data are annual reported exports from the IMF Direction of Trade Statistics and annual GDP are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013. Standard errors are White (1980). t-statistics in parentheses. ***, ,**, and * denote significance at the 1%, 5% and 10% levels.

Given that PMC explains the unconditional carry trade, a risk-based interpretation implies that low interest rate currencies will have lower loadings on PMC and high interest rate currencies will load more on PMC. Table (1.5) presents time series regressions of individual portfolio excess returns in Table (1.2) on PMC

$$rx_{it}^{fac} = \alpha_i + \beta_i PMC_t + \epsilon_{it} \quad t = 1, 2, \ldots, T, \tag{1.37}$$

where rx_{it}^{fac} is the excess return to portfolio $i = 1 \ldots 4$ and fac is either PMC, HML^{FX}, or $UHML^{FX}$, referring to the portfolios used in the construction of the three risk factors.

Table 1.5: Time series regressions of porfolios on PMC

	Panel A: Current $f-s$			
	1	2	3	4
α_i	-1.829	0.728	2.253	2.497
	(-1.448)	(0.593)	(1.610)	(1.558)
β_i	0.355^{***}	0.472^{***}	0.572^{***}	0.844^{***}
	(5.177)	(6.918)	(6.849)	(6.872)
Adj. R^2	0.101	0.175	0.196	0.289
Num. obs.	348	348	348	348
	Panel B: Average $f-s$ (1984-1995)			
	1	2	3	4
α_i	-1.693	-1.350	-1.373	-0.520
	(-1.143)	(-0.877)	(-0.687)	(-0.220)
β_i	0.136^{**}	0.423^{***}	0.654^{***}	1.110^{***}
	(2.068)	(3.692)	(5.473)	(7.132)
Adj. R^2	0.017	0.169	0.214	0.365
Num. obs.	216	216	216	216
	Panel C: Current Centrality			
	1	2	3	4
α_i	1.496	0.880	0.267	0.917
	(1.391)	(0.546)	(0.172)	(0.800)
β_i	0.856^{***}	0.537^{***}	0.636^{***}	0.192^{**}
	(10.072)	(5.377)	(7.590)	(2.539)
Adj. R^2	0.504	0.133	0.201	0.036
Num. obs.	348	348	348	348

The regression specification is $rx_{it}^{fac} = \alpha_i + \beta_i PMC_t + \epsilon_{it}$. rx_{it}^{fac} is the excess return to portfolio $i = 1 \dots 4$ and fac is either HML^{FX}, $UHML^{FX}$, or PMC, which refer to the portfolios used in the construction of the three risk factors. Portfolios are from sorts into quartiles based on current log forward spreads, HML^{FX}, average log forward spreads from 1984-1995, $UHML^{FX}$, and trade network alpha centrality, PMC. Centrality is Katz (1953) centrality of an adjacency matrix of yearly bilateral trade intensities — pair-wise total trade divided by total GDP. Trade data are annual reported exports from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data is monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013. Standard errors are White (1980). t-statistics in parentheses. ***, ,**, and * denote significance at the 1%, 5% and 10% levels.

Panel A presents regressions of portfolios sorted on current forward spreads on PMC. The portfolios show monontonically increasing factors loadings from high to low interest rates, but unexplained returns are increasing and some are marginally significant. Currencies with currently high interest rates have a temporarily high loading on the HML^{FX} factor, which likely leads to the unexplained excess returns.

Panel B presents results for portfolios sorted on average forward spreads from 1984-1995. Factors loadings are monotonically increasing from low average interest rate portfolios to high average interest rate portfolios and unexplained excess returns are insignificant. This shows that sorts on trade network centrality uncover a source of hetereogenity in unconditional exposure to carry risk.

Panel C presents results of portfolios sorted on alpha centrality, as in the construction of PMC. The portfolios have monotonically decreasing factor loadings from the peripheral portfolio to the central portfolio. Unexplained excess returns are statistically indistinguishable from zero and R-squared values are high, implying that PMC can be used to explain the cross section of centrality sorted portfolios, as well as the average interest rate sorted portolfios of $UHML^{FX}$.

1.3 Conclusion

I have shown that trade network centrality is a significant determinant of a country's unconditional interest rates and currency risk premia. This finding motivates a trading strategy of going long in the currencies of high interest rate countries by borrowing in the currencies of low interest rate countries. The returns to the associated risk factor PMC — peripheral minus central — subsume the unconditional returns to the carry trade. Additionally, central countries' consumption growth covaries more with global consumption growth than peripheral countries'.

The empirical findings arise in an international model with network-based production. Shocks that originate in the center of the production network impact global consumption more than shocks that originate in the periphery. Additionally, shocks have a greater impact on the consumption of the country where they originate, causing central countries' consumption to covary more with global consumption growth. This higher exposure to common consumption growth risk causes central country currencies to appreciate in high marginal utility states, resulting in lower currency risk premia and interest rates.

My findings shed light on fundamental sources of risk exposure across countries. Understanding variation in risk exposure leads to a better understanding of why interest rates differ across countries and why some currencies are fundamentally riskier than others. More broadly, I make a connection between international asset prices and quantities — an important relation that has had tenuous success.

1.4 Model Appendix

This appendix provides derivations of the key equations in the theoretical model.

1.4.1 Definitions of Constants

I define $\mathbf{1}$ as the vector of ones and $\boldsymbol{I}$ as the identity matrix — both are assumed to be of the appropriate dimension. The following constants are used throughout the paper. Their derivations can be found below.

$$\begin{aligned}
\Gamma &= \left(\boldsymbol{I} - (1-\alpha)W'\right)^{-1}\left((1-\theta)\mathbf{1}\right), \\
a_i &= \alpha \log\left(\frac{\Gamma_i \alpha}{\rho\theta + \Gamma_i \alpha}\right) + (1-\alpha)\sum_{j=1}^{N} w_{ij} \log\left(\frac{\Gamma_i (1-\alpha) w_{ij}}{\Gamma_j}\right), \\
b_i &= \theta\rho \log\left(\frac{\rho\theta}{\rho\theta + \Gamma_i \alpha}\right) + \frac{1-\theta}{N}\sum_{j=1}^{N} \log\left(\frac{1-\theta}{N\Gamma_j}\right), \\
d_i &= b_i + \frac{1-\theta}{N}\left(\left(\boldsymbol{I} - (1-\alpha)W\right)^{-1} a\right)' \mathbf{1}, \\
F_t &= \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} v_j z_{jt}\right).
\end{aligned}$$

1.4.2 Derivation of Tradables Production

Starting with the social planners problem and taking first order conditions with respect to C_{jit} and X_{jit} gives Equation (1.18) and Equation (1.19), reproduced here:

$$C_{jit} = \frac{(1-\theta)}{N\Psi_{it}}, \tag{1.38}$$

$$X_{jit} = \frac{\Psi_{jt}\overline{X}_{jt}(1-\alpha)w_{ji}}{\Psi_{it}}. \tag{1.39}$$

Substituting Equation (1.38) and Equation (1.39) into the resource constraint for country i tradables given in Equation (1.16) implies

$$\begin{aligned}\overline{X}_{it} &= \sum_{j=1}^{N} X_{jit} + \sum_{j=1}^{N} C_{jit} \\ &= \sum_{j=1}^{N} \frac{\Psi_{jt}\overline{X}_{jt}(1-\alpha)w_{ji}}{\Psi_{it}} + \sum_{j=1}^{N} \frac{(1-\theta)}{N\Psi_{it}}.\end{aligned}$$

Using the definition $\Gamma_{it} = \overline{X}_{it}\Psi_{it}$ and rearranging gives

$$\Gamma_{it} = (1-\alpha)\left(\sum_{j=1}^{N} \Gamma_{jt} w_{ji}\right) + (1-\theta)\mathbf{1}.$$

Stacking into vectors, defining $\Gamma_t = [\Gamma_{1t}, \ldots, \Gamma_{Nt}]'$, and solving results in

$$\begin{aligned}\Gamma_t &= (1-\alpha)W'\Gamma_t + (1-\theta)\mathbf{1} \\ &= \left(\boldsymbol{I} - (1-\alpha)W'\right)^{-1}\left((1-\theta)\mathbf{1}\right).\end{aligned}$$

This shows that Γ_{it} is a time-invariant function of the model parameters. Therefore, I omit the subscript and define $\Gamma_t = \Gamma$.

First order conditions with respect to L_{it}^N and L_{it}^T give

$$L_{it}^N = \frac{\rho\theta}{G_{it}}, \tag{1.40}$$

$$L_{it}^T = \frac{\Psi_{it}\overline{X}_{jt}\alpha}{G_{it}} = \frac{\Gamma_i\alpha}{G_{it}}. \tag{1.41}$$

Plugging these FOCs into the labor market clearing gives

$$1 = L_{it}^N + L_{it}^T = \frac{\rho\theta}{G_{it}} + \frac{\Gamma_i\alpha}{G_{it}} \implies G_{it} = \rho\theta + \Gamma_i\alpha \tag{1.42}$$

Redefining Equation (1.39) in terms of Γ_i and substituting it into the log production function tradables for sector i in Equation (1.8) gives

$$\begin{aligned}
\log\left(\overline{X}_{it}\right) &= \log\left(\left(Z_{it}\right)^{\alpha}\left(L_{it}^T\right)^{\alpha}\prod_{j=1}^{N}\left(X_{ijt}\right)^{(1-\alpha)w_{ij}}\right) \\
&= \alpha\log Z_{it} + \alpha\log L_{it}^T + (1-\alpha)\sum_{j=1}^{N} w_{ij}\log\left(X_{ijt}\right) \\
&= \alpha\log Z_{it} + \alpha\log\left(\frac{\Gamma_i\alpha}{\rho\theta+\Gamma_i\alpha}\right) + (1-\alpha)\sum_{j=1}^{N} w_{ij}\log\left(\frac{\Gamma_i(1-\alpha)w_{ij}}{\Gamma_j}\overline{X}_{jt}\right) \\
&= \alpha\log Z_{it} + a_i + (1-\alpha)\sum_{j=1}^{N} w_{ij}\log\overline{X}_{jt},
\end{aligned}$$

where the constant a_i is defined as:

$$a_i = \alpha\log\left(\frac{\Gamma_i\alpha}{\rho\theta+\Gamma_i\alpha}\right) + (1-\alpha)\sum_{j=1}^{N} w_{ij}\log\left(\frac{\Gamma_i(1-\alpha)w_{ij}}{\Gamma_j}\right).$$

Stacking into vectors and solving gives

$$\begin{aligned}
\overline{x}_t &= \alpha z_t + a + (1-\alpha)W\overline{x}_t \\
&= \left(\boldsymbol{I} - (1-\alpha)W\right)^{-1}\left(\alpha z_t + a\right),
\end{aligned}$$

where $\overline{x}_t = \left[\log(\overline{X}_{1t}), \ldots, \log(\overline{X}_{Nt})\right]'$, $z_t = [\log(Z_{1t}), \ldots, \log(Z_{Nt})]'$, and $a = [a_1, \ldots, a_N]'$.

This is Equation (1.21).

1.4.3 Derivation of Consumption Baskets

Defining Equation (1.18) in terms of Γ_i gives

$$\begin{aligned} C_{jit} &= \frac{(1-\theta)}{N\Psi_{it}} \\ &= \frac{(1-\theta)}{N\Gamma_i}\overline{X}_{it} \end{aligned} \tag{1.43}$$

Taking log of Equation (1.15) gives

$$\begin{aligned} \log \overline{C}_{it} &= \log\left(\left((Z_{it})^{\rho}\left(L_{it}^{N}\right)^{\rho}(Y_{it})^{1-\rho}\right)^{\theta}\prod_{j=1}^{N}(C_{ijt})^{\frac{(1-\theta)}{N}}\right) \\ &= \theta\left(\rho z_{it} + \rho\log\left(L_{it}^{N}\right) + (1-\rho)y_{it}\right) + \frac{1-\theta}{N}\sum_{j=1}^{N}\log C_{ijt} \\ &= \theta\left(\rho z_{it} + \rho\log\left(\frac{\rho\theta}{\rho\theta+\Gamma_i\alpha}\right) + (1-\rho)y_{it}\right) + \frac{1-\theta}{N}\sum_{j=1}^{N}\log\left(\frac{1-\theta}{N\Gamma_j}\overline{X}_{jt}\right) \\ &= \theta\left(\rho z_{it} + (1-\rho)y_{it}\right) + b_i + \frac{1-\theta}{N}\sum_{j=1}^{N}\overline{x}_{jt}, \end{aligned}$$

where the third equality replaces C_{ijt} with Equation (1.43), and b_i is a constant defined as:

$$b_i = \theta\rho\log\left(\frac{\rho\theta}{\rho\theta+\Gamma_i\alpha}\right) + \frac{1-\theta}{N}\sum_{j=1}^{N}\log\left(\frac{1-\theta}{N\Gamma_j}\right).$$

Defining $\overline{c}_t = \left[\log(\overline{C}_{1t}),\ldots,\log(\overline{C}_{Nt})\right]'$, $y_t = [\log(Y_{1t}),\ldots,\log(Y_{Nt})]'$, $b = [b_1,\ldots,b_N]'$, stacking into a vector, and plugging in the production vector Equation (1.21) gives Equation

(1.22):

$$
\begin{aligned}
\overline{c}_t &= \theta\left(\rho z_t + (1-\rho)y_t\right) + b_i + \frac{1-\theta}{N}\overline{x}_t'\mathbf{1} \\
&= \theta\left(\rho z_t + (1-\rho)y_t\right) + b + \frac{1-\theta}{N}\left(\left(\boldsymbol{I} - (1-\alpha)W\right)^{-1}\left(\alpha z_t + a\right)\right)'\mathbf{1} \\
&= \theta\left(\rho z_t + (1-\rho)y_t\right) + \frac{1-\theta}{N}\left(\left(\boldsymbol{I} - (1-\alpha)W\right)^{-1}\left(\alpha z_t\right)\right)'\mathbf{1} + d \\
&= \theta\left(\rho z_t + (1-\rho)y_t\right) + \frac{(1-\theta)\alpha}{N}\left(z_t'\left(\boldsymbol{I} - (1-\alpha)W'\right)^{-1}\mathbf{1}\right) + d,
\end{aligned}
$$

where d is a vector of constants with elements given by

$$
d_i = b_i + \frac{1-\theta}{N}\left(\left(\boldsymbol{I} - (1-\alpha)W\right)^{-1}a\right)'\mathbf{1}. \tag{1.44}
$$

Defining alpha centrality for country i as

$$
v_i = \left[(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}\right]_i, \tag{1.45}
$$

log consumption at time t for country i, given in Equation (1.24), is

$$
\begin{aligned}
\overline{c}_{it} &= \theta\left[\rho z_{it} + (1-\rho)y_{it}\right] + \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} v_j z_{jt}\right) + d_i \\
&= \theta\left[\rho z_{it} + (1-\rho)y_{it}\right] + F_t + d_i,
\end{aligned}
$$

where F_t is given by

$$
F_t = \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} v_j z_{jt}\right).
$$

1.4.4 Proof of Proposition (1)

Using Equation (1.24) and that $z_{i1} = \log(Z_{i1}) = \log(1) = 0$ and $y_{i1} = \log(Y_{i1}) = \log(1) = 0$, change in log consumption in country i is given by

$$\Delta \overline{c}_{it} = \theta \left(\rho z_{i2} + (1-\rho) y_{i2} \right) + \frac{(1-\theta)\alpha}{N} \left(\sum_{j=1}^{N} v_j z_{j2} \right). \tag{1.46}$$

Average global consumption growth is given by

$$\widehat{\Delta \overline{c}_2} = \left(\frac{1}{N} \sum_{j=1}^{N} \left(\theta\rho + v_j \alpha (1-\theta) \right) z_{j2} \right) + \left(\frac{\theta(1-\rho)}{N} \sum_{j=1}^{N} y_{j2} \right).$$

I define σ_z^2 as the variance of z_{i2} for all i. Using that time 2 shocks are i.i.d, as in Equation (1.3) and Equation (1.4), the covariance of country i consumption growth with world average consumption growth is:

$$\mathrm{Cov}(\Delta \overline{c}_{it}, \widehat{\Delta \overline{c}_2}) - \mathrm{Cov}(\Delta \overline{c}_{jt}, \widehat{\Delta \overline{c}_2}) = \frac{\sigma_z^2}{N} \theta \rho \alpha (1-\theta)(v_i - v_j).$$

This immediately implies Proposition (1).

1.4.5 Proof of Proposition (2)

I first show the currency log risk premia equal log interest rate differentials. Equation (1.29) implies that $E\left[\Delta q_{ij2}\right] = E\left[m_{i2}\right] - E\left[m_{j2}\right]$. The log IMRS in each country is given in Equation (1.28):

$$m_{i2} = \delta - \theta \left(\rho z_{i2} + (1-\rho) y_{i2} \right) - \frac{(1-\theta)\alpha}{N} \left(\sum_{j=1}^{N} v_j z_{j2} \right).$$

Using that z_{i2} and y_{i2} are i.i.d. for all i implies $E\left[\Delta q_{ij2}\right] = 0$. Therefore, currency risk premia are equal to interest rate differentials: $E\left[rx_{ij2}\right] = rf_{j1} - rf_{i1}$. Therefore, I focus on interest rate differentials for the remainder of the proof.

Expanding the log interest rate differential from Equation (1.30) gives

$$
\begin{aligned}
rf_{j1} - rf_{i1} &= \log E\left[M_{i2}\right] - \log E\left[M_{j2}\right] \\
&= \log E\left[e^{m_{i2}}\right] - \log E\left[e^{m_{j2}}\right] \\
&= \log E\left[e^{\delta - \theta(\rho z_{i2} + (1-\rho) y_{i2}) - \frac{(1-\theta)\alpha}{N}\left(\sum_{k=1}^{N} v_k z_{k2}\right)}\right] \qquad (1.47) \\
&- \log E\left[e^{\delta - \theta(\rho z_{j2} + (1-\rho) y_{j2}) - \frac{(1-\theta)\alpha}{N}\left(\sum_{k=1}^{N} v_k z_{k2}\right)}\right] \\
&= \left(K_z\left(-\frac{(1-\theta)\alpha}{N} v_j\right) - K_z\left(-\theta\rho - \frac{(1-\theta)\alpha}{N} v_j\right)\right) \qquad (1.48) \\
&- \left(K_z\left(-\frac{(1-\theta)\alpha}{N} v_i\right) - K_z\left(-\theta\rho - \frac{(1-\theta)\alpha}{N} v_i\right)\right), \qquad (1.49)
\end{aligned}
$$

where the last inequality uses the fact that z_{i2} and y_{i2} are i.i.d. and defines the cumulant generating function of z_{i2} as $K_z(h) = \log E\left[e^{hz}\right]$. Cumulant generating functions have nice properties that make them useful for asset pricing[7]. In particular, the expression assuming normality of z_{i2} in Equation (1.32) follows directly from the fact that $K_z(h) = \mu_z h + \sigma_z^2 h^2/2$ when z is normally distributed.

To show in general that $rf_{j1} > rf_{i1}$ when $v_i > v_j$, I exploit the (strict) convexity and differentiability of cumulant generating functions (see Billingsley (2008)). Starting from the term in Equation (1.49), assuming without loss of generality that $v_i > v_j$, and rewriting as an integral gives

[7] See Backus, Chernov, and Zin (2014) and Martin (2013) for recent examples.

$$
\begin{aligned}
K_z\left(-\frac{(1-\theta)\alpha}{N}v_i\right) - K_z\left(-\theta\rho - \frac{(1-\theta)\alpha}{N}v_i\right) \\
&= \int\limits_{-\theta\rho-\frac{(1-\theta)\alpha}{N}v_i}^{-\frac{(1-\theta)\alpha}{N}v_i} K_z'(h)\ \mathrm{d}h \\
&= \int\limits_{-\theta\rho-\frac{(1-\theta)\alpha}{N}v_j}^{-\frac{(1-\theta)\alpha}{N}v_j} K_z'\left(h + \frac{(1-\theta)\alpha}{N}v_j - \frac{(1-\theta)\alpha}{N}v_i\right)\ \mathrm{d}h \\
&< \int\limits_{-\theta\rho-\frac{(1-\theta)\alpha}{N}v_j}^{-\frac{(1-\theta)\alpha}{N}v_j} K_z'(h)\ \mathrm{d}h \\
&= K_z\left(-\frac{(1-\theta)\alpha}{N}v_j\right) - K_z\left(-\theta\rho - \frac{(1-\theta)\alpha}{N}v_j\right).
\end{aligned}
$$

The inequality comes from the fact that for a non-degenerate distribution, the cumulant generating function K_z is strictly convex. This implies that if $x > y$ then $K_z'(x) > K_z'(y)$. The above shows that when $v_i > v_j$ Equation (1.49) is greater than Equation (1.48). Therefore, $rf_{j1} - rf_{i1} > 0$. Because interest rate differentials equal currency risk premia, $E\left[rx_{ij2}\right] > 0$, proving Proposition (2).

1.5 Empirical Appendix

This appendix contains data descriptions, additional empirical tests, and robustness checks.

1.5.1 Data Description

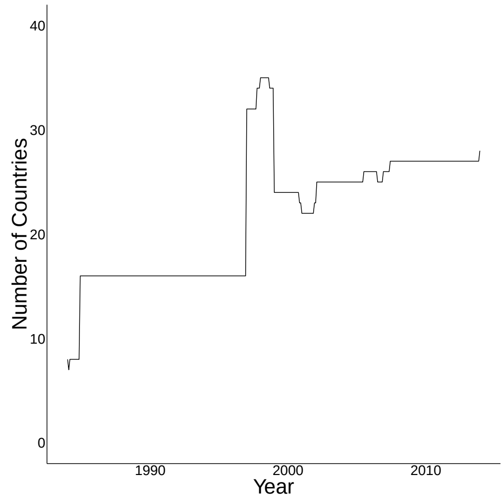
Table (1.6) reports the sample of countries that I have FX data for and which I can calculate trade network centrality. Figure (1.4) shows how the size of the sample changes over time. Following Lustig, Roussanov, and Verdelhan (2011) I omit the following observations due to large deviations from covered interest parity: South Africa in August 1985, Malaysia from September 1998 to June 2005, Indonesia from January 2001 to May 2007, Turkey from November 2000 to November 2001, and United Arab Emirates from July 2006 to November 2006.

Table 1.6: Sample of Countries with FX Data and Trade Data

Country	Start Date	End Date
Australia	Dec 1984	Dec 2013
Austria	Jan 1997	Dec 1998
Belgium	Jan 1997	Dec 1998
Canada	Dec 1984	Dec 2013
Czech Republic	Jan 1997	Dec 2013
Denmark	Dec 1984	Dec 2013
Europe	Jan 1999	Dec 2013
Finland	Jan 1997	Dec 1998
France	Jan 1984	Dec 1998
Germany	Jan 1984	Dec 1998
Greece	Jan 1997	Dec 1998
Hong Kong	Jan 1984	Dec 2013
Hungary	Oct 1997	Dec 2013
India	Oct 1997	Dec 2013
Indonesia	Jan 1997	Dec 2013
Ireland	Jan 1997	Dec 1998
Italy	Mar 1984	Dec 1998
Japan	Jan 1984	Dec 2013
Korea, Republic of	Feb 2002	Dec 2013
Kuwait	Jan 1997	Dec 2013
Malaysia	Dec 1984	Dec 2013
Mexico	Jan 1997	Dec 2013
Netherlands	Jan 1984	Dec 1998
New Zealand	Dec 1984	Dec 2013
Norway	Dec 1984	Dec 2013
Philippines	Jan 1997	Dec 2013
Poland	Feb 2002	Dec 2013
Portugal	Jan 1997	Dec 1998
Saudi Arabia	Jan 1997	Dec 2013
Singapore	Dec 1984	Dec 2013
South Africa	Jan 1998	Dec 2013
Spain	Jan 1997	Dec 1998
Sweden	Dec 1984	Dec 2013
Switzerland	Jan 1984	Dec 2013
Thailand	Jan 1997	Dec 2013
Turkey	Jan 1997	Dec 2013
United Arab Emirates	Jan 1997	Dec 2013
United Kingdom	Jan 1984	Dec 2013
United States	Jan 1984	Dec 2013

This table reports the sample of countries that have both trade data and foreign exchange data. Trade data are annual reported exports from 1973 to 2013 from the IMF Direction of Trade Statistics. Annual GDP is from the World Bank in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

Figure 1.4: Number of Countries in Combined Dataset



This figure plots the number of countries that have both trade data and foreign exchange data across time. Trade data are annual reported exports from 1973 to 2013 from the IMF Direction of Trade Statistics. Annual GDP is from the World Bank. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

1.5.2 Sorts with Alternative Network Weights

For robustness, Table (1.7) presents portfolios sorted on alpha centrality using three different network weights. For comparison, Panel A presents network weights measured as total trade normalized by total output as in Table (1.2). Panel B presents results with network weights measured as exports normalized by total output. Panel C presents results with network weights measured as imports normalized by total output. All results are consistent with Table (1.2). Measuring trade link strength with imports rather than exports produces higher returns and Sharpe ratios, which implies that the model mechanism may operate more through importing relationships.

1.5.3 Sorts on Average Rank

Due to the possibility of structural changes in the trade network as countries enter and exit the sample and as the euro is introduced, I report portfolio sorts using prior year trade network centrality in Panel A of Table (1.2). That said, trade network centrality is an unconditional property of countries, so results should be robust to sorting on the full sample

Table 1.7: Portfolio Sorts Using Alternative Network Weights

	Panel A: Total Trade Network Weights				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.08	1.13	1.19	1.36	−0.28
Forward Spread: $f_t - s_t$					
mean	5.42	1.66	1.42	0.01	5.41
std	1.23	0.56	0.60	0.51	1.24
se	0.23	0.10	0.11	0.09	0.23
Risk Premia: rx_t					
mean	4.62	2.84	2.59	1.62	3.01
std	7.53	9.10	8.80	6.05	5.95
se	1.38	1.66	1.62	1.10	1.10
Sharpe ratio					
mean	0.61	0.31	0.29	0.27	0.50
se	0.21	0.19	0.19	0.19	0.20
Consumption Growth Coefficient: β_i					
mean	0.13	0.52	0.54	0.85	−0.72
se	0.23	0.05	0.07	0.08	0.30
	Panel B: Export Network Weights				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.03	1.06	1.08	1.15	−0.12
Forward Spread: $f_t - s_t$					
mean	4.58	2.27	1.47	0.23	4.35
std	1.25	0.85	0.55	0.49	1.30
se	0.23	0.16	0.10	0.09	0.24
Risk Premia: rx_t					
mean	4.09	3.71	2.15	1.80	2.29
std	7.11	9.41	8.49	6.22	5.79
se	1.33	1.75	1.57	1.15	1.09
Sharpe ratio					
mean	0.57	0.39	0.25	0.29	0.40
se	0.20	0.19	0.19	0.19	0.20
Consumption Growth Coefficient: β_i					
mean	0.11	0.53	0.55	0.84	−0.73
se	0.22	0.03	0.07	0.07	0.29
	Panel C: Import Network Weights				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.03	1.06	1.09	1.16	−0.12
Forward Spread: $f_t - s_t$					
mean	5.49	1.80	1.29	−0.08	5.57
std	1.20	0.62	0.63	0.46	1.25
se	0.22	0.12	0.12	0.09	0.23
Risk Premia: rx_t					
mean	4.58	2.62	2.77	1.74	2.84
std	7.10	9.52	8.97	5.55	5.55
se	1.32	1.75	1.65	1.02	1.04
Sharpe ratio					
mean	0.64	0.27	0.31	0.31	0.51
se	0.21	0.19	0.19	0.19	0.20
Consumption Growth Coefficient: β_i					
mean	0.13	0.50	0.58	0.86	−0.73
se	0.23	0.05	0.07	0.08	0.30

Summary statistics of portfolios sorted on trade network alpha centrality v_{it} using different network weights. For each month t currencies are ranked trade network centrality and sorted into four portfolios. Log risk premia are $rx_t = f_{t-1} - s_t$. Centrality v_{it} is alpha centrality of an adjacency matrix with elements that are either total trade, exports, or imports — all normalized by pair-wise total GDP. Means and standard deviations are annualized. Sharpe ratios are the annualized mean divided by the annualized standard deviation. Standard errors are from bootstrapping 10,000 samples. Trade data are annual reported exports from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

average of countries' trade network centrality. Table (1.8) presents portfolios sorts using the full sample average of countries' trade network centrality ranking. Results are consistent with those found in the main text.

Table 1.8: Portfolios Sorted on Full Sample Average Centrality Ranking

	Panel A: Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Average Centrality Rank					
mean	8.77	17.50	24.09	30.40	-21.62
Forward Spread: $f_t - s_t$					
mean	4.62	2.28	1.17	0.23	4.39
std	0.12	0.06	0.05	0.05	0.13
se	0.22	0.11	0.09	0.10	0.23
Risk Premia: rx_t					
mean	3.03	2.34	1.56	1.69	1.33
std	7.46	8.08	8.86	8.04	6.31
se	1.34	1.47	1.60	1.46	1.15
Sharpe ratio					
mean	0.41	0.29	0.18	0.21	0.21
se	0.19	0.19	0.18	0.18	0.19
Real Interest Differential: $r_{it} - r_t$					
mean	2.07	0.91	0.63	1.06	1.01
std	0.06	0.06	0.05	0.06	0.06
se	0.10	0.12	0.10	0.12	0.11
Consumption Growth Coefficient: β_i					
mean	0.39	0.47	0.71	1.02	-0.63
se	0.19	0.09	0.02	0.05	0.23

Summary statistics of portfolios sorted on full sample average trade network alpha centrality ranking. For each month t currencies are ranked according to their countries' average ranking throughout the sample and placed into four portfolios with equal weights. Rankings each period are normalized to be between 1 and 38 (maximum number of countries in the sample) so that they are comparable across time. The last column is the difference between the high portfolio and the low portfolio. Log risk premia are $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Centrality is Katz (1953) centrality of an adjacency matrix of yearly bilateral trade intensities — pair-wise total trade divided by total GDP. Means and standard deviations are annualized. Sharpe ratios are the annualized mean divided by the annualized standard deviation. Trade data are annual reported exports from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

1.5.4 Sorts Omitting the Euro Aggregate

Table (1.9) presents portfolio sorts on data omitting the euro area aggregate and maintaining the euro countries after 1999. FX observations are still dropped for currencies that secede to the euro. All results are consistent with Table (1.2). Currency risk premia and interest rates are decreasing in centrality and consumption growth coefficients are increasing in centrality.

Table 1.9: Portfolios Sorted on Centrality (No Euro Aggregate)

	Panel A: Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.07	1.13	1.18	1.36	-0.28
Forward Spread: $f_t - s_t$					
mean	5.54	1.56	1.59	0.04	5.50
std	1.26	0.56	0.59	0.51	1.25
se	0.23	0.10	0.11	0.09	0.23
Risk Premia: rx_t					
mean	4.71	2.85	2.63	1.60	3.11
std	7.42	9.30	8.47	6.02	5.89
se	1.39	1.73	1.58	1.12	1.09
Sharpe ratio					
mean	0.63	0.31	0.31	0.27	0.53
se	0.20	0.19	0.19	0.19	0.20
Real Interest Differential: $r_{it} - r_t$					
mean	2.79	1.09	0.96	0.58	2.21
std	0.54	0.58	0.56	0.58	0.62
se	0.10	0.11	0.10	0.11	0.11
Consumption Growth Coefficient: β_i					
mean	0.08	0.56	0.56	0.85	-0.77
se	0.25	0.03	0.07	0.08	0.32

Summary statistics of portfolios sorted on trade network centrality v_{it}. Centrality is calculated only on country observations and does not include an aggregate for the euro area. Each month t currencies are ranked on their prior year trade network centrality. The last column is the difference between the high portfolio and the low portfolio. Log risk premia are $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Real interest rate differentials are forward spreads less the expected inflation differential. Expected inflation is lagged year-over-year change in log CPI. Centrality v_{it} is Katz (1953) centrality of an adjacency matrix of yearly bilateral trade intensities — pair-wise total trade divided by total GDP. Mean, SD, and Sharpe ratios are annualized. Standard errors are from bootstrapping 10,000 samples. Trade data are annual reported exports from the IMF Direction of Trade Statistics and annual output data are GDP from the World Bank, both in dollars. For the euro area, observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

1.5.5 Sorts Using Centrality Constructed with All Countries

Table (1.10) presents portfolio sorts using a centrality measure constructed using all trade data available from the IMF's Direction of Trade Statistics. FX observations are still dropped for currencies that secede to the euro. As in Table (1.2), currency risk premia and interest rates are decreasing in centrality. The consumption growth coefficients are also increasing in centrality.

Table 1.10: Portfolios Sorted on Centrality Constructed with All Trade Data

	Panel A: Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.11	1.17	1.24	1.48	-0.37
Forward Spread: $f_t - s_t$					
mean	4.14	2.81	1.76	0.12	4.02
std	0.87	1.16	0.57	0.48	0.90
se	0.16	0.22	0.11	0.09	0.17
Risk Premia: rx_t					
mean	3.74	2.81	2.58	0.99	2.75
std	7.61	8.32	9.30	5.51	5.64
se	1.45	1.58	1.77	1.05	1.07
Sharpe ratio					
mean	0.49	0.34	0.28	0.18	0.49
se	0.21	0.19	0.20	0.19	0.20
Real Interest Differential: $r_{it} - r_t$					
mean	2.47	1.21	1.23	0.38	2.09
std	0.55	0.58	0.58	0.55	0.71
se	0.10	0.11	0.11	0.10	0.13
Consumption Growth Coefficient: β_i					
mean	0.16	0.40	0.64	0.86	-0.70
se	0.22	0.10	0.04	0.07	0.26

Summary statistics of portfolios sorted on trade network centrality v_{it}. Centrality is calculated using all 173 reporting countries in the IMF DOTS. Each month t currencies are ranked on their prior year trade network centrality. The last column is the difference between the high portfolio and the low portfolio. Log risk premia are $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Real interest rate differentials are forward spreads less the expected inflation differential. Expected inflation is lagged year-over-year change in log CPI. Centrality v_{it} is Katz (1953) centrality of an adjacency matrix of yearly bilateral trade intensities — pair-wise total trade divided by total GDP. Mean, SD, and Sharpe ratios are annualized. Standard errors are from bootstrapping 10,000 samples. Trade data are annual reported exports from the IMF Direction of Trade Statistics and annual output data are GDP from the World Bank, both in dollars. For the euro area, observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

1.5.6 Sorts Omitting Pegs

Table (1.11) presents portfolio sorts using a subset of observations which omits currency pegs. The pegs classification is from Shambaugh (2004) and I omit currency-month observations if a currency is classified as pegged to any other currency. FX observations are still dropped for currencies that secede to the euro. As in Table (1.2), currency risk premia and interest rates are decreasing in centrality. The consumption growth coefficients are also increasing in centrality.

Table 1.11: Portfolios Sort Omitting Pegged Currencies

	Panel A: Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.07	1.12	1.17	1.36	-0.29
Forward Spread: $f_t - s_t$					
mean	6.68	2.15	2.23	0.16	6.52
std	1.75	0.94	0.67	0.56	1.82
se	0.33	0.18	0.13	0.10	0.35
Risk Premia: rx_t					
mean	4.60	2.35	3.09	1.26	3.35
std	8.13	10.89	9.70	6.47	7.54
se	1.55	2.06	1.83	1.22	1.42
Sharpe ratio					
mean	0.57	0.22	0.32	0.19	0.44
se	0.21	0.19	0.19	0.19	0.20
Real Interest Differential: $r_{it} - r_t$					
mean	2.84	1.20	1.28	1.01	1.82
std	0.51	0.71	0.53	0.62	0.65
se	0.10	0.13	0.10	0.11	0.12
Consumption Growth Coefficient: β_i					
mean	0.18	0.49	0.49	0.86	-0.68
se	0.16	0.05	0.07	0.12	0.27

Summary statistics of portfolios sorted on trade network alpha centrality v_{it} using a subset of currencies which are not pegged. For each month t currencies are ranked trade network centrality and sorted into four portfolios. Log risk premia are $rx_t = f_{t-1} - s_t$. Centrality v_{it} is alpha centrality of an adjacency matrix with elements that are either total trade, exports, or imports — all normalized by pair-wise total GDP. Means and standard deviations are annualized. Sharpe ratios are the annualized mean divided by the annualized standard deviation. Standard errors are from bootstrapping 10,000 samples. Trade data are annual reported exports from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013. Data on currency pegs is from Shambaugh (2004).

1.5.7 Sorts on Developed Subset

Table (1.12) presents portfolio sorts using a subset of developed countries: Australia, Austria, Belgium, Canada, Denmark, Europe, France, Germany, Hong Kong, Ireland, Italy, Japan, Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Switzerland,

and United Kingdom. FX observations are still dropped for currencies that secede to the euro. As in Table (1.2), currency risk premia and interest rates are decreasing in centrality. The consumption growth coefficients are no longer monotonically increasing in centrality, although a large spread remains between central and peripheral portfolios.

Table 1.12: Portfolios Sorts With Developed Subset

	Panel A: Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	1.09	1.15	1.20	1.41	-0.31
Forward Spread: $f_t - s_t$					
mean	1.75	0.49	0.73	-0.40	2.15
std	0.68	0.58	0.64	0.45	0.76
se	0.13	0.11	0.12	0.09	0.14
Risk Premia: rx_t					
mean	2.62	2.65	2.15	1.13	1.49
std	8.23	9.65	9.45	6.01	6.81
se	1.53	1.80	1.77	1.11	1.27
Sharpe ratio					
mean	0.32	0.27	0.23	0.19	0.22
se	0.19	0.19	0.19	0.19	0.19
Real Interest Differential: $r_{it} - r_t$					
mean	1.89	0.93	0.81	0.64	1.25
std	0.55	0.52	0.51	0.85	0.94
se	0.10	0.10	0.10	0.16	0.18
Consumption Growth Coefficient: β_i					
mean	0.74	0.40	0.89	1.19	-0.45
se	0.05	0.08	0.08	0.09	0.13

Summary statistics of portfolios sorted on trade network alpha centrality v_{it} using a subset of developed country currencies. For each month t currencies are ranked trade network centrality and sorted into four portfolios. Log risk premia are $rx_t = f_{t-1} - s_t$. Centrality v_{it} is alpha centrality of an adjacency matrix with elements that are either total trade, exports, or imports — all normalized by pair-wise total GDP. Means and standard deviations are annualized. Sharpe ratios are the annualized mean divided by the annualized standard deviation. Standard errors are from bootstrapping 10,000 samples. Trade data are annual reported exports from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

1.5.8 Correlation of Risk Factors

The correlation table of the currency risk factors is in Table (1.13).

Table 1.13: Correlation of Currency Risk Factors

	PMC	HML^{FX}	$UHML^{FX}$
PMC	1.00		
HML^{FX}	0.43	1.00	
$UHML^{FX}$	0.72	0.65	1.00

Risk factors are constructed from excess returns of currencies sorted into four portfolios. PMC is from sorts on prior year trade network alpha centrality — long peripheral countries and short central countries. HML^{FX} is from sorts of currencies on currentl log forward spreads $f_t - s_t$ — long high interest rate currencies and short low interest rate currencies. $UHML^{FX}$ is from sorts of currencies on average log forward spreads from 1/1984 to 12/1995. Summaries for $UHML^{FX}$ are calculated from 1/1996 to 12/2013. All moments are annualized. Trade data are annual reported exports from the IMF Direction of Trade Statistics and annual GDP data are from the World Bank, both in dollars. For the euro area, I construct an aggregate with all countries that adopted the euro, beginning in 1999. Observations are omitted after a country secedes its currency to the euro. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1984 to 12/2013.

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CHAPTER 2

Gravity in FX R^2:

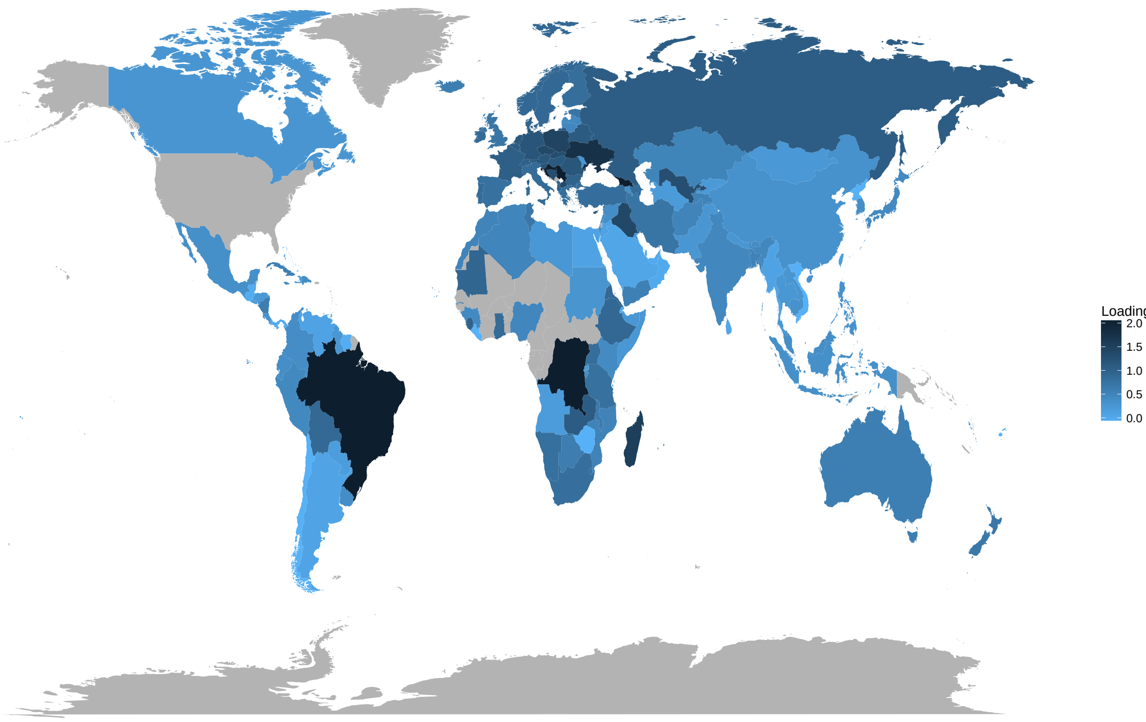
Understanding the Factor Structure in Exchange Rates

(with Hanno Lustig)

Much like the returns on stocks and other assets, changes in spot exchange rates have a strong factor structure (Verdelhan, 2012; Lustig, Roussanov, and Verdelhan, 2011). For example, all currencies co-move against the USD: When the USD appreciates by 1%, some currencies depreciate by much more than 1%, while others depreciate by much less than 1%. We find that distance is a key determinant of exposure to base currency factors. For example, currencies of countries that are close to the U.S. tend to have low exposures to the dollar factor. These currencies depreciate less than 1% when the USD appreciates by 1%, while the currencies of distant countries tend to depreciate by much more than 1%. To visualize this distance effect, Figure (2.1) plots the betas on the USD factor on a map. Physical distance to the U.S. clearly has a large impact on the dollar betas. We refer to this as the gravity effect.

Our measures of distance include not only physical distance, but also shared language, legal origin, shared border, colonial linkages and resource similarity. The average beta for a given base currency is one. Doubling the distance between a country and the base country increases the beta by 0.15. A shared language lowers the beta between 0.11 and 0.15. In the case of U.S. based exchange rates, the beta on the dollar factor decreases by 0.50 when the other country uses English as one of its main languages. Shared border lowers the beta by another 0.08 to 0.14, while colonial linkages lower the betas by up to 0.32. Natural resource similarity further lowers the betas.

Figure 2.1: Loadings on USD Factor



Map of $\beta^{base}_{\$,j}$ from the regression $\Delta s_{\$,j,t} = \alpha_{i,j} + \beta^{base}_{\$,j} base_{\$,t} + e_{i,j,t}$ for each possible base currency i. For each currency j, $base_{\$t}$ 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.

The distance effect is not driven by emerging market currencies. When we exclude emerging market currencies, the distance effect increases from 0.15 to 0.25. Shared legal origin further lowers the betas by 0.31 among this subset of developed countries. When we explicitly control for pegs, some of these effects are mitigated, but the same gravity forces operate on nominal exchange rate betas when we completely drop the pegs from the sample. This mitigating effect is not surprising. We show that the same economic distance measures also determine the likelihood a peg between two currencies. The gravity variables account for about 1/4 of all the variation in the betas. As a result, the covariation structure of exchange rates is determined by largely exogenous initial conditions.

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. 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). In a standard model, shipping costs that increase log-linearly in distance do give rise to a gravity equation indirectly. However, if shipping costs were the sole driver, then the distance effect should have decreased over time, but there is no evidence of this. Our paper is the first to show that distance is also a key determinant of exchange rate covariation.

Our paper examines the determinants of currency betas from regressions of bilateral exchange rate changes on base factors. We model these betas as proportional to distance. The gravity model accounts for a large fraction of the variation in currency betas across countries. When a country is 'close' to the base country, its nominal exchange rate is less sensitive to the common variation. As a result, systematic variation will only account for a small share of the overall variation in its nominal exchange rate against the base currency and the R^2 in these regressions will be lower.

An implication of our gravity-based factor model of exchange rates is that countries that are distant economically from most other countries will tend to 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 in the data: distant countries have high average R^2 in these exchange rate factor regressions, countries at the center tend to have low R^2.

We can rationalize our findings in a no-arbitrage, complete markets model of exchange rates. In the model, the loadings of country's pricing kernel on common sources of risk must differ more for distant country pairs than for close country pairs. This generates larger betas on the base factor for the exchange rates of distant country pairs. Additionally, for 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.

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) and 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), and Harvey, Solnik, and Zhou (2002); world multi-beta models, Ferson and Harvey (1993); and more recently work on time-varying capital market integration by Bekaert and Harvey (1995) and 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.

While we understand the determinants of stock return betas (e.g. leverage or growth options), much less is known about the determinants of currency betas with respect to global risk factors. Currency betas determine a currency's risk characteristics and returns (Lustig, Roussanov, and Verdelhan, 2011; Menkhoff, Sarno, Schmeling, and Schrimpf, 2012). Currencies of countries that are distant from the U.S. have a high beta with respect to the dollar factor and hence add more systematic risk to a U.S. investor's well-diversfied portfolio of long positions in foreign currency. Recently, Hassan (2013), Ready, Roussanov, and Ward (2013) and Richmond (2015) develop theories that shed light on the origins of currency betas. 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 equilibrium model, the real exchange rate of commodity exporters tend to depreciate in case of 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.

Our finding 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. 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. That said, the size and persistence of these effects suggests that shipping costs are only a small part of the story.

The rest of this paper is organized as follows. Section (2.1) describes the data. Section (2.2) documents the factor structure in bilateral exchange rates, extending the work by Verdelhan (2012) who focuses on the factor structure in bilateral exchange rates against the dollar to other base currencies. Section (2.3) tests the gravity model of exchange rate co-variation. Section (2.4) checks the robustness of our findings. Section (2.5) concludes.

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. 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 (2.4) we present robustness tests on the full and developed samples. We provide additional details of the sample construction in Section (2.6).

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 other or they were pegged same currency at any point in the prior 6 years.

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 The Factor Structure in Exchange Rates

We consider a class of linear factor models for exchange rate variation. There are multiple factors driving exchange rate variation:

$$\Delta s_{i,j,t} = \alpha_{i,j} + \boldsymbol{\gamma}'_{i,j}\boldsymbol{f}_t + e_{i,j,t} \ , \tag{2.1}$$

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: $\Delta \boldsymbol{s}_{i,t} = \boldsymbol{\Gamma}_0 + \boldsymbol{\Gamma}_i \boldsymbol{f}_t + \boldsymbol{e}_{i,t}$, where $\boldsymbol{\Gamma}_i$ is the $N \times K$ matrix of loadings. The variance-covariance matrix of exchange rates is $\boldsymbol{\Gamma}_i \boldsymbol{\Gamma}'_i + \boldsymbol{\Sigma}_{e,i}$.

To simplify the analysis, we use a different base factor $base_{i,t}$ for each base currency i.

Each base factor is a different linear combination of the underlying factors $base_{i,t} = \boldsymbol{\delta}_i' \boldsymbol{f}_t$. Base currency betas are estimated for all base currencies in the sample against all other currencies following the procedure in Verdelhan (2012). Starting with US based spot rates, we convert all rates to a specific base currency. Then, we drop each foreign country and calculate base factors, $base_{i,t}$, as the average appreciation of the base currency i against all other currencies at time t. For example, take the case of the U.S. We construct the US dollar factor, $base_{\$,t} = \frac{1}{N-1} \sum_{k \neq j} \Delta s_{\$ j,t}$, by averaging the change in the exchange rate across all bilateral exchange rates against the USD. We exclude currency j from the computation of the base factor. In the case of the USD, when we examine the USD/GBP bilateral exchange rate $\Delta s_{\$,£,t}$, we drop the USD/GBP bilateral exchange rate from the construction of the base factor, to avoid a mechanical relation $base_{\$,t} = \frac{1}{N-1} \sum_{k \neq £} \Delta s_{\$ k,t}$.

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. 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. Table (2.15) in Section (2.7) reports the correlations of the 1st principal component and the base factor by base currency in the MSCI Developed and Emerging sample. For most currencies in the GFD sample, 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.

Base currency betas, $\beta_{i,j}^{base}$, are estimated using the following regression:

$$\Delta s_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t} \ . \tag{2.2}$$

Conditional base factor betas, $\beta_{i,j,t}^{base}$, are estimated using 60 month rolling windows. The regression must have 48 months of available data for the conditional base factor beta to be estimated. Monthly rolling factor betas are averaged to generate yearly observations. The objective of our paper is to explain the betas on the base factor, $\beta^{base}_{i,j}$.

The base factor betas impact numerous important quantities in foreign exchange markets. Consider the R^2 of the regression in Equation (2.2):

$$R^2_{i,j} = \frac{\left(\widehat{\beta}^{base}_{i,j}\right)^2 \sum_t \left(base_{i,t} - \overline{base}_i\right)^2}{\sum_t \left(\Delta s_{i,j,t} - \overline{\Delta s}_{i,j}\right)^2} . \tag{2.3}$$

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 beta 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 (2.1) presents a decomposition of exchange rate variance for each base country. The first column reports the average, across currencies j, of the variance explained by the base factor (the numerator of Equation (2.3)). The second column reports the average variance of the bilateral exchange rates. The third column reports the idiosyncratic variance of the bilateral exchange rates. The numbers in the second column are the sum of the numbers in the first and third column. All columns are multiplied $\times 100$. The fourth column reports average R^2. The last column reports cross-sectional standard deviation of the betas.

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

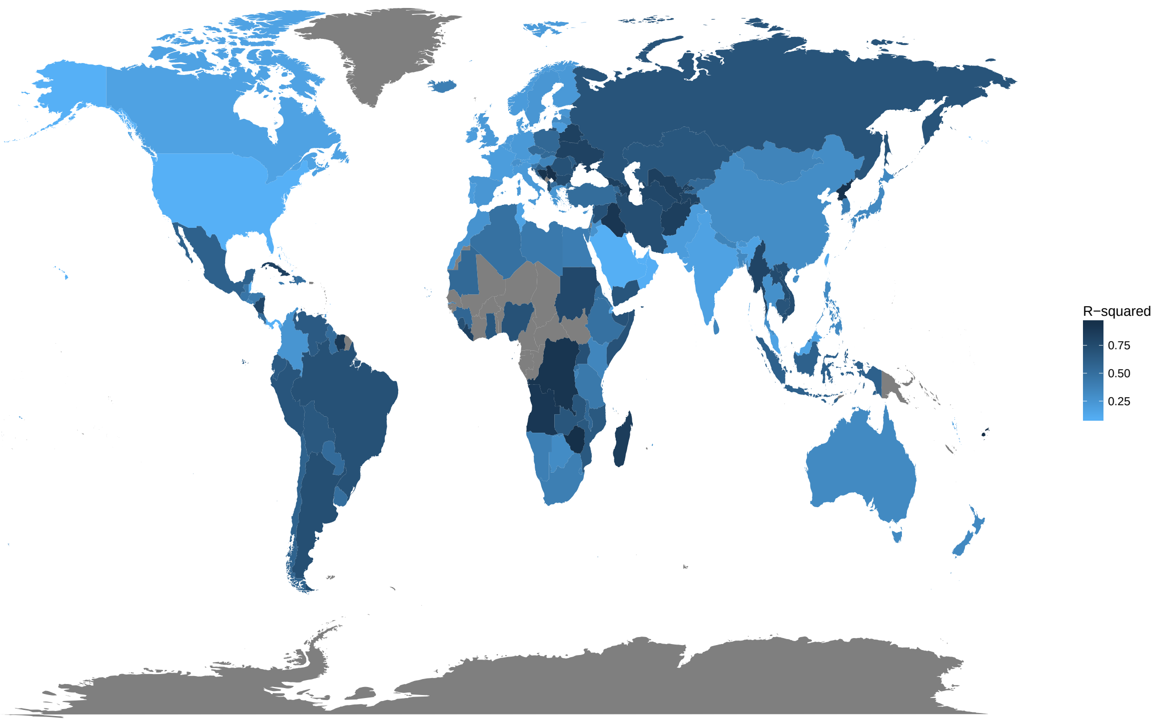
But the composition of the variances are different as well. The average R^2 is 0.36 for developed countries' currencies, compared to an average R^2 of 0.59 for emerging market currencies. This reflects the fact that the ratio of the explained variance to exchange rate variance is higher for the latter than the former. Even within the group of developed cur-

Table 2.1: Variance Decomposition of 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	0.95	2.81	1.86	0.50	0.16	Brazil	11.05	12.57	1.52	0.89	0.07
Austria	0.64	3.20	2.55	0.31	0.59	Chile	9.06	10.75	1.69	0.82	0.03
Belgium	0.67	3.29	2.63	0.32	0.57	China	1.07	2.81	1.74	0.53	0.18
Canada	0.42	2.31	1.89	0.33	0.32	Colombia	0.67	2.48	1.81	0.45	0.37
Denmark	0.52	2.31	1.78	0.29	0.54	Czech Republic	4.40	6.22	1.82	0.76	0.10
Euro Area	0.48	1.11	0.64	0.41	0.49	Egypt	2.01	3.71	1.69	0.66	0.09
Finland	0.51	3.24	2.74	0.31	0.35	Greece	0.67	3.14	2.47	0.39	0.26
France	0.61	3.24	2.63	0.29	0.59	Hungary	1.32	3.08	1.76	0.58	0.12
Germany	0.70	3.32	2.62	0.33	0.57	India	0.44	2.36	1.92	0.34	0.17
Hong Kong	0.41	2.29	1.88	0.30	0.38	Indonesia	4.33	6.03	1.70	0.78	0.05
Ireland	0.53	3.23	2.70	0.29	0.52	Korea	1.32	3.23	1.91	0.56	0.12
Israel	2.48	4.17	1.70	0.69	0.08	Malaysia	0.40	2.30	1.90	0.30	0.32
Italy	0.55	3.28	2.73	0.33	0.35	Mexico	6.42	8.19	1.77	0.81	0.09
Japan	1.04	2.94	1.90	0.51	0.14	Peru	14.71	16.29	1.57	0.88	0.18
Netherlands	0.68	3.30	2.62	0.32	0.58	Philippines	1.04	2.94	1.90	0.52	0.15
New Zealand	0.96	2.87	1.91	0.50	0.11	Poland	4.60	6.36	1.76	0.77	0.12
Norway	0.46	2.31	1.85	0.28	0.42	Qatar	0.46	2.22	1.76	0.32	0.51
Portugal	0.55	3.26	2.71	0.29	0.46	Russian Federation	7.80	8.76	0.96	0.87	0.08
Singapore	0.22	2.11	1.89	0.17	0.44	South Africa	1.40	3.31	1.91	0.58	0.05
Spain	0.65	3.40	2.75	0.37	0.28	Taiwan	0.43	2.31	1.87	0.32	0.38
Sweden	0.54	2.41	1.86	0.34	0.33	Thailand	0.78	2.66	1.89	0.45	0.22
Switzerland	0.77	2.59	1.82	0.42	0.36	Turkey	2.78	4.47	1.69	0.72	0.06
United Kingdom	0.55	2.45	1.90	0.37	0.23	United Arab Emirates	0.44	2.21	1.77	0.31	0.52
United States	0.41	2.25	1.84	0.30	0.51						
All	0.68	2.83	2.15	0.36	0.42	All	3.37	5.15	1.77	0.59	0.23

Summary statistics of data from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t}$ 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. Load Sd is the standard deviation of the betas $\beta_{i,j}^{base}$ 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.

Figure 2.2: Average R^2 by Base Factor



Map of cross-sectional average r-squared from the regression $\Delta s_{US,j,t} = \alpha_{i,j} + \beta^{base}_{US,j} base_{US,t} + e_{i,j,t}$ for each possible base currency i. For each currency j, $base_{US,t}$ 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.

rencies, 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. To clearly visualize the mapping from location to R^2 in currency markets, Figure (2.2) plots the average R^2 on a map. Clearly, countries that are central in the global trade network tend to have low R^2, while peripheral countries do not.

Finally, the last column in Table (2.1) reports the cross-sectional standard deviation of the betas. For developed countries, the standard deviation is 0.42. For emerging market countries, the standard deviation is 0.23. The standard deviation of the base factor betas is negatively related to the average R^2 faced by investors in each base country. Figure (2.3) in Section (2.7) shows this relation. The negative relation holds true within both the developed and the emerging subsets. Countries that are distant from most other countries have a low standard deviation of betas, which corresponds to a high R^2. These peripheral countries have a high average R^2 because of the high variance of their base factors. Conversely, central countries have high average R^2 and low standard deviations of betas due to low variances of their base factors.

Table (2.2) reports the same results for real exchange rates, computed using the ratio of the countries' CPIs. The real base factor betas are computed by running the real version of Equation (2.2). We detect similar variation in the variance of real exchange rates and real base factors. The average variance attributed to real base factors is 0.86 for developed countries, compared to 4.60 for emerging market countries. The average real exchange rate variance is 3.64 for developed countries, and 6.73 for emerging market countries.

2.2.1 Factor Model

We will interpret our findings using 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 Lustig, Roussanov, and Verdelhan (2011) and Verdelhan (2012). The base country is labeled i. There is no time variation in factor betas in the model. The real log SDF, $m_{j,t+1}$, in each country j is given by:

$$-m_{j,t+1} = \alpha_j + \chi_j \sigma_j^2 + \xi_{i,j} \left(\sigma_i^g\right)^2 + \tau_j \sigma_j u_{j,t+1} + \kappa_{i,j} \sigma_i^g u_{i,t+1}^g,$$

where $u_{j,t+1}$ are local shocks and $u_{i,t+1}^g$ is a common shock that originates in base country i, all of which are zero mean and variance 1. 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

Table 2.2: 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 $\Delta s_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t}$ 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 betas $\beta_{i,j}^{base}$ 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.

Section (2.8). In that model, we do not constrain where the shock originates and all results carry through. To give content to the notion that u_i^g originates in country i, we impose that $0 \leq \kappa_{i,j} \leq \kappa_{i,i}$ for all j. To keep the analysis simple, we have also abstracted from time-variation in the σ's.

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

$$\begin{aligned}
\Delta s_{i,j,t+1} &= m_{i,t+1} - m_{j,t+1} \\
&= (\alpha_j - \alpha_i) + (\xi_{i,j} - \xi_{i,i}) \left(\sigma_i^g\right)^2 \\
&+ (\chi_j \sigma_i^2 - \chi_i \sigma_i^2) + (\tau_j \sigma_j u_{j,t+1} - \tau_i \sigma_i u_{i,t+1}) + (\kappa_{i,j}\sigma_j - \kappa_{i,i}\sigma_i^g) u_{i,t+1}^g
\end{aligned}$$

This model produces a single factor structure in bilateral exchange rates, driven by the common shocks $u_{i,t+1}^g$. The base factor (without dropping the foreign currency) for currency i is simply given by:

$$\begin{aligned}
base_{i,t+1} &= \frac{1}{N}\sum_{j=1}^{N} \Delta s_{i,j,t+1} \\
&= (\overline{\alpha} - \alpha_i) + (\overline{\xi_i} - \xi_{i,i}) \left(\sigma_i^g\right)^2 + (\overline{\chi\sigma^2} - \chi_i \sigma_i^2) + (\overline{\tau\sigma u_{t+1}} - \tau_i \sigma_i u_{i,t+1}) + (\overline{\kappa_i} - \kappa_{i,i})\sigma_i^g u_{i,t+1}^g
\end{aligned}$$

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

$$\lim_{N\to\infty} base_{i,t+1} = (\overline{\alpha} - \alpha_i) + (\overline{\xi_i} - \xi_{i,i}) \left(\sigma_i^g\right)^2 + (\overline{\chi\sigma^2} - \chi_i \sigma_i^2) - \tau_i \sigma_i u_{i,t+1} \tag{2.4}$$

$$+ (\overline{\kappa_i} - \kappa_{i,i})\sigma_i^g u_{g,t+1} \tag{2.5}$$

Hence, the base factor is driven by the country-specific shock as well as the common shock that originates in i. Thus, we recover expressions for the variance of the base factor, the covariance of the exchange rate with the base factor and the betas on the base factor:

$$\mathrm{Var}\left(\lim_{N\to\infty} base_{i,t+1}\right) = \tau_i^2\sigma_i^2 + (\overline{\kappa_i} - \kappa_{i,i})^2 \left(\sigma_i^g\right)^2$$

$$\mathrm{Cov}\left(\Delta s_{i,j,t+1}, \lim_{N\to\infty} base_{i,t+1}\right) = \tau_i^2\sigma_i^2 + (\kappa_{i,j} - \kappa_{i,i})(\overline{\kappa_i} - \kappa_{i,i}) \left(\sigma_i^g\right)^2$$

$$\beta_{i,j}^{base} = \frac{\mathrm{Cov}\left(\Delta s_{i,j,t+1}, \lim_{N\to\infty} base_{i,t+1}\right)}{\mathrm{Var}\left(\lim_{N\to\infty} base_{i,t+1}\right)} = \frac{\tau_i^2\sigma_i^2 + (\kappa_{i,j} - \kappa_{i,i})(\overline{\kappa_i} - \kappa_{i,i}) \left(\sigma_i^g\right)^2}{\tau_i^2\sigma_i^2 + (\overline{\kappa_i} - \kappa_{i,i})^2 \left(\sigma_i^g\right)^2}$$

We hypothesize that the common shock exposure, $\kappa_{i,j}$, decreases monotonically in log distance from j to i. If the consumption baskets are identical, then closer countries would share more risks and have more similar loadings: $\kappa_{i,j}$ approaches $\kappa_{i,i}$ from below. If the consumption baskets differ, then relative price shocks matter as well, but these differences would presumably be smaller for countries that are closer. Linked back to the gravity model of trade and financial flows, this result seems sensible: The more countries trade with each other and the larger the bilateral financial flows, the larger the exposure of the pricing kernel in one country to the shock that originates in another country. Distance governs the correlation of the pricing kernel: as the distance to i declines and $\kappa_{i,j}$ increases, the covariance of the pricing kernels in i and j increases as well.

First, the variance of the base factor is higher in countries that are more distant from other countries, because $|\overline{\kappa_i} - \kappa_{i,i}|$ is larger. The variance of the base factor increases with distance from the average neighbor as well. An increase in the variance of the base factor in turn increases the average R^2 in the factor regressions. Table (2.2) shows that distant countries do tend to have larger R^2s.

Second, we interpret the beta, $\beta_{i,j}^{base}$. The only source of cross-sectional variation is $\kappa_{i,j}$, the exposure to the common shock. The country-specific shock does not matter for the betas on the base factor. Since i loads more than average on the common factor, then $\beta_{i,j}^{base} \geq 0$ is always positive since we imposed that $\kappa_{i,j} < \kappa_{i,i}$. Given our assumptions, the betas are bounded by:

$$\left[\frac{\tau_i^2\sigma_i^2}{\tau_i^2\sigma_i^2 + (\overline{\kappa_i} - \kappa_{i,i})^2 \left(\sigma_i^g\right)^2}, \frac{\tau_i^2\sigma_i^2 - \kappa_{i,i}(\overline{\kappa_i} - \kappa_{i,i}) \left(\sigma_i^g\right)^2}{\tau_i^2\sigma_i^2 + (\overline{\kappa_i} - \kappa_{i,i})^2 \left(\sigma_i^g\right)^2}\right].$$

The lower bound is attained when $\kappa_{i,j} = \kappa_{i,i}$. This is the case of perfect risk sharing when commodity baskets are identical. The upper bound is attained when $\kappa_{i,j} = 0$. This is the case of no exposure to common risks. In addition, $\beta_{i,j}^{base}$ increases as $\kappa_{i,j}$ decreases. As $\kappa_{i,j}$ drops below κ_i, $\beta_{i,j}^{base}$ increases above one. In Section (2.3), we test this main prediction of the model; the effect of distance on the currency factor structure.

2.3 The Gravity Effect in the Factor Structure

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

2.3.1 Summary Statistics

We begin by summarizing the key variables in our dataset. Table (2.3) reports summary statistics for all of the variables in our main sample. There are a total of 2,070 base country/foreign country combinations. There is a lot of variation in the betas across currencies. The average betas are close to one. The average standard deviation of the betas 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 (2.4) reports summary statistics for all the variables in 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.

Table 2.3: 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 betas and gravity data. Factor betas, $\beta_{i,j}^{base}$, are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t}$. 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 2.4: Rolling Sample Summary Statistics

	N	Mean	Median	Sd	Min	Max
Loading	61,130	0.92	0.98	0.48	-4.17	4.84
Loading (Real)	47,493	0.92	0.97	0.44	-3.13	5.78
R-squared	61,106	0.48	0.49	0.30	0.00	1.00
R-squared (Real)	47,493	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 betas and gravity data. Factor betas, $\beta_{i,j,t}^{base}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \beta_{i,j,t}^{base} base_{i,\tau} + e_{i,j,\tau}$ 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.

2.3.2 Marginal Propensity to Peg

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 (2.5) reports the estimation results for a logit model. 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.

Table 2.5: Marginal Propensity to Peg in Full Sample

	(1)	(2)	(3)
Log Distance	-0.061^{***}	-0.072^{**}	-0.045^{**}
	(-3.230)	(-2.344)	(-2.057)
Shared Language			0.059
			(1.452)
Shared Legal		0.068^{**}	0.049^{*}
		(2.075)	(1.876)
Shared Border		0.070	0.119^{*}
		(1.080)	(1.904)
Colonial Link		-0.015	-0.004
		(-0.261)	(-0.078)
Resource Similarity		0.309^{**}	0.226^{**}
		(2.289)	(2.196)
Linguistic Proximity		-0.002	
		(-0.284)	
Genetic Distance		0.057^{**}	
		(2.014)	
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.

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).

2.3.3 Understanding the variation in the Betas

To explain the variation in base factors betas, we regress the full sample betas, $\beta_{i,j}^{base}$, on various exogenous measures of the economic distance between i and j. We include the 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 $\beta_{i,j}^{base}$, 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 2.6.3.

Table (2.6) 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 beta. The average beta 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 beta by about 0.13. This number is robust across different specifications, except the no peg specification. Shared language lowers the beta by about 0.11. Shared border lowers the beta by 0.13. Colonial linkages lower the betas by up to 0.23. Resource similarity also lowers the betas. Legal origin, linguistic proximity, and genetic distances, do not have a statistically significant effect on the currency betas. This specification accounts for 1/4 of all the variation in the betas. Given the measurement error in these betas, this is a remarkably high number.

Table 2.6: 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

Regressions $\beta_{i,j}^{base} = \delta + \beta G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta_{i,j}^{base}$, are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t}$. 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. 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.

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 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 betas 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.

2.3.4 Full Sample Nominal Specifications

BR data

In Table (2.7), we compare the nominal betas to the real betas. The real betas 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 betas 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.

To control for the effect of pegs in a targeted way, we use the rolling estimates of the base betas. Table (2.8) reports the results of regressions of base factor betas computed over 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

Table 2.7: Full Sample Regressions with Nominal and Real Base Factor Betas

	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 $\beta_{i,j}^{base} = \delta + \lambda G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta_{i,j}^{base}$, are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t}$. 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.

regressions are substantially lower, presumably because the beta 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 beta 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 beta decreases by 0.53 when the other country has English as one of its major languages (see Table (2.16) in the separate appendix).

Finally, Table (2.9) checks the results of the nominal against the real base factor betas 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 will largely carry over to 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

Table 2.8: Rolling Sample Regressions with Nominal Factor Betas

	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 $\beta^{base}_{i,j,t} = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta^{base}_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \beta^{base}_{i,j,t} base_{i,\tau} + e_{i,j,\tau}$ 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 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 2.9: Rolling Sample Regressions with Nominal and Real Base Factor Betas

	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 $\beta^{base}_{i,j,t} = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta^{base}_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \beta^{base}_{i,j,t} base_{i,\tau} + e_{i,j,\tau}$ 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. * $p<0.10$, ** $p<0.05$, *** $p<0.01$.

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 is evidence that producer-currency pricing (price stickiness) may account for some of these effects[1] (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.

2.4 Robustness

2.4.1 R^2

Table (2.10) 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 betas.

2.4.2 Developed Currencies

Table (2.11) 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 beta is around 0.23, compared to 0.14. Some of the other variables are no longer enter significantly. Shared legal origin lowers the beta by more than 0.3 when pegs are removed. These variables jointly account for about 1/3 of the variation in the betas.

[1]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 2.10: 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 $\beta^{base}_{i,j,t} = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta^{base}_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \beta^{base}_{i,j,t} base_{i,\tau} + e_{i,j,\tau}$ 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. 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 2.11: Rolling Sample Regressions with Nominal Factor Betas (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 $\beta^{base}_{i,j,t} = \alpha_{i,j} + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta^{base}_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \beta^{base}_{i,j,t} base_{i,\tau} + e_{i,j,\tau}$ 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.

2.4.3 All Currencies

Table (2.12) 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 beta by 3 bps, compared to 14 bps in the developed and emerging subset.

Table 2.12: Rolling Sample Regressions with Nominal Factor Betas GFD Data

	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 $\beta^{base}_{i,j,t} = \alpha_{i,j} + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta^{base}_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \beta^{base}_{i,j,t} base_{i,\tau} + e_{i,j,\tau}$ 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.

2.4.4 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 (2.13) 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 betas 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.

Table 2.13: Euro Subsample Real Base Factor Betas 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 $\beta_{i,j}^{base} = \delta + \lambda G_{i,j} + e_{i,j}$ of real base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta_{i,j}^{base}$, are from the regression $\Delta s_{i,j,t} = \alpha + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t}$. 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.

2.5 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.

2.6 Data Appendix

2.6.1 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 [2] as of August 2015.

2.6.2 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

[2] Available at https://www.msci.com/market-classification

after 1945. See Mayer and Zignago (2011).

Resource similarity — We obtain a list of natural resources by country from the CIA world factbok[3]. 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).

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).

2.6.3 Calculation of Standard Errors

The triangular relation between exchange rates requires careful calculation of standard errors in our regressions. Consider the factor model in Equation (2.1):

$$\Delta s_{i,j,t} = \alpha_{i,j} + \boldsymbol{\gamma}'_{i,j}\boldsymbol{f}_t + e_{i,j,t}, \tag{2.6}$$

Suppose that $\alpha_{i,j} = 0$ for all $i,\ j$ then, since $\Delta s_{i,k} = \Delta s_{i,j} - \Delta s_{k,j}$, we have $\boldsymbol{\gamma}_{i,k} = \boldsymbol{\gamma}_{i,j} - \boldsymbol{\gamma}_{k,j}$. This relation is true for any factors $\boldsymbol{f}$, including base factors. Therefore, in our regressions

[3] Available at https://www.cia.gov/library/publications/the-world-factbook/fields/2111.html

of base factor betas on gravity variables any observations that contain the same country may have correlated errors. 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 use in this paper. These standard errors allow for arbitrary correlation when an observation contains the same country — whether base or foreign.

Table (2.14) 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 2.14: Rolling Sample Regressions with Nominal Factor Betas GFD Data (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 $\beta^{base}_{i,j,t} = \delta + \kappa_t + \lambda G_{i,j} + e_{i,j}$ of base factor betas on gravity variables. $G_{i,j}$ is a set of gravity variables. Base factor betas, $\beta^{base}_{i,j,t}$, are from 60-month rolling regressions $\Delta s_{i,j,\tau} = \alpha_{i,j} + \beta^{base}_{i,j,t} base_{i,\tau} + e_{i,j,\tau}$ 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 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.

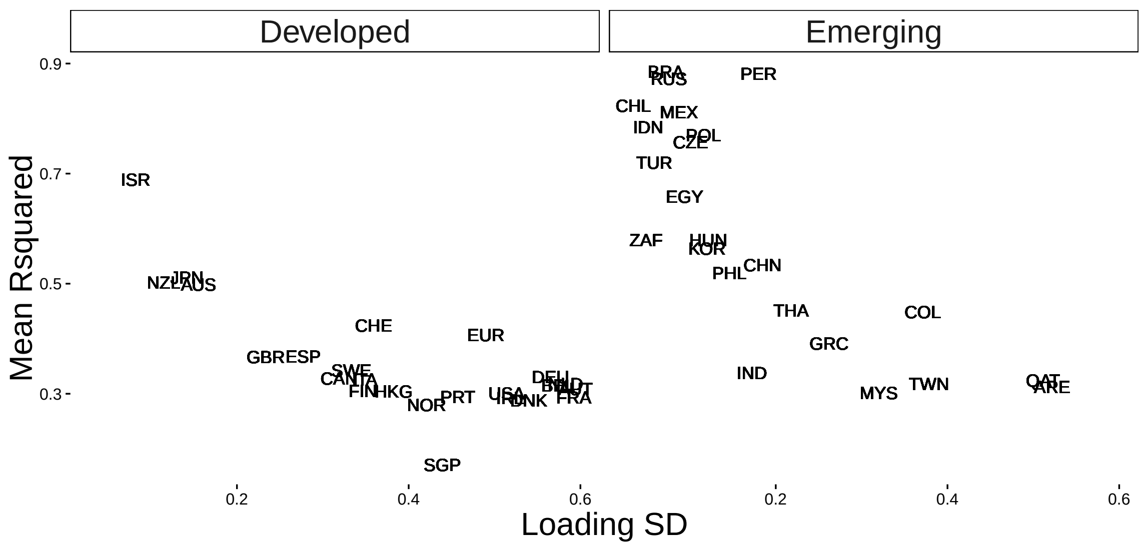
2.7 Empirical Appendix

Table 2.15: 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.

Figure 2.3: Average R-Squared vs SD of Base Factor Betas



Data are from the regression $\Delta s_{i,j,t} = \alpha_{i,j} + \beta_{i,j}^{base} base_{i,t} + e_{i,j,t}$ 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. Mean R^2 is the cross-sectional mean of the R^2 for each base currency. Load Sd is the standard deviation of the betas $\beta_{i,j}^{base}$ 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 2.16: Rolling Sample Regressions with Nominal Factor Betas (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 $\beta^{base}_{\$,j,t} = \alpha_{\$,j} + \kappa_t + \beta G_{\$,j} + e_{\$,j}$ of base factor betas on gravity variables. $G_{\$,j}$ is a set of gravity variables. Base factor betas, $\beta^{base}_{\$,j,t}$, are from 60-month rolling regressions $\Delta s_{\$,j,\tau} = \alpha_{\$,j} + \beta^{base}_{\$,j,t} base_{\$,\tau} + e_{\$,j,\tau}$ 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.

2.8 Model Appendix: Multi-Factor SDF Model

The log SDF, $m_{j,t+1}$ in each country j is given by:

$$-m_{j,t+1} = \alpha_j + \chi_j \sigma_j^2 + \sum_{k=1}^{K} \xi_{k,j} \left(\sigma_k^g\right)^2 + \tau_j \sigma_j u_{j,t+1} + \sum_{k=1}^{K} \kappa_{k,j} \sigma_k^g u_{k,t+1}^g,$$

where $u_{i,t+1}$ 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

$$\begin{aligned}\Delta s_{i,j,t+1} &= m_{i,t+1} - m_{j,t+1} \\ &= (\alpha_j - \alpha_i) + \sum_{k=1}^{K} (\xi_{k,j} - \xi_{k,i}) \left(\sigma_k^g\right)^2 + \tau_j \sigma_j u_{j,t+1} - \tau_i \sigma_i u_{i,t+1} + \sum_{k=1}^{K} (\kappa_{k,j} - \kappa_{k,i}) \sigma_k^g u_{k,t+1}\end{aligned}$$

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

$$\lim_{N\to\infty} base_{i,t+1} = \quad (\overline{\alpha} - \alpha_i) + \sum_{k=1}^{K} (\overline{\xi_k} - \xi_{k,i}) \left(\sigma_k^g\right)^2 - \tau_i \sigma_i u_{i,t+1} + \sum_{k=1}^{K} (\overline{\kappa_k} - \kappa_{k,i}) \sigma_k^g u_{k,t+1} \quad (2.7)$$

If $K = 1$ and $0 \leq \kappa_{1,j} < \kappa_{1,i}$ for all $j \neq i$, then we end up with the same expression for the base factor as in Equation (2.5).

$$\begin{aligned}\mathrm{Var}\left(\lim_{N\to\infty} base_{i,t+1}\right) &= \tau_i^2 \sigma_i^2 + \sum_{k=1}^{K} (\overline{\kappa_k} - \kappa_{k,i})^2 \left(\sigma_k^g\right)^2 \\ \mathrm{Cov}\left(\Delta s_{i,j,t+1}, \lim_{N\to\infty} base_{i,t+1}\right) &= \tau_i^2 \sigma_i^2 + \sum_{k=1}^{K} (\overline{\kappa_k} - \kappa_{k,i})(\kappa_{k,j} - \kappa_{k,i}) \left(\sigma_k^g\right)^2 \\ \beta_{i,j}^{base} = \frac{\mathrm{Cov}\left(\Delta s_{i,j,t+1}, \lim_{N\to\infty} base_{i,t+1}\right)}{\mathrm{Var}\left(\lim_{N\to\infty} base_{i,t+1}\right)} &= \frac{\tau_i^2 \sigma_i^2 + \sum_{k=1}^{K} (\overline{\kappa_k} - \kappa_{k,i})(\kappa_{k,j} - \kappa_{k,i}) \left(\sigma_k^g\right)^2}{\tau_i^2 \sigma_i^2 + \sum_{k=1}^{K} (\overline{\kappa_k} - \kappa_{k,i})^2 \left(\sigma_k^g\right)^2}\end{aligned}$$

The base factor beta $\beta_{i,j}^{base}$ varies due to differences in betas on the K common factors. The term $\sum_{k=1}^{K} (\overline{\kappa_k} - \kappa_{k,i})(\kappa_{k,j} - \kappa_{k,i}) \left(\sigma_k^g\right)^2$ measures this difference. For each factor k, this term is increases $\beta_{i,j}^{base}$ when the betas $\kappa_{k,i}$ and $\kappa_{k,j}$ differ in two ways. First, when $\overline{\kappa_k} < \kappa_{k,i}$, the factor k is relatively important for country i's base factor. In this case, the base factor beta $\beta_{i,j}^{base}$ increases if the factor is less important for j ($\kappa_{k,j} < \kappa_{k,i}$). Second, when $\overline{\kappa_k} > \kappa_{k,i}$ the factor is less important for country i's base factor. In this case, the base factor beta $\beta_{i,j}^{base}$ increases if the factor is more important for j ($\kappa_{k,j} > \kappa_{k,i}$). Our results show that these two effects are stronger when countries are more distant from each other. This is plausible because both conditions imply that a factor is significant for one country when it is insignificant for the other. Countries that are distant from each other have different factor betas — more so for factors that are important for countries' base factor variation ($\overline{\kappa_k} \ll \kappa_{k,i}$).

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