Trade Network Centrality and Currency Risk Premia

Journal of Finance forthcoming

ROBERT J. RICHMOND*

ABSTRACT

I uncover an economic source of exposure to global risk that drives international asset prices. Countries that are more central in the global trade network have lower interest rates and currency risk premia. To explain these findings, I present a general equilibrium model in which 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. Empirically, central countries' consumption growth covaries more with world consumption growth, further validating the proposed mechanism.

*NYU Stern School of Business, 44 West Fourth Street, 9-81, New York, NY 10012. E-mail: rrichmon@stern.nyu.edu. Website: http://robertjrichmond.com. The author has no relevant or material financial interests that relate to the research described in this paper. I am incredibly grateful to Hanno Lustig as well as Mike Chernov, Andrea Eisfeldt, Barney Hartman-Glaser, and Andy Atkeson for invaluable feedback on this research. For helpful comments I thank Daniel Andrei, Ariel Burstein, Bruce Carlin, Ricardo Colacito, Xavier Gabaix, Tarek Hassan, Lars Hansen, Mahyar Kargar, Ralph Koijen, Rob Ready, Nick Roussanov, Jung Sakong, Yinan Su, Adrien Verdelhan, Brian Waters, and seminar participants at Boston College, Carnegie Mellon, Chicago Booth, University of Colorado, Imperial College London, London Business School, MIT Sloan, Northwestern Kellogg, NYU Stern, Stanford SITE, the Annual Conference on International Finance, UT Austin, UCLA Anderson, University of Utah, and WFA.

This article has been accepted for publication and undergone full peer review but has not been through the copyediting, typesetting, pagination and proofreading process, which may lead to differences between this version and the Version of Record. Please cite this article as doi: 10.1111/jofi.12755

Between 2001 and 2016, carry trade investors that 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. 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, that is, their position 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. Figure 1 depicts the global trade network in 2013. Each circle represents a country and each line represents a trade link. The size of each circle corresponds to a country's share of global GDP. Trade links are measured using pair-wise total trade normalized by pair-wise total GDP, and thus only the strongest half of trade links are displayed. The position of each circle corresponds to a country's position in the trade network, or its trade network centrality. Countries are central if they have many strong links to countries that are important for the global output of tradable goods. Due to these trade linkages, central countries turn out to be more exposed to global shocks than peripheral countries. Central countries are not necessarily large. For example, global trade hubs such as Singapore and Hong Kong are central but are not nearly as large as their key trading partners such as the U.S. In contrast, countries that trade only 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 2 illustrates the relations between centrality vis-a-vis interest rates and currency

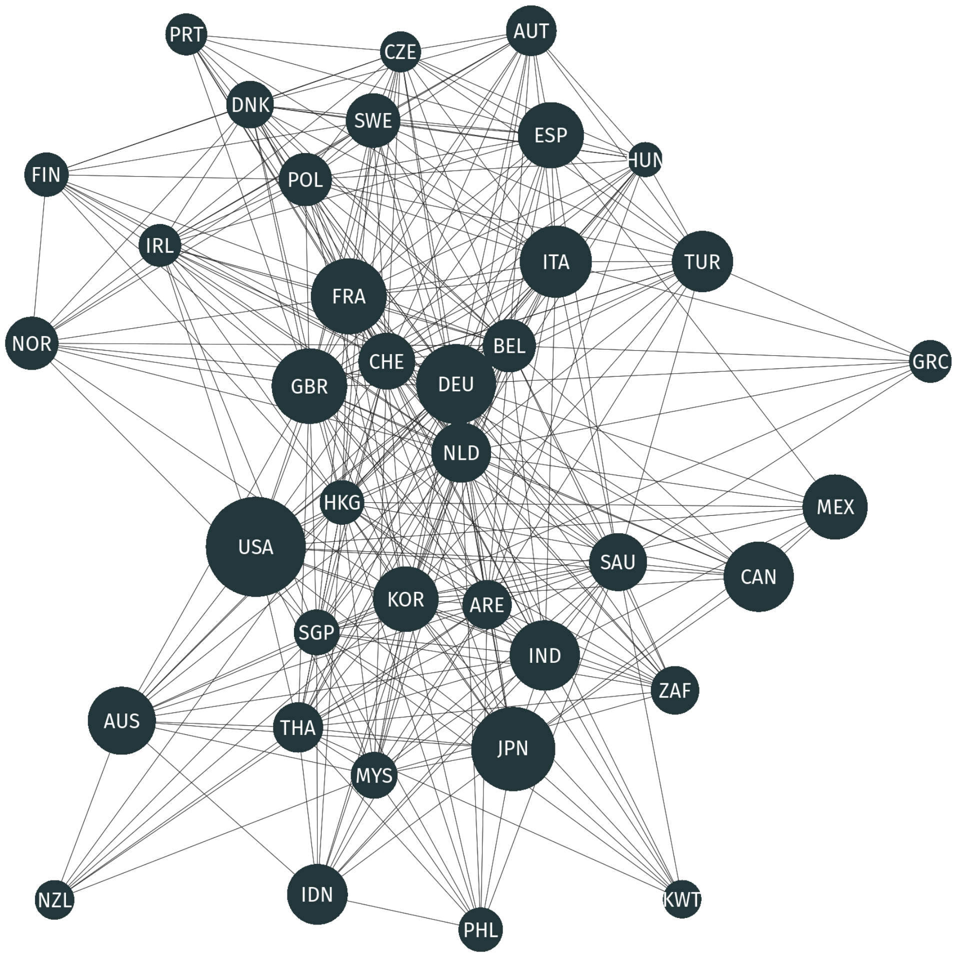

Figure 1. World trade network in 2013. This figure depicts country links as measured by bilateral trade intensity — pair-wise total trade normalized by pair-wise total GDP. Links are drawn if bilateral trade intensity is greater than the cross-sectional median. Circle position corresponds to trade network centrality and circle size corresponds to GDP. Trade data are from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars.

risk 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. In constrast, 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 that went long in a portfolio of peripheral countries' currencies and short in a portfolio of central countries' currencies from 1988 through 2016 received an annualized Sharpe ratio of 0.49 — similar to that of the unconditional carry trade.

Why do central countries have lower interest rates and currency risk premia? To address this question, I develop a tractable multi-country model that shows that the currencies of central countries are a good hedge against global consumption risk. Households in each country consume a nontradable good and a bundle of tradable goods produced in a global production network. Due to the fact that all countries consume a bundle of the tradable goods, there is a common component in all countries' consumption. Shocks in some countries affect this common component more than in other countries because more of global tradables output relies on their goods as intermediate inputs. Additionally, countries are differentially exposed to this common risk due to their trade linkages. Countries that have higher bilateral trade intensities have higher business cycle correlations (Frankel and Rose (1998)). In equilibrium, this implies that central countries, which have strong trade linkages with countries that are important for the output of tradable goods, will be more exposed to common global risk.

Countries' differential exposure to global shocks imputes variation in their real exchange

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

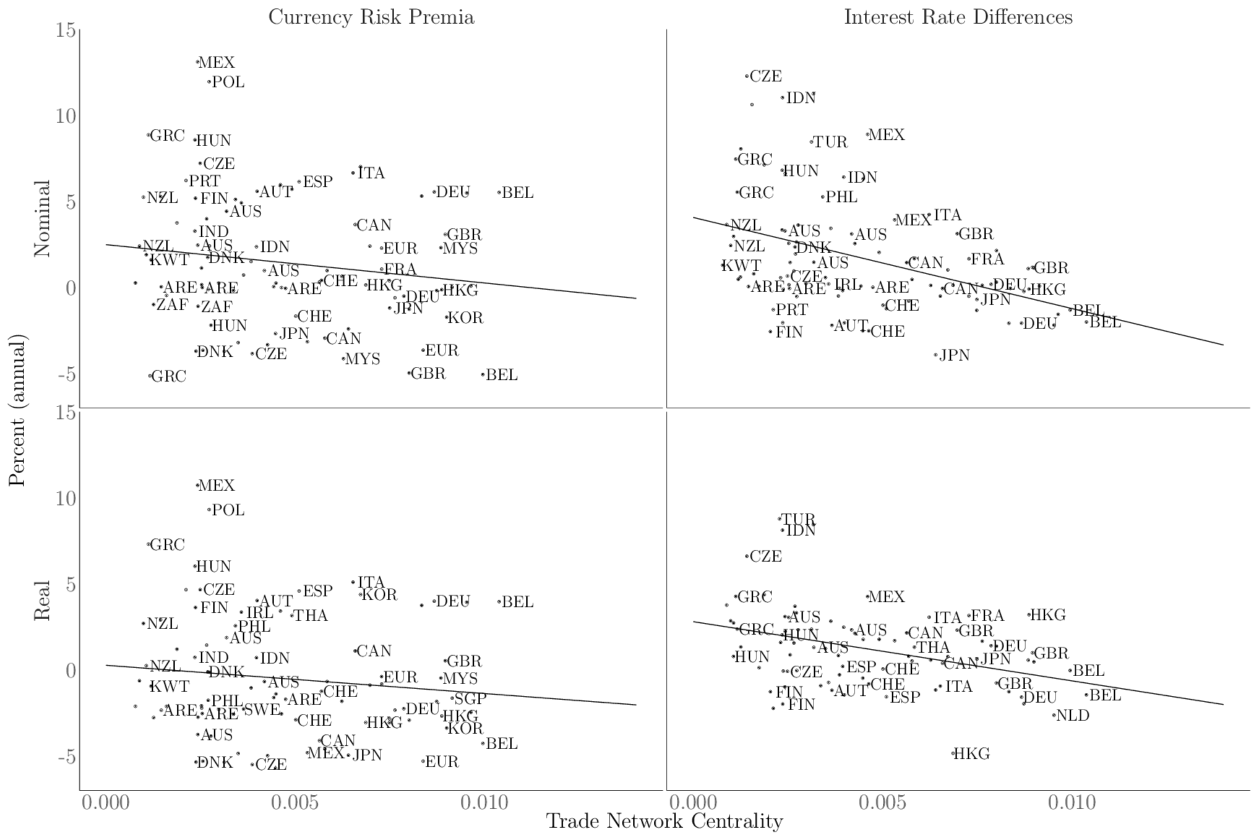

Figure 2. Risk premia and interest rate differentials versus centrality. This figure depicts decade-long averages of annualized risk premia rx and annualized one-month interest rate differences (measured using covered interest rate parity with forward spreads $f - s$) versus trade network centrality 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 three blocks (1988 to 1992, 1993 to 2002, 2003 to 2016). Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Trade data are 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 Barclays and Reuters.

rates. This is because real exchange rates are simply the relative prices of countries' consumption bundles. When a country experiences a bad shock, the price of its consumption bundle will increase relative to that of a country that experiences a less severe shock. In particular, when a large country receives a bad shock, global marginal utility is high. In these high-marginal-utility states, the relative price of central countries' consumption bundle increases, causing 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 one-standard-deviation increase in a country's centrality lowers its annualized currency risk premia by 0.6% and its interest rate differential by 1.3%, 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 2.6% and 4.8%, 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 an effect 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, which leads 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 to be exposed to global shocks through trade, high trade-to-GDP is not enough. Rather, countries must also have strong trade linkages with countries that are important for the global output of tradable goods.

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 helps explain 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 paper shows that production networks can give rise to aggregate economic fluctuations. The model shows in an international context that the global production network can generate heterogeneous exposure to global shocks at the country level. Additionally, the model provides a tractable framework for jointly understanding exchange rate behavior, international quantities, and other asset prices such as interest rates.

Importantly in the context of this paper, the endogenous differences in exposure to ag-

[2]As an implication of Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012), Ahern (2012) shows that firms that are in central industries earn higher equity returns because they are more exposed to market risk. Barrot and Sauvagnat (2016) show that input specificity in production networks propagates idiosyncratic shocks between suppliers and customers.

gregate fluctuations generated by the model lead to variation in real exchange rates. The variation in real exchange rates implied by the model is consistent with Burstein, Eichenbaum, and Rebelo (2006) and Betts and Kehoe (2008). Both papers show that variation in the relative price of nontradables to tradables is important for movement in real exchange rates. Additional variation in real exchange rates arises due to the 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 (2018) decompose the returns to various currency strategies and show how they are related. Lustig and Verdelhan (2007) sort currencies into portfolios based on interest rates and show that U.S. consumption growth risk exposure explains this cross-section of currency returns. Bekaert (1996), Bansal (1997), Backus, Foresi, and Telmer (2001), and Lustig, Roussanov, and Verdelhan (2011) provide restrictions on models that are necessary to explain deviations from UIP. My paper extends this literature by shedding light on the economic source of these deviations, both theoretically and empirically.

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 (1995) examine the global price of risk and stock and FX markets, respectively. Bekaert and Harvey (1995) examine the time-variation in global capital market integration and show that this variation impacts expected returns across countries. Ferson and Harvey (1993) show that predictability in equity markets is related to global economic risks, and Barrot, Loualiche, and Sauvagnat (2018) show that firms in low shipping cost industries carry a risk premium associated with displacement risk.

My results on consumption covariances relate to work on international risk-sharing such as Stockman and Tesar (1995), Obstfeld (1994), Lewis (1995), and Tesar (1995). In particular, the latter paper presents the cross-section of consumption growth covariances, which I show is related to trade network centrality. Additionally, my paper helps us understand how variation in business cycle correlations (Frankel and Rose (1998)) leads to variation in consumption growth covariances. 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 studies that also examine unconditional currency returns using country asymmetries. Hassan (2013) shows that currencies of larger countries hedge investors against greater consumption risk and therefore have lower currency risk premia and interest rates. Ready, Roussanov, and Ward (2017) solve and empirically test a model in which 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.

Theoretical explanations of conditional currency returns include Alvarez, Atkeson, and Kehoe (2009), Verdelhan (2010), Bansal and Shaliastovich (2013), and Gabaix and Maggiori (2015). Della Corte, Riddiough, and Sarno (2016) empirically test the latter 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. Maggiori (2017) presents a model that explains why financially developed countries' currencies become reserve currencies.

This paper is organized as follows. In Section I, I develop a theoretical model that motivates the link between centrality, interest rates, and currency risk premia. In Section II, I construct an empirical measure of centrality and test the model's predictions. I conclude in Section III. Appendix A contains derivations and proofs for the model. Appendix B contains details on the empirical results and robustness checks.

I. Model with Network-Based Production

In this section, I present a tractable multi-country model with network-based production. The model embeds the production structure of Long and Plosser (1983) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) into an international setting with differing goods varieties as in Backus and Smith (1993) and Tesar (1993). This generalization to differing goods varieties generates rich behavior of exchange rates, international asset prices, and consumption correlations. In particular, 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.

I use tractable functional forms to obtain analytic results for the relations between the relevant quantities and trade network centrality. In recent work, Baqaee and Farhi (2017) generalize the standard single-country model from Cobb-Douglas to CES and show that network effects relate to the underlying functional forms. That said, obtaining analytic results in an international setting with differing goods varieties remains limited to functional forms similar to those presented here.

A. Model Environment

The economy consists of N countries indexed by $i = 1, \ldots, N$. Each country has a representative household, a production sector for a unique tradable good, and a production sector for nontradable goods. Tradable goods are used as intermediate goods for the 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 by 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 $\xi_t = \{(Z_{it}, Y_{it})\}_{i=1}^{N}$.

The distributions of the shocks are given by

$$z_{i1} = \log(Z_{i1}) = 0, \tag{1}$$

$$y_{i1} = \log(Y_{i1}) = 0, \tag{2}$$

$$z_{i2} = \log(Z_{i2}) \sim F_{z_i}, \tag{3}$$

$$y_{i2} = \log(Y_{i2}) \sim F_{y_i}. \tag{4}$$

The representative household in country i ranks consumption according to

$$\log\left(\overline{C}_{i1}(\xi_1)\right) + \beta E\left[\log\left(\overline{C}_{i2}(\xi_2)\right)\right], \tag{5}$$

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 nontradable goods as given by

$$\overline{C}_{it}(\xi_t) = (N_{it}(\xi_t))^{\theta}\left(\prod_{j=1}^{N}(C_{ijt}(\xi_t))^{\frac{1}{N}}\right)^{1-\theta}. \tag{6}$$

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

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

$$N_{it}(\xi_t) = (Z_{it})^{\kappa}\left(L_{it}^{N}(\xi_t)\right)^{\kappa}(Y_{it})^{1-\kappa}, \tag{7}$$

where $L_{it}^{N}(\xi_t)$ is the labor supplied to nontradables production and $\kappa \in (0,1]$ is a weighting parameter between the shocks. When $\kappa < 1$, nontradables endowments depend on both shocks, Z_{it} and Y_{it}. When $\kappa = 1$, nontradables endowments are a function only of the shocks Z_{it}. The shocks Z_{it} are the same shocks that impact domestic tradables output specified next. Therefore, low realizations of nontradables 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 nontraded sectors within countries.

Each country produces its unique tradable good in a domestic production sector using other countries' tradable goods as intermediate inputs. The structure of this production network is determined by production weights w_{ij}. These production weights are a key source of assymetries across countries. Specifically, output at $t = 1, 2$ of country i's tradable good is

$$\overline{X}_{it}(\xi_t) = (Z_{it})^{\alpha} \left(L_{it}^{T}(\xi_t)\right)^{\alpha} \prod_{j=1}^{N} (X_{ijt}(\xi_t))^{(1-\alpha)w_{ij}}, \tag{8}$$

where $X_{ijt}(\xi_t)$ is the amount of country j tradables used as an intermediate good in country i's tradables production, Z_{it} is the idiosyncratic shock in country i, and $L_{it}^{T}(\xi_t)$ is the 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 goods' 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.

The output of country i tradables must equal the total amount used as intermediate goods in the production of other tradables plus the total amount consumed. Additionally, the total labor supplied to the nontradables and tradables sectors in each country must equal each representative household's endowment. The market-clearing conditions are thus

$$\overline{X}_{it}(\xi_t) = \sum_{j=1}^{N} X_{jit}(\xi_t) + \sum_{j=1}^{N} C_{jit}(\xi_t) \quad \forall\ i, \tag{9}$$

$$1 = L_{it}^{N}(\xi_t) + L_{it}^{T}(\xi_t) \qquad \forall\ i. \tag{10}$$

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

$$\begin{aligned} & P_{i1}^{N}(\xi_1)N_{i1}(\xi_1) + \sum_{j=1}^{N} P_{j1}(\xi_1)C_{ij1}(\xi_1) + \\ & \int_{\xi_2} \left(P_{i2}^{N}(\xi_2)N_{i2}(\xi_2) + \sum_{j=1}^{N} P_{j2}(\xi_2)C_{ij2}(\xi_2) \right) d\xi_2 \\ \leq\ & \Omega_{i1}(\xi_1) + \Pi_{i1}^{N}(\xi_1) + \Pi_{i1}^{T}(\xi_1) + \int_{\xi_2} \left(\Omega_{i2}(\xi_2) + \Pi_{i2}^{N}(\xi_2) + \Pi_{i2}^{T}(\xi_2) \right) d\xi_2, \end{aligned} \tag{11}$$

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

$$\Pi_{it}^{N}(\xi_t) = P_{it}^{N}(\xi_t)N_{it}(\xi_t) - \Omega_{it}(\xi_t)L_{it}^{N}(\xi_t)\ , \tag{12}$$

$$\Pi_{it}^{T}(\xi_t) = P_{it}^{T}(\xi_t)\overline{X}_{it}(\xi_t) - \Omega_{it}(\xi_t)L_{it}^{T}(\xi_t) - \sum_{j=1}^{N} P_{jt}^{T}(\xi_t)X_{ijt}(\xi_t). \tag{13}$$

The equilibrium definition is as follows.

DEFINITION 1: *An Arrow-Debreu competitive equilibrium consists of nontradable goods prices* $\{P_{it}^{N}(\xi_t)\}_{i=1\ldots N}$*, tradable goods prices* $\{P_{it}^{T}(\xi_t)\}_{i=1\ldots N}$*, wages* $\{\Omega_{it}(\xi_t)\}_{i=1\ldots N}$*, nontradable labor input* $\{L_{it}^{N}(\xi_t)\}_{i=1\ldots N}$*, tradable labor input* $\{L_{it}^{T}(\xi_t)\}_{i=1\ldots N}$*, tradable goods inputs* $\{X_{ijt}(\xi_t)\}_{i,j=1\ldots N}$*, and tradable goods consumptions* $\{C_{ijt}(\xi_t)\}_{i,j=1\ldots N}$ *for each* ξ_t*, such that* *for all i households maximize equation (5) subject to equation (11), nontradables firms maximize equation (12), tradables firms maximize equation (13), tradable goods markets clear, following equation (9), and labor markets clear, following equation (10).*

B. *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 one. Details on the solution in this section can be found in Appendix A.

Because preferences are time-separable and goods are nonstorable, the solution to the planner's 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

$$\underset{\substack{\{C_{ijt},\, X_{ijt}\}_{i,j=1\ldots N}\\ \{L^N_{it},\, L^T_{it}\}_{i=1\ldots N}}}{\text{maximize}} \quad \sum_{i=1}^{N}\Big(\log\left(\overline{C}_{i1}\right)+\beta E\big[\log\left(\overline{C}_{i2}\right)\big]\Big) \tag{14}$$

subject to

$$\overline{C}_{it}=\left((Z_{it})^{\kappa}\left(L^N_{it}\right)^{\kappa}(Y_{it})^{1-\kappa}\right)^{\theta}\left(\prod_{j=1}^{N}(C_{ijt})^{\frac{1}{N}}\right)^{1-\theta} \tag{15}$$

$$(Z_{it})^{\alpha}\left(L^T_{it}\right)^{\alpha}\prod_{j=1}^{N}(X_{ijt})^{(1-\alpha)w_{ij}}=\sum_{j=1}^{N}X_{jit}+\sum_{j=1}^{N}C_{jit} \tag{16}$$

$$1=L^N_{it}+L^T_{it} \qquad \forall\ i,t. \tag{17}$$

Equation (15) is household i's consumption basket with its nontradables endowment substituted in — nontradable goods must be consumed domestically. Equation (16) is the market-clearing condition with output replaced by the tradables production function. Equation (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 $\{X_{ijt}\}_{i,j=1,\ldots,N}$, tradables' final consumptions $\{C_{ijt}\}_{i,j=1,\ldots,N}$, and labor supplies $\left\{L_{it}^{N},\ L_{it}^{T}\right\}_{i=1\ldots N}$. These quantities imply total tradable goods outputs $\left\{\overline{X}_{it}\right\}_{i=1,\ldots,N}$ and consumption baskets $\left\{\overline{C}_{it}\right\}_{i=1,\ldots,N}$.

To solve the model, I assign Lagrange multipliers Ψ_{it} to each resource constraint in equation (16) and H_{it} to each labor market constraint in equation (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

$$C_{jit} = \frac{(1-\theta)}{N\Psi_{it}}, \tag{18}$$

$$X_{jit} = \frac{\Psi_{jt}\overline{X}_{jt}(1-\alpha)w_{ji}}{\Psi_{it}}. \tag{19}$$

Rearranging equation (19) shows how the production weights, w_{ji}, are related to expenditure shares:

$$X_{jit} = \frac{\Psi_{jt}\overline{X}_{jt}(1-\alpha)w_{ji}}{\Psi_{it}} \implies \frac{\Psi_{it}X_{jit}}{\Psi_{jt}\overline{X}_{jt}} = (1-\alpha)w_{ji}. \tag{20}$$

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 (16), implies

$$\begin{aligned} \overline{x}_t &= \left(\boldsymbol{I} - (1-\alpha)W\right)^{-1}(\alpha z_t + a) \\ &= \left(\boldsymbol{I} + (1-\alpha)W + (1-\alpha)^2W^2 + (1-\alpha)^3W^3 + \ldots\right)(\alpha z_t + a), \end{aligned} \tag{21}$$

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 Appendix A. 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 (21) shows that tradables output is a result of the 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 the production of all countries that rely on its goods as intermediate goods and in turn the countries that rely on those. This result is closely related to the findings of Long and Plosser (1983), Horvath (2000), and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). The novel insights of the model in this paper arise due to hetereogenity across countries in their equiblibrium consumption bundles.

Given tradables output of each country in equation (21), log consumption baskets are

$$\bar{c}_t = \theta\left(\kappa z_t + (1-\kappa) y_t\right) + \frac{(1-\theta)\alpha}{N}\left(z_t'(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}\right) + d, \tag{22}$$

where $y_t = [\log(Y_{1t}), \ldots, \log(Y_{Nt})]'$ is the vector of log shocks, $\bar{c}_t = \left[\log(\overline{C}_{1t}), \ldots, \log(\overline{C}_{Nt})\right]'$ is the vector of log consumptions, and d is a vector of constants defined in Appendix A.

The term $(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}$ in equation (22) is known as Katz centrality in the network literature (Katz (1953), Bonacich and Lloyd (2001)) and as the influence vector in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). I define this vector as s, with individual elements given by

$$s_i = \left[(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}\right]_i. \tag{23}$$

The elements of this vector are proportional to the share of output in tradable goods for each country i, as shown in Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012) and Baqaee and Farhi (2017).

Using equation (23), log consumption of country i at time t is

$$\begin{aligned}\overline{c}_{it} &= \theta\left(\kappa z_{it} + (1-\kappa)y_{it}\right) + \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} s_j z_{jt}\right) + d_i \\ &= \theta\left(\kappa z_{it} + (1-\kappa)y_{it}\right) + F_t + d_i,\end{aligned} \tag{24}$$

where the second equality is just a definition of F_t. Each country's consumption depends on two components. The first, $\theta\left(\kappa z_{it} + (1-\kappa)y_{it}\right)$, is country i's nontradable output. The second component is a tradables output-share weighted sum of all countries' production shocks:

$$F_t = \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} s_j z_{jt}\right). \tag{25}$$

This component is symmetric across countries and can be interpreted as the common risk factor in global consumption growth (Lustig, Roussanov, and Verdelhan (2011)). It arises due to the fact that all countries consume a bundle of the globally produced tradable goods and because some countries are more important for the production of these goods than others. Shocks to countries that produce more of the tradable goods impact the common component more than countries that produce less of the tradable goods.

C. Trade Network Centrality

Depending on the correlation structure of the shocks, countries will have heterogeneous exposure to the common factor in consumption in equation (25). To discipline the correlation structure of shocks, I make the following assumptions about the distribution of the shocks:

$$corr(y_{i2}, y_{j2}) = 0 \;\; \forall \; i \neq j \; , \tag{26}$$

$$corr(z_{i2}, y_{i2}) = 0 \;\; \forall \; i \; , \tag{27}$$

$$var(z_{i2}) = \sigma_z^2 \;\; \forall \; i \; , \tag{28}$$

$$var(y_{i2}) = \sigma_y^2 \;\; \forall \; i \; . \tag{29}$$

Equation (26) shows that, across countries, the idiosyncratic shocks to nontradables output are uncorrelated. Equation (27) further shows that these shocks are uncorrelated within a country. Equations (28) and (29) ensure that the variance of shocks is identical across countries so that any heterogeneity that arises does so for reasons other than simply assuming different variances.

The assumptions in the previous paragraph primarily limit the sources of hetereogeneity across countries. A large literature in international macroeconomics studies bilateral business cycle correlations and finds substantial heterogenity in these correlations (Backus, Kehoe, and Kydland (1992), Stockman and Tesar (1995)). Due to this vast literature, for modeling purposes I take as given that countries have hetereogeneous business cycle correlations. In particular, I assume that

$$corr(z_{it}, z_{jt}) = \rho_{ij} \; . \tag{30}$$

While other specifications for cross-sectional variation in business cycle correlations are possible, this form is particularly parsimonious.

Heterogeneity in business cycle correlations has been shown to be related to bilateral trade between countries. In particular, Frankel and Rose (1998) show that bilateral business cycle correlations are increasing in bilateral trade intensity,

$$\frac{\widetilde{X}_{ijt} + \widetilde{X}_{jit}}{\widetilde{G}_{it} + \widetilde{G}_{jt}}, \tag{31}$$

where $\widetilde{X}_{ijt}$ is the total trade between countries i and j and $\widetilde{G}_{it}$ is the GDP of country i, both at time t. Baxter and Kouparitsas (2005) show that this relation between bilateral trade intensity and business cycle correlations is robust to separately considering developed and developing countries, as well as to controlling for numerous other explanatory variables. In the empirical tests in Section II I use bilateral trade intensity to capture the correlation in equation (30). For robustness and to link the results more closely to those of Frankel and Rose (1998) and Baxter and Kouparitsas (2005), I conduct two additional sets of emprical tests in Appendix B. First, I measure ρ_{ij} using correlations of GDP growth. The results are reported in Table BIII. Second, I use predicted values of ρ_{ij} from regressions of business cycle correlations on bilateral trade intensity, as in Frankel and Rose (1998). These results are presented in Table BIV.

Much work has been done in international macroeconomics to explain the positive relation between business cycle correlations and bilateral trade intensity, such as the models in Kose and Yi (2006) and Burstein, Kurz, and Tesar (2008). The assumption of heterogeneous business cycle correlations in equation (30) can be thought of as capturing the equilibrium outcome of the forces described in these papers. While it would be interesting to study asset prices in models such as those previously mentioned, doing so is outside the scope of this paper. The focus here is to show how bilateral trade linkages generate a common factor that countries are differentially exposed to and to understand how these exposures impact asset prices.

A key quantity arises in equilibrium that explains cross-sectional variation in countries' exposure to global shocks. I refer to this quantity as trade network centrality, which for country i is given by

$$v_i = \sum_{j=1}^{N} \rho_{ij} s_j. \tag{32}$$

When ρ_{ij} is proportional to bilateral trade intensity, as discussed above, trade network centrality is effectively the output-share weighted average of a country's bilateral trade intensities with all other countries. Countries are central if they have high bilateral trade intensities with countries that are important for the global output of tradable goods. Countries are peripheral if they have low bilateral trade intensities with most countries or if they do not have high bilateral trade intensities with countries that are important for the global output of tradable goods.

In equilbrium, a country can be highly exposed to global shocks by being large or by being central. When a large country receives a bad shock, it is worse for global consumption of tradable goods than when a small country receives a bad shock. Within a country, shocks to nontradables output are positively correlated with shocks to tradables output because the same shock Z_{it} affects both. Therefore, large countries are more exposed to global shocks because their nontradables consumption falls when global shocks arise from a negative shock to their tradables output — this is the effect in Hassan (2013). Additionally, countries that have business cycles that are more correlated with the large country will be more negatively affected than countries that are less correlated. As a result, central countries — which have business cycles that are on-average highly correlated with countries that are important for the output of tradable goods — are more exposed to global shocks.

To formally study differences in countries' exposure to the common component in consumption growth, I define changes in log consumption between period 1 and 2 as $\Delta\bar{c}_{i2}$ for $i = 1, \ldots, N$, and changes in the common component (equation (25)) as ΔF_2. There are no time 1 shocks in consumption growth because $z_{i1} = y_{i1} = 0$ for all i. The following proposition shows that central countries' consumption growth covaries more with the common component in consumption growth than with peripheral countries' consumption growth.

PROPOSITION 1: *For two countries i and j,*

$$\operatorname{Cov}(\Delta\bar{c}_{i2}, \Delta F_2) - \operatorname{Cov}(\Delta\bar{c}_{j2}, \Delta F_2) = \theta(1-\theta)\alpha\kappa\sigma_z^2 \left(v_i - v_j\right). \tag{33}$$

Therefore, $v_i > v_j$ implies $\operatorname{Cov}(\Delta\bar{c}_{it}, \Delta F_2) > \operatorname{Cov}(\Delta\bar{c}_{jt}, \Delta F_2)$.

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

$$\begin{aligned} m_{i2} &= \delta + \bar{c}_{i1} - \bar{c}_{i2} \\ &= \delta - \theta\left(\kappa z_{i2} + (1-\kappa) y_{i2}\right) - \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} s_j z_{j2}\right), \end{aligned} \tag{34}$$

where $\delta = \log(\beta)$ 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,

$$M_{i2}\frac{Q_{ij1}}{Q_{ij2}} = M_{j2} \implies \Delta q_{ij2} = m_{i2} - m_{j2}, \tag{35}$$

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 indicates 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

$$rf_{j1} - rf_{i1} = \log E[M_{i2}] - \log E[M_{j2}]. \tag{36}$$

Foreign currency investors receive the interest differential over their home country and lose any appreciation of the home currency. Combining equations (35) and (36) gives the log risk premium to going long in currency j for a country i investor:

$$\begin{aligned} E[rx_{ij2}] &= rf_{j1} - rf_{i1} - E[\Delta q_{ij2}] \\ &= (\log E[M_{i2}] - \log E[M_{j2}]) - (E[m_{i2}] - E[m_{j2}]). \end{aligned} \tag{37}$$

To obtain analytical results for asset prices, it is necessary to assume that that the time 2 shocks are normally distributed.[3] With this assumption, the following proposition presents the relation between trade network centrality, currency risk premia, and interest rates (the proof is in Appendix A):

PROPOSITION 2: *Assume that $z_i \sim N(\mu_z, \sigma_z)$ and $y_i \sim N(\mu_y, \sigma_y)$ for all i. Then for any two countries i and j, the* log *currency risk premium for going long in currency j from country i and the* log *interest rate differential satisfy*

$$\mathrm{E}[rx_{ij2}] = rf_{j1} - rf_{i1} = \theta(1-\theta)\alpha\kappa\sigma_z^2 (v_i - v_j).$$

This proposition is the key takeaway from the model. Consider a central country i and and a peripheral country j ($v_i > v_j$). This proposition shows that the risk premium for a long position in j's currency from country i will be positive and country i will have a lower interest rate than country j. In general, central countries have lower interest rates and lower currency risk premia than peripheral countries. This is because central countries'

[3]Additionally, I assume that the mean of each shock is the same across countries. This implies that expected exchange rate changes are equal to zero, consistent with findings that exchange rates follow a random walk (Meese and Rogoff (1983)).

currencies tend to appreciate relative to peripheral countries' currencies in globally high marginal utility states. 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 increase central countries' marginal utility more than that of peripheral countries. Higher marginal utility in bad times causes central countries' 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.

D. *Centrality versus Size*

To further illustrate the implications of the model, I now turn to a numerical exercise that shows that countries can have low risk premia and interest rates because they are large (Hassan (2013)) or because they are central. In particular, I present numerical results from the model for the 38 countries in the sample outlined in Section II (excluding the euro area).

I use utility and production function parameter values that are consistent with those implied by the data, primarily following Stockman and Tesar (1995). I choose $\alpha = 0.61$ to match the labor share in the production of tradable goods, $\theta = 0.5$ so that nontradables and tradables have equal weights in each country's consumption basket, and $\kappa = 0.56$ to match the within-country correlation of shocks to tradables and nontradables output. I use $\sigma_z = 0.03$ and $\sigma_y = 0.01$ so that the variance of productivity shocks is approximately twice as high in the traded goods industry as in the nontraded goods industry. I set each country's export share in tradable goods, equivalent here to size, to its unconditional average over the sample period. Finally, I set the correlation of the z shocks to the bilateral correlation of GDP growth for each country pair over the full sample. Using these parameter values, I calculate countries' centralities (equation (32)), interest rate differentials, and currency risk premia.

To show that both size and centrality explain asset prices in the model, I sort countries into three portfolios based on size and then conditional on size into three portfolios based on centrality. The average currency risk premia are presented in Table AI. The magnitudes of the implied currency risk premia are substantially lower than found in the data, which reflects the fact that agents in the model have log utility.[4] That said, the model still produces interesting variation in risk premia associated with both size and centrality. Across all terciles of size, as centrality increases, risk premia decrease. This result indicates that even conditional on country size, centrality is a significant determinant of currency risk premia in the model.

II. Data and Empirical Trade Network Centrality

In this section, I test the predictions of Propositions 1 and 2:

1. Central countries' consumption growth covaries more with global consumption growth than does peripheral countries' consumption growth.

2. Countries that are central in the global trade network have lower currency risk premia and lower interest rates than peripheral countries.

A. *Data Sources*

Daily spot and forward rates are from Barclays and Reuters.[5] The sample period is 1988 to 2016 following Ready, Roussanov, and Ward (2017). Table BI lists the 39 countries and the dates of their corresponding data availability. 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 Barclays and

[4]To quantitatively match risk premia in the model, extensions would be necessary such as those found in Colacito and Croce (2011).

[5]The data can be obtained through Datastream.

Reuters. Data for Australia and New Zealand are only available on a quarterly basis, and thus 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, and r_{it} to denote the one-month log interest rate. Country indices are omitted anytime a value is with respect the U.S. Assuming that covered interest parity holds,[6] 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

$$rx_{it+1} = r_{it} - r_t - \Delta q_{it+1} \approx f_{it} - q_{it+1}. \tag{38}$$

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 the 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 2016, and cover 173 reporting countries. 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 8.1 (Heston, Summers, and Aten (2002)). The data consist of real per capita GDP and consumption in international prices for 189 countries from 1950 to 2011. For tests of Proposition 1, I need a measure of countries'

[6] Akram, Rime, and Sarno (2008) provide evidence that covered interest parity typically holds at daily frequencies. Due to large deviations from covered interest parity, some observations are omitted as specified in Appendix B. Additionally, Du, Tepper, and Verdelhan (2018) find large deviations from CIP after the financial crisis. In Table BIX I present results limiting the sample to before the financial crisis. All results hold for this sample.

consumption growth exposure to global common consumption growth. Motivated by Tesar (1995), I obtain a measure of each country's consumption growth covariance by regressing its per capita log consumption growth on world consumption growth using 20-year rolling windows,

$$\Delta\widetilde{c}_{i\tau} = \alpha_{it} + \beta_{it}\Delta\widetilde{c}_{W\tau} + \epsilon_{i\tau} \quad \tau = t-19,\ldots,t. \tag{39}$$

I calculate log world per capita consumption, $\widetilde{c}_{Wt}$, by omitting each country i.

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 BVI, results omitting pegged currencies in Table BVII, and results on a developed country subsample in Table BVIII.

B. *Empirical Trade Network Centrality*

I construct the empirical analog to the trade network centrality measure in equation (32) as

$$v_{it} = \sum_{j=1}^{N}\left(\frac{\widetilde{X}_{ijt}+\widetilde{X}_{jit}}{\widetilde{G}_{it}+\widetilde{G}_{jt}}\right)\widetilde{s}_{jt}, \tag{40}$$

where v_{it} is the trade network centrality of countries i at time t, $\frac{\widetilde{X}_{ijt}+\widetilde{X}_{jit}}{\widetilde{G}_{it}+\widetilde{G}_{jt}}$ is the bilateral trade intensity between countries i and j at time t, and $\widetilde{s}_{jt}$ is the share of exports of country i at time t in percent. This measure is simply equation (32), where ρ_{ij} is replaced by bilateral trade intensity, following the findings of Frankel and Rose (1998).[7]

Countries are central if they have high bilateral trade intensity with countries that make

[7] In Table BIII, I present results where I measure ρ_{ij} using correlations of GDP growth and in Table BIV I present results where I use predicted values of ρ_{ij} from regressions of business cycle correlations on bilateral trade intensity, as in Frankel and Rose (1998).

up a large proportion of the global output of tradable goods. Following from the fact that higher bilateral trade intensity leads to higher bilateral business cycle correlations (Frankel and Rose (1998)), central countries turn out to be more exposed to fluctuations in the global business cycle. For example, countries like the Netherlands and Singapore are home to some of the largest ports in the world and as a result are hubs for European, Asian, and global trade. On average, these countries have high bilateral trade intensities and therefore high business cycle correlations with large countries. This leads to them being quite central and exposed to global business cycles. In contrast, countries like New Zealand and Australia trade a significant amount of their total GDP with each other, but they do not trade a significant proportion of pair-wise GDP with many other countries, such as the U.S. and Canada. This leads to them being peripheral and less exposed to global fluctuations.

Figure 3 plots 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 2016, countries' relative centralities are highly persistent. This persistence is part of the reason 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 premia and interest rates are lower than those of peripheral countries. Table I presents results of 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 1.3% and currency risk premia by 0.6%, consistent with Proposition 2. The magnitudes of these effects are large given that the cross-sectional standard deviation of average risk premia and interest rate differentials are 2.6% and 4.8%, respectively.

I also present specifications with various controls in Table I. First, central countries may be larger on average. Therefore, following Hassan (2013), I control for country size

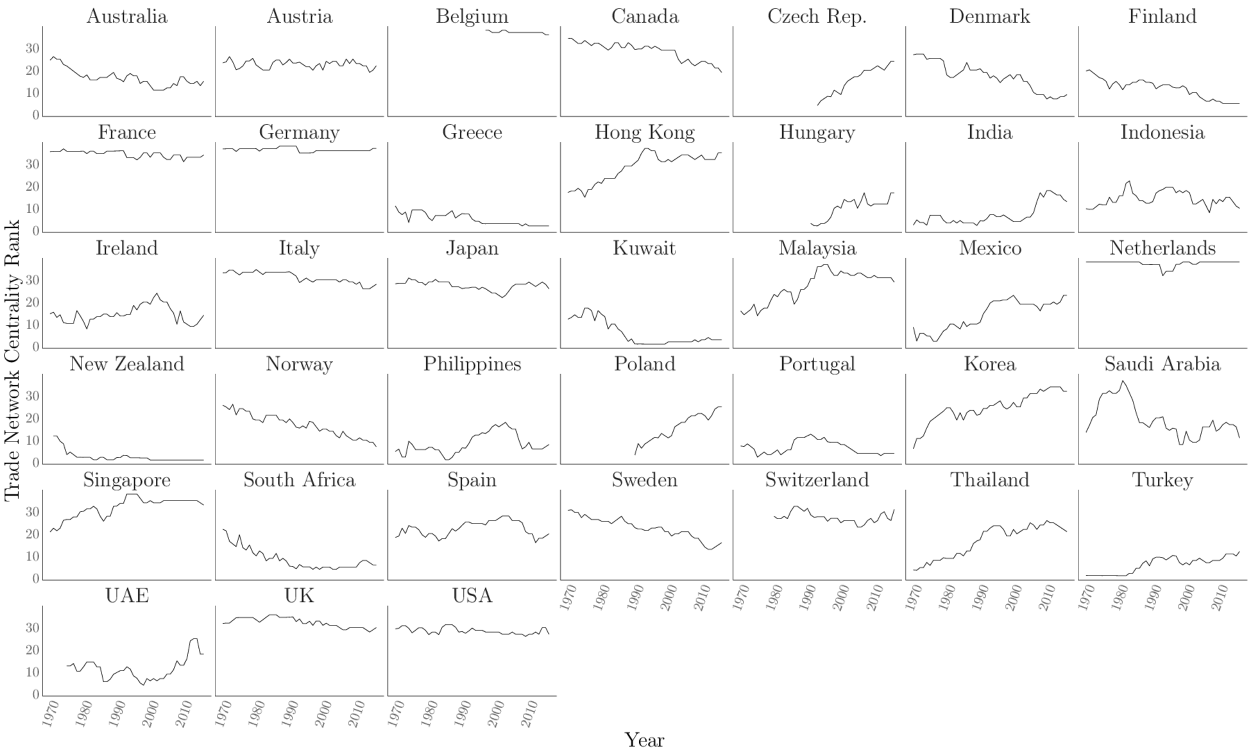

Figure 3. Time series of centrality ranking by country. This figure plots rankings of countries' centrality in the global trade network by year. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Rankings are normalized each year to between 1 and 38 (maximum number of countries in the sample). Trade data are from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. Data are annual from 1973 to 2016.

using countries' GDP shares. Larger countries have lower forward spreads and risk premia — a one-standard-deviation increase in GDP share lowers forward spreads by 0.3% and risk premia by 0.3%. 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 country's total trade normalized by its GDP — a measure of trade openness. This is in contrast to centrality, which measures a country's exposure to global shocks due to trade linkages. As an example, a country could have a large trade-to-GDP ratio because it trades a significant amount of its GDP with one country, but it will not necesarrily 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 affect the magnitude of the centrality coefficients.

Table I

Regressions for Risk Premia and Forward Spreads with Year Fixed Effects

This table presents results of regressions of log risk premia rx_t and forward spreads $f_t - s_t$ on lagged standardized GDP share, standardized trade-to-GDP, and standardized trade network centrality, v_{it-1}. All specifications include year fixed effects. Excess returns and forward spreads are yearly averages of annualized observations. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise 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 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 Barclays and Reuters for 39 countries from 1/1988 to 12/2016. Observations are omitted after a country secedes its currency to the euro. Standard errors in parentheses are clustered by country using Cameron, Gelbach, and Miller (2011). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	rx	rx	rx	$f-s$	$f-s$	$f-s$
Centrality	-0.610^{***}	-0.496^{**}	-0.677^{***}	-1.311^{***}	-1.193^{**}	-1.161^{**}
	(0.221)	(0.227)	(0.227)	(0.499)	(0.504)	(0.481)
GDP Share		-0.289			-0.301	
		(0.229)			(0.326)	
Trade-to-GDP			0.370			-0.826
			(0.353)			(0.718)
R^2	0.413	0.414	0.413	0.116	0.120	0.119
Num. obs.	688	688	688	689	689	689

To illustrate the differences between centrality, size, and the trade composition measure of Ready, Roussanov, and Ward (2017), I present comparison plots in Figure B2. For each measure I take a country's ranking on that measure in a given year and normalize to the maximum number of countries in the sample. I plot the time-series average of these normlized rankings to facilitate comparison of unconditional values. The left figure plots GDP share versus centrality and the right figure plots RRW versus centrality. Countries that are large are often central, but this is not always the case. Countries such as the Netherlands, Belgium, Hong Kong, Singapore, and Malaysia are all central, but not particularly large relative to their centrality. This is consistent with the model as is illustrated in Section I.D. Centrality and the RRW measure are negatively correlated — countries that are central tend to be final goods producers (low RRW), while countries that are peripheral tend to be commodity producers (high RRW). That said, there are differences between the two measures. For example, some central countries such as Hong Kong and the Netherlands have high RRW measures.

Although trade network centrality is a highly persistent characteristic of countries, some countries do increase or decrease in centrality over time. An increase in a country's centrality could lead to a decrease in their risk premia and interest rate spread over time – vice versa for a decrease in centrality. In Table BII I test this hypothesis in regressions of risk premia and forward spreads on centrality, but where I include country fixed effects rather than time fixed effects as in Table I. As predicted, the coefficients on centrality for risk premia and forward spreads are both negative. This suggests that as a country's centrality increases over time, its risk premia and interest rates tend to decrease.

I next present evidence on Proposition 1, which states that consumption covariances with a common global factor in consumption are increasing in centrality. Figure 4 plots the average consumption growth beta for each country from equation (39) versus average trade network centrality. Table II regresses consumption growth betas on centrality and other controls —

including time fixed effects as in Proposition 2. A one-standard-devaiation increase in trade network centrality increases a country's consumption growth beta by 0.17. Additionally, controlling for trade-to-GDP or a country's GDP share does not substantially impact this coefficient. These results indicate that countries that are central in the global trade network have higher consumption growth betas, as suggested by Proposition 1. This connection helps explain the heterogeneity in consumption growth covariances found in papers such as Tesar (1995).

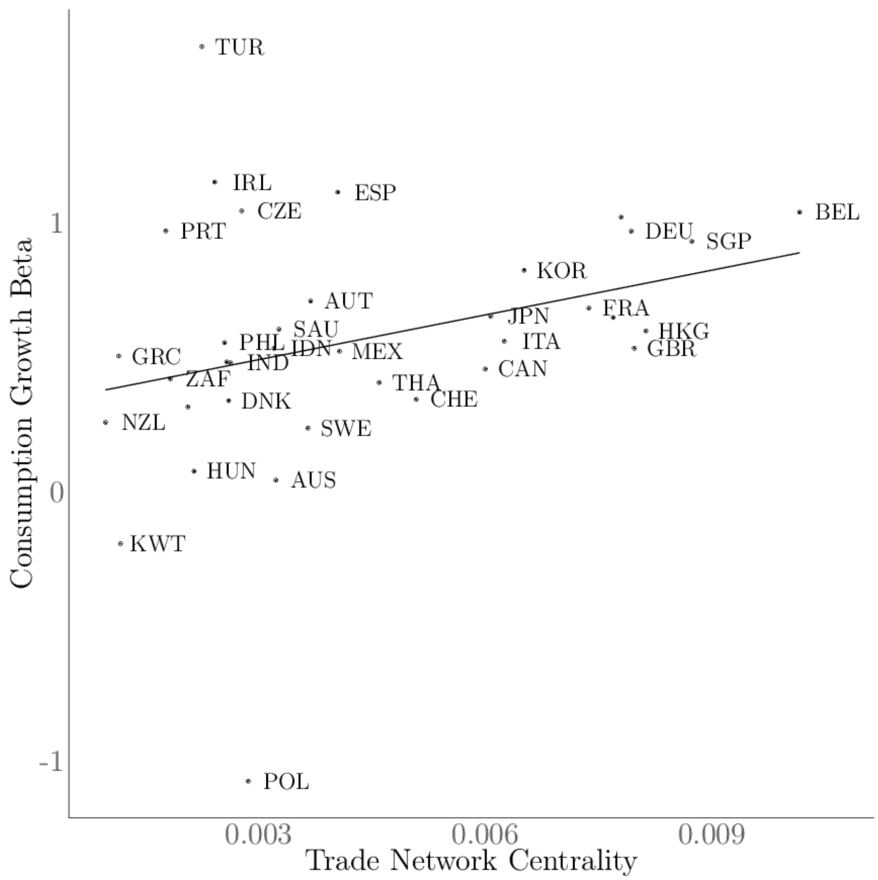

Figure 4. Consumption growth betas versus trade network centrality. This figure plots average consumption growth betas versus average centrality. Consumption growth betas are from regressions of a country's consumption growth on global average consumption growth. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Trade data are from the IMF Direction of Trade Statistics and annual GDP data are from the World Bank, both in dollars. Consumption data are from the Penn World Tables.

Table II

Explanatory Regressions for Consumption Growth Betas

Regressions of consumption growth betas on centrality. Consumption growth betas are from regressions of a countries consumption growth on global average consumption growth. All specifications include time fixed effects. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Trade data are from the IMF Direction of Trade Statistics and annual GDP data are from the World Bank, both in dollars. Consumption data is from the Penn World Tables. Standard errors in parentheses are clustered by country using Cameron, Gelbach, and Miller (2011). *, **, and *** denote significance at the 10%, 5%, and 1% levels respectively.

	Model 1	Model 2	Model 3
Centrality	0.169***	0.174**	0.162**
	(0.064)	(0.067)	(0.065)
GDP Share			0.027
			(0.026)
Trade-to-GDP		−0.009	
		(0.040)	
R^2	0.124	0.124	0.125
Num. obs.	683	683	683

C. *Carry Trade Risk Factors*

While 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 claim, I now use portfolio sorts. 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 III reports the results. In each month t, currencies are sorted into four portfolios using three sorting variables: prior-year trade network centrality, current forward spreads, and average forward spreads from 1988 to 2001. All sorting variables are observable at time t, which makes 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 431 basis points. On average, peripheral country currencies depreciate by 207 basis points, while central country currencies appreciate by 30 basis points. Therefore, the 431 basis point interest rate differential translates into a 255 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 202 basis points. The annualized Sharpe ratio of a long peripheral, short central country portfolio is 0.49.

Panel A also presents more evidence for Proposition 1, where I show that consumption growth covariances are increasing in centrality. The average consumption growth β is increasing from 0.38 for the portfolio of peripheral countries to 0.73 for the portfolio of central countries.[8]

As a benchmark for the portfolio sorts on trade network centrality, in Panels B and C of Table III I sort currencies into portfolios based 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 part of the sample (1988 to 2001 as in Lustig, Roussanov, and Verdelhan (2011)). Sorts on both current forward spreads and average forward spreads produce monotonic cross sections of currency risk premia. Nei-

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

ther 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.

Table III

Portfolios Sorted on Centrality and Forward Spreads

This table presents summary statistics of portfolios sorted on trade network centrality v_{it}, current log forward spreads $f_t - s_t$, and average log forward spreads from 1/1988 to 12/2001. Each month t, currencies are ranked on one of the three criteria and placed into four portfolios with equal weights. The last column reports the difference between the high portfolio and the low portfolio. Log risk premia are given by $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Real interest rate differentials are forward spreads less the expected inflation differential. Expected inflation is the lagged year-over-year change in log CPI. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Means, standard deviations, and Sharpe ratios are annualized. Standard errors are from bootstrapping 10,000 samples. Trade data are 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 1/1988 to 12/2016.

	Panel A: Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.20	0.36	0.54	0.82	-0.63
Forward Spread: $f_t - s_t$					
mean	4.78	2.25	1.38	0.46	4.31
se	0.18	0.15	0.09	0.10	0.20
Risk Premia: rx_t					
mean	2.71	0.49	0.75	0.16	2.55
std	7.65	7.84	6.50	6.95	5.20
se	1.45	1.48	1.23	1.32	0.99
Sharpe Ratio					
mean	0.35	0.06	0.12	0.02	0.49
se	0.20	0.19	0.19	0.19	0.21
Real Interest Differential: $r_{it} - r_t$					
mean	2.69	1.32	1.01	0.67	2.02
se	0.12	0.09	0.08	0.11	0.11
Consumption Growth Coefficient: β_i					
mean	0.38	0.28	0.52	0.73	-0.35
se	0.02	0.07	0.02	0.09	0.08
	Panel B: Unconditional Forward Spread				
	Low	2	3	High	UHML^{FX}
Average Forward Spread (1988-2001)					
mean	-1.04	1.25	3.07	10.02	11.06
Forward Spread: $f_t - s_t$					
mean	-0.62	0.12	2.10	4.05	4.67
se	0.06	0.07	0.08	0.13	0.11
Risk Premia: rx_t					
mean	0.51	0.48	2.91	3.13	2.61
std	4.39	6.13	9.42	8.00	6.01
se	1.13	1.57	2.41	2.05	1.54
Sharpe ratio					
mean	0.12	0.08	0.31	0.39	0.43
se	0.26	0.26	0.27	0.28	0.28
	Panel C: Current Forward Spread				
	Low	2	3	High	HML^{FX}
Previous forward spread: $f_{t-1} - s_{t-1}$					
mean	-1.53	0.32	2.21	8.25	9.78
Forward Spread: $f_t - s_t$					
mean	-1.37	0.35	2.18	7.99	9.36
se	0.08	0.07	0.09	0.27	0.29
std	0.44	0.39	0.48	1.48	1.59
Risk Premia: rx_t					
mean	-2.48	0.93	2.23	3.30	5.78
se	1.15	1.23	1.40	1.77	1.49
std	6.24	6.60	7.58	9.49	7.95
Sharpe Ratio					
mean	-0.40	0.14	0.29	0.35	0.73
se	0.18	0.19	0.19	0.20	0.20

To compare the returns of the three cross sections in Table III, 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 IV presents annualized summaries of the three risk factors. The first three columns correspond to all available data, while the last two columns match the sample period of PMC and HML^{FX} to $UHML^{FX}$. The results show that HML^{FX} has the highest annual return of 5.78% and a Sharpe ratio of 0.73. PMC and $UHML^{FX}$ have similar return profiles, although the Sharpe ratio of PMC is higher due to lower volatility. Over the matched period, $UHML^{FX}$ (2.61%) makes up about half of the returns to HML^{FX} (6.06%). All strategies exhibit crash risk, with negative skewness and large maximum drawdowns.

Table IV

Summary Statistics of Currency Risk Factors

This table presents risk factors are constructed from excess returns of currencies sorted into four portfolios. PMC is from sorts of currencies on prior-year trade network 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 1/1988 to 12/2001 and goes long high average interest rate currencies and short low average interest rate currencies. Summaries for $UHML^{FX}$ are from 1/1996 to 12/2016. Summaries for PMC (2) and HML^{FX} (2) are also are calculated from 1996 to 2016 for comparison with $UHML^{FX}$. All portfolios are rebalanced monthly and moments are annualized. Means and standard deviations are reported in percentage points. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Trade data are 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 1/1988 to 12/2016.

	PMC	HML^{FX}	$UHML^{FX}$	PMC (2)	HML^{FX} (2)
Mean	2.55	5.78	2.61	2.97	6.06
SD	5.20	7.95	6.01	5.49	7.55
Sharpe Ratio	0.49	0.73	0.43	0.54	0.80
Skewness	−0.07	−0.05	−0.08	−0.12	−0.05
Excess Kurtosis	0.79	−0.61	0.60	1.39	−0.49
Maximum Drawdown	0.15	0.25	0.17	0.15	0.17
N	336	347	180	180	180

D. *Cross-Sectional Asset Pricing*

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,

$$(U)HML_t^{FX} = \alpha + \beta PMC_t + \epsilon_t. \tag{41}$$

The results are presented in Table V. I find that PMC is highly correlated with $UHML^{FX}$, with a statistically significant β of 0.8 and an R^2 of 54%. The unexplained excess returns, α, are statistically insignificant and are only 20 basis points annually. While PMC is correlated with HML^{FX}, an unexplained excess return still exists. This finding is not surprising because HML^{FX} is constructed using conditional data in current forward spreads, while trade network centrality is an unconditional property of countries.

Table V

Explanatory Regressions for Benchmark Risk Factors

This table presents results of regressing $fac_t = \alpha + \beta PMC_t + \epsilon_t$. fac_t is either HML_t^{FX} or $UHML_t^{FX}$, which are conditional and unconditional carry trade factors. Specifically, HML_t^{FX} is long currently high forward spread countries and short currently low forward spread countries, and $UHML_t^{FX}$ is from a sort on average forward spreads between 1/1988 and 12/2001 — long high forward spread, short low forward spread. PMC_t is long peripheral countries and short central countries. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. All factors are from sorts into four portfolios. Trade data are 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 1/1988 to 12/2016. Standard errors in parentheses follow Newey and West (1987). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	HML^{FX}	$UHML^{FX}$
α	4.344***	0.203
	(1.604)	(1.151)
β	0.452**	0.810***
	(0.188)	(0.066)
Adj. R^2	0.083	0.545
Num. obs.	336	180

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 VI presents time-series regressions of individual portfolio excess returns in Table III on PMC,

$$rx_{it}^{fac} = \alpha_i + \beta_i PMC_t + \epsilon_{it} \quad t = 1, 2, \ldots, T, \tag{42}$$

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

Panel A presents regressions of portfolios sorted on current forward spreads on PMC. The portfolios show monotonically increasing factor 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 1988 to 2001. 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 centrality, as in the construction of PMC. The portfolios have monotonically decreasing factor loadings from the peripheral portfolio to the central portfolio. Additionally, unexplained excess returns are statistically indistinguishable from zero. This implies that PMC can be used to explain the cross section of centrality-sorted portfolios, as well as the average interest rate-sorted portolfios of $UHML^{FX}$.

Table VI

Time-Series Regressions of Portfolios on PMC

This table presents results of regressing $rx_{it}^{fac} = \alpha_i + \beta_i PMC_t + \epsilon_{it}$. 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 1988 to 2001, $UHML^{FX}$, and trade network centrality, PMC. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Trade data are 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 1/1988 to 12/2016. Standard errors in parentheses follow Newey and West (1987). *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

	1	2	3	4
Panel A: Current $f - s$				
α_i	-2.470^{*}	0.955	2.094	1.874
	(1.300)	(1.517)	(1.816)	(2.034)
β_i	0.094	0.064	0.076	0.546^{*}
	(0.124)	(0.187)	(0.246)	(0.299)
Adj. R^2	0.003	-0.000	-0.000	0.086
Num. obs.	336	336	336	336
Panel B: Average $f - s$ (1988 to 2001)				
α_i	-0.175	-1.194	-0.098	0.028
	(1.029)	(1.404)	(1.995)	(1.337)
β_i	0.232^{***}	0.563^{***}	1.012^{***}	1.042^{***}
	(0.061)	(0.088)	(0.133)	(0.085)
Adj. R^2	0.079	0.250	0.344	0.510
Num. obs.	180	180	180	180
Panel C: Current Centrality				
α_i	0.949	-0.213	0.436	0.949
	(1.575)	(1.732)	(1.445)	(1.575)
β_i	0.689^{***}	0.276	0.124	-0.311
	(0.223)	(0.212)	(0.177)	(0.223)
Adj. R^2	0.217	0.031	0.007	0.051
Num. obs.	336	336	336	336

III. Conclusion

In this paper I show 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 does peripheral countries' consumption growth.

The empirical findings arise in an international model with network-based production. Shocks that originate in large countries impact global consumption more than shocks that originate in small countries. Additionally, shocks have a greater impact on central countries' consumption because their business cycles tend to covary more with larger countries' business cycles. 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 previous work has had limited success uncovering.

Initial submission: June 12, 2017; Accepted: October 14, 2018

Editors: Stefan Nagel, Philip Bond, Amit Seru, and Wei Xiong

REFERENCES

Acemoglu, Daron, Vasco M Carvalho, Asuman Ozdaglar, and Alireza Tahbaz-Salehi, 2012, The network origins of aggregate fluctuations, *Econometrica* 80, 1977–2016.

Ahern, K, 2012, Network centrality and the cross section of stock returns, Working Paper, University of Southern California.

Akram, Q Farooq, Dagfinn Rime, and Lucio Sarno, 2008, Arbitrage in the foreign exchange market: Turning on the microscope, *Journal of International Economics* 76, 237–253.

Alvarez, Fernando, Andrew Atkeson, and Patrick J Kehoe, 2009, Time-varying risk, interest rates, and exchange rates in general equilibrium, *Review of Economic Studies* 76, 851–878.

Atkeson, Andrew, and Lee E Ohanian, 2001, Are Phillips curves useful for forecasting inflation?, *Federal Reserve bank of Minneapolis Quarterly Review* 25, 2–11.

Backus, David K, Silverio Foresi, and Chris I Telmer, 2001, Affine term structure models and the forward premium anomaly, *Journal of Finance* 56, 279–304.

Backus, David K, Patrick J Kehoe, and Finn E Kydland, 1992, International real business cycles, *Journal of Political Economy* 100, 745–775.

Backus, David K, and Gregor W Smith, 1993, Consumption and real exchange rates in dynamic economies with non-traded goods, *Journal of International Economics* 35, 297–316.

Bansal, Ravi, 1997, An exploration of the forward premium puzzle in currency markets, *Review of Financial Studies* 10, 369–403.

———, and Ivan Shaliastovich, 2013, A long-run risks explanation of predictability puzzles in bond and currency markets, *Review of Financial Studies* 26, 1–33.

Baqaee, David Rezza, and Emmanuel Farhi, 2017, The macroeconomic impact of microeconomic shocks: Beyond hulten's theorem, Discussion paper, National Bureau of Economic Research.

Barrot, Jean-Noël, Erik Loualiche, and Julien Sauvagnat, 2018, The globalization risk premium, *Journal of Finance,* forthcoming.

Barrot, Jean-Noël, and Julien Sauvagnat, 2016, Input specificity and the propagation of idiosyncratic shocks in production networks, *Quarterly Journal of Economics* 131, 1543–1592.

Baxter, Marianne, and Michael A Kouparitsas, 2005, Determinants of business cycle comovement: A robust analysis, *Journal of Monetary Economics* 52, 113–157.

Bekaert, Geert, 1996, The time variation of risk and return in foreign exchange markets: A general equilibrium perspective, *Review of Financial Studies* 9, 427–470.

———, and Campbell R Harvey, 1995, Time-varying world market integration, *Journal of Finance* 50, 403–444.

Betts, Caroline M, and Timothy J Kehoe, 2008, Real exchange rate movements and the relative price of non-traded goods, Discussion paper, National Bureau of Economic Research.

Bilson, John FO, 1978, Rational expectations and the exchange rate, in Jacob A. Frenkel, and Harry G. Johnson, ed.: *The Economics of Exchange Rates: Selected Studies* (Addison-Wesley: Boston, MA).

Bonacich, Phillip, and Paulette Lloyd, 2001, Eigenvector-like measures of centrality for asymmetric relations, *Social networks* 23, 191–201.

Burstein, Ariel, Martin Eichenbaum, and Sergio Rebelo, 2006, The importance of nontradable goods' prices in cyclical real exchange rate fluctuations, *Japan and the World Economy* 18, 247–253.

Burstein, Ariel, and Gita Gopinath, 2014, International prices and exchange rates, in Gita Gopinath, Elhanan Helpman, and Kenneth Rogoff, ed.: *Handbook of International Economics, 4th ed.* . vol. 4 (Elsevier).

Burstein, Ariel, Christopher Kurz, and Linda Tesar, 2008, Trade, production sharing, and the international transmission of business cycles, *Journal of Monetary Economics* 55, 775–795.

Cameron, A Colin, Jonah B Gelbach, and Douglas L Miller, 2011, Robust inference with multiway clustering, *Journal of Business & Economic Statistics* 29, 238–249.

Colacito, Riccardo, and Mariano Croce, 2011, Risks for the long-run and the real exchange rate, *Journal of Political Economy* 119, 153–181.

Della Corte, Pasquale, Steven J Riddiough, and Lucio Sarno, 2016, Currency premia and global imbalances, *Review of Financial Studies* 29, 2161–2193.

Du, Wenxin, Alexander Tepper, and Adrien Verdelhan, 2018, Deviations from covered interest rate parity, *Journal of Finance* 73, 915–957.

Dumas, Bernard, and Bruno Solnik, 1995, The world price of foreign exchange risk, *Journal of Finance* 50, 445–479.

Engel, Charles, 1999, Accounting for U.S. real exchange rate changes, *Journal of Political Economy* 107, 507–538.

Fama, Eugene F, 1984, Forward and spot exchange rates, *Journal of Monetary Economics* 14, 319–338.

———, and James D MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607–636.

Ferson, Wayne E, and Campbell R Harvey, 1993, The risk and predictability of international equity returns, *Review of Financial Studies* 6, 527–566.

Frankel, Jeffrey A, and Andrew K Rose, 1998, The endogenity of the optimum currency area criteria, *The Economic Journal* 108, 1009–1025.

Gabaix, Xavier, and Matteo Maggiori, 2015, International liquidity and exchange rate dynamics, *Quarterly Journal of Economics* 130, 1369–1420.

Harvey, Campbell R, 1991, The world price of covariance risk, *Journal of Finance* 46, 111–157.

Hassan, Tarek A, 2013, Country size, currency unions, and international asset returns, *Journal of Finance* 68, 2269–2308.

———, and Rui C Mano, 2018, Forward and spot exchange rates in a multi-currency world, *Quarterly Journal of Economics* 134, 397–450.

Heston, Alan, Robert Summers, and Bettina Aten, 2002, Penn world table, *Center for International Comparisons at the University of Pennsylvania.*

Horvath, Michael, 2000, Sectoral shocks and aggregate fluctuations, *Journal of Monetary Economics* 45, 69–106.

Katz, Leo, 1953, A new status index derived from sociometric analysis, *Psychometrika* 18, 39–43.

Kose, M Ayhan, and Kei-Mu Yi, 2006, Can the standard international business cycle model explain the relation between trade and comovement?, *Journal of International Economics* 68, 267–295.

Lettau, Martin, Matteo Maggiori, and Michael Weber, 2014, Conditional risk premia in currency markets and other asset classes, *Journal of Financial Economics* 114, 197–225.

Lewis, Karen K, 1995, What can explain the apparent lack of international consumption risk sharing?, Discussion paper, National Bureau of Economic Research.

Long, John B, and Charles I Plosser, 1983, Real business cycles, *Journal of Political Economy* 91, 39–69.

Lustig, Hanno, Nikolai Roussanov, and Adrien Verdelhan, 2011, Common risk factors in currency markets, *Review of Financial Studies* 24, 3731–3777.

Lustig, Hanno, and Adrien Verdelhan, 2007, The cross section of foreign currency risk premia and consumption growth risk, *American Economic Review* 97, 89–117.

Maggiori, Matteo, 2017, Financial intermediation, international risk sharing, and reserve currencies, *American Economic Review* 107, 3038–3071.

Meese, Richard A, and Kenneth Rogoff, 1983, Empirical exchange rate models of the seventies: Do they fit out of sample?, *Journal of International Economics* 14, 3–24.

Negishi, Takashi, 1960, Welfare economics and existence of an equilibrium for a competitive economy, *Metroeconomica* 12, 92–97.

Newey, Whitney K, and Kenneth D West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703–708.

Obstfeld, Maurice, 1994, Are industrial-country consumption risks globally diversified?, Discussion paper, National Bureau of Economic Research.

Ready, Robert, Nikolai Roussanov, and Colin Ward, 2017, Commodity trade and the carry trade: A tale of two countries, *Journal of Finance* 72, 2629–2684.

Shambaugh, Jay C, 2004, The effect of fixed exchange rates on monetary policy, *Quarterly Journal of Economics* 119, 301–352.

Solnik, Bruno H, 1974, An equilibrium model of the international capital market, *Journal of Economic Theory* 8, 500–524.

Stockman, Alan C., and Linda L. Tesar, 1995, Tastes and technology in a two-country model of the business cycle: Explaining international comovements, *American Economic Review* 85, 168–185.

Tesar, Linda L, 1993, International risk-sharing and non-traded goods, *Journal of International Economics* 35, 69–89.

———, 1995, Evaluating the gains from international risksharing, *Carnegie-Rochester Conference Series on Public Policy* 42, 95–143.

Verdelhan, Adrien, 2010, A habit-based explanation of the exchange rate risk premium, *Journal of Finance* 65, 123–146.

Appendix A. Model Appendix

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

A.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, which are derived below, are used throughout the paper:

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

A.2 Derivation of Tradables Production

Starting with the social planner's problem and taking first-order conditions with respect to C_{jit} and X_{jit} gives equations (18) and (19), reproduced here:

$$C_{jit} = \frac{(1-\theta)}{N\Psi_{it}}, \tag{A1}$$

$$X_{jit} = \frac{\Psi_{jt}\overline{X}_{jt}(1-\alpha)w_{ji}}{\Psi_{it}}. \tag{A2}$$

Substituting equations (A1) and (A2) into the resource constraint for country i tradables given in equation (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. I therefore omit the subscript and define $\Gamma_t = \Gamma$.

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

$$L_{it}^N = \frac{\kappa\theta}{H_{it}}, \tag{A3}$$

$$L_{it}^T = \frac{\Psi_{it}\overline{X}_{jt}\alpha}{H_{it}} = \frac{\Gamma_i\alpha}{H_{it}}. \tag{A4}$$

Plugging these first-order conditions into the market-clearing condition for labor gives

$$1 = L_{it}^N + L_{it}^T = \frac{\kappa\theta}{H_{it}} + \frac{\Gamma_i\alpha}{H_{it}} \implies H_{it} = \kappa\theta + \Gamma_i\alpha. \tag{A5}$$

Redefining equation (A2) in terms of Γ_i and substituting it into the log tradables production function in equation (8) gives

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

where the constant a_i is defined as

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

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 (21).

A.3 Derivation of Consumption Baskets

Defining equation (18) in terms of Γ_i gives

$$\begin{aligned}
C_{jit} &= \frac{(1-\theta)}{N\Psi_{it}} \\
&= \frac{(1-\theta)}{N\Gamma_i}\overline{X}_{it}. \qquad \text{(A6)}
\end{aligned}$$

Taking the log of equation (15) gives

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

where the third equality replaces C_{ijt} with equation (A6), and b_i is a constant defined as

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

Defining $\overline{c}_t = \left[\log(\overline{C}_{1t}), \ldots, \log(\overline{C}_{Nt})\right]'$, $y_t = [\log(Y_{1t}), \ldots, \log(Y_{Nt})]'$, and $b = [b_1, \ldots, b_N]'$, stacking into a vector, and plugging in the production vector equation (21) gives equation (22):

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

where d is a vector of constants with elements given by

$$d_i = b_i + \frac{1-\theta}{N} \left(\left(\boldsymbol{I} - (1-\alpha) W \right)^{-1} a \right)' \mathbf{1}. \tag{A7}$$

Defining s_i as

$$s_i = \left[(\boldsymbol{I} - (1-\alpha)W')^{-1}\mathbf{1}\right]_i , \tag{A8}$$

log consumption for country i at time t, given in equation (24), is

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

where F_t is given by

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

A.4 Proof of Proposition 1

Using equation (24) and the fact that $z_{i1} = \log(Z_{i1}) = \log(1) = 0$ and $y_{i1} = \log(Y_{i1}) = \log(1) = 0$, the change in log consumption in country i is given by

$$\Delta\bar{c}_{i2} = \theta\left(\kappa z_{i2} + (1-\kappa)y_{i2}\right) + \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} s_j z_{j2}\right). \tag{A9}$$

The change in the common component from equation (25) is given by

$$\Delta F_2 = \frac{(1-\theta)\alpha}{N}\left(\sum_{j=1}^{N} s_j z_{2t}\right).$$

Equations (27), (28), (29), and (30), together with the definition of trade network centrality, v_i, in equation (32) imply

$$\begin{aligned}\text{Cov}(\Delta\bar{c}_{i2}, \Delta F_2) - \text{Cov}(\Delta\bar{c}_{j2}, \Delta F_2) &= \theta(1-\theta)\alpha\kappa\sigma_z^2\left(\frac{1}{N}\left(\sum_{k=1}^{N} s_k\rho_{ik}\right) - \left(\frac{1}{N}\sum_{k=1}^{N} s_k\rho_{jk}\right)\right)\\ &= \theta(1-\theta)\alpha\kappa\sigma_z^2\left(v_i - v_j\right).\end{aligned}$$

This immediately implies Proposition 1.

A.5 Proof of Proposition 2

I first show that currency log risk premia equal log interest rate differentials. Equation (35) 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 (34):

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

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

When z_i and y_i are normally distributed for all i, equation (37) implies (Backus, Foresi, and Telmer (2001)):

$$\begin{aligned}E\left[rx_{ij2}\right] &= \left(\log E\left[M_{i2}\right] - \log E\left[M_{j2}\right]\right) - \left(E\left[m_{i2}\right] - E\left[m_{j2}\right]\right)\\ &= \frac{1}{2}\left(var(m_{i2}) - var(m_{j2})\right)\\ &= \theta(1-\theta)\alpha\kappa\sigma_z^2\left(v_i - v_j\right).\end{aligned}$$

A.6 Quantitiave Results

Table AI

Model Implied Currency Risk Premia (Centrality Conditional on Size)

This table presents currency risk premia in percent for a U.S.-based investor in a theoretical economy. Countries are sorted into three portfolios based on size, and then conditional on size into three portfolios based on trade network centrality. Model parameters are chosen to match unconditional values for 38 countries.

	Centrality		
Size	1	2	3
1	0.00199	0.00137	0.00029
2	0.00217	0.00109	0.00014
3	0.00090	0.00013	-0.00023

Appendix B. Empirical Appendix

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

B.1 Data Description

Table BI reports the sample of countries for which I have FX data and I can calculate trade network centrality. Figure B1 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 BI

Sample of Countries with FX Data and Trade Data

This table lists the sample of countries that have both trade data and foreign exchange data. Trade data are from 1973 to 2016 from the IMF Direction of Trade Statistics. Annual GDP is from the World Bank in dollars. 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 1/1988 to 12/2016.

Country	Start Date	End Date
Australia	Jan 1988	Dec 2016
Austria	Jan 1997	Dec 1998
Belgium	Jan 1997	Dec 1998
Canada	Jan 1988	Dec 2016
Czech Republic	Jan 1997	Dec 2016
Denmark	Jan 1988	Dec 2016
Europe	Jan 1999	Dec 2016
Finland	Jan 1997	Dec 1998
France	Jan 1988	Dec 1998
Germany	Jan 1988	Dec 1998
Greece	Jan 1997	Dec 1998
Hong Kong	Jan 1988	Dec 2016
Hungary	Oct 1997	Dec 2016
India	Oct 1997	Dec 2016
Indonesia	Jan 1997	Dec 2016
Ireland	Jan 1997	Dec 1998
Italy	Jan 1988	Dec 1998
Japan	Jan 1988	Dec 2016
Kuwait	Jan 1997	Dec 2016
Malaysia	Jan 1988	Dec 2016
Mexico	Jan 1997	Dec 2016
Netherlands	Jan 1988	Dec 1998
New Zealand	Jan 1988	Dec 2016
Norway	Jan 1988	Dec 2016
Philippines	Jan 1997	Dec 2016
Poland	Feb 2002	Dec 2016
Portugal	Jan 1997	Dec 1998
Republic of Korea	Feb 2002	Dec 2016
Saudi Arabia	Jan 1997	Dec 2016
Singapore	Jan 1988	Dec 2016
South Africa	Jan 1988	Dec 2016
Spain	Jan 1997	Dec 1998
Sweden	Jan 1988	Dec 2016
Switzerland	Jan 1988	Dec 2016
Thailand	Jan 1997	Dec 2016
Turkey	Jan 1997	Dec 2016
United Arab Emirates	Jan 1997	Dec 2016
United Kingdom of Great Britain and Northern Ireland	Jan 1988	Dec 2016
United States of America	Jan 1988	Dec 2016

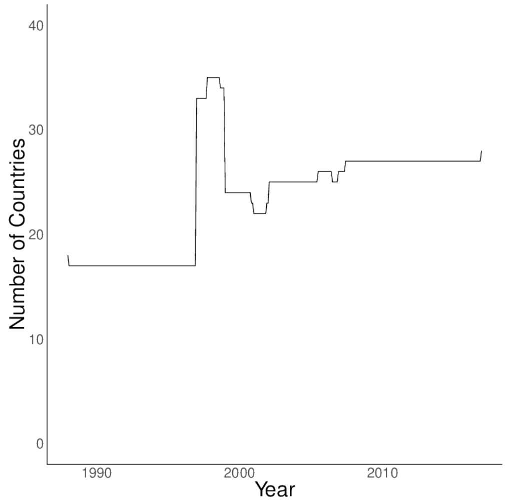

Figure B1. Number of countries in combined data set. This figure plots the number of countries that have both trade data and foreign exchange data over time. Trade data are from 1973 to 2016 from the IMF Direction of Trade Statistics. Annual GDP is from the World Bank. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1988 to 12/2016.

B.2 Plots Comparing Size and RRW

To illustrate the differences between centrality, size, and the trade composition measure of Ready, Roussanov, and Ward (2017), I present comparison plots in Figure B2. For each measure I take a country's ranking on that measure in a given year and normalize to the maximum number of countries in the sample. I plot the time series average of this measure to facililitate comparison of unconditional values. The left figure plots GDP share vs centrality and the right figure plots RRW versus centrality.

B.3 Time-Series Variation in Centrality

In Table BII I present regressions of risk premia and forward spreads on trade network centrality, including country fixed effects. Although not statistically significant, the sign of the coefficients suggests that as a country becomes more central in the global trade network, its interest rates and currency risk premia tend to decrease.

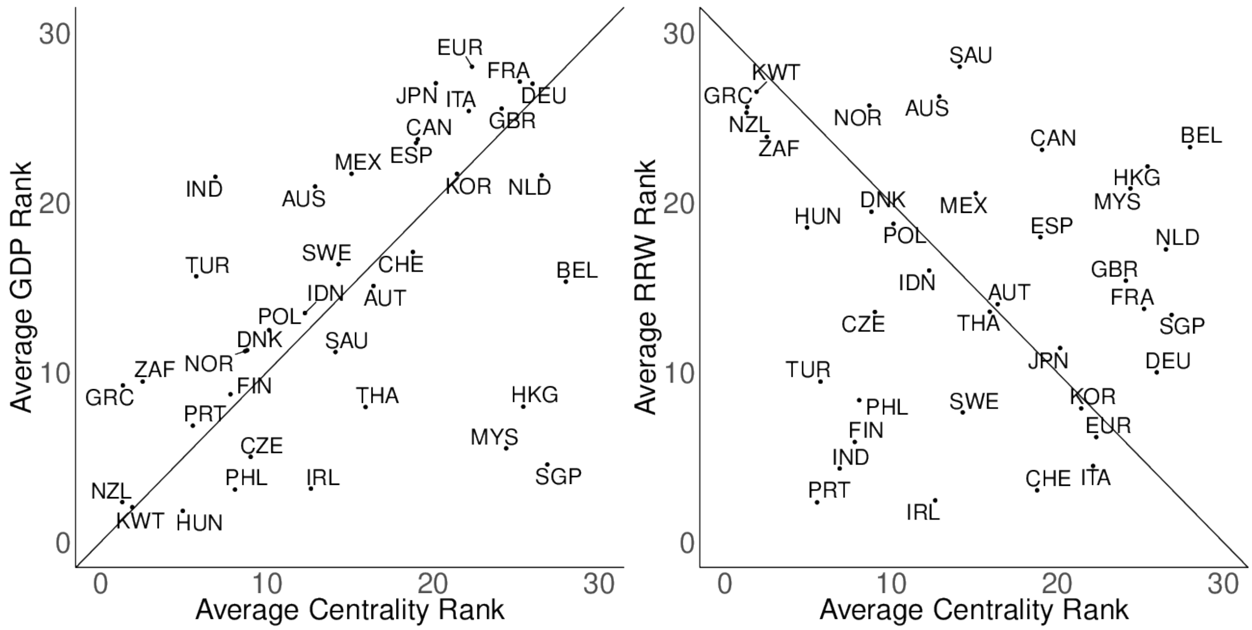

Figure B2. Size and RRW versus centrality. This figure plots average rank of GDP share and RRW versus centrality. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. RRW is constructed as in Ready, Roussanov, and Ward (2017). Trade data are 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 Barclays and Reuters for 39 countries from 1/1988 to 12/2016. Observations are omitted after a country secedes its currency to the euro.

Table BII

Explanatory Regressions for Risk Premia and Forward Spreads

This table presents results of regressions of log risk premia rx_t and forward spreads $f_t - s_t$ on standardized trade network centrality, v_{it}. All specifications include country fixed effects. Excess returns and forward spreads are yearly averages of annualized observations. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Trade data are 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 Barclays and Reuters for 39 countries from 1/1988 to 12/2016. Observations are omitted after a country secedes its currency to the euro. Standard errors in parentheses are clustered by country using Cameron, Gelbach, and Miller (2011). *, **, and *** denote significance at the 10%, 5%, and 1% levels, respectively.

	rx	$f - s$
Centrality	-1.138	-2.008^{*}
	(0.929)	(1.163)
R^2	0.037	0.515
Num. obs.	690	691

B.4 Sorts on Centrality using Business Cycle Correlation

While the main results of the paper focus on a trade-based centrality measure, Table BIII presents portfolio sorts with centrality constructed as in equation (32). I calculate bilateral business cycle correlations, ρ_{ij}, from 20-year rolling correlations of log GDP growth. Panel A presents results for the full sample of countries and Panel B presents results for the developed subset. In both cases, interest rate differentials and currency risk premia are decreasing in the correlation-based centrality measure.

Table BIII

Portfolios Sorted on Correlation-Based Centrality

This table presents summary statistics of portfolios sorted on trade network centrality v_{it}, current log forward spreads $f_t - s_t$, and average log forward spreads from 1/1988 to 12/2001. The last column reports the difference between the high portfolio and the low portfolio. Log risk premia are given by $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Centrality is the export-share weighted average of countries' bilateral GDP growth correlations. Means, standard deviations, and Sharpe ratios are annualized. Standard errors are from bootstrapping 10,000 samples. Trade data are from the IMF Direction of Trade Statistics and annual output data are GDP from the World Bank, both in dollars. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1988 to 12/2016.

	Panel A: Full Sample				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.09	0.21	0.30	0.38	-0.29
Forward Spread: $f_t - s_t$					
mean	5.95	2.45	0.95	0.52	5.43
se	0.31	0.09	0.08	0.12	0.34
Risk Premia: rx_t					
mean	2.30	1.10	-0.51	-0.01	2.31
std	7.44	6.87	6.75	8.53	6.45
se	1.46	1.33	1.31	1.65	1.24
Sharpe Ratio					
mean	0.31	0.16	-0.08	-0.00	0.36
se	0.21	0.20	0.19	0.19	0.20
	Panel B: Developed Sample				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.15	0.31	0.36	0.40	-0.25
Forward Spread: $f_t - s_t$					
mean	1.94	0.41	0.16	0.11	1.83
se	0.11	0.11	0.15	0.12	0.08
Risk Premia: rx_t					
mean	1.21	0.07	-0.32	-0.73	1.93
std	10.24	8.80	8.34	9.74	6.35
se	2.01	1.71	1.62	1.89	1.25
Sharpe Ratio					
mean	0.12	0.01	-0.04	-0.07	0.30
se	0.20	0.20	0.20	0.19	0.20

B.5 Sorts on Centrality using Predicted Business Cycle Correlation

Table BIV presents portfolio sorts with centrality constructed using predicted business cycle correlations. I calculate predicted bilateral business cycle correlations, $\hat{\rho}_{ij}$, from predicted values of annual regressions of business correlations on bilateral trade intensity following Frankel and Rose (1998) and Baxter and Kouparitsas (2005). Business cycle correlations are 20-year rolling correlations of bilateral log GDP growth correlations. Centrality is the export-share weighted average of these predicted correlations as in equation (32). Panel A presents results for the full sample of countries and Panel B presents results for the developed subset. In both cases, interest rate differentials and currency risk premia are decreasing centrality constructed from predicted correlations. The correlation of the PMC factor using bilateral trade intensity is 0.27 with the correlation-based PMC factor and 0.90 with the predicted correlation-based PMC factor. These results suggest that the component of business cycle correlations that is related to bilateral trade is driving variation in unconditional currency risk premia.

B.6 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 III. That said, trade network centrality is an unconditional property of countries, so results should be robust to sorting on the full-sample average of countries' trade network centrality. Table BV presents portfolios sorts using the full-sample average of countries' trade network centrality ranking. Results are consistent with those discussed in the main text.

Table BIV

Portfolios Sorted on Predicted Correlation Centrality

This table presents summary statistics of portfolios sorted on trade network centrality v_{it}, current log forward spreads $f_t - s_t$, and average log forward spreads from 1/1988 to 12/2001. The last column reports the difference between the high portfolio and the low portfolio. Log risk premia are given by $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Centrality is the export-share weighted average of countries' predicted bilateral GDP growth correlations. Predicted bilateral GDP growth correlations are predicted values from yearly regressions of GDP growth correlations on bilateral trade intensity. Means, standard deviations, and Sharpe ratios are annualized. Standard errors are from bootstrapping 10,000 samples. Trade data are from the IMF Direction of Trade Statistics and annual output data are GDP from the World Bank, both in dollars. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1988 to 12/2016.

	Panel A: Full Sample				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.11	0.13	0.15	0.18	-0.07
Forward Spread: $f_t - s_t$					
mean	5.73	2.40	1.07	0.60	5.12
se	0.23	0.09	0.12	0.10	0.24
Risk Premia: rx_t					
mean	2.18	0.63	0.14	-0.24	2.42
std	8.32	6.52	7.40	6.51	5.57
se	1.63	1.27	1.44	1.27	1.09
Sharpe Ratio					
mean	0.26	0.10	0.02	-0.04	0.44
se	0.21	0.20	0.20	0.20	0.21
	Panel B: Developed Sample				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.11	0.13	0.15	0.17	-0.06
Forward Spread: $f_t - s_t$					
mean	1.66	0.99	-0.28	0.33	1.33
se	0.12	0.10	0.14	0.12	0.07
Risk Premia: rx_t					
mean	1.27	0.29	-0.95	-0.14	1.41
std	9.65	10.37	8.84	7.87	7.62
se	1.88	2.04	1.72	1.55	1.50
Sharpe Ratio					
mean	0.13	0.03	-0.11	-0.02	0.19
se	0.20	0.20	0.19	0.20	0.20

Table BV

Portfolios Sorted on Full Sample Average Centrality Ranking

This table presents summary statistics of portfolios sorted on full-sample average trade network centrality ranking. For each month t, currencies are ranked according to their countries' average ranking over the sample and placed into four portfolios with equal weights. Rankings each period are normalized to be between 1 and 39 (maximum number of countries in the sample) so that they are comparable over time. The last column is the difference between the high portfolio and the low portfolio. Log risk premia are given by $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Means and standard deviations are annualized. Sharpe ratios are the annualized mean divided by the annualized standard deviation. Trade data are 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 1/1988 to 12/2016.

	Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Average Centrality Rank					
mean	7.72	17.46	25.96	33.14	-25.42
Forward Spread: $f_t - s_t$					
mean	5.56	1.72	1.30	0.01	5.55
se	0.19	0.11	0.09	0.08	0.19
Risk Premia: rx_t					
mean	2.84	0.36	0.26	0.01	2.83
std	7.90	7.93	6.65	5.99	4.37
se	1.46	1.46	1.22	1.11	0.81
Sharpe Ratio					
mean	0.36	0.05	0.04	0.00	0.65
se	0.19	0.19	0.19	0.19	0.20
Consumption Growth Coefficient: β_i					
mean	0.46	0.22	0.54	0.78	-0.32
se	0.05	0.12	0.06	0.09	0.05

B.7 *Sorts without Euro Aggregate*

Table BVI 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 III. Currency risk premia and interest rates are decreasing in centrality and consumption growth coefficients are increasing in centrality.

Table BVI

Portfolios Sorted on Centrality (No Euro Aggregate)

This table presents 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 reports the difference between the high portfolio and the low portfolio. Log risk premia are given by $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Real interest rate differentials are forward spreads less the expected inflation differential. Expected inflation is the lagged year-over-year change in log CPI. Centrality is the export-share weighted average of countries' bilateral trade intensities — pair-wise total trade divided by pair-wise total GDP. Means, standard deviations, and Sharpe ratios are annualized. Standard errors are from bootstrapping 10,000 samples. Trade data are from the IMF Direction of Trade Statistics and annual output data are GDP from the World Bank, both in dollars. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1988 to 12/2016.

	Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.19	0.35	0.49	0.74	-0.54
Forward Spread: $f_t - s_t$					
mean	4.92	2.45	1.44	0.43	4.49
se	0.17	0.15	0.09	0.10	0.19
Risk Premia: rx_t					
mean	2.62	0.98	0.62	0.22	2.40
std	7.08	7.59	7.45	6.77	5.18
se	1.34	1.43	1.40	1.29	0.97
Sharpe Ratio					
mean	0.37	0.13	0.08	0.03	0.46
se	0.20	0.19	0.19	0.19	0.20
Real Interest Differential: $r_{it} - r_t$					
mean	2.92	1.53	1.03	0.64	2.28
se	0.12	0.10	0.08	0.11	0.11
Consumption Growth Coefficient: β_i					
mean	0.43	0.35	0.42	0.71	-0.27
se	0.04	0.05	0.05	0.08	0.07

B.8 Sorts Omitting Pegs

Table BVII presents portfolio sorts using a subset of observations that omits currency pegs. The pegs classification comes 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 III, currency risk premia and interest rates are decreasing in centrality. The consumption growth coefficients are also increasing in centrality.

Table BVII

Portfolios Sort Omitting Pegged Currencies

This table presents summary statistics of portfolios sorted on trade network centrality v_{it} using a subset of currencies that are not pegged. For each month t, currencies are ranked on trade network centrality and sorted into four portfolios. Log risk premia are given by $rx_t = f_{t-1} - s_t$. Centrality v_{it} is the 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 from the IMF Direction of Trade Statistics and GDP data are from the World Bank, both in dollars. Foreign exchange data are monthly from Barclays and Reuters for 39 countries from 1/1988 to 12/2016. Data on currency pegs come from Shambaugh (2004).

	Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.19	0.34	0.51	0.80	-0.62
Forward Spread: $f_t - s_t$					
mean	6.50	3.12	1.95	0.58	5.91
se	0.26	0.27	0.11	0.12	0.29
Risk Premia: rx_t					
mean	3.67	1.26	1.92	0.22	3.45
std	8.58	10.20	7.15	7.53	7.33
se	1.67	1.99	1.38	1.46	1.42
Sharpe Ratio					
mean	0.43	0.12	0.27	0.03	0.47
se	0.21	0.20	0.20	0.20	0.20
Real Interest Differential: $r_{it} - r_t$					
mean	2.99	1.53	1.22	0.90	2.09
se	0.11	0.10	0.10	0.11	0.12
Consumption Growth Coefficient: β_i					
mean	0.39	0.26	0.47	0.71	-0.32
se	0.05	0.10	0.02	0.07	0.09

B.9 Sorts on Developed Subset

Table BVIII presents portfolio sorts using a subset of developed countries: Australia, Austria, Belgium, Canada, Denmark, Europe, France, Germany, Hong Kong, Ireland, Italy, Japan, the Netherlands, New Zealand, Norway, Singapore, South Korea, Spain, Sweden, Switzerland, and the United Kingdom. FX observations are still dropped for currencies that secede to the euro. As in Table III, 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 BVIII

Portfolio Sorts With Developed Country Subset

This table presents summary statistics of portfolios sorted on trade network centrality v_{it} using a subset of developed country currencies. For each month t, currencies are ranked on trade network centrality and sorted into four portfolios. Log risk premia are given by $rx_t = f_{t-1} - s_t$. Centrality v_{it} is the 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 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 from 1/1988 to 12/2016.

	Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.21	0.39	0.58	0.78	-0.57
Forward Spread: $f_t - s_t$					
mean	1.72	0.71	0.13	0.17	1.55
se	0.10	0.13	0.14	0.12	0.08
Risk Premia: rx_t					
mean	1.54	0.39	-0.05	0.10	1.44
std	9.20	10.66	8.41	8.12	7.82
se	1.73	2.00	1.59	1.54	1.47
Sharpe Ratio					
mean	0.17	0.04	-0.01	0.01	0.18
se	0.19	0.19	0.19	0.19	0.19
Real Interest Differential: $r_{it} - r_t$					
mean	2.04	1.08	0.84	0.73	1.31
se	0.12	0.11	0.10	0.12	0.06
Consumption Growth Coefficient: β_i					
mean	0.26	0.29	0.46	0.56	-0.30
se	0.06	0.07	0.04	0.09	0.04

B.10 Sorts on Sample Ending in 2007

Table BIX presents portfolio sorts using a subset of the data that ends in 2007 due to deviations from covered interest parity documented by Du, Tepper, and Verdelhan (2018). As in Table III, currency risk premia and interest rates are decreasing in centrality. Consumption growth coefficients are also increasing in centrality as in Table III.

Table BIX

Portfolio Sorts With Sample Ending in 2007

This table presents summary statistics of portfolios sorted on trade network centrality v_{it} using a sample that ends in 2007. For each month t, currencies are ranked on trade network centrality and sorted into four portfolios. Log risk premia are given by $rx_t = f_{t-1} - s_t$. Centrality v_{it} is the 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 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 1/1988 to 12/2007.

	Trade Network Centrality				
	Peripheral	2	3	Central	PMC
Previous Centrality: v_{it-12}					
mean	0.18	0.35	0.53	0.80	-0.62
Forward Spread: $f_t - s_t$					
mean	5.72	1.85	1.46	0.45	5.27
se	0.23	0.22	0.12	0.14	0.25
Risk Premia: rx_t					
mean	4.74	1.35	1.60	1.02	3.72
std	6.07	7.27	6.10	7.17	4.89
se	1.39	1.68	1.41	1.65	1.12
Sharpe Ratio					
mean	0.78	0.19	0.26	0.14	0.76
se	0.24	0.24	0.23	0.24	0.23
Real Interest Differential: $r_{it} - r_t$					
mean	3.16	1.19	0.96	1.07	2.09
se	0.14	0.12	0.11	0.15	0.15
Consumption Growth Coefficient: β_i					
mean	0.36	0.27	0.50	0.63	-0.28

B.11 Correlations among Risk Factors

Table BX presents correlations across the currency risk factors.

Table BX

Correlations among Currency Risk Factors

This table presents risk factors constructed from excess returns of currencies sorted into four portfolios. PMC is from sorts on prior-year trade network centrality — long peripheral countries and short central countries. HML^{FX} is from sorts of currencies on current 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 1/1988 to 12/2001. Summaries for $UHML^{FX}$ are calculated from 1/1996 to 12/2016. All moments are annualized. Trade data are from the IMF Direction of Trade Statistics and annual GDP data are from the World Bank, both in dollars. 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 1/1988 to 12/2016.

	PMC	HML^{FX}	$UHML^{FX}$
PMC	1.00		
HML^{FX}	0.29	1.00	
$UHML^{FX}$	0.74	0.85	1.00