# Global Portfolio Network and Currency Risk Premia*

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**Abstract**

I show how foreign equity and debt investments explain cross-sectional variation in currency excess returns. Using bilateral asset holdings of 26 countries from 2001 to 2021, I construct a network centrality measure where a country is more central if it is integrated with core countries which account for a large share in the global asset supply. I find that currency excess returns and interest rates decrease in network centrality. The network centralities are persistent over time and offer a country-specific economic source of risk that drives differences in currency excess returns. Empirical asset pricing tests show that the derived risk factor is priced in a cross section of currency portfolios. Further, negative global shocks cause currencies of central countries to appreciate, while currencies of peripheral countries depreciate; hence investors demand a premium. This is consistent with the idea that currency excess returns compensate for time-varying risk. I rationalize the results in a consumption based model where central countries currencies' appreciate in high marginal utility states, resulting in low currency risk premia.

*JEL-Classification*: F31, E43, E44, G12, G15
*Keywords*: Exchange Rates, Currency Risk Premia, Global Portfolio Holdings, Financial Network, Empirical Asset Pricing

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# 1 Introduction

This paper argues that the position in a global financial network is crucial for currency risk premia. The deviations from uncovered interest rate parity (UIP) and the associated profitability of carry trade strategies - which borrow in low-interest rate currencies and invest in high-interest rate currencies - have been well documented. An extensive literature has derived a series of currency investment strategies using new variables and models to resolve the anomaly. One natural interpretation of the findings is that currency excess returns compensate for persistent asymmetries in countries' risk exposure. Country-specific economic fundamentals offer an explanation for cross-sectional variation in currency risk premia, for instance, the composition of external portfolios (e.g., Dahlquist et al. (2022); Della Corte et al. (2016b); Gourinchas and Rey (2007, 2022); Caballero et al. (2008); Maggiori (2017)).

Over the last decades, international financial integration has increased rapidly and the stock of external assets and liabilities has reached nearly 200% of world GDP (Lane and Milesi-Ferretti (2017)). Foreign portfolio investments create a network of direct and indirect linkages among countries with notoriously flighty capital flows due to high liquidity. In times of negative shocks, global portfolios are sensitive to unexpected payoff innovations affecting countries' consumption. Therefore, it seems rational to expect that exchange rate movements are linked to the composition of external portfolios. Elliott et al. (2014) emphasize how bilateral holdings of core counterparts can decrease the exposure to failures. I follow the research question if asset holdings of core countries makes investors' currencies a good consumption hedge.

In this paper, I connect varying currency risk premia to countries' position in a global portfolio network and introduce a centrality-based risk factor that is priced in the cross section of currency returns. Network centrality measures the investment share weighted average of a country's bilateral foreign portfolio positions of all other countries. Central countries are integrated with core countries which account for a large share in the global asset supply. In particular, Hassan and Mano (2019) provide evidence that carry trade risk premia are more persistent across countries than over time. Asymmetries across centralities offer a missing piece of puzzle in explaining exchange rates. Equipped with portfolio sorting and asset pricing methods, I examine the composition of global portfolios as a fundamental source of risk. My empirical findings are as follows.

First, currency risk premia and interest rates decrease in network centrality. Figure 1 plots averages of currency excess returns and interest rate differentials of a US investor against network centrality. The negative slope implies that investors systematically earn lower excess returns on currencies of central countries. Financial centers and central countries (Eurozone, Japan, Switzerland, and United Kingdom) have lower average currency excess returns and interest rates than peripheral countries (Denmark, Hungary, and New Zealand). A strategy that goes long in currencies of peripheral countries and short in currencies of central countries produces an annualized Sharpe ratio of 0.54. Second, in empirical asset pricing tests, I show that the centrality-based risk factor explains cross-sectional variation in currency excess returns and contains information different from benchmark factors. Third, in times of negative global shocks, the rate of currency depreciation decreases in network centrality. To explain the findings, I present a simple consumption-based model with heterogeneous exposure to global shocks. Central countries' currencies appreciate in high marginal utility states, resulting in low interest rates and currency risk premia.

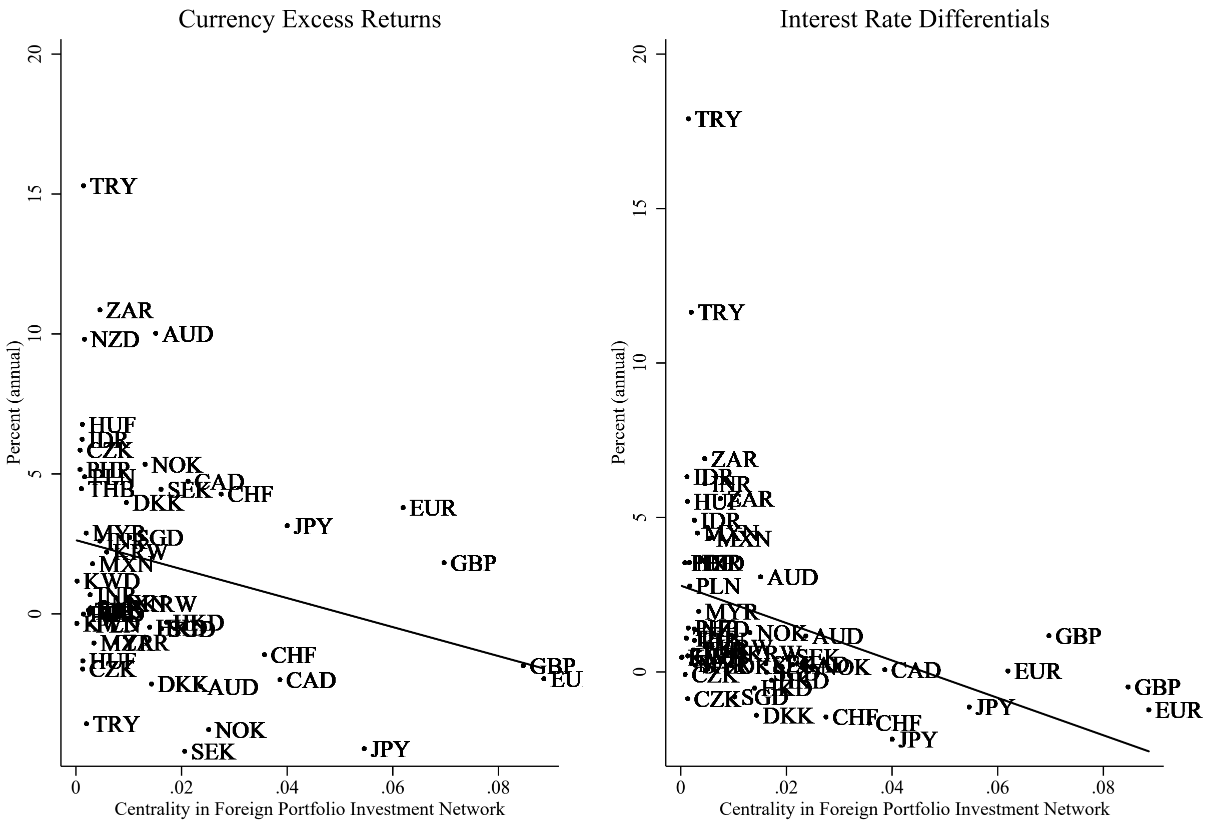


**Figure 1: Currency risk premia and interest rate differentials versus centrality** This figure plots ten-year-long averages of one-month annualized currency excess returns (left) and interest rate differentials (right) to US investors against one-year-lagged centrality in the global portfolio investment network for 26 countries. The log currency excess returns are computed as $f_t - s_t - s_{t+1}$, and using covered interest rate parity, the log interest rate differentials are equivalent to the forward discounts $f_t - s_t$. Exchange rates and returns are reported in US dollar. For each country, monthly observations are averaged in two time blocks (2002 to 2011, and 2012 to 2021). Centrality measures the investment share weighted average of a country's bilateral foreign portfolio positions of all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey and annual GDP data from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Monthly foreign exchange data are from Reuters.

Taken together, the results presented in this paper support the risk-based view of exchange rate determination conditional on persistent differences in economic fundamentals. Thus, currency excess returns can be viewed as compensation for taking time-varying network centrality risk. This is especially relevant for the discussion on safe haven currencies.

**Related Literature.** This paper contributes to a growing literature on cross-sectional variation in currency risk premia conditional on economic fundamentals, e.g., country size (Hassan (2013); Martin (2013)), global imbalances (Della Corte et al. (2016b); Gourinchas and Rey (2007)), commodity exports (Ready et al. (2017a); Ready et al. (2017b)), trade network (Richmond (2019); Jiang and Richmond (2022)), fiscal conditions (Jiang (2021)), capital accumulation (Hassan et al. (2016)), and distance (Lustig and Richmond (2020)). I exploit whether the composition of global portfolios is relevant for the risk factor structure in currency returns.[1] Gourinchas and Rey (2007) and Della Corte et al. (2012) find predictive power in net foreign assets for exchange rates. Della Corte et al. (2016b) associate carry trade returns to persistent imbalances in net foreign assets.[2] In Dahlquist et al. (2022), time-varying risk appetite produces asymmetric portfolios, resulting in wealth transfers to the US in stress periods. Camanho et al. (2022) connect foreign equity returns to portfolio rebalancing motives that affect exchange rates.

To the best of my knowledge, my paper is first studying how financial network integration explains the cross section of currency risk premia. Elliott et al. (2014) and Acemoglu et al. (2015) provide evidence that integrated financial institutions can be more resistant to systemic shocks. The authors emphasize the identification of systematically important institutions that act as shock absorbers. Integration with such core counterparties may lower the idiosyncratic risk exposure.[3] In constructing the measure on network centrality, I follow Richmond (2019), who connects currency risk premia to bilateral export intensities. The motivation to consider financial integration stems from the fact of a positive association between bilateral trade and capital allocation (e.g., Bénétrix et al. (2015); Lane and Milesi-Ferretti (2008)).

More broadly, this paper is related to a large literature on systematic deviations from the UIP condition, stating that exchange rate movements should offset interest rate differentials.[4] Lustig and Verdelhan (2007) provide seminal evidence of UIP failing in the cross section of currency portfolios. A well-established asset pricing literature documents that currency excess returns

[1]There is a broad empirical and theoretical literature connecting external wealth to exchange rates. See, among many others, Lane and Milesi-Ferretti (2002, 2003, 2004, 2007, 2017), Lane and Shambaugh (2010), Bénétrix et al. (2015), Hau and Rey (2006), Habib and Stracca (2012), Ranaldo and Soederlind (2010), and Liao and Zhang (2020).

[2]Gabaix and Maggiori (2015) provide a framework of portfolio-balance exchange rate determination in incomplete financial markets that rationalizes risk premia of net external debtors' currencies in the spirit of Kouri (1982).

[3]For more evidence on financial networks see, for instance, Allen and Gale (2000), Glasserman and Young (2016), Cabrales et al. (2017), and Gai and Kapadia (2010).

[4]See Hansen and Hodrick (1980), Bilson (1981), and Fama (1984) for early findings on the carry trade anomaly.

compensate for exposure to common risk factors.[5] This reduced-form evidence does not reveal the ultimate source of risk. Following the idea that carry trade returns arise from variations in stochastic properties of countries, my paper contributes an economic mechanism behind the cross section of currency risk premia.

Finally, the results contribute to the design of safe haven currencies. Hassan and Zhang (2021) review safe haven characteristics that allow countries to offer lower interest rates, e.g., countries with riskier portfolios have to pay on average higher returns. Most of the recent work pays attention to the exorbitant privilege of the US (Gourinchas and Rey (2007); Gourinchas and Rey (2022)) and the dominance of the US dollar (Farhi and Maggiori (2018); Maggiori (2017); Jiang et al. (2021)). Caballero et al. (2008) highlight the increasing importance of US assets in global portfolios. Lilley et al. (2020) find that US residents decrease foreign bond holdings in times of high global risk aversion, followed by an appreciation of the US dollar. Forbes and Warnock (2012) document correlations between capital outflows and currency depreciation. My paper offers a mechanism that connects global portfolio payoffs to exchange rates in a multi-currency framework. For the empirical analysis, I focus on two testable hypotheses:

(1) Countries which are central in the global portfolio network offer lower currency risk premia than peripheral countries.

(2) When global risk aversion is high, currencies of central countries in the global portfolio network experience an appreciation while currencies of peripheral countries depreciate.

## 2 Model

In this section, I present a model of exchange rate determination. There are $N$ countries, indexed by $i = 1, ..., N$. Each country is populated by a representative household that can consume one good. There are two time periods: $t = 0, 1$. Time 0 is the planning period where households purchase assets. In time 1, the economy experiences a global shock with risky assets being sensitive to payoff innovations. Note that country $i$ refers to the residence of the holder of the asset and country $j$ refers to the residence of the issuer of the asset.

**Assets.** The households can either invest in $N$ country-specific risky assets or in a risk-free bond in their domestic currency. The price of country $j$'s risky asset is $P_j$ and the payoff in time 1 is

[5] Cross-sectional and time-varying currency risk factors can be proxied, for instance, by carry trade risk (Lustig et al. (2011)), US dollar risk (Lustig et al. (2014); Verdelhan (2018)), FX volatility (Menkhoff et al. (2012); Della Corte et al. (2016a); Mueller et al. (2017)), downside risk (Lettau et al. (2014)), crash risk (Brunnermeier et al. (2008); Burnside et al. (2011); Farhi and Gabaix (2016)), country risk (Colacito et al. (2020); Menkhoff et al. (2017); Asness et al. (2013)), endowment shocks (Colacito et al. (2018)), term risk (Lustig et al. (2019)), intermediary risk (Du et al. (2018); Cenedese et al. (2021)).

$$X_j = 1 + \varepsilon_j + \theta_j \varepsilon_g, \tag{1}$$

where $\varepsilon_j$, $\varepsilon_g \sim N(0, \sigma^2)$ are country-specific and global shocks, respectively. The constant term is 1, which is simply a normalization. The country-specific shocks have following distributions $corr(\varepsilon_j, \varepsilon_i) = corr(\varepsilon_j, \varepsilon_g) = 0$. Consistent with the literature (e.g., Colacito et al. (2018)), heterogeneity in the exposure to global shocks is introduced by $\theta_j \in (0, 1)$. The domestic bond pays off one unit of domestic consumption in time 1, and is in zero net supply. Returns in time 1 can be written as

$$R_j = \frac{X_j}{P_j}, \tag{2}$$

$$R_f = \frac{1}{P_f}, \tag{3}$$

and the portfolio return of country $i$ at time 1 is then given by

$$R_i^P = \sum_{j=1}^{N} \alpha_{ij} R_j + (1 - \sum_{j=1}^{N} \alpha_{ij}) R_f, \tag{4}$$

where $\alpha_{ij}$ is the portfolio weight invested in assets of country $j$.

**Market capitalization.** Let's introduce cross-country variation in the exposure to global shocks, $\theta_j$. In this model, the response of payoffs to global shocks depends on countries' share in the world market capitalization, i.e., how important is the country for global portfolios. The share of country $j$ is measured by the sum of bilateral claims against country $j$ relative to world market capitalization

$$\theta_j = \frac{\sum_{i=1}^{N} A_{ij}}{\sum_{i=1}^{N} \sum_{j=1}^{N} A_{ij}}, \tag{5}$$

with $A_{ij}$ being asset holdings of country $i$ issued by country $j$. The denominator gives the market value of the total supply of foreign assets. Considering differences in financial market development across countries as a driver of heterogeneous shock exposure is motivated by Caballero et al. (2008) and Maggiori (2017). Countries with the most developed financial sector, here measured by a greater ability to supply financial assets, take on a larger proportion of global risk because their financial intermediaries are better able to deal with funding problems following negative shocks.

**Network centrality.** Taken together Eq. (4) and Eq. (5), a measure on network centrality can be constructed according to

$$v_i = \sum_{j=1}^{N} \alpha_{ij}\theta_j, \tag{6}$$

where countries are central if they have large portfolio weights invested in countries that are important for the global capital allocation. For instance, if country $i$ is more central than country $j$ ($v_i > v_j$), then Eq. (1) implies that portfolio returns of country $i$ decrease more than returns of country $j$ when the world gets hit by a negative global shock ($\varepsilon_g < 0$).

**Consumption.** Households in country $i$ derive utility from consumption $C_i$ in both periods according to

$$u(C_{i0}, C_{i1}) = \frac{(C_{i0})^{1-\gamma}}{1-\gamma} + E[\beta\frac{(C_{i1})^{1-\gamma}}{1-\gamma}], \tag{7}$$

where $\beta \in (0,1)$ and $\gamma \in (0,1)$ are the subjective time discount factor and the relative risk aversion parameter, respectively. The budget is constrained with subject to

$$C_{i0} = Y_{i0} - \sum_{j=1}^{N} \xi_{ij} P_{j0} - \xi_{if} P_{f0}, \tag{8}$$

$$C_{i1} = Y_{i1} + R_{i1}^{P}. \tag{9}$$

Households have an original consumption level $Y_i$ absent at any asset purchase. $\xi$ is the amount of the asset the investor chooses to buy. In period 0, households decide how much to consume and how to allocate their endowment across assets. In period 1, the households' consumption level depends on the portfolio payoff.

**Exchange rate movements.** In a simple consumption-based asset pricing model, exchange rate movements can be defined by differences in consumption growth rates across countries. For each country, assets that pay off in units of the domestic consumption good are priced by the intertemporal marginal rate of substitution of the country's household or the stochastic discount factor (SDF) $M_{t+1} = \left(\frac{u'_{t+1}}{u'_t}\right)$. In this model, the SDF of country $i$ is given by

$$M_{i1} = \beta \left(\frac{C_{i1}}{C_{i0}}\right)^{-\gamma}. \tag{10}$$

As noted by Backus et al. (2001) and Lustig and Verdelhan (2007), among others, since the SDF is unique in complete financial markets, the change in the real exchange rate equals the ratio of the SDFs for foreign currency- and domestic-denominated assets

$$\frac{Q_{ij1}}{Q_{ij0}} = \frac{M_{i1}}{M_{j1}} \Rightarrow \Delta q_{ij1} = m_{i1} - m_{j1}, \tag{11}$$

where $Q_{ij}$ is the real exchange rate in units of currency $j$ per unit of currency $i$, i.e., a positive $\Delta q_{ij1}$ means an appreciation of currency $i$. Exchange rates are the relative price of two consumption bundles. As such, they should adjust to reflect differences in both current and future relative consumption across countries. When the world experiences a negative global shock ($\varepsilon_g < 0$), the consumption level of country $i$ decreases with its network centrality $v_i$, which leads to a higher marginal utility growth that appreciates the real exchange rate of country $i$. To sum up, negative global shocks increase central countries' marginal utility more than that of peripheral countries.

## 3 Data

This section describes the data used in the empirical analysis, the computation of currency excess returns, and the construction of the measure on network centrality.

**Data on Exchange Rates.** The data on daily spot and one-month forward exchange rates visá-vis the US Dollar are obtained from Thomson Reuters via Datastream. I sample end-of-month rates from January 2001 to August 2021. The sample comprises at most 26 countries: Australia (AUD), Canada (CAD), Czechia (CZK), Denmark (DKK), Eurozone (EUR), Hong Kong (HKD), Hungary (HUF), India (INR), Indonesia (IDR), Japan (JPY), Kuwait (KWD), Malaysia (MYR) Mexico (MXN), New Zealand (NZD), Norway (NOK), Philippines (PHP), Poland (PLN), Saudi Arabia (SAR), Singapore (SGD), South Africa (ZAR), South Korea (KRW), Sweden (SEK), Switzerland (CHF), Thailand (THB), Turkey (TRY), and United Kingdom (GBP). For the Eurozone, I construct an aggregate with all countries that adapted the Euro until the beginning of my sample by summing up their positions with other non-Euro countries into one entity (Austria, Belgium, Finland, France, Germany, Greece, Ireland, Italy, Luxembourg, Netherlands, Portugal, and Spain).

**Currency Excess Returns.** Let denote $s_t$ and $f_t$ as the log spot and forward exchange rates in units of foreign currency per one unit of US Dollar at time $t$. An increase in $s_t$ indicates an appreciation of the US Dollar. From the perspective of a US investor, the log currency excess returns $rx_{t+1}$ on buying a foreign currency in the forward market at time $t$ and selling it in the spot market after one month, in $t+1$, is computed as

$$rx_{t+1} = f_t - s_{t+1}, \tag{12}$$

which is equivalent to the log forward discount minus the change in the spot exchange rate: $rx_{t+1} = f_t - s_t - \Delta s_{t+1}$. If covered interest rate parity (CIP) holds, the forward discount is approximately equal to the interest rate differential: $f_t - s_t \approx i_t^* - i_t$, where $i_t^*$ and $i_t$ denote the foreign and US nominal risk-free interest rates, respectively.[6] In line with the literature, I compute currency excess returns using forward rates rather than interest rate differentials. First, government bonds may contain sovereign default risk and second, commercial dealers mostly trade using forward contracts (e.g., Koijen et al. (2018)). The log currency excess return is approximately equal to the interest rate differential minus the spot exchange rate return

$$rx_{t+1} \approx i_t^* - i_t - \Delta s_{t+1}. \tag{13}$$

The moments of returns are annualized by simply multiplying the monthly return by 12 and the standard deviation by $\sqrt{12}$. I adjust the log currency excess returns for transaction costs using bid-ask quotes on spot and forward rates. The net log currency excess return of an investor who is long in the foreign currency for one month is $rx_{t+1}^l = f_t^b - s_{t+1}^a$ where $a$ indicates the ask price and $b$ the bid price. The return accounts for the full round-trip transaction costs of buying the foreign currency at time $t$ and selling at $t+1$ in the spot market. Similarly, the net log currency excess return of an investor who is long in the US Dollar, or equivalently short in the foreign currency, is $rx_{t+1}^s = f_t^a - s_{t+1}^b$.

**Data on Foreign Portfolio Investment.** The end-of-year series of bilateral portfolio holdings are drawn from the Coordinated Portfolio Investment Survey (CPIS) released by the International Monetary Fund (IMF). The investments are reported on a residency level. For each reporting investor country, the survey reports the market value on investments (divided into equity and investment fund shares, long-term debt (maturity longer than one year), and short-term debt (maturity one year or less)) by residence of the issuer country. Foreign assets are held from following sectors: central banks, banks and other financial intermediaries, general government, nonfinancial corporations, and households. The annual CPIS data is available from 2001 to 2020. To match monthly exchange rate observations, I keep end-of-period data constant until a new observation becomes available. Except for 2008, the value of total investments increased continuously over the last two decades. Lane and Milesi-Ferretti (2008) point out limitations using CPIS data: in-

[6] See Akram et al. (2008) for CIP holding on daily and lower frequency data prior to the financial crisis in 2008. However, recent literature shows CIP violations in the aftermath (Ivashina et al. (2015); Du et al. (2018)).

complete country coverage (e.g., large portfolio holders as Kuwait, Taiwan, and the United Arab Emirates) and underreporting due to offshore centers or third-party holdings. I restrict my analysis to flexible exchange rates wherefore aforementioned countries are excluded. The second limitation can be addressed with implications from Coppola et al. (2021) who highlight the 'residency vs. nationality' problem in using CPIS data. Global firms often finance themselves through foreign subsidiaries located in tax havens, which results in a distorted view of global portfolios when the offshore issuing affiliate, instead of the issuer's ultimate parent country, is reported.[7] In a robustness check, I address this problem by restating the residency-based CPIS data on a nationality basis. Therefore, I use reallocation matrices based on the work in Coppola et al. (2021) obtained from www.globalcapitalallocation.com. The reallocation matrices are only available for the year 2017. I have to assume stable matrices and apply them to all years. The reallocation matrices are not available for all investor countries, wherefore I keep original CPIS data.

**Construction of Global Portfolio Network Centrality.** I construct the network centrality measure analog to Richmond (2019) but instead of bilateral trade intensities, I measure the intensity of bilateral foreign investments. For each country $i$ in period $t$, I build the network centrality measure as

$$v_{it} = \sum_{j=1}^{N} \left( \frac{A_{ijt} + A_{jit}}{G_{it} + G_{jt}} \right) s_{jt}, \tag{14}$$

where $A$ are total bilateral portfolio holdings between country $i$ and $j$ normalized by the pairwise total GDP $G$ of country $i$ and $j$. The annual GDP data is from the World Bank. The investment share $s_j$ are portfolio assets from country $j$ relative to the total portfolio positions of all countries

$$s_j = \frac{\sum_{i=1}^{N} A_{ij}}{\sum_{i=1}^{N} \sum_{j=1}^{N} A_{ij}}, \tag{15}$$

that gives the contribution of a country to the global portfolios. Weighting the bilateral portfolio holdings with country-specific investment shares yields a measure of conditional financial integration, i.e., central countries are integrated with countries that contribute substantially to global portfolios.

Figure 2 plots time series of network centrality rankings of 27 countries from 2001 to 2020. It is not surprising that the Eurozone, United Kingdom, and United States are the most central countries due to their dominance in global portfolios and strong integration. More interestingly, Canada and Japan are central because they have significant portfolio holdings of these core countries. In

[7] For instance, on residency basis, Eurozone holdings of a Cayman-Islands based subsidiary of a Brazil firm are reported as investments in the Cayman Islands, while on nationality basis, the investments are classified towards Brazil.

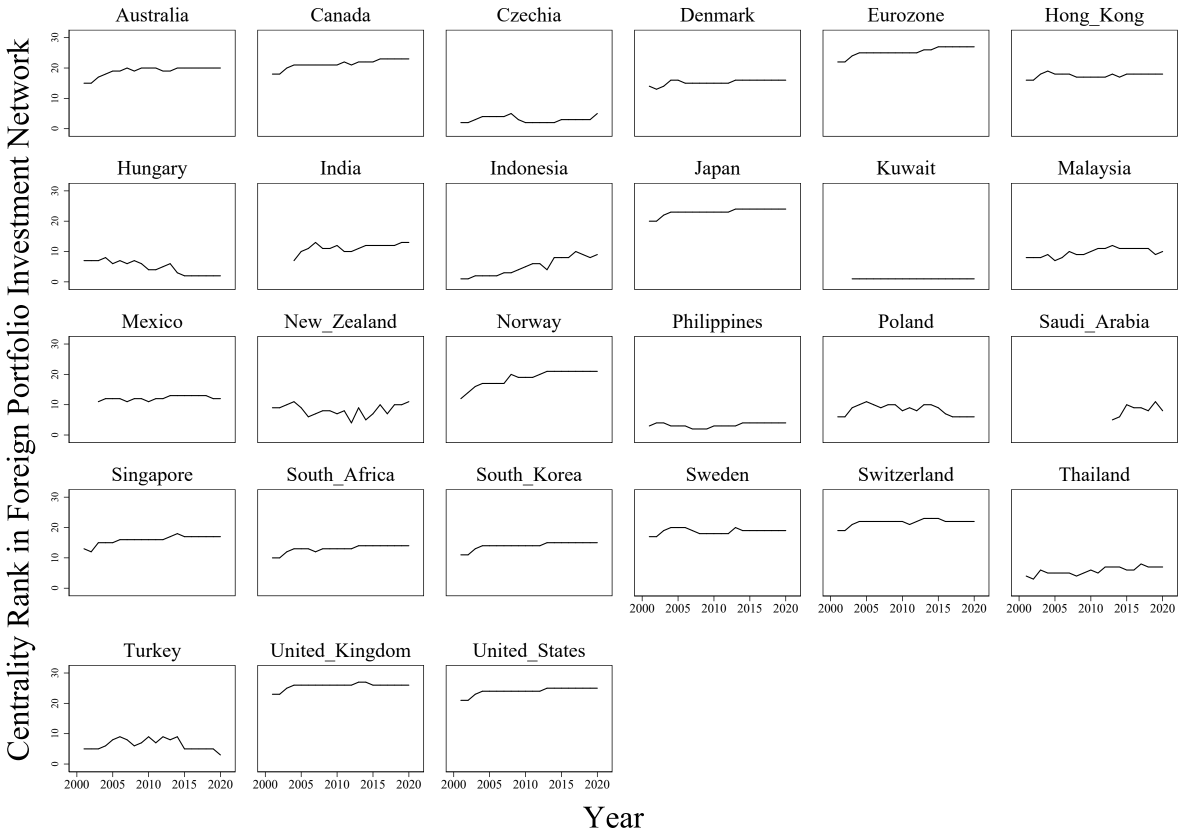


**Figure 2: Time series of network centrality ranking by country** This figure shows the rankings of countries' centrality in the foreign portfolio investment network by year. Centrality measures the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. The rankings are rebalanced each year to between 1 and 27. Portfolio data are from IMF Coordinated Portfolio Investment Survey and annual GDP data from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Data is annual from 2001 to 2020.

contrast, we see that the financial hub Singapore is not as central as one might expect. Singapore has sizeable foreign portfolio holdings but investments are biased towards the financial periphery. For instance, top investment countries of Singapore are South Korea, India, and Malaysia.

## 4 Network Centrality and Currency Portfolios

This section presents empirical evidence that currency risk premia decrease in network centrality. Exploiting this result, I construct currency portfolios sorted on centrality and for further test assets, I allocate currencies to different portfolios variants.

### 4.1 Explanatory Power of Network Centrality

I run the most parsimonious regressions of currency excess returns and forward discounts on one-year lagged network centrality and a set of controls, a constant term, and time fixed-effects. The econometric model for currency excess returns can be written as

$$rx_{it} = \alpha + \delta_t + \beta v_{it-12} + X_{it-12} + \varepsilon_{it}. \tag{16}$$

The results are reported in Table 1. A one-standard-deviation increase in countries' centrality in the network decreases currency risk premia by 0.93% and forward discounts by 1.29%. This result suggests that US investors tend to earn 0.93% less on currency forwards of a country which is central in the network (such as Canada) than they earn in a peripheral country (such as New Zealand). The effect is economically large, given that the cross-sectional standard deviation of average currency excess returns and forward discounts are 3% and 0.4%, respectively. The high $R^2$ implies that network centrality captures information related to interest rate differentials and matters for currency returns. The results provide first evidence for Hypothesis 1.

Table 1 also presents specifications of other controls. First, following Hassan (2013), I control for country size by using GDP shares (i.e., countries' fraction of world GDP). I find no systematic effect of country size on currency risk premia and forward discounts, and the coefficient of investment centrality is effectively unchanged. Next, central countries may be on average more financially open. Therefore, I control for countries' total foreign portfolio holdings normalized by GDP. For example, Singapore has a sizeable investment-to-GDP ratio but is not central. Consistent with my expectations, the network centrality coefficient is not affected by controlling for investment-to-GDP. Not unconditional external wealth but integration with core countries matters for exchange rate determination. Finally, I control for centrality in a global trade network. This measure is calculated analog to Richmond (2019) in Eq. (14) with $A$ being bilateral exports. Trade network centrality measures the output share weighted average of a country's bilateral exports intensities with all other countries relative to total bilateral GDP. Interestingly, controlling for both network centrality measures decreases the coefficient but results remain statistically significant. Investment network centrality captures different economic linkages between countries than trade network centrality but both measures complement each other in explaining currency returns.

### 4.2 Cross Section of Currency Portfolios

Following Lustig et al. (2011) and other studies, I sort currencies into portfolios to average idiosyncratic risk and focus on systematic risk. This sorting generates a cross section of currency excess returns. At the end of each month $t$, currencies are allocated into portfolios based on different signals. The log currency excess returns $rx_{t+1}^k$ for portfolio $k$ are computed as an equally weighted average of the log currency excess returns within portfolio $k$. Portfolios are rebalanced monthly.

**Table 1: Regressions of currency excess returns and forward discounts** This table presents the results of regressions of log currency risk premia $rx$ and log forward discounts $fd$ on standardized one-year lagged investment network centrality $v_{it-12}$, investment-to-GDP ratio, and trade network centrality. All specifications include a constant and month fixed effects. The log currency excess returns are computed as $f_t - s_t - \Delta s_{t+1}$, and using covered interest rate parity, the log interest rate differentials are equivalent to the forward discounts $f_t - s_t$. Exchange rates and returns are reported in US dollar. The moments of returns and forward discounts are annualized. Investment centrality is the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. GDP share is country's fraction of the total GDP of all available countries in the sample for that year. Investment-to-GDP is country's total foreign portfolio holdings relative to GDP. Trade centrality is the output share weighted average of a country's bilateral trade intensities with all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey, trade data are from IMF Direction of Trade Statistics, and annual GDP data are from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Foreign exchange data are monthly from Reuters via Datastream for 26 countries from January 2001 to August 2021. Standard errors are clustered by country and month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

| | $rx$ | $rx$ | $rx$ | $rx$ | $fd$ | $fd$ | $fd$ | $fd$ |
|---|---|---|---|---|---|---|---|---|
| Invest. Centrality | -0.93*** | -0.89** | -0.73*** | -0.58* | -1.29** | -1.61* | -0.87** | -0.79* |
| | (0.27) | (0.32) | (0.19) | (0.28) | (0.48) | (0.80) | (0.36) | (0.41) |
| GDP Share | | -0.05 | | | | 0.44 | | |
| | | (0.30) | | | | (0.51) | | |
| Investment-to-GDP | | | -0.55*** | | | | -1.14*** | |
| | | | (0.18) | | | | (0.41) | |
| Trade Centrality | | | | -0.66* | | | | -0.95* |
| | | | | (0.38) | | | | (0.52) |
| Num. obs. | 5,728 | 5,728 | 5,728 | 5,728 | 5,728 | 5,728 | 5,728 | 5,728 |
| $R^2$ | 0.46 | 0.46 | 0.46 | 0.46 | 0.17 | 0.17 | 0.22 | 0.20 |

**Investment Centrality Portfolios.** First, I construct investment centrality portfolios by sorting on prior-year network centrality $v_{it-12}$. The portfolios are ranked from low to high centrality. Portfolio 1 contains currencies of peripheral countries, and Portfolio 4 contains currencies of central countries. Table 2 summarizes the currency composition of the network centrality-sorted portfolios and the respective frequency entering the portfolio. The first portfolio contains mostly emerging and developing countries, while the fourth portfolio is tilted towards developed countries. The turnover is relatively low, implying a persistence of network centrality over time. The currency investment strategy that is long Portfolio 1 and short Portfolio 4 is called $CEN$. It is noteworthy that the composition differs from carry trade portfolios, i.e., the information contained in the sorting process is not solely driven by interest rate differentials. For instance, the Norwegian krone is a typical investing currency in carry trades, while being a funding currency in network centrality portfolios.

**Table 2: Composition of investment centrality portfolios** This table presents the currency composition of four investment network centrality portfolios. Portfolio 1 (4) contains currencies of countries with the lowest (highest) network centrality. I report the top six currencies and their frequencies entering each portfolio. Portfolios are rebalanced monthly, and foreign exchange data are from Reuters via Datastream for 26 countries from January 2001 to August 2021.

| *Investment Centrality Portfolios* | | | | | | | |
|---|---|---|---|---|---|---|---|
| PF1 | Frequency | PF2 | Frequency | PF3 | Frequency | PF4 | Frequency |
| CZK | 0.15 | MXN | 0.15 | HKD | 0.17 | CHF | 0.17 |
| PHP | 0.15 | INR | 0.14 | DKK | 0.16 | EUR | 0.17 |
| THB | 0.14 | MYR | 0.13 | SGD | 0.16 | GBP | 0.17 |
| KWD | 0.13 | ZAR | 0.12 | KRW | 0.14 | JPY | 0.17 |
| HUF | 0.13 | NZD | 0.11 | AUD | 0.14 | CAD | 0.17 |
| TRY | 0.10 | PLN | 0.10 | SEK | 0.10 | NOK | 0.08 |

**Carry Trade Portfolios.** I form four carry trade portfolios sorted on the current forward discounts $f_t - s_t$ (see Lustig et al. (2011)). The portfolios are ranked from low- to high-interest rate differentials relative to the US. Currencies with the lowest (highest) forward discounts are assigned to Portfolio 1 (Portfolio 4). The currency investment strategy that is long Portfolio 4 and short Portfolio 1 is referred to as $HML$ (high-minus-low).

**Trade Network Centrality Portfolios.** Following Richmond (2019), I form four portfolios based on prior-year trade network centrality. The portfolios are ranked from low to high trade centrality. Portfolio 1 contains currencies of peripheral countries, and Portfolio 4 contains currencies of central countries. The currency investment strategy that is long Portfolio 1 and short Portfolio 4 is called $PMC$ (peripheral-minus-central).

**Dollar Portfolio.** I build an equally weighted portfolio of all available foreign currencies, namely the Dollar portfolio $DOL$. The return on $DOL$ is the average return of a US investor who buys the foreign currency market. This is essentially the currency market return of a US investor against a basket of foreign currencies.

**Summary Statistics of Currency Portfolios.** Table 3 reports descriptive statistics of the currency portfolios. While centrality portfolios are based on unconditional economic fundamentals, the carry trade strategy is derived from the time series of the returns themselves. All sorting variables are observable at time $t$, which makes these sorts implementable trading strategies.

Panel A shows that interest rates mostly monotonically decrease from peripheral to central countries, resulting in an average interest rate spread of 384 basis points. According to the UIP condition, the average change in the spot exchange rates should equal the average forward discount. Currencies in the first portfolio trade at a forward discount of 341 basis points but only depreciate by 38 basis points, adding up to an average currency excess return of 303 basis points. The 384 basis point interest rate differential translates into an average spread in currency excess returns of 245 basis points. This result provides more evidence for Hypothesis 1.

The findings in Panel B are in line with Lustig et al. (2011) where average currency excess returns increase monotonically from Portfolio 1 to Portfolio 4. The difference in average currency excess returns is unsurprisingly large with 508 basis points given the well-documented profitability of carry trade strategies. Panel C replicates the results of Richmond (2019) by sorting on trade centrality. I confirm that currency returns decrease with trade network centrality.

**Summary Statistics of Currency Risk Factors.** Table 4 presents descriptive statistics of the currency risk factors. $CEN$ has a currency excess return of 2.45% and a Sharpe ratio of 0.54. Compared with $PMC$ and $HML$, the performance is slightly smaller but still remarkable. Interestingly, the performance of $PMC$ exceeds the findings of Richmond (2019), which could indicate the increasing relevance of global trade linkages for exchange rates. In contrast to $CEN$, the risk factors $HML$, $PMC$, and $DOL$ strategies have large kurtosis paired with negative skewness, implying high exposure to sudden crash risk (Brunnermeier et al. (2008)).

## 5 Asset Pricing Tests

This section describes the cross-sectional asset pricing approach for currency portfolios and the network centrality risk factor. Since network centrality exhibits a substantial persistence over time,

**Table 3: Currency portfolios sorted on different signals** This table presents annualized summary statistics of portfolios sorted on prior-year investment centrality, current forward discounts, and prior-year trade centrality. Each month $t$, the currencies are ranked on one of these variables and sorted into four portfolios with equal weights. $CEN$ and $PMC$ are long-short strategies that buy Portfolio 1 and sell Portfolio 4 (PF1-PF4). $HML$ buys Portfolio 4 and sells Portfolio 1 (PF4-PF1). The log currency excess returns are computed as $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$, and using covered interest rate parity, the log interest rate differentials are equivalent to the forward discounts $fd_t = f_{t-1} - s_{t-1}$. Exchange rates and returns are reported in US dollar. Mean and standard deviations are percentage points. Investment centrality is the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. Trade centrality is the output share weighted average of a country's bilateral trade intensities with all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey, trade data are from IMF Direction of Trade Statistics, and annual GDP data are from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Foreign exchange data are monthly from Reuters via Datastream for 26 countries from January 2001 to August 2021.

| | *Panel A: Investment Centrality Portfolios* | | | | |
|---|---|---|---|---|---|
| | PF1 | PF2 | PF3 | PF4 | $CEN$ |
| Previous centrality | | | | | |
| mean | 0.12 | 0.36 | 1.40 | 4.80 | -4.68 |
| Currency excess returns | | | | | |
| mean | 3.03 | 3.44 | 1.40 | 0.58 | 2.45 |
| std | 7.10 | 8.83 | 7.34 | 7.34 | 4.50 |
| Forward discount | | | | | |
| mean | 3.41 | 3.86 | 0.47 | -0.43 | 3.84 |
| Sharpe ratio | | | | | |
| mean | 0.43 | 0.39 | 0.19 | 0.08 | 0.54 |
| | *Panel B: Carry Trade Portfolios* | | | | |
| | PF1 | PF2 | PF3 | PF4 | $HML$ |
| Previous fd | | | | | |
| mean | -1.19 | 0.11 | 1.52 | 6.41 | 7.60 |
| Currency excess returns | | | | | |
| mean | -0.47 | 1.88 | 2.29 | 4.61 | 5.08 |
| std | 6.57 | 7.25 | 7.72 | 9.45 | 7.49 |
| Forward discount | | | | | |
| mean | -1.24 | 0.09 | 1.49 | 6.46 | 7.70 |
| Sharpe ratio | | | | | |
| mean | -0.07 | 0.26 | 0.30 | 0.49 | 0.68 |
| | *Panel C: Trade Centrality Portfolios* | | | | |
| | PF1 | PF2 | PF3 | PF4 | $PMC$ |
| Previous centrality | | | | | |
| mean | 0.19 | 0.35 | 0.57 | 0.94 | -0.75 |
| Currency excess returns | | | | | |
| mean | 4.32 | 1.88 | 1.62 | 0.66 | 3.66 |
| std | 8.76 | 8.83 | 6.93 | 5.68 | 5.09 |
| Forward discount | | | | | |
| mean | 4.09 | 2.48 | 0.47 | 0.20 | 3.89 |
| Sharpe ratio | | | | | |
| mean | 0.49 | 0.21 | 0.23 | 0.12 | 0.72 |

**Table 4: Summary statistics of currency strategies** This table presents the annualized summary statistics of three currency risk factors from excess returns sorted into four portfolios. $CEN$ sorts currencies on prior-year investment centrality and goes long foreign currencies of least central countries and short foreign currencies of most central countries. $HML$ sort currencies on current forward discounts and goes long foreign currencies of high-interest rate countries and short foreign currencies of low-interest rate countries. $PMC$ sorts currencies on prior-year trade centrality and goes long foreign currencies of least central countries and short foreign currencies of most central countries. $DOL$ is the average excess return of an US investor investing in all available foreign currencies. Portfolios are rebalanced monthly. The log currency excess returns are computed as $rx_t = f_{t-1} - s_{t-1} - \Delta s_t$. Exchange rates and returns are reported in US dollar. Mean and standard deviations are percentage points. Investment centrality is the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. Trade centrality is the output share weighted average of a country's bilateral trade intensities with all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey, trade data are from IMF Direction of Trade Statistics, and annual GDP data are from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Foreign exchange data are monthly from Reuters via Datastream for 26 countries from January 2001 to August 2021.

| | $CEN$ | $HML$ | $PMC$ | $DOL$ |
|---|---|---|---|---|
| Mean | 2.45 | 5.08 | 3.66 | 2.18 |
| SD | 4.50 | 7.49 | 5.09 | 7.12 |
| Sharpe ratio | 0.54 | 0.68 | 0.72 | 0.31 |
| Skewness | -0.18 | -0.64 | -0.15 | -0.65 |
| Excess kurtosis | 1.44 | 1.81 | 2.02 | 2.01 |
| $N$ | 236 | 236 | 236 | 236 |

it is reasonable to think of it as a pricing factor. I find that network centrality is priced in the cross section of currencies even when controlling for other risk factors.

## 5.1 Methodology

The benchmark in empirical asset pricing relies on a stochastic discount factor (SDF) approach (e.g., Cochrane (2009)). Lustig et al. (2011), Menkhoff et al. (2012), and Della Corte et al. (2016b) consider a two- or three-factor pricing kernel $M$. The discrete excess returns on portfolio $k$ in period $t$ are denoted as $RX_t^k$ for $k = 1, \ldots, N$ and $t = 1, \ldots, T$.[8] In the absence of arbitrage opportunities, risk-adjusted excess returns have a price of zero and satisfy the Euler equation

$$\mathbb{E}\left[M_{t+1} RX_{t+1}^k\right] = 0, \tag{17}$$

with $M_{t+1}$ being a SDF that is linear in the vector of risk factors $f_{t+1}$, given by

$$M_{t+1} = 1 - b'(f_{t+1} - \mu), \tag{18}$$

[8] In the empirical asset pricing tests, I consider discrete currency excess returns (instead of log returns) to satisfy the Euler equation. See Lustig et al. (2011) for further remarks on this. The discrete currency excess returns are computed as $RX_{t+1} = \frac{F_t - S_{t+1}}{S_t}$ , where $F$ and $S$ are the level of forward and spot exchange rates, respectively.

where $b$ is the vector of factor loadings, and $\mu$ are factor means.[9] This expression implies a beta pricing model

$$\mathbb{E}\left[RX^k\right] = \lambda'\beta^k, \tag{19}$$

where the expected excess return on portfolio $k$ is equal to the factor risk prices $\lambda$ times the risk quantities of each portfolio $\beta^k$. The price of risk is $\lambda = \sum_f b$ and can be obtained via the covariance matrix of the risk factors, and $\beta^k$ are regression coefficients of each portfolio $k$'s excess return $RX^k_{t+1}$ on the risk factors $f_{t+1}$.

I estimate the factor loadings $b$ in Eq. (18) via a generalized method of moments (GMM) following Hansen (1982). The estimation uses a prespecified weighting matrix based on the identity matrix and focuses only on unconditional moments (i.e., no instruments other than a constant vector of ones are employed). This one-step procedure accounts for uncertainty from pre-estimated betas (see Burnside (2011)). I also report results from a two-stage estimation following Fama and MacBeth (1973) (FMB). In the first step, I run time-series regressions of currency excess returns for each portfolio on a constant and the factors to estimate in-sample betas. In the second step, I run cross-sectional regressions of currency excess returns on the time-series betas at each time period to estimate the factor risk prices. There is no constant in the second step.

### 5.2 Results

In the asset pricing tests, I investigate whether currencies which are more exposed to network centrality risk offer higher risk premia by estimating variants of the following SDF

$$M_{t+1} = 1 - b_{DOL}(DOL_{t+1} - \mu_{DOL}) - b_{HML}(HML_{t+1} - \mu_{HML}) - b_{CEN}(CEN_{t+1} - \mu_{CEN}), \tag{20}$$

where $DOL$ denotes the excess return of the Dollar factor, $HML$ denotes the excess return to a carry trade strategy, and $CEN$ denotes the excess return to a portfolio sorted on network centrality. I consider three cross sections as test assets (carry trade, investment network centrality, and trade network portfolios). As emphasized by Lewellen et al. (2010), I include network centrality-sorted portfolios to the set of test assets.

**Cross-Sectional Regressions.** Table 5 shows GMM and FMB estimates of factor risk prices $\lambda$. Standard errors are based on Newey and West (1987) with optimal lag selection according to Andrews (1991). In the first specification, I consider a two-factor SDF including $DOL$ and $CEN$ as risk factors. I find a positive and statistically significant estimate of the factor $CEN$ with a risk

[9] Eq. (18) implies an unconditional asset pricing model since factor loadings $b$ are constant over time (i.e., $b_t = b$). See Colacito et al. (2020) for conditional asset pricing test with time-varying parameters.

price of 0.28% (i.e., 3.36% per annum). A positive estimate of $\lambda_{CEN}$ implies higher risk premia for currencies whose returns positively comove with the network centrality risk factor, whereas currencies with negative comovement offer lower risk premia. The exposure to network centrality risk can be seen as a fundamental source of risk that needs to be compensated by a premium. In the second specification - including $DOL$ and $HML$ as risk factors - the size of $\lambda_{HML}$ is unsurprisingly large and similar to the results presented in Lustig et al. (2011). The $R^2$ is higher than in the first specification. I eventually employ a three-factor SDF to assess whether $CEN$ has independent pricing power beyond $HML$. The size of the risk price from $CEN$ decreases to 0.19% and remains significant in the FMB approach. The $R^2$ ranges satisfactory from 38% to 53%. This horse race between carry and network centrality risk suggest that both factors are related but still capture different information.

**Time-Series Regressions.** Table 6 presents estimates of time-series betas from the first-step FMB procedure with the risk factors $DOL$, $HML$, and $CEN$ for three cross sections. Standard errors are based on Newey and West (1987) with optimal lag selection according to Andrews (1991). All currency portfolios load strongly on the $DOL$ factor and beta estimates are approximately one. The Dollar factor does not explain cross-sectional variation in currency excess returns but is necessary for the average level of excess returns. The estimates of $\beta^{CEN}$ shrink when including $HML$ but carry trade portfolios and network centrality portfolios still load strongly on $CEN$ and $HML$.

**Model Fit.** Figure 3 plots realized mean excess returns versus predicted excess returns for 12 currency portfolios. The left panel presents cross-sectional pricing errors for a two-factor SDF with $DOL$ and $CEN$. The model prices not all assets perfectly, especially excess returns of the first (CT1) and fourth (CT4) forward discount-sorted portfolios are over- and underestimated. However, both portfolios form an almost straight line. The right panel shows pricing errors of a three-factor SDF with $DOL$, $HML$, and $CEN$. This specification is able to capture the spread between the excess returns quite well. Even if $HML$ prices currency returns adequately, $CEN$ offers an economic mechanism behind cross-sectional variation in currency excess returns and has risk-adjusted returns in its own rights. For instance, the expected excess return implied by the model of the first network centrality-sorted portfolio IC1 is 2.83% per annum. The excess return share contributed by the exposure to network centrality risk is $12 \times \beta^{IC1}_{CEN} \times \lambda_{CEN} = 12 \times 0.60 \times 0.19 =$ 1.37%, meaning that nearly half of the risk premium is compensation for network centrality risk. For the fourth network centrality-sorted portfolio IC4, the $DOL$ risk premium of 2.18% is nearly offset by a network centrality risk premium of -0.91% and a carry trade risk premium of -0.82%.

**Table 5: Factor risk prices.** This table presents cross-sectional asset pricing results for the linear SDF model that includes the Dollar factor ($DOL$), the carry trade factor ($HML$), and the investment network centrality factor ($CEN$). The test assets include currency excess returns to four carry trade portfolios (sorted on current forward discounts), four investment centrality portfolios (sorted on prior-year centrality in a foreign portfolio investment network), and four trade centrality portfolios (sorted on prior-year centrality in a trade network). The estimates are obtained via GMM and FMB and standard errors are based on Newey and West (1987) with optimal lag selection according to Andrews (1991). Investment centrality is the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. Trade centrality is the output share weighted average of a country's bilateral trade intensities with all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey, trade data are from IMF Direction of Trade Statistics, and annual GDP data are from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Foreign exchange data are monthly from Reuters via Datastream for 26 countries from January 2001 to August 2021. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

| | Factor Prices | | | |
|---|---|---|---|---|
| | $DOL$ | $CEN$ | $HML$ | $R^2$ |
| $GMM_1$ | 0.18*** | 0.28** | | |
| | (0.04) | (0.13) | | |
| | 0.18*** | | 0.42** | |
| | (0.04) | | (0.17) | |
| | 0.18*** | 0.19 | 0.42** | |
| | (0.04) | (0.17) | (0.17) | |
| $GMM_2$ | 0.18*** | 0.28** | | |
| | (0.04) | (0.13) | | |
| | 0.18*** | | 0.42** | |
| | (0.04) | | (0.17) | |
| | 0.18*** | 0.19 | 0.41** | |
| | (0.04) | (0.17) | (0.17) | |
| $FMB$ | 0.18 | 0.28*** | | 0.38 |
| | (0.15) | (0.10) | | |
| | 0.18 | | 0.42*** | 0.42 |
| | (0.15) | | (0.16) | |
| | 0.18 | 0.19** | 0.42*** | 0.53 |
| | (0.15) | (0.08) | (0.16) | |

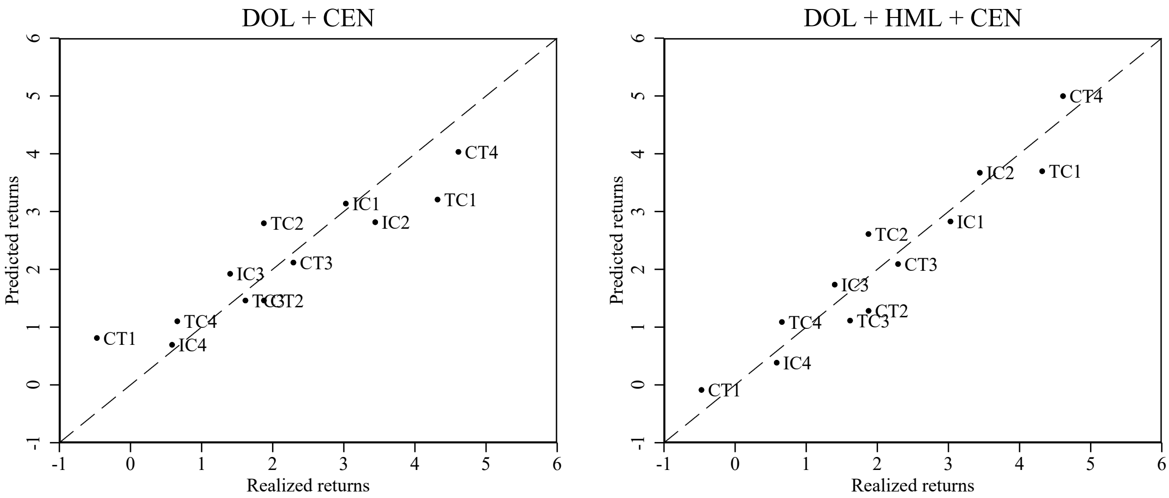


**Figure 3: Pricing Errors** This figure shows the cross-sectional pricing errors for the two-factor SDF (left) and three-factor SDF (right). The FMB estimates are obtained using 12 currency portfolios as test assets: CT denotes carry trade portfolios (sorted on current forward discounts), IC denotes investment centrality portfolios (sorted on prior-year centrality in a foreign portfolio investment network), and TC denotes trade centrality portfolios (sorted on prior-year centrality in a trade network). The sample period covers monthly data from January 2001 to August 2021.

**Table 6: Time-series betas.** This table presents time-series betas for regressions of $RX^k_{t+1} = \alpha^k + \beta^k Factors_{t+1} + \varepsilon^k_{t+1}$, where $Factors$ denotes the Dollar factor ($DOL$), the carry trade factor ($HML$), and the investment network centrality factor ($CEN$). $RX^k$ are excess returns to carry trade portfolios (sorted on current forward discounts), investment centrality portfolios (sorted on prior-year centrality in a foreign portfolio investment network), and trade centrality portfolios (sorted on prior-year centrality in a trade network). The beta estimates are first-stage FMB regressions and standard errors are based on Newey and West (1987) with optimal lag selection according to Andrews (1991). Exchange rates and returns are reported in US dollar. Investment centrality is the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. Trade centrality is the output share weighted average of a country's bilateral trade intensities with all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey, trade data are from IMF Direction of Trade Statistics, and annual GDP data are from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Foreign exchange data are monthly from Reuters via Datastream for 26 countries from January 2001 to August 2021. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

| Factor Betas | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| *Panel A: Carry Trade Portfolios* | | | | | | *Panel B: Investment Centrality Portfolios* | | | | | | *Panel C: Trade Centrality Portfolios* | | | | | |
| PF | $\alpha$ | DOL | CEN | HML | $R^2$ | PF | $\alpha$ | DOL | CEN | HML | $R^2$ | PF | $\alpha$ | DOL | CEN | HML | $R^2$ |
| 1 | -1.28** | 0.79*** | -0.37*** | | 0.80 | 1 | -0.11 | 0.94*** | 0.44*** | | 0.96 | 1 | 1.11 | 1.16*** | 0.27*** | | 0.91 |
| | (0.56) | (0.04) | (0.04) | | | | (0.34) | (0.02) | (0.04) | | | | (0.87) | (0.04) | (0.07) | | |
| 2 | 0.38 | 0.94*** | -0.24*** | | 0.88 | 2 | 0.63 | 1.14*** | 0.13 | | 0.85 | 2 | -0.92 | 1.19*** | 0.08 | | 0.92 |
| | (0.45) | (0.03) | (0.04) | | | | (0.83) | (0.04) | (0.08) | | | | (0.63) | (0.05) | (0.08) | | |
| 3 | 0.20 | 1.03*** | -0.06** | | 0.91 | 3 | -0.52 | 0.99*** | -0.09*** | | 0.91 | 3 | 0.16 | 0.89*** | -0.19*** | | 0.85 |
| | (0.47) | (0.04) | (0.03) | | | | (0.56) | (0.02) | (0.03) | | | | (0.44) | (0.03) | (0.04) | | |
| 4 | 0.58 | 1.20*** | 0.57*** | | 0.89 | 4 | -0.11 | 0.94*** | -0.56*** | | 0.96 | 4 | -0.44 | 0.74*** | -0.21*** | | 0.89 |
| | (0.73) | (0.03) | (0.05) | | | | (0.34) | (0.02) | (0.04) | | | | (0.40) | (0.03) | (0.02) | | |
| 1 | -0.39* | 0.99*** | 0.09*** | -0.48*** | 0.96 | 1 | 0.20 | 1.01*** | 0.60*** | -0.17*** | 0.97 | 1 | 0.62 | 1.05*** | 0.03 | 0.26*** | 0.94 |
| | (0.22) | (0.03) | (0.03) | (0.02) | | | (0.24) | (0.02) | (0.05) | (0.02) | | | (0.62) | (0.04) | (0.06) | (0.05) | |
| 2 | 0.57 | 0.98*** | -0.15*** | -0.10*** | 0.89 | 2 | -0.23 | 0.95*** | -0.30*** | 0.46*** | 0.93 | 2 | -0.74 | 1.23*** | 0.18*** | -0.10** | 0.92 |
| | (0.44) | (0.04) | (0.04) | (0.03) | | | (0.52) | (0.03) | (0.06) | (0.03) | | | (0.58) | (0.05) | (0.07) | (0.04) | |
| 3 | 0.23 | 1.04*** | -0.05 | -0.01 | 0.91 | 3 | -0.33 | 1.03*** | 0.00 | -0.10** | 0.92 | 3 | 0.50 | 0.96*** | -0.02 | -0.19*** | 0.87 |
| | (0.47) | (0.04) | (0.04) | (0.03) | | | (0.52) | (0.03) | (0.06) | (0.04) | | | (0.44) | (0.05) | (0.06) | (0.06) | |
| 4 | -0.39* | 0.99*** | 0.09*** | 0.52*** | 0.98 | 4 | 0.20 | 1.01*** | -0.40*** | -0.17*** | 0.98 | 4 | -0.43 | 0.74*** | -0.20*** | -0.01 | 0.89 |
| | (0.22) | (0.03) | (0.03) | (0.02) | | | (0.24) | (0.02) | (0.05) | (0.02) | | | (0.42) | (0.03) | (0.04) | (0.03) | |

# 6 Currency Returns in Bad Times

I now turn to test Hypothesis 2, stating that in bad times when global risk aversion is high, the rate of currency depreciation decreases with countries' network centrality. Following Della Corte et al. (2016b) and other studies, I use changes in the VIX volatility index for global risk aversion shocks. First, I estimate a panel regression by regressing monthly spot exchange rate returns $\Delta s_{it}$ on the one-year lagged network centrality variable $v_{it-12}$, the change in the VIX index $\Delta VIX_t$, and most importantly an interaction term between both variables. The econometric model is

$$\Delta s_{it} = \alpha_i + \delta_t + \beta_1 v_{it-12} + \beta_2 \Delta VIX_t + \beta_3 \Delta VIX_t \times v_{it-12} + \varepsilon_{it}. \tag{21}$$

Since I add a constant, year and country fixed effects, the regressions can be interpreted as how currencies behave relative to average currency movements in the sample. I also capture global risk aversion shocks with a dummy variable of VIX that takes the value of one when changes in VIX are larger than one standard deviation and zero otherwise. Hypothesis 2 requires a positive interaction coefficient, implying that in bad times when risk aversion increases, countries that are central experience a less strong currency depreciation. The results are reported in Table 7. The interaction terms are positive and statistically significant in both specifications. In addition, changes in VIX enter the regressions significantly with a negative sign, meaning that bad times are associated with foreign currency depreciation.

**Table 7: Panel regressions of spot returns on changes in the VIX index** This table presents results for panel regressions of monthly spot exchange rate returns $\Delta s_{it}$ on one-year lagged investment network centrality $v_{it-12}$, changes in the VIX index $\Delta VIX_t$, and an interaction term between both variables. The dummy variable equals one if $\Delta VIX_t$ is greater than one standard deviation as estimated across the entire sample, and zero otherwise. All specifications include a constant, year fixed effects, and country fixed effects. Exchange rates and returns are reported in US dollar. The monthly changes in the VIX volatility index are from the Chicago Board Options Exchange that measure the implied volatility of S&P 500 index options. Investment centrality is the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey, trade data are from IMF Direction of Trade Statistics, and annual GDP data are from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Foreign exchange data are monthly from Reuters via Datastream for 26 countries from January 2001 to August 2021. Standard errors are clustered by country and month. *, **, and *** denote significance at the 10%, 5%, and 1% level, respectively.

| | $\Delta$s | $\Delta$s |
|---|---|---|
| Investment centrality | -1.61 | -5.25** |
| | (3.66) | (2.53) |
| $\Delta$ VIX | -0.22*** | |
| | (0.04) | |
| Investment centrality $\times\Delta$VIX | 1.48* | |
| | (0.75) | |
| $\Delta$VIX dummy | | -2.61*** |
| | | (0.67) |
| Investment centrality $\times\Delta$VIX dummy | | 16.95* |
| | | (9.29) |
| Num. obs. | 5,728 | 5,728 |
| Adj. $R^2$ | 0.14 | 0.09 |

Next, I estimate marginal effects of changes in the VIX index on spot exchange rate returns conditional on different network centrality levels. Average marginal effects are calculated by taking the derivative of spot exchange rate returns with respect to changes in the VIX index for different network centrality levels. The results are presented in Figure 4. With increasing network centrality, the impact of an one-point increase in the VIX index on exchange rate returns decreases significantly, i.e., periods of bad times affect currencies of peripheral countries more negatively, which results in a more substantial depreciation. This finding can be interpreted as network centrality being a safe haven property of currencies that hedges against global risk aversion shocks.

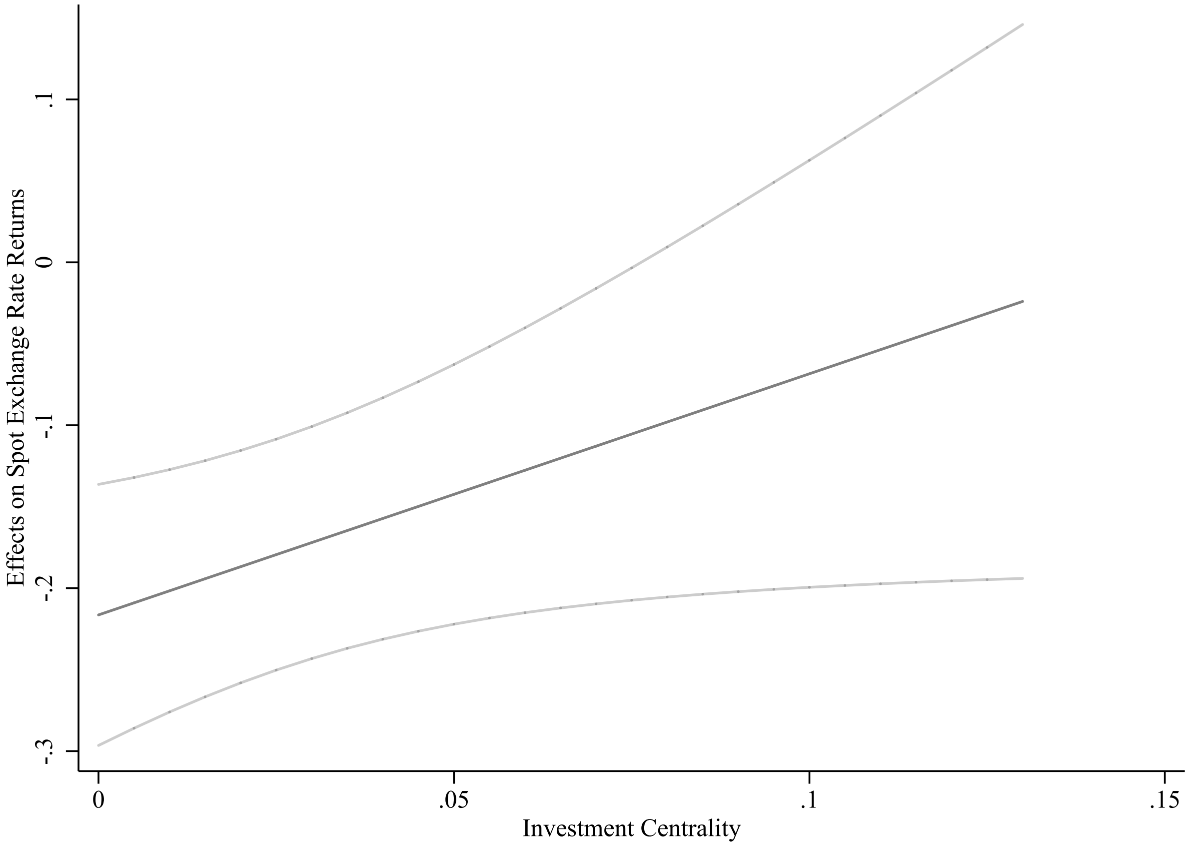


**Figure 4: Average marginal effects of changes in the VIX index** This figure plots the average marginal effects of $\Delta VIX_t$ for different levels of network centrality in a 95% confidence interval after running the panel regression $\Delta s_{it} = \alpha_i + \delta_t + \beta_1 v_{it-12} + \beta_2 \Delta VIX_t + \beta_3 \Delta VIX_t \times v_{it-12} + \varepsilon_{it}$, where $\Delta s_{it}$ are monthly log spot exchange rate returns, $v_{it-12}$ are one-year lagged network centrality, and $\Delta VIX_t$ are monthly changes in the VIX volatility index. Year fixed effects and country fixed effects are included. Standard errors are clustered by country and month. Exchange rates and returns are reported in US dollar. The monthly changes in the VIX volatility index are from the Chicago Board Options Exchange that measure the implied volatility of S&P 500 index options. Investment centrality is the investment share weighted average of a country's bilateral foreign portfolio holdings of all other countries relative to total bilateral GDP. Portfolio data are from IMF Coordinated Portfolio Investment Survey, trade data are from IMF Direction of Trade Statistics, and annual GDP data are from the World Bank. The Eurozone is an aggregate with all countries that adapted the Euro until the beginning of the sample by summing up their positions with other non-Euro countries into one entity. Foreign exchange data are monthly from Reuters via Datastream for 26 countries from January 2001 to August 2021.

# 7 Conclusion

This paper provides empirical evidence of a strong relationship between the composition of foreign portfolio holdings and currency risk premia. Currencies of countries that are central in a foreign portfolio investment network, measured by their integration with core countries which account for a large share in the global portfolios, have lower currency excess returns and interest rates. This result is statistically and economically significant, and robust to other economic fundamentals that drive exchange rates. Consistent with empirical asset pricing implications, I find that network centrality risk is priced in the cross section of currency portfolios.

The findings are in line with the idea that currency excess returns compensate for time-varying risk. This paper offers an economic mechanism behind cross-sectional variation in currency risk premia. High-interest rate currencies positively load on the network centrality risk factor and pay low returns in bad times when global risk aversion is high. Low-interest rate currencies are negatively related to the network centrality risk factor and appreciate in bad times, thus providing a hedge. I shed light on fundamental sources of countries' exposure to risk and contribute to the explanations of cross-sectional variation in currency excess returns based on country-specific economic fundamentals.

The rationale behind the results is that expectations about unfavorable payoff innovations during bad times are priced in currency returns. The riskier the portfolios of countries, given by the integration with financial periphery countries, the higher are required currency excess returns. This contributes to the risk-based view on exchange rate determination. Investors demand a currency risk premium to hold currencies of peripheral countries *because* these currencies depreciate stronger in bad times. On the other side, integration with core countries which are able to produce tradeable financial assets makes the investor country itself safer. This paper offers a new risk factor that allows a deeper examination of currencies' *safe haven* properties.

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