Journal of Financial Economics

The trade imbalance network and currency returns☆

Ai Jun Hou [a], Lucio Sarno [b], Xiaoxia Ye [c,*]

[a] Stockholm University, Stockholm Business School, Sweden
[b] University of Cambridge, Cambridge Judge Business School, Girton College and the Centre for Economic Policy Research, United Kingdom
[c] University of Nottingham, Nottingham University Businss School, United Kingdom

ARTICLE INFO

JEL classification:
F31
F37
G12
G15

Keywords:
Trade imbalance network
Currency premia
Carry trade
Network centrality

ABSTRACT

We introduce in the theory of Gabaix and Maggiori (2015) a network structure to capture the complexity of the balance sheets of financial intermediaries, using the Leontief inverse-based centrality. We use this framework in a multi-country world with imperfect financial markets to study how currency risk premia are connected to financiers' risk bearing capacity. Guided by the theory, we construct a Centrality Based Characteristic (CBC), based on the centrality of the trade imbalance network and variance–covariance matrix of currency returns. Sorting currencies on CBC generates a high Sharpe ratio, and the resulting excess returns reflect a novel source of predictability.

1. Introduction

International trade and trade imbalances across countries play crucial roles in determining macroeconomic and financial outcomes around the world.[1] They are also a driving force of exchange rate fluctuations and currency risk premia in a variety of theories of exchange rate determination (see, e.g., Gourinchas and Rey, 2007; Gabaix and Maggiori, 2015; Colacito et al., 2018; Maggiori, 2022). Motivated by this literature, empirical research has documented a predictive link between external imbalances and currency excess returns in the cross section of countries (see, e.g., Della Corte et al., 2012, 2016; Della Corte and Krecetovs, 2021).

However, a potential tension exists between theory and empirical research in this area. Specifically, the theory of international trade and exchange rate dynamics is typically set up in a two-country framework, whereas empirical work on currency asset pricing is conducted in the cross-section of countries, under the implicit assumption that theories about bilateral relationships between countries can be readily generalized to a multi-country setting.[2] This is not necessarily the case without additional assumptions. More importantly, it seems likely that generalization of two-country theories to a multi-country setting can generate additional insights about exchange rate dynamics by capturing

☆ *Acknowledgments*. Nick Roussanov was the editor for this article. We are greatly indebted for comments and constructive suggestions to Nick Roussanov, an anonymous Referee, and Matteo Maggiori. We also thank Valentina Bruno, Vasco Carvalho, Magnus Dahlquist, Pasquale Della Corte, Ziran (Josh) Ding, Ilias Filippou, Minyou Fan, Xiang Fang, Po-Hsuan Hsu, Zhengyang Jiang, Olga Kolokolova, Ingomar Krohn, Jiadong Liu, Jiatao Liu, Yang Liu, Juan Lin, Dong Lou, Jiaming Mao, Thomas Maurer, Danny Mcgowan, Linlin Niu, Junghum Park, Ilaria Piatti, Swapnil Singh, Yajun Xiao, Ran Xing, Gang Zhang, Yaoyuan Zhang, Yinggang Zhou, and participants at presentations given at the University of Cambridge, Stockholm University, the Bank of Lithuania, the 13th Workshop on Exchange Rates at the Bank of Canada, Queen's Business School, SUFE, XJTLU, WISE Xiamen University, Frontiers of Factor Investing 2024 Conference, the Swiss Society for Financial Market Research (SGF) Conference 2024, WFA 2024, CFRC 2024, CICF 2024, and EFA 2024, for their helpful comments and discussions. We are grateful to Gian Maria Milesi-Ferretti, Philip Lane, and Agustín Bénétrix for kindly sharing with us updated data of their papers. For the purpose of open access, the authors have applied a Creative Commons Attribution (CC BY) license to any Author Accepted Manuscript version arising from this submission. All errors are our responsibility.

[1] For example, Caballero and Krishnamurthy (2009) find that trade imbalances are a crucial part of the mechanism that led to the global financial crisis.
[2] By "multi-country" we mean more than one exchange rate or, equivalently, more than two countries.

Received 18 April 2024; Received in revised form 29 May 2025; Accepted 31 May 2025
Available online 24 June 2025
0304-405X/

indirect relationships in the trade imbalance network that are hidden in a two-country setting. Indeed, Richmond (2019) provides theory and empirical evidence that the total trade network is linked to currency risk premia in a model that assumes complete financial markets.

In this paper, we build on this line of research by extending the theory of Gabaix and Maggiori (2015) to study currency risk premia in a multi-country world with imperfect financial markets and a fully-fledged trade imbalance network.[3] In the theory, currency returns are linked to financiers' limited risk bearing capacity, captured by the complexity of their balance sheets in the trade imbalance network. Then, guided by the theory, we construct a Centrality Based Characteristic (hereafter *CBC*), based on the centrality of the imbalance network and the variance–covariance of currency returns. We show that sorting currencies on *CBC* generates strong predictability of currency excess returns in the cross section of countries, and a high Sharpe ratio. The source of this predictability is novel in the sense that the resulting excess returns from the cross-sectional strategy that sorts on *CBC* cannot be explained by various standard currency factors and intermediary asset pricing factors. In turn, we find that this multi-country extension provides both fresh insights into the link between trade imbalances and exchange rate dynamics, and a novel investment strategy.

In the theory of Gabaix and Maggiori (2015), countries run trade imbalances in imperfect financial markets and financiers bear the resulting currency risk by buying the currency of the deficit country and shorting the currency of the surplus country.[4] However, the financiers' ability to take long (short) positions (i.e., risk-bearing or risk-absorbing capacity) depends on the riskiness of their balance sheets. To incentivize financiers, the currency of the deficit country has to depreciate contemporaneously and is expected to appreciate in the future to compensate for the risk financiers take. Essentially, the imbalance presents the financiers with investment options, but financial constraints limit their ability to take buy and sell positions. This leads financiers to alter the size and composition of their balance sheets, ultimately affecting the exchange rate. Two important determinants of currency premia arise in the model: financiers' risk-bearing capacity (or limited commitment of risk-bearing), and the external imbalance of individual countries.[5] In their Online Appendix, Gabaix and Maggiori (2015, OA) show that their two-country model can be readily extended to a multi-country setting, where the limited risk-bearing capacity is proxied using the variance–covariance matrix of exchange rates. However, this multi-country extension is a direct generalization of the two-country model and, therefore, it does not explore the effects of the trade imbalance network on financiers' risk-bearing capacity and its implications for currency asset pricing.

In the global trading system, bilateral imbalances and interdependence between countries constitute a global trade imbalance network that contains rich information on financier's balance sheets and risk-bearing capacity. Yet, the effect of the imbalance network structure on financiers' limited risk-bearing commitment and currency premia has been largely overlooked in the literature. Therefore, we extend the theory of Gabaix and Maggiori (2015) to explicitly incorporate the information contained in the trade imbalance network into financiers' limited risk-bearing commitment. We use the Leontief inverse of the adjacency matrix of the global trade imbalance network to represent the financiers' risk-bearing capacity and show that the Leontief inverse-based centrality effectively captures the complexity of financiers' global balance sheets.[6]

Specifically, the complexity of financiers' balance sheets increases with the centrality of countries they intermediate by offering more investment options (Aldasoro and Alves, 2018) sasidevan2019systemic.[7] From the financiers' point of view, the net deficit (surplus) of a country constitutes an investment opportunity to take a long (short) position in this country's currency on their balance sheets, which has to be balanced by a short (long) position in other currencies. Long (short) positions increase (decrease) financiers' investment options. For any individual country, its net deficit only partially measures the investment options financiers have with its currency since its net deficit induces deficit and surplus in some other countries, which further contribute to financiers' investment options with the currency depending on the closeness of this particular country with the other countries in the global trade imbalance network. This complexity can be precisely quantified by the Leontief inverse-based centrality of the global trade imbalance network.

We argue that exploring the extensive information implicit in the global imbalance network offers deeper insights on currency premia beyond those offered in studies focusing only on the size of the imbalance of individual countries (e.g., Della Corte et al., 2016). We undertake this exploration from both theoretical and empirical perspectives. Theoretically, we extend the framework developed by Gabaix and Maggiori (2015) to a multi-country setting that allows financiers' limited risk-bearing commitment to be a function of the adjacency matrix of the global imbalance network. An equilibrium can be obtained by solving a fixed point problem in recursive optimizations. As in Gabaix and Maggiori (2015), the linear pricing function of currency premia is maintained in equilibrium, i.e. the expected currency return can be written as a linear function of net deficits, with the coefficient capturing outside investment options. This linear pricing function provides the flexibility to incorporate both imbalance network centrality, which is a function (the Leontief inverse) of the adjacency matrix, and the variance–covariance matrix of currency returns into the financiers' limited risk-bearing commitment. The model has two key parameters that capture the contributions of centrality and the variance–covariance of exchange rate returns, respectively, to financiers' limited risk-bearing commitment. These two parameters can be readily calibrated to test the hypothesis that the centrality of the imbalance network and the variance–covariance of exchange rates explain the cross-section of expected currency excess returns beyond the individual countries' net deficit size.

In the empirical analysis, we employ data for up to 41 currencies from 1995 to 2021. First, we provide evidence, using a training subsample of the data from 1995 to 2002, that these two parameters are significantly different from zero, controlling for net deficits. Secondly, based on the calibrated parameters and keeping them constant out of the sample, we construct *CBC* for each currency and use it to conduct

[3] We refer to Gabaix and Maggiori (2015) for the two-country model of exchange rate determination in their published paper, and to Gabaix and Maggiori (2015, OA) for a simple demonstration of the extension to the multi-country framework in their Online Appendix.

[4] A related literature examines the impact of frictions in international financial markets. For example, Du and Schreger (2016) show that currency market frictions have important implications on local currency credit spreads.

[5] The pricing power of the imbalance risk factor identified by Della Corte et al. (2016) empirically supports the trade imbalance's impact on currency premia in Gabaix and Maggiori (2015)'s theory.

[6] The Leontief inverse of matrix $\mathbf{A}$ is given by:

$$(\mathbf{I}-\mathbf{A})^{-1}=\sum_{k=0}^{\infty}(\mathbf{A})^{k}$$

and is closely related to the Katz-Bonacich centrality, which captures the sum of the direct and indirect influence of each node in a network (Simonovits, 1975).

[7] Du and Schreger (2022b) demonstrate that currency mismatch on corporate balance sheets can be a source of sovereign default risk. Avdjiev et al. (2019) show that currencies with higher exposures to the dollar factor exhibit larger covered interest-rate parity (CIP) deviations and thereby offer greater potential arbitrage profits for traders who have balance sheet capacity to exploit them.

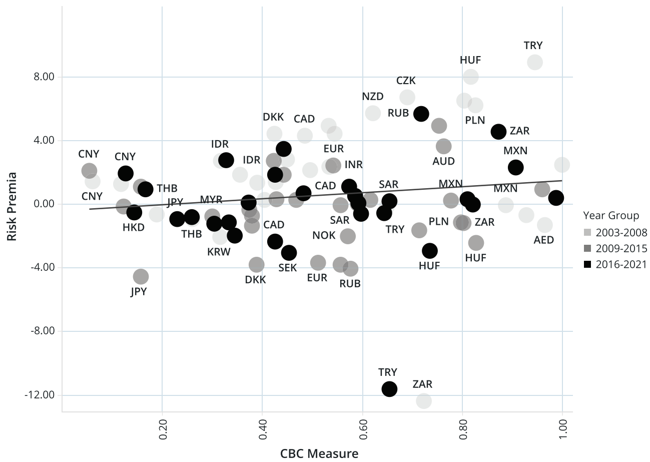


Fig. 1. *CBC* versus currency risk premia.
Notes: This figure plots the global trade *CBC* measure of 41 currencies versus the average of annualized risk premia. The plots contain averages over three seven-year periods, i.e., 2003–2008, 2009–2015, 2016–2021. The trade data are collected from the UN Comtrade Database. The foreign exchange (spot and forward currency rates) are collected from Thomson Reuters Datastream. The centrality measure is log-scaled. For the *Euro* area, we construct a region by aggregating trade information from all economic regions that adopted the euro in 1999.

portfolio sorts and formal asset pricing tests.[8] The results from portfolio sorts show that, going from low *CBC* countries to high *CBC* countries, the currency portfolio returns increase monotonically. The high-minus-low portfolio (long the portfolio with the highest *CBC*, and short the portfolio with the lowest *CBC*) generates an annualized Sharpe ratio of 0.65. This is higher than the Sharpe ratios obtained from sorting on the total trade network centrality of Richmond (2019, *TTNC*), the global imbalance measure of Della Corte et al. (2016, *GImb*), and the carry trade based on our sample. Existing currency factors and intermediate asset pricing factors (Adrian et al., 2014; He et al., 2017) cannot subsume the information in the *CBC* factor (defined as the time series of excess returns from the strategy that sorts on *CBC*), indicating that the *CBC* factor captures different information.

To illustrate the intuition, Fig. 1 shows a clear positive relation between the *CBC* and currency premia, and nicely summarizes the insight of our exploration on the global imbalance trade network. This figure shows the scatter plot of the time series average of currency excess returns for a U.S. investor (vertical axis) versus the time series average of *CBC*s (horizontal axis) for three different subsample periods. Countries with higher *CBC*, such as Mexico and New Zealand, have higher currency premia. On the contrary, countries with lower *CBC*, such as Japan and Thailand, have lower currency premia. This illustrative evidence suggests that *CBC* is a key characteristic to understand currency premia, which we document through formal tests in the paper.

The theory allows us to decompose currency risk premia into three components that are related to total imbalance, individual importance, and neighborhood importance. Via a variance decomposition, we empirically show that the neighborhood component explains about 68% of the total variation in cross-sectional currency premia, highlighting the importance of the network structure in understanding the dynamics of currency premia, and hence the value added by our extension of the Gabaix–Maggiori theory. To complement this variance decomposition, we also run panel regressions of currency risk premia on the three components, providing corroborating evidence of the dominant role of the neighborhood component in terms of explanatory power. To further demonstrate the usefulness of this framework, we also conduct counterfactual analyses to study the impacts of the 2018–2019 China–US trade war and the international sanctions against Russia in 2022 on currency premia via the trade imbalance network. We find that these two events have far-reaching effects on premia of currencies that are not directly involved in the events, emphasizing the complexity of the chain effect of international events and the usefulness of a quantitative framework like the one developed in this paper.

We carry out several other additional analyses, and we mention here two especially relevant ones. First, we empirically explore alternative networks to replace the trade imbalance network. These include two variants of the capital flow network—the portfolio investment network and the foreign direct investment (FDI) network—as well as the total trade network. We find that the connection between currency excess returns and any of these networks is substantially weaker than the connection with the trade imbalance network. Second, we explore the relationship between *CBC* and various proxies of risk bearing capacity used in the relevant literature, including the TED spread, the VIX, indices of implied volatility in currency markets, i.e., the VXY index for G7 countries (VXY-G7) and the VXY index for emerging market countries (VXY-EM), the amount of financial commercial paper outstanding, and a measure of global illiquidity in currency markets. The correlation between the *CBC* factor and each of these variables has the expected sign, suggesting that *CBC* captures information embedded in all of these proxies and is, therefore, intuitively related to risk bearing capacity. However, none of these variables subsumes fully the information in *CBC* (i.e., the correlations are imperfect), suggesting that *CBC* cannot easily be replaced by any available individual variable. Further, we provide evidence that domestic financial intermediaries hold less of the outstanding debt for countries with higher *CBC*, again suggesting that *CBC* is negatively related to risk bearing capacity.

Related literature. Our theoretical work relates to several areas of the foreign exchange literature. This paper is distinct within this thread of the literature in that we push forward the development of multi-country settings and the trade imbalance network in the theory of currency asset pricing with *financial frictions*. First, the theoretical model augments Gabaix and Maggiori (2015, OA)'s multi-country setting with imperfect financial markets by incorporating global imbalance network centrality (via the Leontief inverse) as a measure of financiers' outside investment options. With different emphases, Jiang (2021) extends Gabaix and Maggiori (2015)'s two-country model by adding the government to study the implications of the US government debt issuance on the US dollar exchange rate; Della Corte and Fu (2021) also use the two-country setting of Gabaix and Maggiori (2015) and introduce global tariff uncertainty to analyze how different tariff policies in the US affect the US dollar exchange rate. In contrast, our paper is the first to introduce a network into the framework of Gabaix and Maggiori (2015) to capture the complexity of financiers' balance sheets through a multi-country lens.[9]

There are also theoretical studies that focus on the connection between currency risk and country-level characteristics while assuming frictionless financial markets. For example, Colacito et al. (2018) develops a frictionless risk-sharing model with recursive preferences and shows that heterogeneous exposure to global growth shocks results in the reallocation of international resources and currency adjustments. Richmond (2019) builds a general equilibrium model with perfect financial markets and shows that the consumption growth

[8] We also carry out the exercise using a recursively updated *CBC* measure where the two calibrated parameters are updated as new information becomes available, whilst still conditioning only on available information at the time of sorting. We find that the results are qualitatively identical to the case where we do not update the calibrated parameters, because they are quite stable over time.

[9] Subsequent papers are following suit to explore related issues; for example, Bahaj et al. (2024) explore the role of cross-border financial connections, proxied through a network of gross financial positions, in mitigating or amplifying trade shocks.

of countries with high centrality in the total trade network is more exposed to global consumption growth shocks, resulting in lower interest rates, and thereby currency risk premia. There are three key differences between Richmond's theory and ours: (a) Our imbalance network differs significantly from Richmond (2019)'s total trade network. Richmond (2019)'s trade network is based on bilateral total trade (export plus import, i.e., the total trade intensity), forming an un-directional network, while our imbalance trade network is based on bilateral trade deficit (export minus import, the total trade imbalance), forming a directional network. This difference generates distinct predictions for the mechanism that drives currency risk premia. In Richmond (2019)'s trade network, central countries' currencies appreciate during bad times due to the increased relative price of their consumption bundle, whereas in our imbalance network, central countries' currencies depreciate contemporaneously and appreciate in the future to compensate for the risk financiers take. These fundamental differences imply a negative relation between our CBC and Richmond (2019)'s centrality characteristics, which we will observe in the data.[10] (b) Richmond (2019)'s theory focuses on fundamental risks (global consumption growth risks), while our emphasis is on financial intermediaries' risk-bearing capacity.[11] (c) Richmond (2019) circumvents financial intermediation risks by assuming perfect financial markets (i.e., unlimited risk-bearing capacity), while we allow for imperfect financial markets (i.e., limited risk-bearing capacity of financial intermediaries). Therefore, while our model shares the focus on the international trade network and currency returns with Richmond (2019), the mechanism through which trade imbalances impact on currency risk premia is fundamentally different, and the definition of centrality itself is also different. We examine the relationship between the centrality measure of Richmond (2019) and ours later in the paper, both empirically and through simulation exercises.

Second, our empirical work contributes to the literature on currency asset pricing and cross-sectional currency investment strategies. Lustig et al. (2011) identify a "slope" factor in exchange rates by sorting currencies on their forward discounts and show that this factor accounts for much of the cross-sectional variation in currency returns. Menkhoff et al. (2012b, 2017) show momentum and value strategies in foreign exchange markets deliver high excess returns. Using individual country-level net deficit as a risk characteristic, Della Corte et al. (2016) identify an imbalance risk factor with significantly positive currency risk premia.[12] Ready et al. (2017) demonstrate that countries producing commodity goods are distinct from countries producing final goods, and provide evidence that sorting currencies based on the import ratio (the ratio of net imports of finished goods to net exports of basic commodities) generates a sizable spread in average currency excess returns. Colacito et al. (2020) find that business cycle risk has significant pricing power for currency portfolio returns. Dahlquist and Hasseltoft (2020) find that a risk factor based on a trading strategy that goes long currencies with strong economic momentum and short currencies with weak economic momentum captures cross-country differences in carry. Our paper adds to this strand of the literature a novel, theoretically motivated characteristic that is valuable for designing a profitable currency investment strategy.

Third, our paper is also related to the literature that studies how international trade affects currency risk. Recent studies suggest that common factors account for a large portion of the variation in bilateral exchange rates (e.g., Verdelhan, 2018). Furthermore, international trade significantly influences a country's exposure to the common factors. Lustig and Richmond (2020) show that the trade network centrality, as defined by Richmond (2019), is the best predictor of a country's average exposure to systematic risk. Jiang and Richmond (2023) further find that global trade network closeness has explanatory power for exchange rate comovements. Hassan et al. (2023) show that bilateral trade agreements can substantially reduce systematic exchange rate risk, using Richmond (2019)'s measure of total trade centrality. Moreover, Fang and Liu (2021) show, both theoretically and empirically, that financiers' leverage constraints drive exchange rates, with capital inflows (i.e., net exports) increasing as these constraints become more pronounced. Our paper contributes by providing a comprehensive investigation into the direct and indirect impact of the trade imbalance (net exporter) network on the cross-sectional variation in currency risk premia, hence discovering new facts on the relationship between international trade and currency asset pricing.

Additionally, our paper also joins the literature on the role of financial intermediaries in the pricing of financial assets (see, e.g., He and Krishnamurthy, 2013; Adrian et al., 2014; He et al., 2017; Fleckenstein and Longstaff, 2020, 2022; Du et al., 2023; Maggiori, 2022; Du and Schreger, 2022a; Wang and Zhang, 2025). Differently from this literature, the focal point of this paper is on the *international* trade imbalance network and currency markets. In the context of the foreign exchange literature, other than the theoretical study of Gabaix and Maggiori (2015), there is empirical evidence in Cenedese et al. (2021) that regulation on the leverage ratio requirement of financial intermediaries is related to deviations from covered interest parity. Also, Fang (2021) finds a positive relation between country-level banking sector capital ratios and currency returns; Fang and Liu (2021) provide further evidence that exchange rates and capital flows are related to intermediaries' leverage constraints. Our paper provides both theoretical developments and empirical results that the role of financial intermediaries is key to understanding the pricing of foreign exchange risk.

2. The model

In this section, we introduce in the theory of Gabaix and Maggiori (2015) a network structure to capture the complexity of the balance sheets of financial intermediaries, using the Leontief inverse-based centrality. We use this framework to guide our subsequent empirical analysis. Moreover, based on the intuition that financiers' limited commitment is related to their outside investment options, we extend the theory to explicitly connect currency risk premia to their centrality in the global trade imbalance network, which can be considered as a proxy for the financiers' credit constraint. We conclude the section by providing elements of a microfoundation for the proposed specification of the credit constraint.

2.1. Multi-country setting

There are two periods: $t = 0, 1$ and n countries in the model. We define $\{x_t\}_i$ as the US dollar (USD) bilateral exchange rate of country i at period t, where $i = 1, 2, \ldots, n$. An increase in $\{x_t\}_i$ indicates an appreciation of country i's currency against the USD. The US is the

[10] Therefore, the factor (trading strategy) returns are defined differently: in Richmond (2019), the factor portfolio is Peripheral minus Central (PMC), i.e., buying peripheral and selling central countries' currencies, while in our imbalance framework, the factor portfolio represents a strategy of buying high CBC currencies and selling low CBC currencies.

[11] In Richmond (2019)'s theory, the key driver of the variation in cross-sectional currency returns is the countries' heterogeneous exposure to global consumption shocks. Countries with different total trade links to countries that are important for the production of tradable goods have different exposures to global shocks. Hence, currencies' centrality in the total trade network measures the exposure to consumption risk.

[12] Global imbalances play an important role in our understanding of the international financial system. As stated by Jiang et al. (2024), these imbalances have manifested in the sustained net capital flows into U.S. financial markets. Using a demand system-based approach, Jiang et al. (2024) find that the supply of global savings and issuances as well as monetary policies contribute to the increasingly negative U.S. net foreign asset position, while shifts in investors' demand partially offset this trend.

primary country 1, for which we normalize $\{x_t\}_1 = 1$ in both periods; x_t is the vector of exchange rates at period t.

We define the global trading imbalance networks in the two periods via an $n \times n$ adjacency matrix $\mathbf{A}_t$ of a directed weighted graph on n vertices, where $\{\mathbf{A}_t\}_{ii} = 0$ for $i = 1, \ldots, n$, and $\{\mathbf{A}_t\}_{ij} > 0$ for $j \neq i$ is the USD value of country j's net import from country i. In other words, if $\{\mathbf{A}_t\}_{ij} > 0$, then country j is a net debtor of country i with deficit of $\{\mathbf{A}_t\}_{ij}$. The global trading network can also be described in terms of the exports and imports matrix, e.g., the ξ matrix in Gabaix and Maggiori (2015, OA). We show the explicit relation between $\mathbf{A}$ and ξ below.

Gabaix and Maggiori (2015, OA) use the export and import matrix ξ_t in the derivations of their multi-country model (see Section A.3.B): for $i \neq j$, $\{\xi_t\}_{ij} < 0$ and represents exports of country i to country j in country j's currency; the diagonal term $\{\xi_t\}_{jj} > 0$ represents the total imports of country j in its currency from all other countries and is defined as: $\{\xi_t\}_{jj} \triangleq -\sum_{i\neq j}\{\xi_t\}_{ij}$.

Let q_i be the USD value of country i's bonds held by financiers; hence, q is the vector of the bonds' values of all countries. Also, the fact that financiers have zero initial capital implies $\sum_{j=1}^{n} q_j = 0$. The net demand for currency i in the spot market, expressed in USD, must be zero in period 0's equilibrium:

$$-\sum_{j=1}^{n}\{\xi_0\}_{ij}\{x_0\}_j + q_i = 0. \tag{1}$$

In matrix form, Eq. (1) can be written as:

$$-\xi_0 x_0 + q = 0. \tag{2}$$

By the definitions of $\mathbf{A}$ and ξ, we have:

$$\{\mathbf{A}_t\}_{ij} = \left(\{\xi_t\}_{ji}\{x_t\}_i - \{\xi_t\}_{ij}\{x_t\}_j\right)^+ \tag{3}$$

where $(z)^+ = z$ if $z > 0$, and 0 otherwise. Given Eq. (3), the following holds:

$$\mathbf{A}_t - \mathbf{A}_t^{\intercal} = \left(\xi_t\mathbf{D}_t\right)^{\intercal} - \xi_t\mathbf{D}_t, \tag{4}$$

where $\mathbf{D}_t = \operatorname{diag}(x_t)$.

In equilibrium, financiers absorb all imbalances in the trading network in period 0. Given the definition of $\mathbf{A}_t$, we have the following proposition.

Proposition 1. *In equilibrium at period 0, the USD value of the bonds' held by financiers, q, must satisfy:*

$$\left(\mathbf{A}_0 - \mathbf{A}_0^{\intercal}\right)\ell + q = 0, \tag{5}$$

where ℓ is an $n \times 1$ column vector of ones.

Proof. By the definition of $\mathbf{A}_0$, each element in the ith row (jth column) of $\mathbf{A}_0$ represents the net USD value surplus (deficit) the ith (jth) country has with each country. This means that each element in the ith row of $\left(\mathbf{A}_0^{\intercal} - \mathbf{A}_0\right)$ represents the net imbalance in USD the ith country has with each country, and the ith element of vector $\left(\mathbf{A}_0^{\intercal} - \mathbf{A}_0\right)\ell$ is the USD total net imbalance of the ith country.

When the market clears, these imbalances have to be absorbed by the financiers. Therefore, we have $\left(\mathbf{A}_0^{\intercal} - \mathbf{A}_0\right)\ell = q$. This completes the proof. □

It can be easily shown that Eq. (5) is equivalent to Eq. (1):

$$q = \left(\mathbf{A}_0^{\intercal} - \mathbf{A}_0\right)\ell = \xi_0\mathbf{D}_0\ell - \left(\xi_0\mathbf{D}_0\right)^{\intercal}\ell = \xi_0 x_0. \tag{6}$$

The second equality is by Eq. (4), and the third equality is by the fact that $\left(\xi_0\mathbf{D}_0\right)^{\intercal}\ell = 0$ and $\mathbf{D}_0\ell = x_0$.[13] Financiers will unwind their positions in period 1. Therefore, we also have

$$\left(\mathbf{A}_1 - \mathbf{A}_1^{\intercal}\right)\ell - q = 0. \tag{7}$$

[13] $\left(\xi_0\mathbf{D}_0\right)^{\intercal}\ell = 0$ is immediately implied by the definition of $\{\xi_t\}_{jj}$, i.e., $\{\xi_t\}_{jj} \triangleq -\sum_{i\neq j}\{\xi_t\}_{ij}$.

2.2. Demand function of credit constrained financiers

To incorporate interest costs in the financiers' objective function, we define the vector of interest-adjusted exchange rates in period 1 as $\bar{x}_1 \triangleq \delta x_1$ with

$$\boldsymbol{\delta} = \begin{bmatrix} 1 & 0 & \cdots & 0 \\ 0 & \frac{1+r_2}{1+r_1} & \cdots & 0 \\ & \ddots & & \\ 0 & \cdots & \cdots & \frac{1+r_n}{1+r_1} \end{bmatrix}$$

where r_i is the risk-free interest rate of country i.[14] Since financiers only have limited commitment, there is a downward-sloping demand curve, which can be derived from the financiers' objective function. In period 0, the financiers optimally set $\theta^\star = \mathbf{D}_0^{-1}q^\star$ to maximize their expected return (objective function) while subject to a quadratic outside option constraint[15]:

$$\max_{\theta^\star} \mathbb{E}\left(\bar{x}_1 - x_0\right)^{\intercal}\theta^\star, \quad s.t. \;\; \mathbb{E}\left(\bar{x}_1 - x_0\right)^{\intercal}\theta^\star \geq (\theta^\star)^{\intercal}(\boldsymbol{\Gamma}\mathbf{D}_0)\theta^\star, \tag{8}$$

where

$$\boldsymbol{\Gamma} = \left[w\mathbf{I} + (1-w)\mathbf{V}\right]\boldsymbol{\Omega}, \quad \boldsymbol{\Omega} = \left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}, \tag{9}$$

$\mathbf{I}$ is the $n \times n$ identity matrix, $\mathbf{V}$ is the variance–covariance matrix of x_t, $\boldsymbol{\Omega}$ is the Leontief inverse of $\mathbf{A}_0$, and both w and α are in [0, 1]. This specification of $\boldsymbol{\Gamma}$ nests Gabaix and Maggiori (2015)'s variance–covariance matrix setup, with $\boldsymbol{\Gamma} = \mathbf{V}$ when $w = \alpha = 0$.[16] Gabaix and Maggiori (2015) emphasize that financiers' outside options should increase with the size, volatility, or complexity of their balance sheets. Closely related to imbalance network centrality, $\boldsymbol{\Omega}$ captures the complexity of financiers' balance sheets. Therefore, incorporating both $\boldsymbol{\Omega}$ and $\mathbf{V}$ in $\boldsymbol{\Gamma}$ allows us to more accurately capture (Gabaix and Maggiori, 2015)'s idea regarding financiers' outside option constraints than the variance–covariance matrix alone. We provide a deeper discussion of $\boldsymbol{\Omega}$ in relation to the trade imbalance network in Section 2.3 and its risk-sharing foundation in Section 2.4.

Since financiers only have limited commitment, there is a downward-sloping demand curve. Following Gabaix and Maggiori (2015, OA), this demand for assets — which establishes a relation between all currencies' interest-adjusted expected appreciation (currency risk premia) $\mathbb{E}\left(\bar{x}_1 - x_0\right)$ and q — can be solved from the constrained optimization problem in (8) using linear programming (all technical details are presented in Internet Appendix A) and is given by:

$$\mathbb{E}\left(\bar{x}_1 - x_0\right) = \boldsymbol{\Gamma}q. \tag{10}$$

[14] As in Gabaix and Maggiori (2015), the model treats interest rates as exogenous. It is worth emphasizing that the interest rate differential does not completely account for currency risk premia. The positive excess return and depreciation of a country's currency are associated with a decrease in risk-bearing capacity. This effect manifests itself even when all countries have the same interest rate, thus being fundamentally different from the pure carry trade. We also address this issue empirically in later sections.

[15] The quadratic constraint in (8) is equivalent to having two quadratic terms:

$$(\theta^\star)^{\intercal}(\boldsymbol{\Gamma}\mathbf{D}_0)\theta^\star = (\theta^\star)^{\intercal}(\boldsymbol{\Gamma}_1\mathbf{D}_0)\theta^\star + (\theta^\star)^{\intercal}(\boldsymbol{\Gamma}_2\mathbf{D}_0)\theta^\star$$

where $\boldsymbol{\Gamma}_1 = \mathbf{V}(1-w)\boldsymbol{\Omega}$ and $\boldsymbol{\Gamma}_2 = w\boldsymbol{\Omega}$. $\boldsymbol{\Gamma}_1$ represents an imbalance-network-adjusted version of the variance–covariance matrix constraint in the original Gabaix and Maggiori (2015, OA)'s specification, and $\boldsymbol{\Gamma}_2$ represents a centrality constraint accounting for the complexity of financiers' balance sheets (in reduced form).

[16] This setup captures the impact of riskiness measured by the variance of the currency. Della Corte et al. (2016) use changes in the VXY (implied-volatility) index as a proxy for conditional FX volatility and report evidence supporting Gabaix and Maggiori (2015)'s setup.

This key equation establishes a fundamental relation connecting all currencies' interest-adjusted expected appreciation (currency risk premia), $\mathbb{E}\left(\bar{x}_1 - x_0\right)$ to the trade imbalance network via $\boldsymbol{\Gamma}_q$ and provides the theoretical guidance for our empirical analysis. The model captures the essence of financiers' limited commitment in the context of complex trade networks, i.e., financiers based in countries with higher centrality face more outside options. In other words, the model predicts that currency risk premia are closely related to imbalance network centrality. The mechanism described above implies a testable prediction, which we summarize in Hypothesis 1.

Hypothesis 1. Cross-sectional currency risk premia are positively associated with currencies' centrality in the trade imbalance network, i.e. currencies with higher (lower) centrality offer larger (smaller) risk premia.

In this setting, x_0 and x_1 are endogenous variables solved from Eqs. (5), (7) and (10).[17] For now, since the focus is on the relation between $\mathbb{E}\left(\bar{x}_1 - x_0\right)$ and $\mathbf{A}_0$, we concentrate on Eqs. (5) and (10). Assuming the existence of a solution to a fixed point problem, we can treat both $\mathbf{A}_0$ and x_0 as given, and $\boldsymbol{\Gamma}$ as a function of $\mathbf{A}_0$, with Eq. (10) still holding. The detailed derivations are provided in Internet Appendix B. We will explore the relation between $\boldsymbol{\Gamma}$ and $\mathbf{A}_0$, which is the functional form of $\boldsymbol{\Gamma}$ in $\mathbf{A}_0$, in detail shortly.

2.3. Trade imbalance network and risk bearing capacity of financiers

Financiers' risk bearing capacity captures the limited commitment to intermediating in international financial markets. It is inversely related to the financiers' outside options and liquidity shocks, which are represented by $\boldsymbol{\Gamma}$ in the model. Financiers' outside options increase in the *complexity* of their balance sheet. Here we echo Gabaix and Maggiori (2015) and refer to balance sheet complexity as the idea that financiers' balance sheets become more complex when they hold larger and riskier positions, increasing the cost for creditors to unwind their positions in the event of default. This underscores the importance of centrality in the trade imbalance network —- countries at the core of the network have financiers with more complex portfolios, resulting in higher intermediation costs and reduced risk-bearing capacity. Gabaix and Maggiori (2015) employ the variance–covariance matrix of exchanges rate returns as a proxy for such complexity, intended to be related to the size and volatility of the balance sheet.

In a multi-country setting, however, centrality is also an important dimension of the complexity of balance sheets, and hence of the outside options of financiers. Albeit in a different context, this idea is in the essence of the theoretical results of Hojman and Szeidl (2008), who show that there is a positive relation between network centrality and agents' payoffs. Intuitively, a country's financial constraints are affected not just by its own imbalances but also by the imbalances of its trade partners. A financier dealing with a country that has significant trade linkages with other countries must consider second-order effects—imbalances in connected countries affect liquidity and risk exposure. This creates higher intermediation costs because the financier must adjust for additional risk layers.

Incorporating the Leontief inverse of $\mathbf{A}_0^{\intercal}$ into $\boldsymbol{\Gamma}$, as in Eq. (9), elegantly captures the above intuition and effectively weights countries based on their centrality in the global trade imbalance network. The Leontief inverse is closely related to Katz/Bonacich centrality (see, e.g., Ballester et al., 2006; Acemoglu et al., 2012; Sharkey, 2017). To see the intuition more clearly, we spell out the financiers' outside option in dollar values (see eq. (A.29) and Proposition A.8 in Gabaix and Maggiori, 2015, OA):

$$\theta^{\intercal}\left[w\mathbf{I} + (1-w)\mathbf{V}\right]\left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1} q, \tag{11}$$

where $\theta = \mathbf{D}^{-1}q$ and $\mathbf{D} = \operatorname{diag}\left(x_0\right)$. θ can be expressed in the normal form as θ_i, which captures the holdings of country i's bonds by financiers, expressed in number of bonds, and the outside option is the weighted sum of θ_is with the weight being the importance of the ith country in the imbalance network:

$$\theta^{\intercal}\left[w\mathbf{I} + (1-w)\mathbf{V}\right]\left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1} q = \sum_{i=1}^{n}\theta_i\left[w + (1-w)\sum_{j=1}^{n}\mathbf{V}_{ij}\right]c_i, \tag{12}$$

where $c = \left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1} q$. Here c is a variant of Bonacich centrality (Bonacich, 1987) and is defined by: $c = q + \alpha\mathbf{A}^{\intercal}c$.[18] Following Sharkey (2017), c is a measure of centrality that can be interpreted as the sum of two components: the first one is q, which can be thought of as the basic centrality that each country has; and the second one, $\alpha\mathbf{A}^{\intercal}$ is the additional centrality driven by how important its neighbors are in the network. The parameter α, which is non-negative and less than one, controls the contribution of the second component to c. When $\alpha = 0$, $c = q$. In Internet Appendix C, we demonstrate through a numerical analysis that the rankings of elements in rp and q can significantly differ under the setting of $\boldsymbol{\Gamma} = \left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}$.

2.4. A risk-sharing microfoundation for the leontief inverse

Section 2.3 establishes the centrality implication of $\boldsymbol{\Omega}$ being the Leontief inverse. In this subsection, we delve deeper into the implications of $\boldsymbol{\Gamma}$ for individual financiers, aiming to establish the basic elements of a microfoundation for Eq. (9).

In Internet Appendix D, we show that all financiers' collective optimization is attained through the implementation of individually optimal strategies by financiers in each country. For the financier in charge of the ith country, the individual constrained optimization is:

$$\max_{q_i^{\star}}\mathbb{E}\left(\frac{\bar{x}_{(i,1)}}{x_{(i,0)}} - 1\right)q_i^{\star}, \quad s.t.\ \mathbb{E}\left(\frac{\bar{x}_{(i,1)}}{x_{(i,0)}} - 1\right)q_i^{\star} \geq \sum_{j=1}^{n}\frac{1}{q_i}\boldsymbol{\Gamma}_{ij}q_j\frac{(q_i^{\star})^2}{x_{(i,0)}}. \tag{13}$$

In equilibrium, $q_i = q_i^{\star}$ and the ith financier's divertable funds (DF_i) in dollar value are:

$$\mathrm{DF}_i = \frac{1}{x_{(i,0)}}\left[\underbrace{\{\boldsymbol{\Gamma}\}_{ii}\,q_i^2}_{\text{primary risk}} + \underbrace{\sum_{j\neq i}\boldsymbol{\Gamma}_{ij}q_jq_i}_{\text{risk adjustment}}\right]. \tag{14}$$

Funding a country with a net deficit results in the establishment of long positions in domestic bonds and short positions in foreign bonds on the financier's balance sheet. Conversely, financing a net surplus country leads to the creation of long positions in foreign bonds and short positions in domestic bonds. Creditors, in their lending to the financier, correctly foresee the incentives for fund diversion, leading them to set the divertable funds in Eq. (14) as a credit constraint in their dealings with the financier. Consequently, Eq. (14) captures risks that creditors encounter. An effective risk metric should account for both domestic and foreign bonds, along with the risk-sharing among creditors from different countries within the trade network. The first term in the square brackets above is the *primary risk* of providing the intermediating service to country i, which is the two-country case of Gabaix and Maggiori (2015, Eq. (8)). Nevertheless, this term only addresses domestic bonds on the financier's balance sheet, overlooking the positions of foreign bonds and the risk-sharing among creditors. The second term, *risk adjustment*, within the square brackets above, explicitly encompasses these additional risk adjustments.[19] We illustrate this argument using a simple three-currency example.

[17] The detailed derivations are in Internet Appendix B.

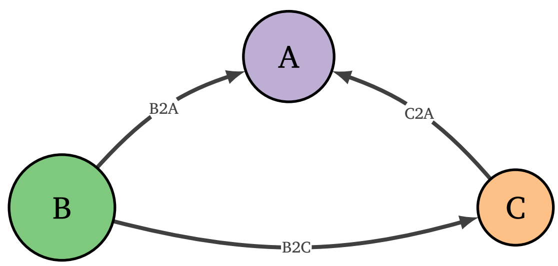
[18] The Bonacich centrality, as defined e.g. in Sharkey (2017), is: $r = \mathbf{A}^{\intercal}\ell + \alpha\mathbf{A}^{\intercal}r \Rightarrow r = (\mathbf{I} - \alpha\mathbf{A}^{\intercal})^{-1}\mathbf{A}^{\intercal}\ell$.

[19] Here we use 'risk sharing' and 'risk adjustment' to describe the components in the ith financier's divertable funds that are related to other countries' trade imbalance, i.e., q_j for $j \neq i$.

Table 1
A three-currency example with financiers' long and short positions and their divertable funds.

	Long	Short	Net imbalance q	DB and FB adjusted divertable funds	Risk sharing adjustment
Financier A	DB: B2A DB: C2A	FB: B2A FB: C2A	B2A + C2A	$\left[\underbrace{\Gamma_{AA}(\text{B2A}+\text{C2A})}_{\text{long positions}}-\underbrace{(\Gamma_{AB}\text{B2A}+\Gamma_{AC}\text{C2A})}_{\text{short positions}}\right]\underbrace{(\text{B2A}+\text{C2A})}_{q_A}$	$-\text{B2C}(\Gamma_{AB}-\Gamma_{AC})(\text{B2A}+\text{C2A})$
Financier B	FB: B2A FB: B2C	DB: B2A DB: B2C	-B2A - B2C	$\left[\underbrace{(\Gamma_{BA}\text{B2A}+\Gamma_{BC}\text{B2C})}_{\text{long positions}}-\underbrace{\Gamma_{BB}(\text{B2A}+\text{B2C})}_{\text{short positions}}\right]\underbrace{(-\text{B2A}-\text{B2C})}_{q_B}$	$-\text{C2A}(\Gamma_{BA}-\Gamma_{BC})(\text{B2A}+\text{B2C})$
Financier C	DB: B2C FB: C2A	FB: B2C DB: C2A	B2C - C2A	$\left[\underbrace{(\Gamma_{CC}\text{B2C}+\Gamma_{CA}\text{C2A})}_{\text{long positions}}-\underbrace{(\Gamma_{CB}\text{B2C}+\Gamma_{CC}\text{C2A})}_{\text{short positions}}\right]\underbrace{(\text{B2C}-\text{C2A})}_{q_C}$	$-\text{B2A}(\Gamma_{CB}-\Gamma_{CA})(\text{B2C}-\text{C2A})$

Notes: This table summarizes the balance sheet information of the financiers in a simple three-currency network example. The first and second columns show the long and short positions, respectively. DB denotes Domestic Bonds and FB denotes Foreign Bonds. The third column shows the net imbalance, i.e. the elements in q. The fourth and fifth columns show the two components in the divertable funds: DB and FB adjusted divertable component and risk-sharing component, respectively. The imbalance network is shown in the directed graph below in which the arrow of the edge in each pair points towards the deficit country in that pair:



The trade deficit adjacent matrix is:

$$\begin{array}{c} \\ \text{A} \\ \text{B} \\ \text{C} \end{array}\begin{array}{c} \begin{array}{ccc} \text{A} & \text{B} & \text{C} \end{array} \\ \left[\begin{array}{ccc} 0, & 0, & 0 \\ \text{B2A}, & 0, & \text{B2C} \\ \text{C2A}, & 0, & 0 \end{array}\right] \end{array}.$$

We denote the risk bearing capacity matrix by Γ in this example. For simplicity, we assume that $\Gamma_{ij} > 0$ for all i and j.[20] Full details of this three-currency example are outlined in Table 1. In this illustration, Country A registers trade deficits with both Countries B and C, denoted by deficit amounts B2 A and C2 A, respectively. Country B, conversely, records trade surpluses against both Countries A and C, represented by surplus amounts B2 A and B2C, respectively. Lastly, Country C experiences a trade surplus of C2 A with Country A and a deficit of B2C with Country B. As mentioned above, financing trades between countries create long–short positions of domestic and foreign bonds on the balance sheet of financiers. This information is summarized in the first two columns of Table 1. Applying Eq. (14) to this example, we have: (see the Eqs. (15) to (17) given as in Box I).

Checking Eqs. (15) to (17) with the first two columns in Table 1, we find that the off-diagonal terms in Γ allow the divertable funds to adjust for risks related to the positions of foreign bonds. Non-zero off-diagonal terms in Γ also capture the risk-sharing adjustments in the last terms of Eqs. (15) to (17) (see the last column in Table 1 as well). We categorize financiers into two types: deficit and surplus. A financier's risk-sharing term is proportionate to the edge weight of the other pair of financiers. It reduces (increases) the financier's risks if the financier has a stronger connection to a financier of the opposite (same) type within the pair. To spell out this intuition, consider Financier A's risk-sharing term: $-\text{B2C}(\Gamma_{AB}-\Gamma_{AC})(\text{B2A}+\text{C2A})$. Here, $\Gamma_{AB}-\Gamma_{AC}$ compares the connection between A and B with that between A and C. In the B and C pair, B is the surplus type, and C is the deficit type. Given that Country A is in net deficit ($q_A = \text{B2A}+\text{C2A} > 0$), if $\Gamma_{AB} > \Gamma_{AC}$ — indicating that A has a stronger connection with the opposite-type B — the risk-sharing term reduces A's risks; otherwise, it increases them.

To further elaborate on the mechanism, the risk-sharing term in Eqs. (15) to (17) can be interpreted as reflecting the diversification benefits of holding bonds across multiple countries. A financier's balance sheet risk is mitigated when exposures to different countries partially offset one another — particularly when those countries are interconnected through trade and belong to different categories (deficit or surplus).[21] In this context, the trade imbalance network serves as a reduced-form proxy for real-side economic linkages. For instance, the term Γ_{AB} captures the extent to which bonds from countries A and B can hedge each other's risks. A higher value of Γ_{AB} indicates stronger trade ties and greater diversification potential, especially when the countries belong to opposite trade categories. However, when a country is highly central in the trade imbalance network — linked to many other deficit countries — the risks borne by its financiers tend to co-move with global factors, thereby limiting potential diversification benefits. Consequently, financiers demand higher risk premia to intermediate these central countries' trade imbalances.[22] In summary, this risk-sharing mechanism incentivizes financiers to facilitate a better balance between

[20] This assumes, when there are negative off-diagonal terms in $\mathbf{V}$, the diagonal terms in $\mathbf{V}$ and $\mathbf{\Omega}$ are positive enough to ensure the off-diagonal terms in $\mathbf{\Gamma} = \left[w\mathbf{I} + (1-w)\mathbf{V}\right]\mathbf{\Omega}$ are positive. This is generally true as covariance is typically smaller than variance in magnitude.

[21] Several existing studies document that bilateral goods trade helps explain patterns in capital holdings; see, e.g., Chau (2022) and Lane and Milesi-Ferretti (2008).

[22] While the exchange rate variance–covariance matrix offers a similar perspective, it is an ex post measure and provides limited insight into the structural drivers of exchange rate co-movements. In contrast, the trade

$$\mathrm{DF}_A = \Bigg[\underbrace{\Gamma_{AA}(\mathrm{B2A}+\mathrm{C2A})}_{\text{long positions}} - \underbrace{(\Gamma_{AB}\mathrm{B2A}+\Gamma_{AC}\mathrm{C2A})}_{\text{short positions}}\Bigg]\underbrace{(\mathrm{B2A}+\mathrm{C2A})}_{q_A} - \underbrace{\mathrm{B2C}(\Gamma_{AB}-\Gamma_{AC})(\mathrm{B2A}+\mathrm{C2A})}_{\text{risk-sharing with B and C}}, \tag{15}$$

$$\mathrm{DF}_B = \Bigg[\underbrace{(\Gamma_{BA}\mathrm{B2A}+\Gamma_{BC}\mathrm{B2C})}_{\text{long positions}} - \underbrace{\Gamma_{BB}(\mathrm{B2A}+\mathrm{B2C})}_{\text{short positions}}\Bigg]\underbrace{(-\mathrm{B2A}-\mathrm{B2C})}_{q_B} - \underbrace{\mathrm{C2A}(\Gamma_{BA}-\Gamma_{BC})(\mathrm{B2A}+\mathrm{B2C})}_{\text{risk-sharing with A and C}}, \tag{16}$$

$$\mathrm{DF}_C = \Bigg[\underbrace{(\Gamma_{CC}\mathrm{B2C}+\Gamma_{CA}\mathrm{C2A})}_{\text{long positions}} - \underbrace{(\Gamma_{CB}\mathrm{B2C}+\Gamma_{CC}\mathrm{C2A})}_{\text{short positions}}\Bigg]\underbrace{(\mathrm{B2C}-\mathrm{C2A})}_{q_C} - \underbrace{\mathrm{B2A}(\Gamma_{CB}-\Gamma_{CA})(\mathrm{B2C}-\mathrm{C2A})}_{\text{risk sharing with A and B}}. \tag{17}$$

Box I.

$$\boldsymbol{\Omega}_{ij} = 1_{\{i=j\}} + \alpha\left\{\mathbf{A}_0^{\intercal}\right\}_{i,j} + \alpha^2\sum_{r=1}^{n}\left\{\mathbf{A}_0^{\intercal}\right\}_{i,r}\left\{\mathbf{A}_0^{\intercal}\right\}_{r,j} + \alpha^3\sum_{r=1}^{n}\left\{\left(\mathbf{A}_0^{\intercal}\right)^2\right\}_{i,r}\left\{\mathbf{A}_0^{\intercal}\right\}_{r,j} + \dots, \tag{18}$$

Box II.

deficit and surplus countries in the global trade network, thereby reducing overall systemic risk.

Generalizing from the simple example above, when specifying $\boldsymbol{\Gamma}$, it is essential that for any $i \neq j$, the off-diagonal element $\boldsymbol{\Gamma}_{ij}$ encapsulates the degree of connection between countries i and j in the imbalance network. Simply treating $\boldsymbol{\Gamma}$ as the variance–covariance matrix or a diagonal matrix does not meet this requirement. To illustrate, if country i serves as both a direct debtor and a two-step indirect debtor to country j, country i is directly linked to country j through the direct edge from vertex i to vertex j – the (normalized) weight of this edge quantifies the direct connection. Moreover, country i is indirectly linked to country j via two connected edges from vertex i to vertex j, and the product of the (normalized) weights of these edges measures the indirect connection. It is important to assign a lower weight to an indirect connection compared to a direct contribution. Mathematically, this degree of connection can be precisely defined using the adjacency matrix $\mathbf{A}_0$ as: (see the Eq. (18) given as in Box II) where $1_{\{i=j\}} = 1$ if $i = j$ and 0 otherwise. When $i \neq j$, the second term in Eq. (18) accounts for country i's role as a direct debtor to country j, the third term accounts for country i's role as a debtor to country j's debtors, and so on. In terms of the network representation of the economy, $\boldsymbol{\Omega}_{ij}$ accounts for all possible deficit chains (net import relations) that connect country i to country j across the network (Carvalho and Tahbaz-Salehi, 2019). It is straightforward to see that given Eq. (18), $\boldsymbol{\Omega}$ is the Leontief inverse of the imbalance network adjacency matrix $\mathbf{A}_0$ as it can be expressed in terms of the convergent power series (see, Stewart, 1998, Theorem 4.20)[23]:

$$\boldsymbol{\Omega} = \left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1} = \sum_{k=0}^{\infty}\left(\alpha\mathbf{A}_0^{\intercal}\right)^k. \tag{19}$$

Specifying $\boldsymbol{\Gamma} = \left[w\mathbf{I} + (1-w)\mathbf{V}\right]\boldsymbol{\Omega}$ as in Eq. (9) flexibly integrates both degrees of connection between countries within the imbalance network with currency volatility and covariance into financiers' credit constraints.

To validate the risk reduction mechanism, we perform a numerical example based on the aforementioned simple three-currency scenario. To flesh out the crucial role played by $\boldsymbol{\Omega}$ in the divertable funds, we set $w = 1$, i.e., $\boldsymbol{\Gamma} = \boldsymbol{\Omega}$, in this numerical example, without loss of generality. We assess the DF Ratio, defined as the ratio of total divertable funds to the overall imbalance size, $\frac{\sum_{j\in\{A,B,C\}}\mathrm{DF}j}{\sum_{j\in\{A,B,C\}}|q_j|}$, under three different settings of Γ. The first setting (Diagonal Γ) involves setting Γ as a diagonal matrix, representing a scenario where neither foreign bonds nor risk-sharing are considered. The second setting (Uninformative Off-diagonal Γ) incorporates a Γ with uninformative off-diagonal elements in each row, accounting for foreign bonds but excluding risk-sharing. The third setting (Leontief Inverse Γ) considers both foreign bonds and risk-sharing. The comparative results are presented in Fig. 2. We observe that configuring Γ as the Leontief inverse yields the most significant reduction in the DF Ratio, providing confirmation of the risk reduction mechanism. While there may be alternative settings of Γ that could yield similar effects, we contend that the Leontief inverse offers an elegant and parsimonious approach that addresses the benefits and costs of foreign bond positions and encourages risk-sharing. It seems reasonable to expect that creditors and financiers may naturally incorporate a Leontief inverse-like structure in negotiations, integrating it into financiers' credit constraints.[24]

It is important to point out that the microfoundations presented here only show a risk-based explanation of why $\boldsymbol{\Gamma}$ can be related to $\left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}$. This illustrates, for example, how in a three-country setting q_B and q_C matter differently for q_A due to differences in Γ_{AB} and Γ_{AC}. However, a caveat is in order. The network structure is linked to $\boldsymbol{\Gamma}$ in our generalization of the Gabaix–Maggiori setup via the augmented (quadratic) outside option constraint in Eqs. (8) and (9). We postulate that the Leontief inverse $\boldsymbol{\Omega}$ captures the trade imbalance network, given the central role of trade imbalances for financial intermediation in this theory. However, it is conceivable that the network structure relevant

imbalance network yields a more structural understanding of risk-sharing and diversification, particularly through its implications for intermediaries' balance sheets.

[23] See also Ballester et al. (2006). Here we assume α is smaller than the norm of the inverse of the largest eigenvalue of $\mathbf{A}_0^{\intercal}$.

[24] Exploring the deeper foundations of these constraints lies beyond the scope of this paper. The reader can consider it a reduced-form specification of a more complex contracting problem. Such foundations might be elaborated in financial complexity models, where larger and riskier balance sheets create more intricate positions. These complex positions, in turn, become harder to manage and more costly for creditors to unwind when they seek to recover their funds in the event of a financier's default.

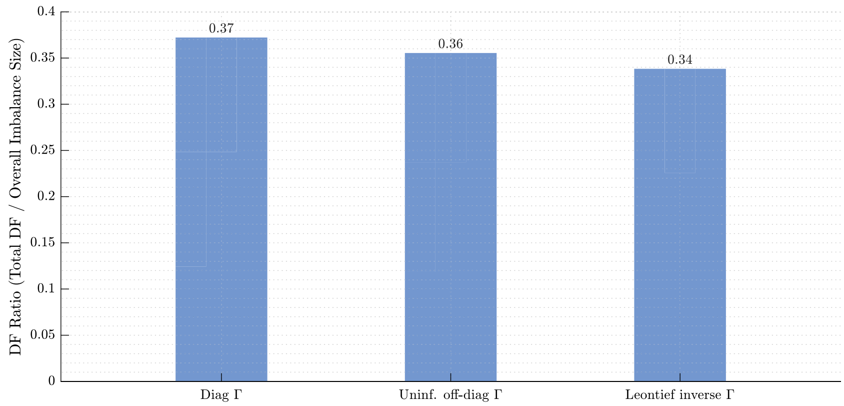


Fig. 2. Risk reduction effect of the Leontief inverse Γ.

Note: The bar chart in this figure compares the DF Ratio defined as the ratio of total divertable funds to overall imbalance size, $\frac{\sum_{j\in\{A,B,C\}} \mathrm{DF}_j}{\sum_{j\in\{A,B,C\}} \|q_j\|}$, across three different settings of Γ in the three-currency example. Diag Γ is the setting with a diagonal Γ; Uninf. off-diag Γ is a Γ with uninformative off-diagonal elements in each row; Leontief inverse Γ is $(I-0.6A^{\intercal})^{-1}$. The off-diagonal elements on row j of the Uninf. off-diag Γ are the average value of the off-diagonal elements on row j of the Leontief inverse Γ. The numerical values are B2 A = 0.25, C2 A = 0.1, and B2C = 0.2 and the numerical value of the three different Γs are as below: Diag $\Gamma = \begin{array}{c} \\ \text{A} \\ \text{B} \\ \text{C} \end{array} \begin{array}{c} \begin{array}{ccc} \text{A} & \text{B} & \text{C} \end{array} \\ \begin{bmatrix} 1 & 0 & 0 \\ 0 & 1 & 0 \\ 0 & 0 & 1 \end{bmatrix} \end{array}$, Uninf. off-diag $\Gamma = \begin{array}{c} \\ \text{A} \\ \text{B} \\ \text{C} \end{array} \begin{array}{c} \begin{array}{ccc} \text{A} & \text{B} & \text{C} \end{array} \\ \begin{bmatrix} 1 & 0.12 & 0.12 \\ 0 & 1 & 0 \\ 0.07 & 0.07 & 1 \end{bmatrix} \end{array}$, Leontief inverse $\Gamma = \begin{array}{c} \\ \text{A} \\ \text{B} \\ \text{C} \end{array} \begin{array}{c} \begin{array}{ccc} \text{A} & \text{B} & \text{C} \end{array} \\ \begin{bmatrix} 1 & 0.17 & 0.07 \\ 0 & 1 & 0 \\ 0 & 0.13 & 1 \end{bmatrix} \end{array}$.

to the outside option constraint captures (also) other dimensions of the international economic ties across countries, such as the capital flow network, or others. Thus, we will explore different networks empirically to establish the adequateness of the trade imbalance network relative to other plausible network structures.[25]

3. Data and variable construction

This section provides details on all data employed in the subsequent empirical analysis. The dataset consists of bilateral trade, bilateral capital flows, and currency returns data.

3.1. Data on trade imbalance and capital networks

Trade imbalance network. The Global Trade Deficit Network is constructed based on yearly bilateral trade data (in USD), which is collected from the United Nations Commodity Trade Statistics Database (UN Comtrade) from 1995 to 2021.[26,27] For the Euro area, from 1999, we aggregate all Euro countries into one entity by summing up all their trades with other non-Euro countries. These data allow us to construct the export/import matrix ξ described in Section 2.1, from which we can further construct $\mathbf{A}_{ij}$ using Eq. (3). To avoid $\mathbf{A}_{ij}$ being affected by country size, we also normalize $\mathbf{A}_{ij}$ to be the ratio of the net imbalance to its corresponding value of total trade. More technical details are presented in Internet Appendix H.

Capital flow networks. Besides the trade imbalance network, we construct several capital flow networks and compare their performance with the trade imbalance network in the empirical analysis. Bilateral capital flows consist of both portfolio investment and Foreign Direct Investment (FDI). We collect the bilateral portfolio investment data from the IMF's Coordinated Portfolio Investment Survey (CPIS) database, and bilateral FDI stocks and flows from the United Nations Conference on Trade and Development (UNCTAD)'s statistics database. Since the original CPIS data is known to be subject to the ''residency'' bias (Coppola et al., 2021),[28] we use the restated CPIS data from Coppola et al. (2021) for the available countries and then merge it with the original

[25] In theory one could microfound the outside option constraint to link explicitly the trade imbalance network to the $\mathbf{\Gamma}$ matrix. This could possibly be achieved, for example, by adding an additional layer of theory with a trade matching search model (e.g. Melitz, 2003; Helpman et al., 2004; Eaton et al., 2024; Ahn et al., 2011; Benguria, 2021). We leave this task to future research since, even doing so, the empirical question remains open on whether alternative network structures are more relevant than the trade imbalance network in driving $\mathbf{\Gamma}$. Therefore, we explore this issue empirically in the paper.

[26] Each country reports import and export values relative to each of its trading partners. However, there is a well-known inconsistency in their reported values. One reason for this is that imports are normally reported at Cost, Insurance, and Freight (CIF) value, while exports are normally reported at Freight On Board (FOB) value. Therefore, we choose to only use the reported export value and set the country's import value as its partner's reported export to this country. If we cannot find the corresponding bilateral export data, we use the import data reported by the partner country.

[27] The bilateral trade data we collect here include both intermediate goods and final goods. Ready et al. (2017) elucidate the rationale behind countries producing intermediate goods typically offering higher average interest rates, whereas countries exporting final goods tend to maintain lower interest rates. Consequently, they contend that the trade composition within various countries influences exchange rates through the currency carry trade. Chau (2022) shows that overlooking intermediate input linkages in portfolio analysis results in a weaker explanation of the data, highlighting the need to consider the entire trade network structure when making portfolio decisions. In a global economy where financiers exhibit limited commitment, such as in our model, comprehending currency returns hinges on grasping the dynamics of currency demand and supply in global trade. The aggregation of both intermediate and final goods provides a holistic depiction of the currency demand and supply landscape spanning various countries.

[28] For example, when global companies finance themselves via foreign subsidiaries located in tax havens, standard economic data associates such offshore securities with the location of the issuing affiliates, rather than the country of their ultimate parents. Coppola et al. (2021) demonstrate that residency-based CPIS data can offer a highly distorted view of global portfolios. For instance, US investments into China are understated, while investments into tax havens are overstated. To address this issue, Coppola et al. (2021) propose a new methodology to restate equity flows into tax havens to the correct ultimate issuing countries. We are grateful to Antonio Coppola and Matteo Maggiori for their help in understanding the CPIS data.

CPIS data for other countries in our entire sample. The restated CPIS data from Coppola et al. (2021) is available from 2007 to 2020 and is obtained from the global capital allocation project website.[29]

3.2. Currency excess returns

Spot and forward exchange rates. The currency data are taken from Thomson Reuters Datastream for the period from 1995 to 2021. We use daily spot and forward (at various maturities) exchange rates against USD. Following Lustig et al. (2011) and Richmond (2019), among others, we build end-of-month series based on daily data for 41 economic regions: Australia, Austria, Belgium, Canada, Mainland China, Czech Republic, Denmark, Europe, Finland, France, Germany, Greece, Hong Kong (China), Hungary, India, Indonesia, Ireland, Italy, Japan, Kuwait, Malaysia, Mexico, Netherlands, New Zealand, Norway, Philippine, Poland, Portugal, Russia, Saudi Arabia, Singapore, South Korea, South Africa, Spain, Sweden, Switzerland, Thailand, Turkey, U.K., United Arab Emirates, United States of America. Data for some currencies do not cover the whole period. For the Euro area, we subsume all countries included in the Euro zone after 1999. The sample size varies for different currencies, most importantly because some currencies cease to exist due to the adoption of the euro. Hence, the panel of individual currencies is unbalanced. The detailed data availability is presented in Table A1 in the Internet Appendix.

Currency excess returns. We use $s_{it} = log(S_{it})$ to denote the log spot exchange rate in units of foreign currency per US dollar, and $f_t = log(F_t)$ for the log forward exchange rate, also in units of foreign currency per US dollar. Hence, an increase in s means an appreciation of the home currency (USD). For any variables that pertain to the home country (the US), we drop the subscript. The log excess return $rx_{i,t}$ from buying foreign currency i in the forward market and then selling it in the spot market after one month is:

$$rx_{i,t} = f_{i,t-1} - s_{i,t}. \tag{20}$$

This excess return can also be stated as Forward Discount (FD) plus Spot Return (SR):

$$rx_{i,t} = \underbrace{f_{i,t-1} - s_{i,t-1}}_{FD} + \underbrace{s_{i,t-1} - s_{i,t}}_{SR}. \tag{21}$$

Under covered interest parity (CIP), the interest rate differential is approximately equal to FD, i.e. $r_{i,t} - r_t \approx f_{i,t} - s_{i,t}$, where $r_{i,t}$ and r_t denote country i's and US nominal risk-free rates over the maturity of the forward contract, respectively. Following common practice in the literature, we compute currency excess returns using forward rates rather than interest rate differentials for two main reasons. First, marginal investors (such as, e.g., hedge funds and large banks) that are responsible for the determination of exchange rates trade mostly using forward contracts (e.g., Koijen et al., 2018). Second, for many countries, forward rates are available for longer time periods than short-term interest rates.

3.3. Empirical construction of CBC

We spell out $\mathbf{\Gamma}$ in Eq. (9) as a function of $\mathbf{V}$ and $\mathbf{A}_0$:

$$\mathbf{\Gamma}\left(\mathbf{V}, w, \mathbf{A}_0, \alpha\right) = \left[w\mathbf{I} + (1-w)\mathbf{V}\right]\left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}, \tag{22}$$

where $0 \le w \le 1$ and $0 \le \alpha < 1$. This function nests $\mathbf{V}$ and $\left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}$ as special cases:

$$\mathbf{\Gamma}\left(\mathbf{V}, 0, \mathbf{A}_0, 0\right) = \mathbf{V}, \tag{23}$$

$$\mathbf{\Gamma}\left(\mathbf{V}, 1, \mathbf{A}_0, \alpha\right) = \left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}. \tag{24}$$

[29] https://www.globalcapitalallocation.com.

Given Proposition 1, currency risk premia can be written as:

$$\mathbb{E}\left(\bar{x}_1 - x_0\right) = \left[w\mathbf{I} + (1-w)\mathbf{V}\right]\left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}\left(\mathbf{A}_0^{\intercal} - \mathbf{A}_0\right)\ell. \tag{25}$$

As w and α are unknown non-negative parameters, we construct a characteristic based on Eq. (25) for a range of combinations of positive w and α. If such characteristic has significant predictive power on observed currency risk premia for some reasonable values of w and α, then trade imbalance network centrality contains valuable information about risk premia in the FX market. Hereafter, we refer to this centrality-based characteristic as *CBC*, i.e.,

$$CBC = \left[w\mathbf{I} + (1-w)\mathbf{V}\right]\left(\mathbf{I} - \alpha\mathbf{A}_0^{\intercal}\right)^{-1}\left(\mathbf{A}_0^{\intercal} - \mathbf{A}_0\right)\ell. \tag{26}$$

It is apparent that a plausible calibration of w and α requires some in-sample estimation. However, once we calibrate w and α over a training sample period, we rely purely on out-of-sample analysis that keeps w and α constant for the purpose of evaluating the predictive performance of *CBC* in a cross-sectional investment strategy and for comparing it to other predictive variables studied in the literature as well as to alternative network types.

Next, we describe the details of the empirical construction of *CBC*. Given the adjacency matrix $\mathbf{A}$ of the imbalance networks and currency risk premia, we calibrate w and α to compute the *CBC*s using Eq. (26). We allow w and α to vary every year and calibrate conditioning only on information available. Specifically, at each year t, we match $\mathbf{A}$ and $\mathbf{V}$ from previous years (up to $t-1$) to their next year's realized currency risk premia (up to t) and conduct a 300 × 300 grid search from 0 to 1 for both w and α to find all combinations of w and α that result in positive and statistically significant (with p-value < 0.005) Spearman correlations between *CBC*s and the realized currency risk premia (all data up to t).[30] The estimates of w and α at year t are the weighted average of the points identified on the grid with the weights being the Spearman correlation coefficients. The calibrated w and α at year t are then the averages of all estimates up to year t. The calibrated w and α, alongside year-t $\mathbf{A}$ and $\mathbf{V}$, are used to compute *CBC* at time t via Eq. (26) for predicting currency excess returns at time $t+1$. This setup ensures that the constructed *CBC* is only based on the information available up to the point of construction, for each exchange rate. We use the sample from 1995 to 2002 for initial calibration and start the out-of-sample *CBC* construction from 2003 to the end of the sample in 2021.

We plot the calibrated w and α and the resulting Spearman correlations in Fig. 3. Both w and α appear remarkably stable over time. For example, w stabilizes around 0.52 early in the sample, confirming the information from the variance–covariance matrix is useful in predicting currency risk premia. More importantly for the purpose of our paper, we find that α is in the range between 0.68 and 0.74 and converges to around 0.68, clearly very far from zero. This suggests that the imbalance network centrality has significant predictive power for the cross-sectional variation of currency excess returns, even controlling for the variance–covariance matrix of returns. The Spearman correlations between *CBC*, calculated using these calibrated values of w and α, and currency excess returns (risk premia) are large, in the range from 0.12 to 0.3 (Fig. 3(b)). In Fig. 3(b), we also plot the Spearman correlations for cases assuming $\mathbf{\Gamma} = \mathbf{V}$ ($w = 0, \alpha = 0$) and $\mathbf{\Gamma} = \mathbf{I}$

[30] To make Spearman correlations meaningful, we apply a rank-preserving transformation to the original *CBC*s at $t-1$ so that their max and min values match those of the currency risk premia at $t-1$. Again no future information is used in the calibration at each time t. Also, we require a p-value < 0.005 to establish statistical significance rather than a conventional significance level of, e.g., 0.05, because we are considering a large number of combinations of w and α. Hence we face a potential multiple hypothesis testing bias, which calls for more conservative p-values (see, e.g., Harvey et al., 2016).

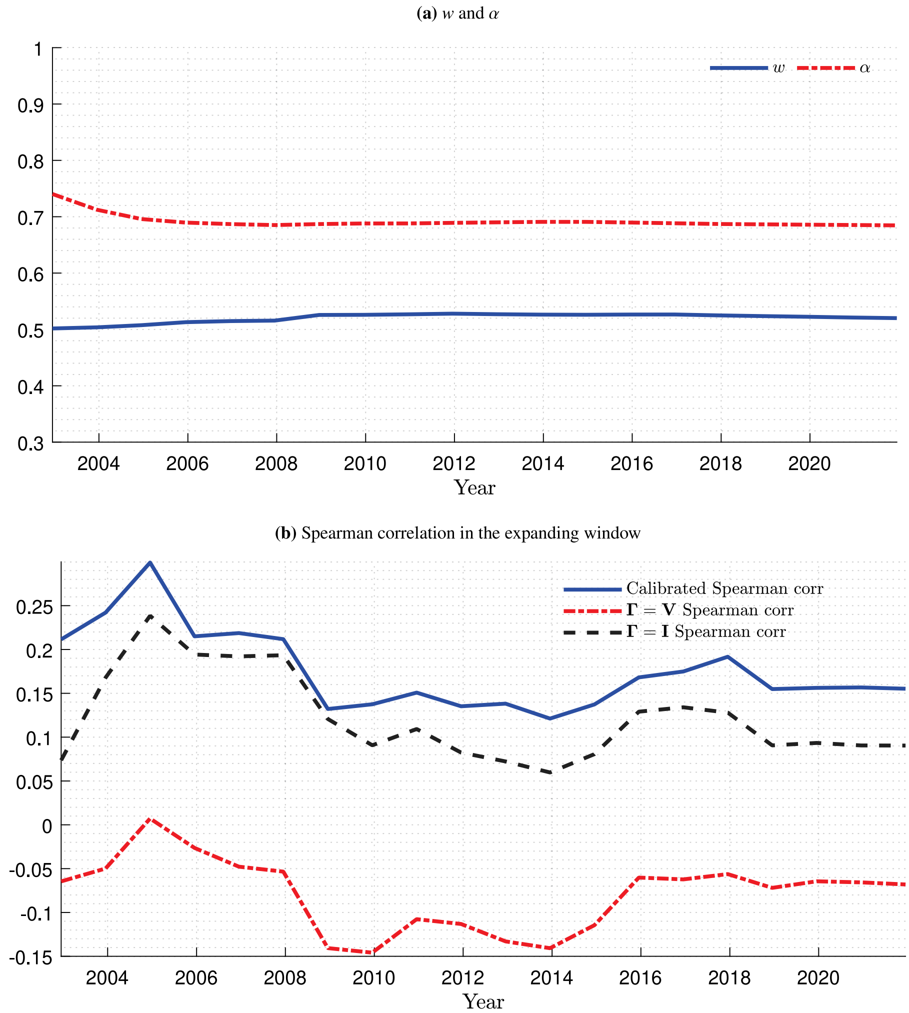


Fig. 3. Calibrated w and α over time.
Note: In this figure, Panel (a) plots the calibrated w and α over time; Panel (b) plots Spearman correlations coefficient between all *CBC*s and currency risk premia over time. The sample period is from 2003 to 2021 (and the initial values of w and α are calibrated using data from 1995 to 2002). The data frequency is yearly and the calibration is done in yearly expanding windows. In Panel (b), the solid line is the Spearman correlation of the currency risk premia and the model expected currency return based on calibrated w and α shown in Panel (a), and the dashed line (dash-dotted line) is the Spearman correlation of the currency risk premia and the model expected currency return assuming $w = 0$ and $\alpha = 0$ ($w = 1$ and $\alpha = 0$), i.e., $\mathbf{\Gamma} = \mathbf{V}$ ($\mathbf{\Gamma} = \mathbf{I}$).

($w = 1, \alpha = 0$). When $\mathbf{\Gamma} = \mathbf{V}$, the Spearman correlation is negative, albeit small in magnitude, indicating that $\mathbf{V}$ per se is not a strong candidate for $\mathbf{\Gamma}$ empirically. The case of $\mathbf{\Gamma} = \mathbf{I}$ essentially only uses the total imbalance to explain currency risk premia. We find that the Spearman correlation is consistently lower than the correlation obtained for the case of *CBC* with calibrated w and α. In essence, augmenting the variance–covariance matrix of currency excess returns with trade imbalance network information significantly improves the model's ability to explain currency risk premia, consistent with the theory.

To show how the relative positions of the *CBC*s change, we plot the positions of the top, middle and bottom three currencies in the percentage ranks over time in Fig. 4. Net importing economic regions (e.g., Kuwait, Mexico, South Africa) are clearly in the top panel, whereas net exporting economic regions (e.g., Mainland China, Hong Kong (China), Thailand) are in the bottom panel. We also observe that currencies in the middle panel display higher turnover in the relative ranks than those in the top and bottom, indicating pronounced time-variation of the premia for the majority of currencies.

In short, the calibration exercise provides a first indication of the usefulness of the information implicit in the imbalance network and variance–covariance matrix that goes beyond the total imbalance. We then test whether the constructed *CBC*s have stronger performance in explaining currency risk premia than existing factors that are based solely on total imbalances in an out-of-sample setting. In the out-of-sample analysis we use *CBC* in two different variants: one where w and α are updated when constructing *CBC* in the way described above, conditioning on new information becoming available at time t; and another where we simply set w and α equal to the calibrated values obtained during the 1995–2002 period and never change them over the out-of-sample period. In the latter, more conservative case, for given values of w and α, variation in *CBC* across currencies and time is driven exclusively by international trade data and the variance–covariance matrix of returns. In our empirical analysis below, we report evidence for both cases, i.e. using either constant w and α or time-varying w and α, and show that the our central results are qualitatively the same under either of these settings.

4. Empirical analysis

In this section, we first show that sorting currencies into portfolios based on their *CBC*s generates a sizable spread in excess returns, and a *CBC* long–short cross-sectional strategy yields high average excess returns and Sharpe ratio in an out-of-sample setting. These excess returns are driven not only by interest rate differentials (as is the case for carry), but also by spot predictability in the cross section of currencies.

Fig. 4. *CBC* relative percentage ranks over time.
Note: The top, middle, and bottom panels in this figure show the over-time dynamics of the positions of the top, middle, and bottom three currencies, respectively, in the percentage ranks. The currencies in different panels are identified through their full sample average percentage ranks, which are shown in the parentheses right next to their legends in the plot. For example, the top three currencies are the top three currencies with the highest full sample average *CBC* ranks in descending order.

We also consider other networks as alternatives to the trade imbalance network in the Leontief inverse. Since the theoretical framework allows for the Leontief inverse to capture any of, for example, the trade imbalance network, the capital flow network (either portfolio flows or FDI) or the total trade network to be plausibly considered, we construct *CBC* using all of these candidate networks. We find that constructing *CBC* with the trade imbalance network performs much better than any of the alternatives considered, as its predictive power for the cross-section of currency excess returns turns out to be stronger than the alternative networks. We then compare the performance of various risk factors relative to a *CBC* factor (computed as the excess return of the *CBC* strategy described above) using Barillas–Shanken regressions, and find that none of the factors considered subsumes the information in the *CBC* factor.

Next, we show that there is a strong link between the *CBC* factor and the cross-section of currency excess returns within a standard asset pricing framework. We also present both panel regressions and a variance decomposition to quantify the importance of the trade network effects in explaining the variation in currency premia across countries. Additionally, we conduct a counterfactual analysis to demonstrate the usefulness of this framework in assessing the impact of significant international events on currency premia.

4.1. CBC and other portfolio sorts

4.1.1. The predictive power of CBC in the cross section.

We start this analysis by assessing the predictive power of *CBC* for the cross-section of currency excess returns. We form four portfolios sorted on *CBC*, and five other benchmarks variables: the Total trade network centrality (*TTNC*) proposed by Richmond (2019); the trade imbalance (*TImb*) defined as the total net import (this is equivalent to setting $\boldsymbol{\Gamma}$ equal to $\mathbf{I}$); the forward discount (*FD*), the carry trade characteristic used in a vast literature; global imbalances (*GImb*) studied by Della Corte et al. (2016); the variance–covariance weighted trade imbalance ($\mathbf{V}$-weighted *TImb*) denoted as $\mathbf{V}q$ (this is equivalent to setting $\boldsymbol{\Gamma}$ equal to $\mathbf{V}$).

Monthly currency excess returns are used in this exercise, consistent with the vast majority of papers in the currency asset pricing literature. However, portfolio sorts are based on variables constructed using the information from the year prior to the realized currency returns, since *CBC* can only be constructed at the yearly frequency. Hence, the sorted portfolios are re-balanced yearly. To ensure a level playing field across all sorting variables, we construct the benchmark variables using yearly data even though some of them (e.g., *FD*) are available at higher frequency. The portfolio sorts are carried out such that the safest currencies are in the low (short) portfolio and the riskiest in the high (long) portfolio. Specifically, currencies are sorted in ascending order of *CBC*, *TImb*, *FD*, and $\mathbf{V}$-weighted *TImb*, and in descending order of *TTNC* into four groups (G1 to G4) because according to Richmond (2019), more central countries' currencies in the total trade network have lower risk premia.[31] For *CBC* portfolios, we use two construction

[31] For *GImb*, the portfolios are formed from a 2 × 2 conditional double sort by nfa and ldc, following Della Corte et al. (2016), where nfa is the net foreign asset position (the difference between foreign assets and foreign liabilities) relative to the size of the economy (GDP) and ldc is the proportion of external liabilities denominated in domestic currency. The end-of-year

Table 2
Portfolio sorting performance comparison.

Sorting Var.		G1	G2	G3	G4	G4 - G1				
						Return	Sharpe	FD	SR	$\frac{\text{SR}}{\text{Return}}$
CBC (updated)		−0.06	0.13	0.20	3.14	3.21**	0.54	2.54	0.67	0.21
CBC (static)		−0.33	−0.05	0.50	3.25	3.58***	0.65	2.73	0.85	0.24
Panel A	*TTNC*	0.74	−0.54	1.30	1.78	1.04	0.23	3.04	−2.00	−1.92
	TImb	0.37	0.37	1.71	0.76	0.40	0.08	2.05	−1.65	−4.18
	FD	−0.12	0.49	1.41	1.49	1.61	0.21	7.01	−5.40	−3.36
	GImb	−1.00	0.96	1.72	1.01	2.01*	0.45	1.41	0.60	0.30
	V-weighted *TImb*	0.21	−0.17	1.69	1.44	1.23	0.13	1.15	0.08	0.06
	DOL	–	–	–	–	0.83	0.13	1.39	−0.56	−0.67
Panel B	$CPIS$	−0.74	−0.33	−1.68	−0.79	−0.06	−0.01	1.66	−1.72	30.21
	$CPIS_{TH}$	−0.56	−0.40	−1.80	−0.77	−0.21	−0.02	1.64	−1.85	8.80
	$CPIS_{FR}$	−0.62	−0.38	−1.80	−0.73	−0.12	−0.01	1.71	−1.82	15.75
	FDI	−0.41	−0.50	−2.05	−0.53	−0.12	−0.01	1.96	−2.08	17.65
	RM_{ADJ}	0.19	−0.15	1.34	1.83	1.63	0.18	1.33	0.30	0.18

Note: This table compares the performance of *CBC*-sorted portfolio with that of various characteristic-sorted portfolios. Panel A includes: total trade network centrality (*TTNC*), trade imbalance (*TImb*), forward discount (*FD*), and global imbalance (*GImb*), variance–covariance weighted trade imbalance (**V**-weighted *TImb*), as well as the average currency excess return (*DOL*). *TTNC* is proposed by Richmond (2019), *TImb* is inspired by Gabaix and Maggiori (2015), *FD* is the carry trade characteristic from Lustig et al. (2011), *GImb* is used by Della Corte et al. (2016), and **V**-weighted *TImb* is inspired by Gabaix and Maggiori (2015, OA). The *DOL* is the currency "market" return in dollars available to a U.S. investor (Lustig et al., 2011). Panel B includes alternative CBCs calibrated on other networks: $CPIS$, $CPIS_{TH}$, $CPIS_{FR}$, FDI, and RM_{ADJ}. $CPIS$ is the network based on the original financial linkages without any restatements reported in Coordinated Portfolio Investment Survey (CPIS). $CPIS_{TH}$ denotes the network based on the CPIS financial linkages but reallocates only securities that, under residency, are issued by affiliates located in tax havens. $CPIS_{FR}$ refers to the network based on the CPIS financial linkages and reallocates all securities that, under residency, are issued by affiliates from all countries. Detailed restatement procedures can be found in Coppola et al. (2021). FDI is based on bilateral foreign direct investment stocks of all sample countries. RM_{ADJ} refers to the network from Richmond (2019), which is based on the adjacency matrix of total trade. For the characteristics in Panel A and RM_{ADJ}, the sample period is from 2003 to 2021, which is the out-of-sample period for α and w calibration. For the alternative CBCs based on $CPIS$, $CPIS_{TH}$, $CPIS_{FR}$, and FDI, the sample period is from 2008 to 2021 due to the data availability. Two sets of results, "updated" and "static", are reported for *CBC* where *CBC* (updated) is calculated based on annually updated α and w while *CBC* (static) is based on static α and w calibrated from the initial sample before 2003. The sorted portfolios are rebalanced yearly. All returns and Sharpe ratios are annualized. All returns are in percentage. All characteristics except the alternative CBCs based on $CPIS$, $CPIS_{TH}$, $CPIS_{FR}$, and FDI are constructed based on information from the previous calendar year-end. For the alternative CBCs based on $CPIS$, $CPIS_{TH}$, $CPIS_{FR}$, and FDI, α and w are calibrated in sample using their available sample period from 2008 to 2021. Currencies are sorted in ascending order into quartiles (G1 to G4) for all characteristics except *TTNC* and *GImb*. Currencies are sorted in the descending order of *TTNC*. For *GImb* the G1 to G4 are formed from a 2×2 conditional double sorting by nfa and ldc following Della Corte et al. (2016). The last five columns, respectively, report Return (average return), Sharpe, FD (forward discount), SR (spot return), and $\frac{\text{SR}}{\text{Return}}$ of the factors from longing G4 and shorting G1. ***, **, and * indicate the statistical significance level of 1%, 5%, and 10%, respectively. The significance level for the average return is calculated from t-test.

methods for the sorting variable over the out-of-sample period 2003-2021: recursive, where w and α are updated over time conditioning on new information becoming available (*CBC* updated); and constant, based on the calibrated values of w and α obtained over the 1995–2002 sample period (*CBC* static).

Using the excess returns of the long–short strategy, we define a tradable factor for each sorting variable mentioned above. For example, the *CBC* factor is defined as the excess return of the long–short strategy (G4 minus G1), where G1 and G4 portfolios are the first and fourth quartile portfolios sorted by *CBC*, respectively. We also consider a dollar factor as in Lustig et al. (2011), i.e. the currency excess return on a portfolio strategy long all foreign currencies with equal weights and short the domestic currency, and denoted as DOL. This gives us seven factors: *CBC* (which is available in two variants, updated and static), *TTNC*, *TImb*, *FD*, *GImb*, **V**-weighted *TImb*, and *DOL*. *DOL* is routinely used as the first factor in candidate pricing kernels in a vast literature on currency asset pricing, essentially playing the role of a level currency factor similar to the market factor in equity asset pricing models.

The results for the portfolio sorts for *CBC* and the benchmark strategies described above are shown in Panel A of Table 2. Columns G1 to G4 present the equal-weighted average excess returns of the different portfolios. Recall that we use *CBC* in two different ways in this out-of-sample analysis. Starting from the case where w and α are updated over time conditioning on new information becoming available (*CBC* updated), we find that the average returns increase monotonically from the first portfolio G1 to the last portfolio G4. When using *CBC* constructed based on the calibrated values of w and α obtained over the 1995–2002 period (*CBC* static), the results are qualitatively identical. This result is not surprising given the stability displayed by w and α over time illustrated earlier, and it is reassuring in that it should allay any concern about potential look-ahead bias. The monotonic increase in the excess returns of portfolios G1 to G4 also occurs for *FD*, i.e. carry. Comparing the average excess returns of the long–short portfolio (long G4 and short G1) shows that *CBC* clearly delivers, across all strategies, the highest average return (statistically significant at least at the 5% significance level), and the highest annualized Sharpe ratio, i.e., 0.54 and 0.65 for *CBC* updated and static, respectively.

To see how the various characteristics perform over time, we also plot the long–short portfolios' cumulative returns from 2003 to 2021 in Fig. 5. Several characteristics have strong performance before 2008, but after 2008 *CBC* clearly dominates relative to other sorting variables.

While our theoretical framework directly models the currency risk premium rp as in Eq. (10), and the variable $rx_{i,t}$ as defined in Eq. (20) serves as a precise empirical counterpart to rp, it is instructive to dissect the factor returns outlined in Table 2 into FD and SR. This allows us to scrutinize the relative contributions of these two components to the average excess returns resulting from various sorting variables, and to ascertain whether a characteristic (strategy) generates returns only by capturing the interest rate differential (carry, FD) across countries or whether it also has predictive power for spot exchange rate returns (SR). The results from decomposing the excess returns into the interest rate component, FD, and the spot rate component, SR, are presented in the last three columns of Table 2. We find that for *CBC* (updated), 2.5%, out of the 3.21% excess return, is attributable to FD, with a similar value of 2.7% observed for *CBC* static. Consequently, the spot component contributes around 21% (24%) of the excess return for the *CBC* updated (static) factor, which is non-trivial. The spot component represents 30% of the *GImb* factor, and 6% of the **V**-weighted *TImb* factor. However, for *TTNC*, *TImb*, and *FD*, the spot component is negative,

series on foreign assets and liabilities and gross domestic product (GDP) are from Lane and Milesi-Ferretti (2001, 2007), kindly updated by Gian Maria Milesi-Ferretti. The end-of-year series on the proportion of external liabilities denominated in domestic currency are from Bénétrix et al. (2015), who update the data from Lane and Shambaugh (2010), kindly provided by Philip Lane and Agustín Bénétrix.

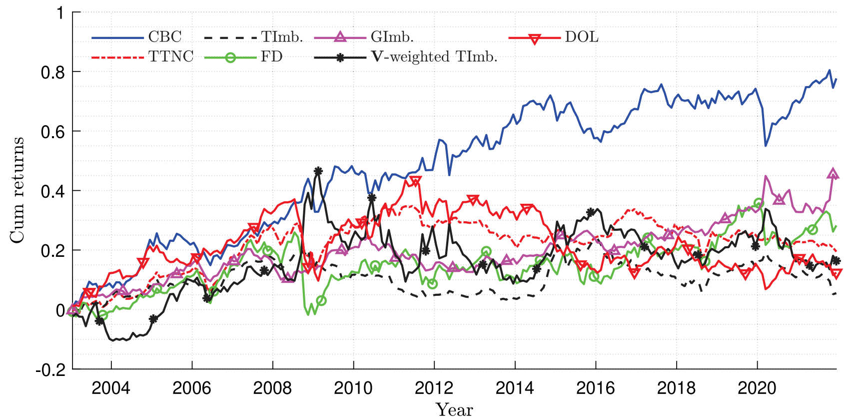


Fig. 5. Cumulative returns over time in portfolio sorting comparison.
Note: This figure plots the cumulative returns of buying G4 and selling G1 in the portfolio sorting using as characteristics: *CBC*, total trade network centrality (*TTNC*), trade imbalance (*TImb*), forward discount (*FD*), global imbalance (*GImb*), and variance–covariance weighted trade imbalance (**V**-weighted *TImb*), as well as the average currency excess return (*DOL*). *TTNC* is proposed by Richmond (2019), *TImb* is inspired by Gabaix and Maggiori (2015), *FD* is the carry trade characteristic from Lustig et al. (2011), *GImb* is used by Della Corte et al. (2016), and **V**-weighted *TImb* is inspired by Gabaix and Maggiori (2015, OA). *DOL* is the currency "market" return in dollars available to a U.S. investor (Lustig et al., 2011). The sample period is 2003–2021, which is the out-of-sample period in our out-of-sample analysis. All returns are in percentage. All characteristics are constructed based on information one year prior to the realized currency returns. Currencies are sorted in the ascending order of *CBC*, *TImb*, *FD*, and **V**-weighted *TImb*, and in the descending order of *TTNC* into quartiles (G1 to G4). For *GImb* the G1 to G4 are formed from a 2 × 2 conditional double sorting by nfa and ldc following Della Corte et al. (2016). The sorted portfolios are rebalanced yearly.

indicating that these characteristics extract all of the positive excess return from interest rate differentials. The *FD* factor (carry trade) stands out with the highest FD component at 7%, but its spot component is also the most negative at −5.4%, consistent with the literature and the mechanics of the currency carry trade. Overall, with the spot predictability component accounting for over 20% of its excess return, *CBC* is a currency characteristic that does not only capture interest rate differentials but also predicts currency returns out of sample.

4.1.2. Trade imbalance network v.s. alternative networks.

In this section, we present the results from comparing the trade imbalance network with alternative networks. These include: the CPIS network, which is based on bilateral financial asset and liability linkages; the FDI network, which is based on bilateral FDI; and the total trade network of Richmond (2019). This allows us to analyze in more depth the potential differences between the trade imbalance network centrality and the centrality of the total trade network of Richmond (2019), as well as network centrality measures based on both short-term (portfolio) flows and long-term (FDI) flows. To mitigate "residency" bias, we use the restated CPIS data from Coppola et al. (2021) for the available countries and then merge it with the original CPIS data for other countries in our sample. The restated CPIS data covers the period from 2007 to 2020, while the currency data spans 2008–2021.

Due to the limited sample period and the low frequency of the data, conducting both in-sample and out-of-sample analyses for the alternative networks based on CPIS and FDI is not feasible. Therefore, we restrict our analysis of the alternative networks to in-sample estimation and apply the same method as in Section 3.3 to estimate the parameters α and w of Eq. (26) for each alternative CBC constructed in this section.

We compare the performance of these alternative CBCs against the trade imbalance network-based *CBC*, and report the results in Panel B of Table 2. The *CPIS* network is based on the original CPIS financial linkages without restatements. $CPIS_{TH}$ adjusts the CPIS network by reallocating securities issued by affiliates in tax havens. $CPIS_{FR}$ extends this reallocation to securities issued by affiliates in all countries. The *FDI* network is constructed from bilateral data covering all sample countries. RM_{ADJ}, from Richmond (2019), is based on the adjacency matrix of total trade. These networks yield five alternative CBCs. The results in Panel B of Table 2 make clear that none of the alternative networks exhibit comparable performance to *CBC* constructed using the trade imbalance network. Specifically, all long–short (G4-G1) portfolios constructed from these alternative CBCs yield average excess returns that are low and statistically insignificantly different from zero, and low Sharpe ratios. Furthermore, the excess returns from G1 to G4 do not display a monotonic pattern. These results suggest that the trade imbalance network is empirically superior to these alternative networks in terms of predictive power for the cross-section of currency excess returns, which we interpret as evidence that the trade imbalance network is (more) naturally aligned with our *CBC* measure, as predicted by the theoretical framework.[32]

4.1.3. Spanning regressions

Next, we ask how the time-series variation of the *CBC* factor is related to that of various factors. By design, this *CBC* factor captures financiers' limited commitment embedded in the global imbalance network. Therefore, it is also interesting to check if the *CBC* factor is correlated with intermediary asset pricing factors, in addition to all other factors considered so far in Panel A of Table 2. To this end, we consider two well-known intermediary asset pricing factors due to Adrian et al. (2014, AEM) and He et al. (2017, HKM). The details for constructing the tradable AEM and HKM factors are presented in Internet Appendix I.

According to Barillas and Shanken (2017), when all factors are tradable, OLS regressions are all that is needed to establish whether one factor prices another and the focus can be directly on the alpha of the regression. Therefore, we regress the *CBC* factor on each of the above existing factors and examine the size and statistical significance of the alpha in the regression to test whether any of these factors subsumes the information in *CBC*. In essence, the alpha coefficients alongside their statistical significance allow us to assess whether the *CBC* factor is subsumed by these factors. The results are reported in Table 3a. These results show that the alpha coefficients are statistically significant for

[32] This result is particularly clear-cut, given that the alternative networks are tested in sample, rather than out of sample, and yet they underperform relative to CBC based on trade imbalances. We present in Internet Appendix J.2 the in-sample results from estimating α and w for all alternative CBCs on the same, overlapping sample period (2008–2021), for comparison. Given these estimates of α and w, the results also confirm over a common sample period that the CBC measure constructed using the trade imbalance network displays the strongest correlation with (predictive power for) currency excess returns across all of the networks considered.

Table 3
Time-series variation of *CBC* factor in relation to various factors.

(a) How well various factors explain the *CBC* factor

CBC is on LHS	Alpha (%)	T-Alpha	Beta	T-Beta	R^2
TTNC	2.78**	2.43	0.41***	3.51	10.00%
TImb	3.18***	2.73	0.06	0.50	0.24%
FD	2.75**	2.24	0.29**	2.23	13.44%
GImb	3.35***	3.00	−0.07	−0.40	0.29%
V-weighted *TImb*	3.48***	3.07	−0.22**	−2.38	12.02%
DOL	2.84**	2.42	0.44***	3.33	23.98%
AEM	3.91***	2.82	0.23	1.45	4.14%
HKM	3.04**	2.56	0.11	0.91	0.54%

(b) How well the *CBC* factor explains various factors

CBC is on RHS	Alpha (%)	T-Alpha	Beta	T-Beta	R^2
TTNC	0.26	0.26	0.25***	3.80	10.00%
TImb	0.27	0.25	0.04	0.49	0.24%
FD	0.10	0.07	0.47***	3.65	13.44%
GImb	2.13**	1.97	−0.04	−0.39	0.29%
V-weighted *TImb*	2.97	1.56	−0.55***	−3.05	12.02%
DOL	−0.90	−0.68	0.54***	5.63	23.98%
AEM	−1.52	−1.02	0.18	1.53	4.14%
HKM	1.39	1.43	0.05	0.98	0.54%

Notes: Panel (a) in this table presents the Alpha and Beta coefficients from regressing the *CBC* factor (defined as the G4 - G1 portfolio returns) on various factors. Panel (b) presents the Alpha and Beta coefficients from regressing various factors on the *CBC* factor. The column labeled 'T-Alpha' ('T-Beta') reports the t-statistics of Alpha (Beta) estimates based on Newey–West standard errors. Alpha estimates are in annualized percentage. ***, **, and * indicate 1%, 5%, and 10% significance levels, respectively. The sample period is 2003–2021.

all regressions, and they are economically large. This is clear evidence that the *CBC* factor captures information that cannot be spanned by these currency pricing factors or the intermediary asset pricing factors considered.

We then ask the question whether and how well the *CBC* factor explains other factors by regressing each of these factors on the *CBC* factor. Again, we focus on the size and statistical significance of the alpha in the regression to test whether *CBC* subsumes the information in each of the factors considered.[33] The results are reported in Table 3b. We find that all of the alphas except one are statistically insignificantly different from zero. The only exception is that the alpha coefficient of the *GImb* factor of Della Corte et al. (2016) is statistically significant. This suggests that although the *GImb* factor delivers a lower return than the *CBC* factor in the performance comparison shown in Panel A of Table 2, it carries some information that cannot be explained by the *CBC* factor, amounting to an alpha of just over 2% per annum.[34]

4.1.4. Summing up

In summary, the performance comparison in this section confirms the predictive power of *CBC* both in- and out-of-sample, and further suggests that its information content cannot be subsumed by any of the alternative factors considered. In the following section, we proceed to a formal cross-sectional asset pricing test.

4.2. Cross-sectional asset pricing tests

4.2.1. Motivating cross-sectional asset pricing tests

Let us start by noting that it is not obvious analytically that our theoretical framework implies heterogeneous risk exposures of *CBC*-sorted portfolios and, hence, the validity of cross-sectional asset pricing tests. This consideration applies equally to the Gabaix–Maggiori theory on which our theory builds. We address this issue at the outset of this section by studying the cross-sectional implications of the Gabaix–Maggiori model via simulation.

We report this simulation analysis in detail in Internet Appendix B, whereas we summarize here only its main features and learning points. We first show that the model can be rewritten as a nonlinear one-factor model for currency returns. Unsurprisingly, the cross-section of currency returns cannot be expressed as an analytical function of the risk exposure, say β, of a portfolio excess return sorted on *CBC*. In our simulation design, we consider a two-period version of the model, and allow for a generic source of uncertainty in the second period.[35] We then calibrate the model and conduct a simulation analysis to explore the relationship between the model's expected returns, *CBC* and β.

The results of 1000 simulations (see Figure A4 in Internet Appendix E) show clearly how the currencies of countries with positive (negative) β experience positive (negative) average returns in equilibrium. This evidence confirms the intuition that the model implies *CBC*-sorted portfolios should have different risk exposures to a common risk factor, justifying the use of cross-sectional asset pricing tests to verify the validity of the model. See Internet Appendix B for a detailed discussion of the design and results of these simulations. It is important to note, however, that in the simulation *CBC*-sorted portfolios are not by design related to risk exposures to the common factor, as we are *not* assuming that *CBC* is correlated with risk exposures; put another way, currency returns' heterogeneous risk exposures arise endogenously instead of exogenously from the simulation design.

4.2.2. Results from asset pricing tests

In the cross-sectional asset pricing tests, we consider a set of 24 test assets, which are the four portfolio excess returns (G1 to G4) for each

[33] See Hou and Robinson (2006) for a similar practice of placing a key factor on either side of regressions separately.

[34] This is presumably because *GImb* is constructed using not only information on external imbalances but also data on the proportion of external liabilities denominated in domestic currency, which does not enter the construction of *CBC*.

[35] We refer to a "generic" source of uncertainty here because in the data generating process uncertainty is not structurally related to financial intermediation. However, in light of the empirical evidence presented later in the paper that CBC-sorted excess returns comove with financial intermediation capacity, it is tempting to think of this generic source of uncertainty as capturing financial intermediation risk.

of the six sorting variables: *CBC* static, *TTNC*, *TImb*, *FD*, *GImb* and **V**-weighted *TImb*. We then perform the two-step Fama–Macbeth (FMB) procedure using a two-factor pricing kernel with *DOL* and *CBC*.[36]

In Panel A of Table 4, we present the results of the first step of the FMB procedure applied to the *CBC* portfolios, i.e., the time series regression of each *CBC* portfolio excess return on an intercept (alpha), the *DOL* factor and the *CBC* factor. The estimated coefficients of the *DOL* factor are positive and strongly statistically significant, but they are also similar for the four portfolio returns, as expected from a level factor and consistent with the literature (Lustig et al., 2011; Della Corte et al., 2016). In contrast, the estimated coefficients on the *CBC* factor increase monotonically from G1 (−0.417) to G4 (0.583), indicating clear heterogeneous exposures of the four *CBC*-sorted portfolios and suggesting that *CBC* is a slope, pricing factor. Panel A also reports the average absolute alpha, both for the four time series regressions of the *CBC* portfolio excess returns and for all 24 time series regressions. These average absolute alphas are small, and the Gibbons–Shanken–Ross tests (GRS4 and GRS24) suggest that the null hypothesis that the alphas are jointly zero cannot be rejected at conventional statistical significance levels. In turn, this evidence indicates that the two-factor model can price both the cross-section of *CBC*-sorted portfolio returns and the full cross-section of 24 portfolio excess returns.

Panel B reports the results of the second step of the FMB procedure, i.e., the cross-sectional regression, where we estimate the price of risk of *CBC*. In addition to the 24 average portfolio excess returns, we also add the six benchmark factors (G4 - G1, see Section 4.1) to the test assets, as suggested by Lewellen et al. (2010). The risk premium estimate for *DOL* (λ_{DOL}) is statistically significant, but it is small in magnitude, less than one percent annualized ($0.056 \times 12 = 0.672$), which is not surprising and consistent with the literature. The risk premium estimate of the *CBC* factor (λ_{CBC}) is positive and strongly statistically significant; its magnitude implies a risk premium of more than four percent annualized ($0.344 \times 12 = 4.128$). The cross-sectional regression has an R^2 of 0.753, suggesting that the model adequately captures the cross-sectional variation in the test asset returns. Furthermore, the result from the χ^2 test for the null that the alphas are jointly zero confirms the earlier conclusion from the GRS test and indicates that the pricing errors are statistically insignificantly different from zero.

In Panel C, we report results from the second step of FMB where we fix the risk premium of *CBC* to its sample mean, which is 0.298. By no-arbitrage, since *CBC* is a return-based factor, the estimate of the risk premium must equal the factor mean. However, in Panel B, we find that the 95% confidence interval of the estimated λ_{CBC} does not include (by a very small margin) the sample mean of the *CBC* factor.[37] Therefore, it seems useful to check that the two-factor model prices the test assets when the risk premium of *CBC* is set to be the factor mean. We find that the R^2 is lower in this case (0.454), but the χ^2 test continues to confirm that the pricing errors are zero and hence the results are qualitatively identical. This verifies that the pricing ability of the two-factor model does not depend on the ability to treat λ_{CBC} as a free parameter in estimation.

Overall, the asset pricing test results in this section confirm that currency risk premia are tightly linked to the *CBC* factor, which is strongly priced in the cross-section of test assets considered in our setting.

[36] In the asset pricing tests below, we use *CBC* in its static variant, but the results are qualitatively unchanged when using its updated variant.

[37] Specifically, given the estimate of the standard error of 0.041, the lower bound of the 95% confidence interval is 0.303, whereas the sample mean of the CBC factor is 0.298, which is consistent with the annualized value of 3.58% reported in Panel A of Table 2.

Table 4
Results from cross-sectional asset pricing tests.

Panel A: Fama–MacBeth regression step one			
	β_{DoL}	β_{CBC}	R^2
CBC 1	0.879***	−0.417***	0.945
Std err	0.014	0.022	
CBC2	1.031***	−0.135***	0.881
Std err	0.026	0.045	
CBC3	1.184***	−0.028	0.932
Std err	0.023	0.027	
CBC4	0.879***	0.583***	0.972
Std err	0.014	0.022	
	p-value		
GRS4	0.712		
GRS24	0.167		
$\bar{\alpha}_{abs,4}$	0.035		
$\bar{\alpha}_{abs,24}$	0.041		
Panel B: Fama–MacBeth regression step two			
λ_{DOL}	0.056	R^2	0.753
Std err	0.007	χ^2_{n-k}	
λ_{CBC}	0.344	p-value	0.999
Std err	0.024		
Panel C: Fama–MacBeth regression step two with λ_{CBC} fixed			
λ_{DOL}	0.055	R^2	0.454
Std err	0.006	χ^2_{n-k}	
λ_{CBC}	0.298	p-value	0.999

Note: In this table, we report the results from the Fama–Macbeth cross-sectional regression. The test assets include four portfolios sorted on *CBC* (static), and the five other benchmark characteristics: Total trade network centrality (*TTNC*), proposed by Richmond (2019); trade imbalance (*TImb*), defined as total net import (equivalent to setting **Γ** equal to **I**); forward discount (*FD*), a common carry trade characteristic in the literature, e.g., Lustig et al. (2011); global imbalances (*GImb*), studied by Della Corte et al. (2016); and variance–covariance weighted trade imbalance (**V**-weighted *TImb*), denoted as $\mathbf{V}q$ (equivalent to setting **Γ** equal to **V**). DOL represents the currency excess return on a portfolio strategy that longs all foreign currencies with equal weights and shorts the domestic currency (USD). Panel A reports the results from the first step of the Fama–MacBeth regression, conducted using the 24 test assets of the six characteristics. 'Std err' denotes the standard error. GRS4 and GRS24 are tests for the four CBC and the 24 test assets, respectively, as described by Gibbons et al. (1989) testing whether the intercepts of the regression are jointly different from zero. The p-values are reported. $\bar{\alpha}_{abs,4}$ and $\bar{\alpha}_{abs,24}$ represent the averages of the absolute values of the alphas obtained from regressions of the four and 24 test assets, respectively. Panel B reports the results from the second step of the Fama–MacBeth regression using both the 24 test assets and the six factors. χ^2_{n-k} tests if the intercepts are jointly zero. The p-values are reported. Panel C repeats the same regression as Panel B, but with the CBC risk premium fixed at 0.298, the sample mean return of the *CBC* factor. All regressions are based on the monthly log returns. ***, **, and * indicate the statistical significance level of 1%, 5%, and 10%, respectively.

4.3. The dominant role of neighborhood importance

In the Gabaix–Maggiori theory, the external imbalances in the trading network are a key characteristic explaining currency risk premia, as the expected currency appreciation in a country is positively related to the long position in bonds that financiers hold in this country. The value of this position is the total imbalance (deficit defined to be positive, and surplus defined to be negative) of this country in Gabaix and Maggiori (2015). As shown in Proposition 1, the result that q is both the total imbalance and the position financiers hold can be generalized to a multi-country setting. However, whether the cross-sectional relation between the currency risk premia and q is positive is not straightforward given that $\mathbf{\Gamma}$ is now a matrix, while it is a scalar in a two-country setting.

To see this point in our setting, we spell out from Eq. (10) the ith element of $\mathbb{E}\left(\bar{x}_1 - x_0\right)$, which we call rp_i (i.e., risk premia for currency i) for convenience: $rp_i = \mathbf{\Gamma}_{ii} q_i + \sum_{k \neq i} \mathbf{\Gamma}_{ik} q_k$. The difference between the risk premia of two currencies i and j is: (see the Eq. (27) given as in Box III) where $\Delta q_{ij} = q_i - q_j$. Thus Eq. (27) makes clear that the

$$rp_i - rp_j = \mathbf{\Gamma}_{ii} q_i + \sum_{k \neq i} \mathbf{\Gamma}_{ik} q_k - \mathbf{\Gamma}_{jj} q_j - \sum_{k \neq j} \mathbf{\Gamma}_{jk} q_k$$
$$= \left(\mathbf{\Gamma}_{ii} - \mathbf{\Gamma}_{ji}\right) q_i - \left(\mathbf{\Gamma}_{jj} - \mathbf{\Gamma}_{ij}\right) q_j + \sum_{k \neq i \text{ or } j} \left(\mathbf{\Gamma}_{ik} - \mathbf{\Gamma}_{jk}\right) q_k$$
$$= \underbrace{\left(\mathbf{\Gamma}_{ii} - \mathbf{\Gamma}_{ji}\right) \Delta q_{ij}}_{\text{total imbalance}} + \underbrace{\left[\left(\mathbf{\Gamma}_{ii} - \mathbf{\Gamma}_{ji}\right) - \left(\mathbf{\Gamma}_{jj} - \mathbf{\Gamma}_{ij}\right)\right] q_j}_{\text{individual importance}} + \underbrace{\sum_{k \neq i \text{ or } j} \left(\mathbf{\Gamma}_{ik} - \mathbf{\Gamma}_{jk}\right) q_k}_{\text{neighborhood importance}} \quad (27)$$

Box III.

Table 5
Panel regression results for three components.

	Pair-wise currency premia difference			
Total Imb.	0.142***			0.064**
	(4.62)			(2.18)
Indiv.		0.075***		0.074***
		(3.57)		(3.73)
Neighb.			0.339***	0.326***
			(18.06)	(16.33)
Observations	7211	7211	7211	7211
Adjusted R^2 (%)	2.42	2.16	8.13	8.39
Fixed Effects	Pair & year	Pair & year	Pair & year	Pair & year

Note: This table presents the standardized beta coefficients from panel regressions of the pair-wise currency premia differences on total imbalance (Total Imb.), individual importance (Indiv.) and neighborhood importance (Neighb.), univariate (columns 2 to 4) and multivariate (column 5). The regressions use 7211 pair-year data. t-statistics based on robust standard errors are reported in parentheses. Number of observations and adjusted R^2's are reported at the bottom. Both pair-specific and year fixed effects are controlled. The sample period is 2003–2021.

Table 6
Variance decomposition of model-implied currency premia.

(a) Mean and variance ratio

	$\Delta rp_{i,j}$	Total Imb.	Indiv.	Neighb.
Mean	−0.014	−0.007	0.005	−0.013
	(0.116)	(0.039)	(0.026)	(0.096)
VR	–	0.114	0.049	0.684
		(0.055)	(0.037)	(0.131)

(b) Correlation matrix

	$\Delta rp_{i,j}$	Total Imb.	Indiv.
Total Imb.	0.568		
	(0.159)		
Indiv.	0.073	−0.424	
	(0.261)	(0.305)	
Neighb.	0.958	0.392	−0.007
	(0.032)	(0.159)	(0.244)

Note: Panel (a) presents the sample mean (Mean) of $\Delta rp_{i,j}$, total imbalance (Total Imb.), individual importance (Indiv.) and neighborhood importance (Neighb.), and the variance ratio (VR) of Total Imb., Indiv. and Neighb. VR is defined as ratio of sample variance of one of the three components to that of $\Delta rp_{i,j}$. Panel (b) presents the correlation coefficient matrix of $\Delta rp_{i,j}$, Total Imb., Indiv. and Neighb. Standard errors are shown in parentheses. The standard error of Mean is the sample standard deviation. Other standard errors are the time-series standard deviation of yearly estimates. The sample period is 2003–2021.

cross-sectional variation in rp_i has three components: total imbalance, individual importance, and neighborhood importance. This means that the total imbalance q is not the sole driver of the cross-section of currency risk premia. Indeed, $q_i > q_j$ does not necessarily imply $rp_i > rp_j$ except for most simplified cases, e.g., when $\mathbf{\Gamma}$ is a diagonal matrix with $\mathbf{\Gamma}_{ii}$ positively related to q_i. In essence, Eq. (27) highlights the importance of the network structure reflected in $\mathbf{\Gamma}$ for explaining the cross-section of currency risk premia. Next, we explore the role of $\mathbf{\Gamma}$ as a function of $\mathbf{A}$ in explaining currency risk premia. Guided by Eq. (27), we can empirically analyze the relative importance of these three components in driving the cross-section of currency premia via both panel regressions and a variance decomposition.

First, using panel regressions, we regress pair-wise realized currency premia differences on these three components. To gauge the relative explanatory power of each component, we follow Johannesson et al. (2023) and report the standardized beta coefficients for these regressions in Table 5, enabling direct comparison across regressions. The univariate regressions in Columns 2 to 4 of Table 5 reveal that the neighborhood importance component has a standardized beta coefficient of about 0.34, more than twice that of the total imbalance component (0.14) and four times that of the individual importance component (0.08). In the multivariate regression (column 5 of Table 5), the standardized beta coefficients for the individual and neighborhood importance components remain nearly unchanged, while that of the total imbalance component decreases by half. This pattern is also reflected in the adjusted R^2 values. Overall, this panel regression exercise showcases the dominant role of neighborhood importance in explaining the actual pair-wise currency premia differences and, therefore, the value added of allowing for network effects to explain currency risk premia.

Second, we use the model to decompose all unique pair-wise currency premia differences, $\Delta rp_{i,j} = rp_i - rp_j$ defined in Eq. (27), into the three components over all sample years, allowing for a variance decomposition. Thus, in this variance decomposition, we focus on model-implied (rather than realized) pair-wise currency premia differences. We adjust the three components so that each year's model-implied premia have the same min and max values as their empirical counterparts in that year via an affine rank-preserving transformation.[38] The variance decomposition exercise is in the spirit of Nozawa (2017). Pooling all these pair-year data together (both cross-sectional and time-series) allows us to compute the variance ratios of the three components relative to $\Delta rp_{i,j}$.[39]

The results are presented in Table 6. The sample means of the three components are close to zero, so is the sample mean of $\Delta rp_{i,j}$, as shown in Table 6a. The variance ratio (VR) results in Table 6a provide interesting insights: the total imbalance component explains about 11% of the cross-sectional variation in the implied currency premia; the individual importance component explains very little of the variation, about 5%; the majority, around 68%, of the variation is explained by the neighborhood importance component. This result further highlights the importance of considering all three components rather than just total imbalances, as predicted by the theory.

[38] Given a vector of v, a target maximum a, and a target minimum b, the affine rank-preserving transformation is defined as:

$$\bar{v} = \left[\frac{a}{\max(v) - \min(v)} - \frac{b}{\max(v) - \min(v)}\right] v + \left[\frac{\max(v) b}{\max(v) - \min(v)} - \frac{\min(v) a}{\max(v) - \min(v)}\right].$$

Since $\bar{v}$ is an affine transformation of v, it preserves the rankings of elements in v. From the above definition, $\max(\bar{v}) = a$ and $\min(\bar{v}) = b$.

[39] The elements of q are involved in the variance decomposition through all three components as shown in Eq. (27).

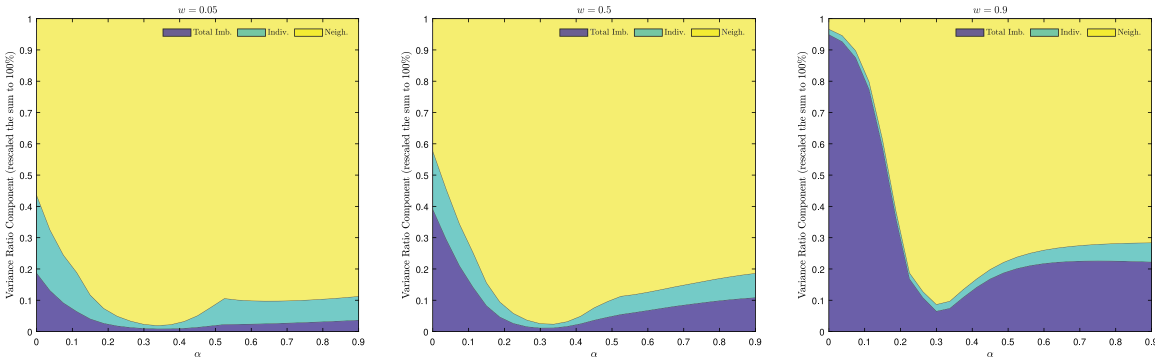


Fig. 6. Variance decomposition with varying α and w.
Note: The panels in this figure plot the (re-scaled) variance ratios of total imbalance (Total Imb.), individual importance (Indiv.), and neighborhood importance (Neigh.) given different values of α and w. α goes from 0 to 0.9 in all three panels. The left panel shows the variance ratios components for $w = 0.05$, the center panel for $w = 0.5$, and the right panel for $w = 0.9$. The results are generated based on the data in the out-of-sample period, from 2003 to 2021. For ease of presentation, the variance ratios are re-scaled to sum of one, with their relative importance preserved for each combination of α and w.

It is worth noting that the VRs do not add up to one as the three components are not orthogonal by construction. Their correlation coefficients are shown in Table 6b. Again, among the three components, the neighborhood importance has a very high correlation with $\Delta rp_{i,j}$ (0.96 with a standard error of 0.03). The total imbalance component is also significantly positively correlated with $\Delta rp_{i,j}$ (0.57 with standard error of 0.16). The individual importance component is not significantly correlated with $\Delta rp_{i,j}$ or either of the other two components. The total imbalance and the neighborhood importance components are positively correlated, which is intuitively consistent with the notion that countries with a larger imbalance tend to have larger centrality and stronger connections with other countries.

To show the extent to which α and w affect the distribution of the VRs, we vary α and w from zero to one and recompute these VRs for various combinations of α and w from the variance decomposition. The results are shown in Fig. 6. Overall, the results confirm that the neighborhood component is crucial in explaining the cross-sectional variation in the implied currency premia when α is not zero and w is not one. The total imbalance dominates the other two components only when α approaches zero and w approaches one, i.e., when $\mathbf{\Gamma}$ approaches the identity matrix, $\mathbf{I}$.[40]

As specified in Eq. (22), our empirical setup has much flexibility that accommodates the total imbalance component-only scenario as a special case ($w = 1$ and $\alpha = 0$). The fact that the calibrated model is far away from the total imbalance component-only scenario speaks directly to the importance of the trade imbalance network in explaining the variation of the implied currency premia. The results in Table 6 and Fig. 6 quantify the relative importance of the three components, echoing the same message from the panel regressions in Table 5. The dominance of the neighborhood importance component highlights the essential role of trade imbalance network centrality emphasized in our theoretical motivation.

4.4. Relationships between trade imbalance network and risk bearing capacity

In this section, we present more direct evidence on the relationship between the trade imbalance network and financiers' risk-bearing capacity. Risk bearing capacity as such is not observable since it is a concept that captures various dimensions that affect the willingness and/or ability of financiers to bear risk.

4.4.1. Evidence from excess returns and common proxies of risk-bearing capacity

First, we examine how the currency excess returns obtained from portfolios sorted on *CBC* correlate with various proxies for risk-bearing capacity. To this end, we consider various proxies for risk-bearing capacity proposed in the existing literature. In Gabaix and Maggiori (2015)'s framework, risk-bearing capacity is influenced by shocks to conditional foreign exchange (FX) volatility. Della Corte et al. (2016) utilize changes in the VXY index as a stand-in for conditional FX volatility risk to approximate risk-bearing capacity. Two VXY indices (VXY-G7 and VXY-EM), developed by JP Morgan, serve as the FX equivalent of the VIX index and track the implied volatility of currencies in G7 and emerging countries, respectively. They capture overall currency volatility by using a turnover-weighted approach. This method aggregates volatility data from three-month, at-the-money forward options for each currency group (G7 or emerging markets). Meanwhile, Fang and Liu (2021) theoretically and empirically show that leverage constraints of financiers drive exchange rates, using the TED spread, exchange rate volatility, and the liquidity-based measure of financial commercial paper outstanding (FCPO) as proxies.

Following this literature, we proxy financiers' risk-bearing capacity using the TED spread, defined as the interest rate difference between three-month interbank deposit rate and three-month Treasury bill; the foreign exchange volatility indices VXY-G7 and VXY-EM; and the liquidity-based measure FCPO. In addition, we also employ another illiquidity-based proxy specific for the FX market, the global FX bid–ask spread (GBAS), introduced by Menkhoff et al. (2012a).[41] Finally, we also consider the Chicago Board Options Exchange (CBOE) Volatility Index, VIX.

All of the above indicators are counter-cyclical (the TED spread, volatility indices, illiquidity), except for FCPO. Therefore, risk bearing capacity is expected to be high (low) when the TED spread, volatility indices VIX, VXY-G7, VXY-EM, and the illiquidity measure GBAS are low (high), and when FCPO is high (low). Since the excess returns of the CBC strategy are pro-cyclical (given their positive average mean), they are expected to be high in good times (when risk bearing capacity is high), and low in bad times (when risk bearing capacity is low). This means that one would expect that CBC excess returns are correlated negatively with all of these proxies of risk-bearing capacity except for

[40] It is interesting to note that the effect of α on the neighborhood importance is nonlinear: as α moves away from zero towards one, the impact increases and peaks around $\alpha = 0.3$, and then decreases slightly and stabilizes. This observation could be a feature embedded in the global trade imbalance network.

[41] The GBAS measure from Menkhoff et al. (2012a), denoted as ψ_t^{FX}, is calculated as, $\psi_t^{FX} = \frac{1}{T_t}\sum_{\tau\in T_t}\left[\sum_{\kappa\in K_\tau}\left(\frac{\psi_\tau^\kappa}{K_\tau}\right)\right]$, where ψ_t^κ is the percentage bid–ask spread of currency κ on day τ. Higher BAS values indicate lower liquidity, so the aggregate measure ψ_t^{FX} serves as a global proxy for FX market illiquidity. T_t denotes the total number of trading days in month t.

Table 7
Link between imbalance network and risk bearing capacity.

Returns	TED	VIX	VXY-G7	VXY-EM	FCPO	GBAS
CBC strategy	−0.214***	−0.345***	−0.356***	−0.338***	0.097	−0.138**
t-statistic	−3.297	−5.530	−5.020	−4.735	1.459	−2.102
p-value	0.001	0.000	0.000	0.000	0.146	0.037
Group 1	−0.061	−0.280***	−0.341***	−0.503***	0.243***	−0.170***
t-statistic	−0.922	−4.388	−4.787	−7.680	3.770	−2.597
p-value	0.357	0.000	0.000	0.000	0.000	0.010
Group 2	−0.150**	−0.372***	−0.454***	−0.562***	0.279***	−0.277***
t-statistic	−2.274	−6.031	−6.713	−8.952	4.369	−4.338
p-value	0.024	0.000	0.000	0.000	0.000	0.000
Group 3	−0.150**	−0.404***	−0.472***	−0.615***	0.298***	−0.212***
t-statistic	−2.275	−6.645	−7.069	−10.275	4.695	−3.254
p-value	0.024	0.000	0.000	0.000	0.000	0.001
Group 4	−0.196***	−0.445***	−0.502***	−0.6081***	0.242***	−0.220***
t-statistic	−3.007	−7.471	−7.658	−10.103	3.744	−3.384
p-value	0.003	0.000	0.000	0.000	0.000	0.001

Note: This table shows correlations between the excess returns from portfolios sorted on CBC and various proxies for risk-bearing capacity, including the TED spread (TED, defined as the interest rate difference between three-month interbank deposit rate and three-month Treasury bill); implied volatility indices for the equity market (VIX) and foreign exchange markets (VXY-G7 for G7 countries and VXY-EM for emerging markets); financial commercial paper outstanding (FCPO); and the global bid–ask spread (GBAS, the global foreign exchange illiquidity measure proposed by Menkhoff et al. 2012a). The table presents the correlations between the excess returns of the CBC strategy (G4 minus G1) and the four groups of portfolios (G1 to G4) sorted in ascending order of CBC, with the proxies for risk bearing capacity. All returns are annualized. All risk bearing capacity proxies are in the form of log differences, except for GBAS, which is in first differences. ***, **, and * indicate statistical significance levels of 1%, 5%, and 10%, respectively. The sample period is 2003–2021.

FCPO. One would also expect that the exposure of G4 portfolio excess returns sorted on CBC is strongly negative (positive) for counter-cyclical (pro-cyclical) indicators, and that G1 portfolio excess returns are less strongly exposed to these proxies.

We calculate the correlations between the annualized returns of the CBC strategy (G4 minus G1) and the four portfolio groups (G1 to G4) sorted in ascending order of CBC, with each of the proxies for risk-bearing capacity — namely, the TED spread, VIX, VXY-G7, VXY-EM, FCPO, and GBAS.[42] The correlation results, presented in Table 7, show that the excess returns of the CBC strategy (G4-G1) are negatively correlated with all risk-bearing capacity measures, except for FCPO, consistent with the notion that CBC excess returns are higher when risk bearing capacity is high. The correlation with FCPO is not statistically significantly different from zero, although it has the expected positive sign, whereas the correlations with all other proxies are strongly statistically significantly different from zero.

We also note from Table 7 that the individual portfolio excess returns sorted on CBC (G1 to G4) comove with these proxies for risk-bearing capacity with the same sign as the CBC strategy excess returns (and statistically significant), but the correlation of the excess returns for G4 is higher (in absolute size) than the correlation for G1. Indeed, for three indicators (the TED spread, VIX, VXY-G7), the exposures display a monotonic pattern as one moves from G1 to G4. This is again consistent with what one would expect if the trade imbalance network is related to risk bearing capacity. However, it is also clear that the correlations are far from being perfect, with the strongest correlation reaching about −0.615 (for VXY-EM with the CBC Group 3 returns). In turn, this suggests that, while CBC excess returns are related to all of these proxies that capture different dimensions of risk bearing capacity, none of these proxies is likely to subsume fully the information in CBC excess returns.

4.4.2. Evidence from CBC and sovereign debt holdings

Next, we explore the direct association between CBC and sovereign debt holdings. As highlighted by Fang et al. (2025), the evolving composition of sovereign debt investors offers valuable insights into financiers' sensitivity to financing costs and sovereign debt sustainability. Given that sovereign debt is primarily held by institutional investors, we argue that net sovereign holdings – defined as domestic investors' holdings minus foreign investors' holdings – are related to their risk-bearing capacity and outside options. Specifically, when financiers have better outside options (e.g., due to the greater complexity of their balance sheets stemming from operating in a more central position in the global trade imbalance network), their risk-bearing capacity is lower (Gabaix and Maggiori, 2015). In such cases, they can secure higher currency returns by investing their capital abroad, leading them to reduce their holdings of domestic bonds. In our model, CBC is expected to be negatively associated with risk bearing capacity and, therefore, positively associated with outside options. Consequently, the mechanism in our theoretical framework implies a negative correlation between CBC and net sovereign holdings. In Fig. 7 we provide evidence that supports this logical implication of the mechanism.

For this exercise, we employ a subset of the data used and made available by Fang et al. (2025), to match our sample period and universe of countries. These data contain the domestic and foreign holdings of sovereign debt in 27 currencies. The domestic holdings are decomposed into domestic central bank (CB), domestic bank (DB), and domestic non-bank holdings (DN); the foreign holdings are decomposed into foreign official (OF), foreign bank (FB), and foreign non-bank holdings (FN).[43] The holdings of bank and non-bank institutions are of course very different from the holdings of central banks and international agencies, as the latter are far less (or not at all) motivated by risk-return considerations, and indeed (Fang et al., 2025) argue that (changes in) these holdings are largely inelastic to changes in prices. Therefore, we consider not only total net sovereign holdings, but also net sovereign holdings net of the official sector (i.e. net of the central banks and official groups), and the net holdings of the official sector, separately. Specifically, we define three net sovereign debt holdings ratios: (1) the net sovereign debt non-official holding ratio, defined as domestic bank plus domestic non-bank minus foreign bank minus foreign non-bank, scaled by total sovereign debt outstanding, $[DB + DN - FB - FN]/D$; (2) the net sovereign debt holding ratio, defined

[42] All risk-bearing capacity proxies are calculated as log differences, except GBAS, which is calculated in first differences. We have also tested AR(1) residuals and percentage change transformations for these variables and the results are qualitatively the same.

[43] For more details of the data, the reader is referred to the data section and Internet Appendix of Fang et al. (2025).

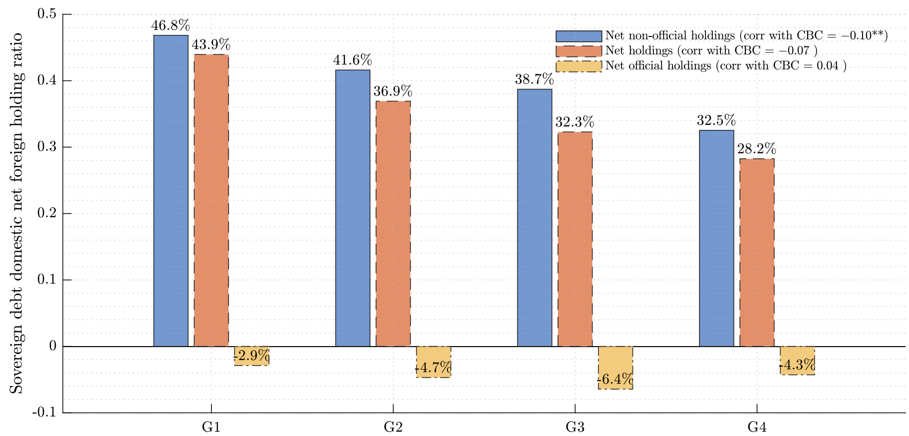


Fig. 7. CBC and sovereign debt net (domestic - foreign) holdings.
Note: This figure presents the average net sovereign debt holding ratios across four groups, G1 to G4, based on three distinct definitions: (1) net sovereign debt non-official holding ratio, defined as domestic bank plus domestic non-bank minus foreign bank minus foreign non-bank, scaled by total sovereign debt outstanding (represented by bars with solid outlines); (2) net sovereign debt holding ratio defined as domestic total holdings minus foreign total holdings, scaled by total sovereign debt outstanding (represented by bars with dashed outlines); (3) net sovereign debt official holding ratio defined as domestic central bank holdings minus foreign official holdings, scaled by total sovereign debt outstanding (represented by bars with dash-dotted outlines). These net sovereign debt holding ratios are sorted annually into quartiles (G1 to G4) in ascending order based on their currency's *CBC*. The sample period spans from 2000 to 2018. Sovereign debt holding data are sourced from Fang et al. (2025). The figure legends display the correlation coefficients between CBC and the three net sovereign debt holding ratios, with statistical significance denoted by stars: ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively.

as domestic holdings minus foreign holdings, scaled by total sovereign debt outstanding, $[DB + DN - FB - FN + (CB - OF)]/D$; (3) the net sovereign debt official holding ratio, defined as domestic central bank holdings minus foreign official holdings, scaled by total sovereign debt outstanding, $[CB - OF]/D$. These net sovereign debt holding ratios are sorted annually into quartiles (G1 to G4) in ascending order based on their currency's CBC. Fig. 7 shows the over-time average values of these ratios across the four groups, G1 to G4. Among the three investor types, non-official investors (bank and non-bank investors) are conceptually closest to the financiers in our model, and hence our primary interest is on the behavior of the net sovereign debt non-official holding ratio.

The results shown in Fig. 7 indicate that the net sovereign debt non-official holding ratio decreases monotonically from G1 to G4, which suggests domestic bank and non-bank institutions hold less of the outstanding debt for higher CBC countries. This is consistent with CBC being associated negatively with risk-bearing capacity. This interpretation is further supported by the negative correlation between CBC and the net sovereign debt non-official holding ratio (about −0.1), which is statistically significant at the 5% level.

This monotonicity pattern also holds for the net sovereign debt holding ratio, which is not surprising because the net holdings of the official sector, $[CB - OF]/D$ are fairly small relative to the non-official sector. However, although the net sovereign debt holding ratio decreases monotonically from G1 to G4, the negative correlation of −0.07 is not statistically significant, which raises the question of whether the official sector net holdings are unrelated to the CBC and their inclusion in the net holdings ratio weakens the correlation with CBC. Indeed, official investors – such as central banks, governments, and international organizations – are likely to be less sensitive to outside options, and Fig. 7 shows clearly that net sovereign debt holdings by official investors display a non-monotonic and fairly flat pattern across the CBC groups. This corroborates the presumption that these holdings are not related to risk-bearing capacity. In this sense, the lack of a statistically significant relationship between the net official holding ratio and CBC serves as a placebo test, reinforcing the argument that CBC is related to the risk-bearing capacity of financial intermediaries.[44]

In summary, we find clear relationships between the returns of the CBC strategy as well as the CBC measure per se and various risk-bearing capacity proxies, implying that the trade imbalance network centrality is indeed related to financiers' risk-bearing capacity. Of course, this statement needs to be interpreted with caution as risk bearing capacity is not directly observable, and the proxies we use in this analysis may well capture information that is not solely related to risk bearing capacity.

4.5. Centrality in the trade imbalance network v.s. the total trade network

In this section we dig deeper into the differences between Richmond (2019)'s centrality, which is based on total trade, and our proposed trade imbalance network centrality. It is clear from our earlier discussion that, although both measures of centrality focus on international trade, they are very different in terms of both their definitions and the mechanism via which they impact on the cross-section of currency risk premia. This is the case for a number of reasons, not least because Richmond's theory is based on a model with complete financial markets, whereas in our theoretical extension of the Gabaix–Maggiori theory, we allow for incomplete financial markets.

Throughout the paper we have worked within our theoretical framework with incomplete financial markets. In this section we consider, indirectly, if this is necessary or, instead, one could rationalize our results in complete markets within the Richmond model. We report this analysis in detail in Internet Appendix G, whereas we summarize here only its main features and learning points.

We simulate currency returns data based on the theoretical framework of Richmond (2019), and hence under complete financial markets. Given that we are simulating from Richmond's model, the total trade centrality measure is linked perfectly with currency risk premia by construction. We then compute the trade imbalance network centrality, under our definition of centrality, within the model of Richmond (2019), and explore the relationship between the trade imbalance network and currency risk premia in this setting.

[44] A caveat is in order. This exercise is carried out using holdings data, but ideally one would want to estimate the cross-demand elasticity between demand for countries i and j's bonds as a function of the trade relationship between countries i and j. This would require estimating a structural model, or identifying demand for sovereign bonds using a fully-fledged asset demand system as in Fang et al. (2025), preferably country by country. This is a nontrivial task that is not possible to carry out on our data given the short sample period and the small number of observations at our disposal.

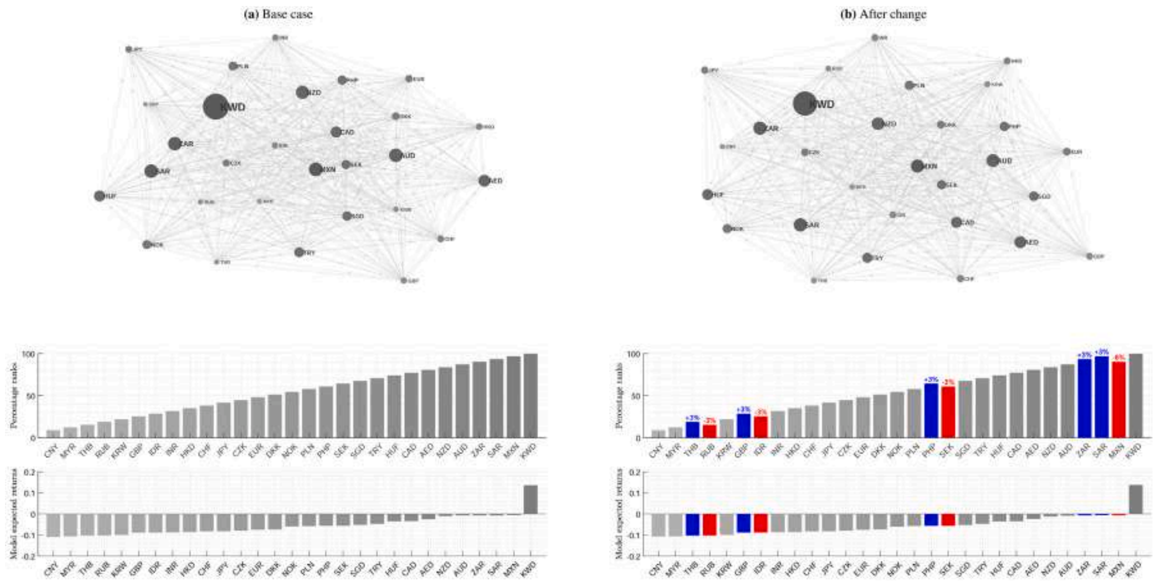


Fig. 8. Counterfactual analysis: the effect of US–China trade war on currency premia.
Note: In this figure, Panel (a) plots the global trade imbalance network based on 2017 pairwise bilateral imports and exports, Panel (b) plots the same network with pairs CNY and USD replaced by the data in 2019. The upper parts of the panels are network graphs in which the arrows in edges point towards the debtors (deficit parties), the length of edges is inversely proportional to the size of the relative deficit, and the size of nodes is proportional to their *CBC*. The middle and lower parts in Panel (a) show respectively the percentage ranks of all currencies' *CBCs* in ascending order and rank-preserved transformed *CBCs* matching the cross-sectional mean and standard deviation of currency risk premia in 2017 for the base case; while the middle part in Panel (b) shows the same order with currencies, whose ranks have changed, highlighted: currencies becoming lower (higher) in the ranks are highlighted in red (blue) bars and the size of changes is indicated on the top of the bars; the lower part in Panel (b) shows the rank-preserved transformed *CBCs* after the change. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

The results indicate that the relationship we observed in our empirical work disappears in this model, i.e., the currencies of central countries in the trade imbalance network do not offer higher risk premia anymore. This implies that the trade imbalance network in a complete-markets setting like the one of Richmond (2019) is not related to the cross-section of currency risk premia. We view this as indirect evidence that incomplete markets are required for the link between the trade imbalance network and currency risk premia to arise.

As a note of caution, it should be clear that this simulation exercise is not a test of Richmond's theory against our theory. It is merely an exercise to address the question of whether our empirical findings in this paper could be rationalized in a complete-markets setting, and the theory of Richmond (2019) is the logical candidate model for this purpose.

4.6. Counterfactual analysis

In this subsection, we apply our framework to assess the impact of two recent international events on global currency premia via counterfactual analyses. We look at the US–China trade war starting in 2018, and the collective trade sanctions against Russia in the wake of its 2022 invasion of Ukraine.

In 2018, the US and China escalated tariffs that ultimately covered about $450 billion in trade flows. By late 2019, the US had imposed tariffs on roughly $350 billion of Chinese imports, and China had retaliated on $100 billion US exports, with many of the escalated tariffs persisting beyond 2021 (Fajgelbaum and Khandelwal, 2022; Fajgelbaum et al., 2023). In response to the 2022 Russian invasion of Ukraine, a broad swathe of countries have imposed a bevy of sanctions against Russia. More than 35 countries (including many large industrialized economies) have participated in efforts to limit Russia's access to the global economy (Allen, 2022). Existing studies on the US–China trade war and the sanctions against Russia focus on real economic impact (Fajgelbaum and Khandelwal, 2022; Allen, 2022) and costs for equity markets (Huang and Lu, 2022). Using counterfactual analyses, our framework allows us to pin down the effects of these events on the trade imbalance network and the implications on global currency risk premia.

4.6.1. US-China trade war

In our data, we find the relative deficit (defined as the ratio of net import to total trade) the US had with China went up to 0.60 in 2019 from 0.54 in 2017. This indicates that the trade war had a larger reduction in China's imports from the US than the other way around. This is consistent with existing evidence that US consumers of imported goods have borne the brunt of the tariffs through higher prices (Fajgelbaum and Khandelwal, 2022). The effect of the US–China trade war clearly goes beyond impacting these two countries, as bystander countries increased their trades with the US and China (Fajgelbaum et al., 2023). In our counterfactual analysis, we take the adjacency matrix of the global trade imbalance network in 2017 as the base and replace its rows and columns corresponding to the US and China with those from the adjacency matrix in 2019. By doing so, we essentially isolate changes in the adjacency matrix due to the trade war. We attribute any resulting changes in the *CBC* ranks to the impact of the US–China trade war. We present the results in Fig. 8. Interestingly, we find that the rank of CNY has not changed and the seven currencies noticeably affected are THB (3% raise in the percentage ranks), RUB (3% drop), GBP (3% raise), IDR (3% drop), PHP (3% raise), SEK (3% drop), ZAR (3% raise), SAR (3% raise), and MXN (6% drop). The fact that these currencies are not directly involved in the US–China trade war shows that within a complex trade imbalance network, one international event could have far-reaching effects on seemingly unrelated currencies.

4.6.2. Russia-Ukraine conflict

Next, we turn to study the impact of the collective trade sanctions against Russia in response to its 2022 invasion of Ukraine. With reference to Funakoshi et al. (2022), we identify a group of currencies, USD, EUR, GBP, AUD, JPY, CAD, CHF, NOK, PLN, KRW, and NZD, corresponding to the countries/economies that have imposed severe trade sanctions against Russia. For illustration purposes, we simply assume the sanctions make Russia's trade activities with these currencies

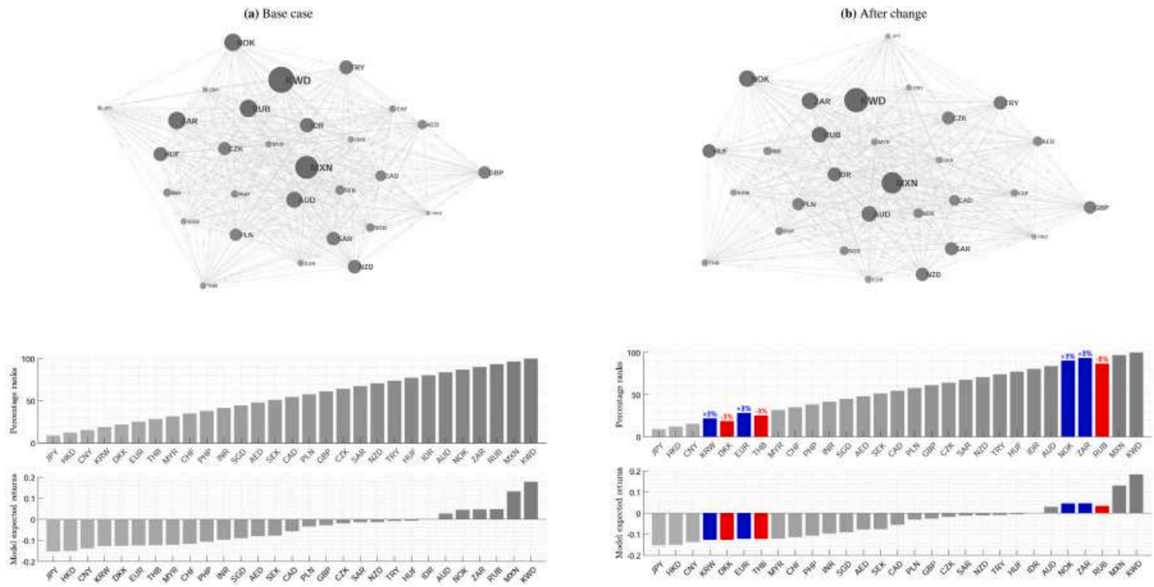


Fig. 9. Counterfactual analysis: the effect of collective sanctions on Russia on currency premia.
Note: In this figure, Panel (a) plots the global trade imbalance network based on 2021 pairwise bilateral imports and exports, Panel (b) plots the same network with the values of elements in the adjacency matrix related to RUB and a group of currencies shrink by 90%. The group of currencies are USD, EUR, GBP, AUD, JPY, CAD, CHF, NOK, PLN, KRW, and NZD, with reference to Funakoshi et al. (2022). The upper parts of the panels are network graphs in which the arrows in edges point towards the debtors (deficit parties), the length of edges is inversely proportional to the size of the relative deficit, and the size of nodes is proportional to their *CBC*. The middle and lower parts in Panel (a) show respectively the percentage ranks of all currencies' *CBC*s in ascending order and rank-preserved transformed *CBC*s matching the cross-sectional mean and standard deviation of currency risk premia in 2021 for the base case; while the middle part in Panel (b) shows the same order with currencies, whose ranks have changed, highlighted: currencies becoming lower (higher) in the ranks are highlighted in red (blue) bars and the size of changes is indicated on the top of the bars; the lower part in Panel (b) shows the rank-preserved transformed *CBC*s after the change. (For interpretation of the references to color in this figure legend, the reader is referred to the web version of this article.)

shrink by 90% of the figures in 2020.[45] Specifically, we implement the reduction of trade activities by multiplying 0.1 to the values of elements related to RUB and the group of currencies in the adjacency matrix of the trade imbalance network in 2020. Then, we compare the ranks of *CBC* before and after this reduction. The results, shown in Fig. 9, suggest a significant impact on global currency premia in this case. There are seven currencies whose *CBC* ranks change noticeably. Among the seven currencies, RUB has the largest drop, 6%, in the percentage ranks. It is worth noting that DKK (3% drop), THB (3% drop), and ZAR (3% raise) are not in the group of countries that imposed severe sanctions on Russia but display noticeable changes, while GBP, AUD, JPY, CAD, CHF, and PLN, which are in the group, do not display much of a change. This analysis again shows that the global trade imbalance network brings complexity in assessing the effect of significant international events on currency premia. Our framework provides a useful tool for conducting such analyses.

5. Conclusions

Imbalances in trade and capital flows shape our understanding of foreign exchange rate fluctuations and currency risk premia. Different strands of the literature have studied how currency risk premia are determined either in frictionless markets characterized by a rich global trade network or in imperfect financial markets where frictions generate limited risk-bearing capacity in a two-country setting. In this paper, we consider a model of currency risk premia determination that combines these two important features of currency risk premia determination: imperfect financial markets and a global trade network. In the theory, the expected returns of currencies are connected to their centrality in the global trade imbalance network through financiers' limited commitment, captured using the Leontief inverse-based centrality of the global trade imbalance network.

The theory provides clear testable implications and hence, guided by the model, we construct a currency-level risk characteristic (*CBC*) based on a score from the calibrated model that combines network centrality and variance–covariance of currency returns. Empirically, we find that sorting currencies on *CBC* generates a large spread in excess returns, implying that *CBC* embeds strong predictive power for the cross-section of currency excess returns and carries a significantly positive risk premium. The time series variation in the *CBC* excess returns generated by this cross-sectional strategy cannot be explained by a variety of currency pricing factors or by well-known intermediary asset pricing factors. Taken together, these results point to a novel, systematic source of currency risk embedded in the *CBC* factor.

Overall, this study provides theoretical and empirical support for the existence of a connection between currency returns, risk-bearing capacity and the global trade imbalance network, which is a robust relation largely overlooked in previous research. However, more work remains to be done. Further research is warranted, for example, to fully endogeneize the trade imbalance network in models of imperfect financial markets by providing a deeper microfoundation of our results, and to explore empirically the role of disaggregated trade data on international goods and services at different stages of production. We leave these challenges to future research.

CRediT authorship contribution statement

Ai Jun Hou: Writing – review & editing, Writing – original draft, Visualization, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Lucio Sarno:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Formal analysis, Conceptualization. **Xiaoxia Ye:** Writing – review & editing, Writing – original draft, Visualization, Validation, Software, Methodology, Investigation, Formal analysis, Data curation, Conceptualization.

45 We choose 2020 instead of 2021 as the reference year to avoid the unusual impact of Russia's abnormal trading activities in 2021 on the network. There was a dramatic increase in Russia's exports in 2021 relative to the average level from previous years. According to Russian official sources, its goods exports totaled $492 billion in 2021, up 46% from 2020 (CRS, 2023).

Declaration of competing interest

The corresponding author confirms that he have NO affiliations with or involvement in any organization or entity with any financial interest (such as honoraria; educational grants; participation in speakers' bureaus; membership, employment, consultancies, stock ownership, or other equity interest; and expert testimony or patent-licensing arrangements), or non-financial interest (such as personal or professional relationships, affiliations, knowledge or beliefs) in the subject matter or materials discussed in this manuscript.

References

Acemoglu, D., Carvalho, V.M., Ozdaglar, A., Tahbaz-Salehi, A., 2012. The network origins of aggregate fluctuations. Econometrica 80 (5), 1977–2016.

Adrian, T., Etula, E., Muir, T., 2014. Financial intermediaries and the cross-section of asset returns. J. Financ. 69 (6), 2557–2596.

Ahn, J., Khandelwal, A., Wei, S.-J., 2011. The role of intermediaries in facilitating trade. J. Int. Econ. 84, 73–85.

Aldasoro, I., Alves, I., 2018. Multiplex interbank networks and systemic importance: An application to European data. J. Financ. Stab. 35, 17–37.

Allen, S.H., 2022. The uncertain impact of sanctions on Russia. Nat. Hum. Behav. 6 (6), 761–762.

Avdjiev, S., Du, W., Koch, C., Shin, H.S., 2019. The dollar, bank leverage, and deviations from covered interest parity. Am. Econ. Rev.: Insights 1 (2), 193–208.

Bahaj, S., Massacci, D., Corte, P.D., Seyde, E., 2024. Beyond bilateral flows: indirect connections and exchange rates. http://dx.doi.org/10.2139/ssrn.4951075, Available At SSRN: https://ssrn.com/abstract=4951075.

Ballester, C., Calvó-Armengol, A., Zenou, Y., 2006. Who's who in networks. Wanted: The key player. Econometrica 74 (5), 1403–1417.

Barillas, F., Shanken, J., 2017. Which alpha? Rev. Financ. Stud. 30 (4), 1316–1338.

Bénétrix, A.S., Lane, P.R., Shambaugh, J.C., 2015. International currency exposures, valuation effects and the global financial crisis. J. Int. Econ. 96, 98–109.

Benguria, F., 2021. The matching and sorting of exporting and importing firms: Theory and evidence. J. Int. Econ. 131, 100430.

Bonacich, P., 1987. Power and centrality: A family of measures. Am. J. Sociol. 92 (5), 1170–1182.

Caballero, R.J., Krishnamurthy, A., 2009. Global imbalances and financial fragility. Am. Econ. Rev. 99 (2), 584–588.

Carvalho, V.M., Tahbaz-Salehi, A., 2019. Production networks: A primer. Annu. Rev. Econ. 11, 635–663.

Cenedese, G., Della Corte, P., Wang, T., 2021. Currency mispricing and dealer balance sheets. J. Financ. 76 (6), 2763–2803.

Chau, V.T., 2022. International portfolio investments with trade networks. Work. Pap..

Colacito, R., Croce, M.M., Gavazzoni, F., Ready, R., 2018. Currency risk factors in a recursive multicountry economy. J. Financ. 73 (6), 2719–2756.

Colacito, R., Riddiough, S.J., Sarno, L., 2020. Business cycles and currency returns. J. Financ. Econ. 137 (3), 659–678.

Coppola, A., Maggiori, M., Neiman, B., Schreger, J., 2021. Redrawing the map of global capital flows: The role of cross-boarder financing and tax havens. Q. J. Econ. 1499–1556.

CRS, 2023. Russia's Trade and Investment Role in the Global Economy. Technical Report, the Congressional Research Service.

Dahlquist, M., Hasseltoft, H., 2020. Economic momentum and currency returns. J. Financ. Econ. 136 (1), 152–167.

Della Corte, P., Fu, H., 2021. US political cycles and international stock returns. In: 2021 AFA Conference Paper.

Della Corte, P., Krecetovs, A., 2021. Current account uncertainty and currency premia. Manag. Sci..

Della Corte, P., Riddiough, S.J., Sarno, L., 2016. Currency premia and global imbalances. Rev. Financ. Stud. 29 (8), 2161–2193.

Della Corte, P., Sarno, L., Sestieri, G., 2012. The predictive information content of external imbalances for exchange rate returns: how much is it worth? Rev. Econ. Stat. 94 (1), 100–115.

Du, W., Hebert, B., Huber, A.W., 2023. Are intermediary constraints priced? Rev. Financ. Stud. 36 (4), 1464–1507.

Du, W., Schreger, J., 2016. Local currency sovereign risk. J. Financ. 71 (3), 1027–1070.

Du, W., Schreger, J., 2022a. CIP deviations, the dollar, and frictions in international capital markets. In: Handbook of International Economics. Vol. 6, Elsevier, pp. 147–197.

Du, W., Schreger, J., 2022b. Sovereign risk, currency risk, and corporate balance sheets. Rev. Financ. Stud. 35 (10), 4587–4629.

Eaton, J., Eslava, M., Jinkins, D., Krizan, C.J., Tybout, J., 2024. A search and learning model of export dynamics. Pa. State Univ..

Fajgelbaum, P., Goldberg, P.K., Kennedy, P.J., Khandelwal, A., Taglioni, D., 2023. The US-China Trade War and Global Reallocations. Working Paper 29562, National Bureau of Economic Research.

Fajgelbaum, P.D., Khandelwal, A.K., 2022. The economic impacts of the US–China trade war. Annu. Rev. Econ. 14, 205–228.

Fang, X., 2021. Intermediary leverage and the currency risk premium. Available At SSRN 3290317.

Fang, X., Hardy, B., Lewis, K.K., 2025. Who holds sovereign debt and why it matters. The Review of Financial Studies hhaf031.

Fang, X., Liu, Y., 2021. Volatility, intermediaries, and exchange rates. J. Financ. Econ. 141 (1), 217–233.

Fleckenstein, M., Longstaff, F.A., 2020. Renting balance sheet space: Intermediary balance sheet rental costs and the valuation of derivatives. Rev. Financ. Stud. 33 (11), 5051–5091.

Fleckenstein, M., Longstaff, F.A., 2022. The market risk premium for unsecured consumer credit risk. Rev. Financ. Stud. 35 (10), 4756–4801.

Funakoshi, M., Lawson, H., Deka, K., 2022. Tracking Sanctions Against Russia. Report, Thomson Reuters, URL https://www.reuters.com/graphics/UKRAINE-CRISIS/SANCTIONS/byvrjenzmve/.

Gabaix, X., Maggiori, M., 2015. International liquidity and exchange rate dynamics. Q. J. Econ. 130 (3), 1369–1420.

Gibbons, M.R., Ross, S.A., Shanken, J., 1989. A test of the efficiency of a given portfolio. Econometrica 57, 1121–1152.

Gourinchas, P.-O., Rey, H., 2007. International financial adjustment. J. Political Econ. 115 (4), 665–703.

Harvey, C.R., Liu, Y., Zhu, H., 2016. ...And the cross-section of expected returns. Rev. Financ. Stud. 29 (1), 5–68.

Hassan, R., Loualiche, E., Pecora, A.R., Ward, C., 2023. International trade and the risk in bilateral exchange rates. J. Financ. Econ. 150 (103711).

He, Z., Kelly, B., Manela, A., 2017. Intermediary asset pricing: New evidence from many asset classes. J. Financ. Econ. 126 (1), 1–35.

He, Z., Krishnamurthy, A., 2013. Intermediary asset pricing. Am. Econ. Rev. 103 (2), 732–770.

Helpman, E., Melitz, M.J., Yeaple, S.R., 2004. Export versus FDI with heterogeneous firms. Am. Econ. Rev. 94, 300–316.

Hojman, D.A., Szeidl, A., 2008. Core and periphery in networks. J. Econom. Theory 139 (1), 295–309.

Hou, K., Robinson, D.T., 2006. Industry concentration and average stock returns. J. Financ. 61 (4), 1927–1956.

Huang, L., Lu, F., 2022. The cost of Russian sanctions on the global equity markets. Available At SSRN 4060927.

Jiang, Z., 2021. US fiscal cycle and the dollar. J. Monet. Econ. 124, 91–106.

Jiang, Z., Richmond, R., 2023. Origins of international factor structures. J. Financ. Econ. 147, 1–26.

Jiang, Z., Richmond, R.J., Zhang, T., 2024. A portfolio approach to global imbalances. J. Financ. 79 (3), 2025–2076.

Johannesson, E., Ohlson, J.A., Zhai, S.W., 2023. The explanatory power of explanatory variables. Rev. Account. Stud. 1–31.

Koijen, R.S.J., Moskowitz, T.J., Pedersen, L., Vrugt, E.B., 2018. Carry. J. Financ. Econ. 127 (2), 197–225.

Lane, P.R., Milesi-Ferretti, G.M., 2001. Measures of foreign assets and liabilities for industrial and developing countries. J. Int. Econ. 55, 263–294.

Lane, P.R., Milesi-Ferretti, G.M., 2007. The external wealth of nations mark II: Revised and extended estimates of foreign assets and liabilities, 1970–2004. J. Int. Econ. 73, 223–250.

Lane, P., Milesi-Ferretti, G.M., 2008. International investment patterns. Rev. Econ. Stat. 90, 538–549.

Lane, P.R., Shambaugh, J.C., 2010. Financial exchange rates and international currency exposure. Am. Econ. Rev. 100 (1), 518–540.

Lewellen, J., Nagel, S., Shanken, J., 2010. A skeptical appraisal of asset pricing tests. J. Financ. Econ. 96, 175–194.

Lustig, H., Richmond, R.J., 2020. Gravity in the exchange rate factor structure. Rev. Financ. Stud. 33 (8), 3492–3540.

Lustig, H., Roussanov, N., Verdelhan, A., 2011. Common risk factors in currency markets. Rev. Financ. Stud. 24 (11), 3731–3777.

Maggiori, M., 2022. International macroeconomics with imperfect financial markets. In: Handbook of International Economics. Vol. 6, Elsevier, pp. 199–236.

Melitz, M.J., 2003. The impact of trade on intra-industry reallocations and aggregate induatry productivity. Econometrica 71, 1695–1725.

Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012a. Carry trades and global foreign exchange volatility. J. Financ. LXVII (2), 681–718.
Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2012b. Currency momentum strategies. J. Financ. Econ. 106 (3), 660–684.
Menkhoff, L., Sarno, L., Schmeling, M., Schrimpf, A., 2017. Currency value. Rev. Financ. Stud. 30 (2), 416–441.
Nozawa, Y., 2017. What drives the cross-section of credit spreads?: A variance decomposition approach. J. Financ. 72 (5), 2045–2072.
Ready, R., Roussanov, N., Ward, C., 2017. Commodity trade and the carry trade: A tale of two countries. J. Financ. 72 (6), 2629–2684.
Richmond, R.J., 2019. Trade network centrality and currency risk premia. J. Financ. 74 (3), 1315–1361.
Sharkey, K.J., 2017. A control analysis perspective on Katz centrality. Sci. Rep. 7, 17247.
Simonovits, A., 1975. A note on the underestimation and overestimation of the Leontief inverse. Econ.: J. Econ. Soc. 493–498.
Stewart, G.W., 1998. Matrix Algorithms: Volume 1: Basic Decompositions. SIAM.
Verdelhan, A., 2018. The share of systematic variation in bilateral exchange rates. J. Financ. 73 (1), 375–418.
Wang, X., Zhang, M., 2025. Financially constrained intermediaries and the international pass-through of monetary policy. Available At SSRN 4478436.