The Network Drivers of Trade Currency Invoicing

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Abstract

Using an equilibrium network model and a large international panel of cross-border trade, we analyse empirically the drivers of foreign currency invoicing. First, we find strong evidence of strategic complementarity in currency invoicing across countries: Exporting countries tend to invoice more in a given currency when their main trade partners invoice in that same currency. This in turn leads to an amplification of domestic shocks through the trade network. Second, key players for a given currency are not only countries that invoice most of their exports in that foreign currency (e.g., China, South Korea, and Russia), but also countries that are central in the international trade network (e.g., Japan, Germany, and Canada). Third, at the country-level, we find evidence of strategic complementarity, or natural hedging, between the choices of export and import currencies. Fourth, in counterfactual analysis we find that, due to the large network externalities that we identify, the position of the USD as dominant trade currency is inherently fragile with respect to the currency invoicing choices of EU and BRICS countries.

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I Introduction

It is well documented that the vast majority of international trade is invoiced in a small number of dominant currencies, with the USD playing an outsized role (Goldberg and Tille, 2016; Gopinath, 2015). Dominant currency pricing has significant implications for monetary policy spillovers, transaction costs, and financial market development (Gopinath, Boz, Casas, Díez, Gourinchas, and Plagborg-Møller, 2020). In this paper, in addition to the factors proposed by the literature on dominant currency, we examine whether the currency invoicing decisions of the firms in a country are affected by those of its trading partners.

Specifically, in the theoretical model, a representative firm in a country chooses the size of invoicing in a dominant currency for international trade transactions based on a cost-benefit analysis. The cost and benefit, as identified by the literature, can be due to a multitude of factors. For example, the interaction of nominal price stickiness with pricing complementarities and input-output linkages across firms generates complementarities in currency choice (Gopinath, 2015; Doepke and Schneider, 2017; Mukhin, 2022; Eren and Malamud, 2022). That is, exporters coordinate on the same currency of invoicing to be competitive in output pricing and to be able to hedge their balance sheet against exchange rate shocks with the denominated currency of imported intermediate (real and financial) inputs. This indicates that the size of the market is an important driver of the dominant currency (Mukhin, 2022), as well as various price index levels and other macroeconomic and financial variables at the country-level. Additionally, a large body of literature on international finance emphasizes the safety feature of the dominant currencies. Differences in financial development, and hence the differences in access to safe assets (Maggiori, 2017), or risk aversion of participants (Gourinchas and Rey, 2022) may drive the demand for an international safe asset. The dominant currency preserves value added in exchange transactions, leading to its wide use in the global financial market.[1] This indicates that safety or volatility of the currency is potentially a major determinant of its

[1] Furthermore, Gopinath and Stein (2021) argue that assets denominated in the dominant currency can be used as a savings device for export producers to hedge against invoicing risk. Chahrour and Valchev (2022) additionally suggest that safe assets are used as collateral to overcome contractual frictions in cross-border transactions.

dominant status. Importantly, the network of international trade underlies how these factors affect each country's invoicing decisions. The network of international trade not only captures the potential network effects of neighbouring countries in choosing a dominant currency for pairwise transactions (for stable transactions or cheaper access to working capital or financial borrowing) but also reflects the input-output linkages across countries. Furthermore, the trade network might also give rise to the need for balance sheet currency hedging: A representative firm in a country that is invoiced in a certain dominant currency in its imports has more incentive to invoice their exports in the same currency to hedge its currency risk exposure. These trade-offs are captured in our paper by a network model.

In the model, the currency invoicing decision of a representative firm in a country is affected not only by its own economic conditions, such as the size of the economy, inflation, financial market conditions, and other relevant economic variables, but also the invoicing decision of its trading partners and its trading partner country's economic variables. Similarly, the currency invoicing decisions of its trading partners are affected by those of their own trading partners, as well as their economic variables, and so forth. In equilibrium, we show that this network dependency is captured by a network attenuation factor ϕ, the key parameter whose sign determines whether the Nash equilibrium features strategic substitution ($\phi < 0$) or complementarity ($\phi > 0$) in agents' invoicing decisions. Each agent's equilibrium invoicing amount in the dominant currency depends not only on the network attenuation factor ϕ but also on its network centrality measure.

We estimate the equilibrium based on four different sets of restrictions on the model parameters, that is, four models – Panel, Spatial Error (SEM), Spatial Lag (SLM) and Spatial Durbin (SDM) – using Bayesian methods. For example, setting $\phi = 0$ in the equilibrium condition yields a simple panel structure for the data. We use a Bayesian procedure for model specification and assess whether the data support the presence of network externalities and if so, which spatial specification. Our empirical analysis focusses on excessive USD or EUR invoicing for each country to assess the use of the USD or EUR as a vehicle currency in international trade.[2] The measure is constructed at monthly frequency based on the payment share dataset by Boz, Casas, Georgiadis, Gopinath, Le Mezo, Mehl, and Nguyen (2022) and the Direction of Trade Statistics database by the International Monetary Fund. We further augment the payment share dataset with a proprietary dataset obtained from the Society for Worldwide Interbank Financial Telecommunications (SWIFT) to increase the cross-sectional coverage. The final dataset contains 84 countries from January 2004 to December 2019 and covers on average 91% (93%) of worldwide exports (imports).

Our analysis shows that there is overwhelming evidence of network spillovers: The panel specification with no spatial dependency is never preferred by the data. There is strong evidence of strategic complementarity in currency invoicing across countries: Exporting countries tend to invoice more in a given currency when their main trade partners invoice in that same currency. This in turn leads to an amplification of domestic shocks through the trade network. In fact, the SDM model – the specification of our theoretical formulation – is always strongly preferred by the data. We conduct analysis based on the SDM specification and include among the control variables the lagged values of the dependent variables to capture time series autocorrelation. Therefore, the model not only captures the contemporaneous, or short-term, impact of a shock originating from any of the independent variables but also their long-term effects. Due to the network specification we are further able to decompose these effects into direct and indirect effects, the latter being impacts originating from trade partners propagated through the trade network. The network attenuation factor for USD excessive invoicing is around 0.24, while that of the EUR is 0.16. This indicates that USD excessing invoicing is inherently less stable: A small negative shock might lead to a substantial reduction in the use of the USD as a vehicle currency. Moreover, among the covariates, we find that the inverse of a country's trade size, the existence of a USD swap line, inflation risk, and the fraction of corporate debts denominated in USD have statistically significant positive impacts on its aggregate and excessive USD invoicing decisions.

[2] For robustness, we also use aggregate currency invoicing amounts in USD or EUR. The results are similar and reported in the appendix.

We find that key players for a given currency are not only countries that invoice most of their exports in that foreign currency (e.g., China, South Korea, and Russia) but also countries that are central in the international trade network (e.g., Japan, Germany, and Canada). The driver of the former set of countries is based on their large direct impacts, while that of the latter set of countries is due to the network amplification and to the central position that these countries have in the trade network. Furthermore, at the country-level, we find evidence of *strategic complementarity* between exports and imports in a given currency, lending support to the natural hedge hypothesis proposed in the literature (Doepke and Schneider, 2017; Amiti, Itskhoki, and Konings, 2022). This investigation is based on a reduced form Vector Autoregression (VAR) in our SDM specification with four dependent variables (and their respective controls): Excessive currency invoicing in EUR and USD of *both* export and import. We employ identification via cross-sectional heteroskedasticity. That is, we exploit heterogeneity across residuals' covariances of our panel dataset to pin down structural parameters. The key identification assumption this requires is that all countries have identical contemporaneous reactions to USD or EUR import- or export-based shocks.

Finally, we conduct a counterfactual analysis to examine the impact of a set of countries choosing to abandon the USD for excessive invoicing. We conduct this exercise for Russia, Brazil, India and China, the EU block, and the members of BRICS in our sample, i.e. Brazil, Russia, India and China jointly. The estimated effects are quantitatively large, with the effects of the BRIC(S) block (EU) abandoning the USD for excess invoicing resulting in a 42% (11%) reduction in the overall use of this currency. More so, the channels through which these reductions arise are quite different. For the BRIC(S) block, most of the effect is driven by the direct reduction in the use of the USD by these countries. For the EU, almost half of the effect is driven by indirect network externalities. This underlines the fragility of a dominant trade currency such as the USD – coordinated abandonment can have substantial impacts on the overall use of a dominant currency for trade invoicing, specifically as the network externalities highlighted in this paper lead to an amplification.

The remainder of this paper is organized as follows. In Section II, we review the related literature. In Section III, we present a network model to guide our analysis of currency choice for invoicing. In Section IV we present our estimation methodology. In Section V, we describe the data and variable construction. In Section VI we present and discuss the estimation results and conduct the counterfactual analysis. Section VII concludes.

II Related Literature

The current international macro literature has shown that the choice of currency in trade invoicing is an active firm-level decision with some degree of persistence over time (Amiti, Itskhoki, and Konings, 2022). This evidence is contrary to the conventional international literature, which assumes exogenous producer currency pricing (PCP) or local currency pricing (LCP), that is, trades are denominated either in the producer's currency or the importer's currency. Instead, recent studies postulate the existence of dominant currencies for international trade that can endogenously emerge – dominant currency pricing (DCP) – and focus on their determinants and implications for optimal monetary policies with different spillover dynamics.

The DCP literature on international trade proposes that the interaction of nominal price stickiness with pricing complementarities and input-output linkages across firms generate complementarities in currency choice (Gopinath, 2015; Doepke and Schneider, 2017; Gopinath, Boz, Casas, Díez, Gourinchas, and Plagborg-Møller, 2020; Mukhin, 2022; Eren and Malamud, 2022). That is, exporters coordinate on the same currency of invoicing for the following two reasons: to be competitive in output pricing; and to be able to hedge their balance sheet against exchange rate shocks with the denominated currency of imported intermediate (real and financial) inputs. Financial intermediate inputs can be thought of as working capital, trade credit, or any form of financial borrowing. According to this line of research, important determinants for dominant currencies include the competitiveness or importance of the destination market and the currencies that denominate the intermediate inputs. Exporting firms that import a lot of intermediate products, or borrow capitals in the international markets, are more likely to choose DCP. The theoretical result in Mukhin (2022) also indicates that the market size is important in determining the dominant currency. Our model of the network effects of currency invoicing choices is motivated by this line of research. The complementarities in invoicing currency choice we identify are via the import/export network channel.

Additionally, there are many other determinants for currency choices in trade invoicing. Existing empirical work using transactions of firm-level import or export data shed light on these determinants. Gopinath, Itskhoki, and Rigobon (2010) and Goldberg and Tille (2016) analyze transaction-level data on currency invoicing for, respectively, US and Canadian imports, and find that USD pricing is more common in sectors classified as producing homogeneous goods and hence likely substitutes. Chung (2016) finds that a 1% decrease in the share of imported inputs priced in sterling decreases the probability that UK exporters invoice in sterling by about 18% using UK trade transaction data with non-EU countries. Studying the currency invoicing choices of Belgian exporting firms, Amiti, Itskhoki, and Konings (2022) find that large and import-intensive firms tend to invoice their exports in USD. There is also evidence supporting firms choosing their invoicing currency to hedge their financial input risk. BIS (2014) document that traded financial contracts are mostly USD denominated even though they are sourced through local banks, indicating most trades are financed in USD. Bahaj and Reis (2020) find that when the cost of financing working capital in Renminbi (RMB) is lower due to swap arrangements by central banks, trades are more likely to be denominated in RMB. Furthermore, although invoicing and settlement currencies do not necessarily coincide, in most transaction they are the same currency (Gopinath, Boz, Casas, Díez, Gourinchas, and Plagborg-Møller, 2020). Therefore, the choice of an invoicing currency also depends on its liquidity level. In our estimation, we control for these determinants identified by the trade literature and examine whether these determinants might have additional impact propagated through the trade network.

Finally, recent work in the DCP literature also emphasizes financial frictions in cross-border transactions as an important factor in currency choices. A dominant currency such as the USD preserves its value during global market crises, and thus is widely used as an international reserve or safe asset. This safety feature offered by assets denominated in dominant currency means that the dominant currency preserves value added in exchange transactions, leading to its wide use in global financial market. Differences in financial development or the differences in access to safe asset (Maggiori, 2017) or risk aversion of participants (Gourinchas and Rey, 2022) may drive the demand for an international safe asset. Chahrour and Valchev (2022) propose that safe assets are used as collateral to overcome contractual frictions in cross-border transactions. Gopinath and Stein (2021) argue that assets denominated in the dominant currency can be used as saving devices for export producers to hedge against invoicing risk. In our analysis, we also examine the impact of these financial frictions for dominant currencies at the country-level in relation to the trade network.

III The Network Model

In this section, we construct a network model of currency invoicing decisions for international trade transactions. This framework directly guides our empirical estimation of network effects. In this model, there is a representative firm in each country. They simultaneously decide in which currency to invoice their trades given the import and export trade network structure. For the ease of exposition, the optimizing agent in the model is described as a country (rather than a representation of firms in a country). A country's optimal currency invoicing decision not only depends on its own characteristics but also responds to all other countries' invoicing decisions (and potentially characteristics) through the given trade network. In Section IV, we lay out the steps for structurally estimating the model.

The network. There are n countries. The time-t trade network is predetermined, characterized by an n-square adjacency matrix $\mathbf{G}_t$. If its element $g_{ij\neq i,t}$ are not null, country i and j are connected. To construct $\mathbf{G}_t$ in the structural estimation, we use country-level bilateral trade data. Specifically, we focus on the case where $g_{ij\neq i,t}$ is the fraction of imports or exports by country i from or to country j in the previous month.

The matrix $\mathbf{G}_t$ keeps track of all direct connections – links of order one – between any pair of countries in the network. Similarly, the matrix $\mathbf{G}_t^h$, for any positive integer h, encodes all links of order h between countries, that is, the paths of length h between any pair of countries. The coefficient in the (i,j)th cell of $\mathbf{G}_t^h$, i.e., $\left\{\mathbf{G}_t^h\right\}_{ij}$, gives the exposure of country i to country j in h steps. Since $\mathbf{G}_t$ is a right stochastic matrix (with each row summing up to one), it can be interpreted as a Markov chain transition kernel, and $\mathbf{G}_t^h$ as the h-step transition matrix.

Countries and their invoice currency preference. We study the amount of *excessive* currency countries choose to invoice their trade partners at the beginning of each period t. The amount of excessive currency invoiced for a given currency is defined as any amount above the corresponding bilateral trade volume. For example, it is natural for a country to invoice their trade counterparts located in the US in USD. However, if this country invoices trades with other countries in USD, we define these transactions as excessive USD invoicing. We aim to explain this decision at the country level.

Let $y_{i,k,t}$ denote the total excessive currency k invoiced by country i. We model the impact of the trade network on country i's choice of $y_{i,k,t}$. In the rest of the paper, we drop the index k for expositional simplicity and often refer to k as the dominant currency (DC).

Given the predetermined network $\mathbf{G}_t$ measured by trade links, each country chooses excessive DC invoicing simultaneously to maximize its own payoff. In our model, we specify the per-unit value $\tilde{\mu}_{i,t}$ of excess DC for country i in network $\mathbf{G}_t$ as

$$\tilde{\mu}_{i,t} := \mu_{i,t} + x_{i,t}\delta + x_{p,t}\rho + \phi \sum_j g_{ij,t} y_{j,t} + \sum_j g_{ij,t} x_{i,j,t}\theta \tag{1}$$

where $x_{i,t}$ is a row vector of country-specific characteristics, $x_{p,t}$ denotes aggregate common controls, $x_{i,j,t}$ captures pair-specific covariates, $\mu_{i,t} := \bar{\mu}_i + \epsilon_{i,t}$ contains a countries specific fixed effect ($\bar{\mu}_i$), and shock ($\epsilon_{i,t}$), δ, ρ and θ are conformable column vectors and ϕ is a scalar coefficient. The first and second set of variables capture the country-level variables that directly affect the value of a unit of DC such as bilateral (local versus the invoicing currency) exchange rate volatility, inflation, and other macro variables. The third set of variables capture aggregate factors that might affect all countries' choices.

The fourth term in equation (1) is a network-dependent component of valuation of extra unit of DC invoicing: $\phi \sum_j g_{ij,t} y_{j,t}$. It is motivated by the DCP hypothesis. According to DCP, firms in country i have a preference for invoicing their exports in the same currency as their imports so to minimize the currency mismatch on their assets and liabilities. Network effects lead to certain currencies such as the USD emerging as the dominant currency for countries to coordinate their invoices.

The last term in equation (1) highlights that the network-dependent mechanism may also operate via the characteristics of the trading partners. Variable $x_{i,j,t}$ denotes match-specific control variables and the characteristics of other countries, and θ is a vector of suitable dimension. That is, in addition to the aggregate information embedded in the neighbouring countries' level of excessive DC invoicing, macro variables and the neighbouring countries' characteristics affect the per-unit valuation of the excessive DC invoicing. For example, suppose that country j has a well-developed financial market denominated in EUR instead of USD. This means that trade financing, work capital financing, and currency risk hedging in EUR would be cheaper and readily available. Firms in country j would have more incentives to invoice their trades in EUR, which can impact the invoicing decision of country i. The DCP empirical literature has identified several such determinants for $x_{i,j,t}$, such as the size of the economy, financial market development, foreign direct investment, foreign debt, and inflation.

Next, assuming a quadratic cost for holding $y_{i,t}$ amounts of DC, we specify country i's utility from DC invoicing as

$$u_i(y_t|g_t) = \tilde{\mu}_{i,t} y_{i,t} - \frac{1}{2} y_{i,t}^2. \tag{2}$$

The bilateral network influences in our model are captured by the following cross-derivatives for $i \neq j$:

$$\frac{\partial^2 u_i(y_{i,t}, \{y_{j,t}\}_{j \neq i} |\mathbf{G}_t)}{\partial y_{i,t} \partial y_{j,t}} = \phi g_{ij,t},$$

where ϕ is the network attenuation factor, the key parameter whose sign determines whether the Nash equilibrium features strategic substitution ($\phi < 0$) or complementarity ($\phi > 0$). We are agnostic about the sign of ϕ, and we instead estimate it empirically.

We solve countries' optimal excessive DC invoicing decision in the Nash equilibrium of simultaneous action. The optimal response function for each country is then

$$y^*_{i,t} = \mu_{i,t} + x_{i,t}\delta + x_{p,t}\rho + \phi \sum_j g_{ij,t} y_{j,t} + \sum_j g_{ij,t} x_{i,j,t}\theta. \tag{3}$$

Note that the empirical counterpart of the above best response is the spatial Durbin model.

Let us denote $\mu_{i,t} + x_{i,t}\delta + x_{p,t}\rho + \sum_j g_{ij,t} x_{i,j,t}\theta$ by $\breve{\mu}_t$. The following result is immediate.

Proposition 1 *Suppose that $|\phi| < 1$. Then, there is a unique interior solution for the individual equilibrium outcome given by*

$$y^*_{i,t}(\phi, g) = \{\mathbf{M}(\phi, \mathbf{G}_t)\}_{i.}\, \breve{\mu}_t, \tag{4}$$

where $\{\}_{i.}$ is the operator that returns the i-th row of its argument, $\breve{\mu}_t := [\breve{\mu}_{1,t}, ..., \breve{\mu}_{n,t}]^\top$, $y_{i,t}$ denotes the total excessive DC invoicing by country i, and

$$\mathbf{M}(\phi, \mathbf{G}_t) \equiv \mathbf{I} + \phi \mathbf{G}_t + \phi^2 \mathbf{G}_t^2 + \phi^3 \mathbf{G}_t^3 + ... = \sum_{k=0}^{\infty} \phi^k \mathbf{G}_t^k = (\mathbf{I} - \phi \mathbf{G}_t)^{-1}, \tag{5}$$

where I is the $N \times N$ identity matrix.

Proof. The first-order condition identifies the individual country's optimal response. Applying Theorem 1(b) in Calvo-Armengol, Patacchini, and Zenou (2009), we know that the necessary equilibrium condition is $|\phi\lambda^{max}(\mathbf{G}_t)| < 1$, where the function $\lambda^{max}(\cdot)$ returns the largest eigenvalue. Since $\mathbf{G}_t$ is a right stochastic matrix, its largest eigenvalue is 1. Hence, the condition requires $|\phi| < 1$, and if so, the infinite sum in equation (5) is finite and equal to the stated result (Debreu and Herstein (1953)). ■

The condition $|\phi| < 1$ states that network externalities must be small enough in order to prevent the feedback triggered by such externalities to escalate without bounds. In vector form,

$y_t \equiv [y_{1,t}, ..., y_{N,t}]^\top$, and in equilibrium,

$$y_t^* = \mathbf{M}(\phi, \mathbf{G}_t)\, \breve{\mu}_t \tag{6}$$

Network propagation. In equilibrium, the matrix $\mathbf{M}(\phi, \mathbf{G}_t)$ contains information about the *centrality* of network players.[3] Multiplying the rows (columns) of $\mathbf{M}(\phi, \mathbf{G}_t)$ by a unit vector of conformable dimensions, we recover the indegree (outdegree) Katz–Bonacich centrality measure. The indegree centrality measure provides the weighted count of the number of ties directed to each node (i.e., inward paths), while the outdegree centrality measure provides the weighted count of ties that each node directs to the other nodes (i.e., outward paths). That is, the i-th row of $\mathbf{M}(\phi, \mathbf{G}_t)$ captures how country i loads on the trade network as whole, while the i-th column of $\mathbf{M}(\phi, \mathbf{G}_t)$ captures how the trade network as a whole loads on country i. Therefore, the trade network centrality of a country affects the dominance status of its currency, potentially also through its characteristics (captured by variables x_i).

IV Estimation Method

Making explicit the role of the shocks, $\epsilon_{i,t}$, and country fixed effects, $\bar{\mu}_i$, in the first order condition (3), yields the empirical representation

$$y_{i,t} = \bar{\mu}_i + x_{i,t}\delta + x_{p,t}\rho + \phi \sum_j g_{ij,t} y_{j,t} + \sum_j g_{ij,t} x_{i,j,t}\theta + \epsilon_{i,t} \tag{7}$$

where the covariates, $x_{i,t}$, are contemporaneously independent from the time t shock. Hence, we can also accommodate, among other controls, the lagged value of the both import and export excess currency invoicing. The above formulation is the so-called spatial Durbin model (SDM – see, e.g., LeSage and Pace (2009b)). We estimate the model using monthly data, and we

[3] This centrality measure takes into account the number of both direct and indirect connections in a network. For more on the Bonacich centrality measure, see Bonacich (1987) and Jackson (2010). For other economic applications, see Ballester, Calvo-Armengol, and Zenou (2006) and Acemoglu, Carvalho, Ozdaglar, and Tahbaz-Salehi (2012). For an excellent review of the literature, see Jackson and Zenou (2012).

include year fixed effects to control for unobserved macro factors. At time t, the network is predetermined and $g_{ij,t}$ is measured by the fraction of country i's imports or exports from or to country j. We include a very broad set of country-, and pair-specific, characteristics suggested in the previous literature (such as existence of swap line, bilateral exchange rate volatility, consumer price index volatility, financial market development, denomination of corporate sector FX liability), and lagged values of the excess currency invoicing of both exports and imports. All control variables are lagged by one period for predeterminancy.

The general formulation in equation (7) nests several more restrictive models considered in the previous literature on network spillovers. For instance, setting the vector θ to zero, i.e. shutting down the direct dependency of country i's outcome variable on the covariates of all other countries, we have a simple spatial lag (SLM) as in Ozdagli and Weber (2023). Furthermore, restricting $x_{i,j,t} = [x_{j,t}, x_{p,t}]$ and $\theta = -\phi[\delta^\top, \rho^\top]^\top$, we have a spatial error model (SEM) as in Denbee, Julliard, Li, and Yuan (2021). As shown in Bramoullé, Djebbari, and Fortin (2009), the identification conditions for SDM and SLM boils down to the requirement of linear independence of the identity matrix, the adjacency matrix containing the network weights ($g_{ij,t}$), and the square of this matrix, while in SEM identification arises from the implied restriction on the covariance matrix of the error terms.[4]

Note that in all three formulations for the spatial dependency (SDM, SLM, and SEM), assessing the presence of network externalities boils down to testing whether the coefficient ϕ is different from zero, and setting $\phi = 0$ yields a simple panel structure for the data. Frequentist estimation of these models is possible via e.g., (quasi) maximum likelihood and the Generalized Method of Moments (see, e.g. Anselin (1988)). Nevertheless, we opt for a Bayesian procedure, since we aim to select a specification, and assess whether the data support the presence of network externalities (i.e., a $\phi \neq 0$), with a procedure that is robust to model misspecification in that it does not require testing under the null of a correctly specified model. Nevertheless, since we employ flat priors for the parameters,[5] and we assume Gaussianity for the error terms, the

[4]See Denbee, Julliard, Li, and Yuan (2021) for a detailed discussion.

[5]We use improper flat priors for δ, ρ, and θ, since these parameters are common across specifications, and consequently the improper prior does not invalidate the posterior model probabilities. For ϕ instead we employ

posterior modes coincide with the quasi maximum likelihood estimates (a consistent estimator in this setting). When comparing models (the SDM, SLM, SEM, and panel specifications), we assign equal prior probability to each formulation, and posteriors are sampled via the Gibbs sampling procedure detailed in Appendix A.2.

Furthermore, the estimate of ϕ also reveals the type of equilibrium on the network, i.e., strategic substitution (when $\phi < 0$) or complementarity (when $\phi > 0$). Note also that from equation (3) we have that the conditional covariance of y_t is

$$Var_{t-1}(y_t) = Var_{t-1}\left(\mathbf{M}\left(\phi, \mathbf{G}_t\right)\epsilon_t\right) = \mathbf{M}\left(\phi, \mathbf{G}_t\right)\Sigma_\epsilon \mathbf{M}\left(\phi, \mathbf{G}_t\right)^\top \tag{8}$$

since $\mathbf{G}_t$ is predetermined at time t and $\Sigma_\epsilon \equiv Var(\epsilon_t)$. Hence, the variance is increasing in ϕ: The stronger the degree of strategic complementarity, the larger is the endogenous amplification of shocks to the system, and the higher is the volatility of total excess invoicing in the network. To see this, note that the variance of total excess invoicing is $Var_{t-1}(\mathbf{1}^\top y_t)$, hence, a unit shock equally spread among all N countries has a contemporaneous impact on total excess invoicing equal to $\mathbf{1}_N^\top \mathbf{M}\left(\phi, \mathbf{G}_t\right)\mathbf{1}_N/N = 1/(1-\phi)$, where $\mathbf{1}_N$ denotes a vector of ones with length N.[6]

V Variable Construction and Data Description

The main focus of our analysis is excessive currency invoicing, $y^x_{i,k,t}$, where i denotes a country, t the time period, k the currency (USD or EUR), and x the trade direction (export or import). To construct the variable we rely on the dataset by Boz, Casas, Georgiadis, Gopinath, Le Mezo, Mehl, and Nguyen (2022) and the Direction of Trade Statistics database by the International Monetary Fund. The former is augmented with data from SWIFT to increase cross-sectional coverage[7] and provides data on the shares of aggregate exports or imports invoiced in USD and

a Gaussian prior and modify the acceptance rate to ensure proper support.

[6]Since $\mathbf{1}_N = (I_N - \phi\mathbf{G}_t)^{-1}(I_N - \phi\mathbf{G}_t)\mathbf{1}_N = (I_N - \phi\mathbf{G}_t)^{-1}\mathbf{1}_N(1-\phi)$ due to $\mathbf{G}_t$ being a right stochastic matrix. Hence, $\mathbf{M}\left(\phi, \mathbf{G}_t\right)\mathbf{1}_N = (1-\phi)^{-1}\mathbf{1}_N$.

[7]Crucially, the SWIFT dataset allows us to cover China, Hong Kong, Mexico, Canada, the United Arab Emirates, Singapore, Vietnam, and Sri Lanka. For details on the augmentation see appendix section A.1.1.

EUR by country over time, which we denote as $PS^x_{i,k,t}$. The latter provides data on the value of merchandise exports or imports disaggregated according to a country's trading partners over time, which we denote as $T^x_{i,j,t}$.

It is natural to assume that when exporting to the United States (Euro Area) merchants in country i invoice these exports in USD (EUR). However, if they also invoice in USD (EUR) when exporting to other destination countries these are not the local official currency, we refer to these transactions as excessive USD (EUR) invoicing.

To calculate our variable of interest from the data, let j_k be the set of countries j with home currency k, e.g., if $k = EUR$, then j_k denotes all Euro Area countries. Using the previously defined variables, we then have

$$y^x_{i,k,t} = PS^x_{i,k,t} \sum_{j \in J_{i,t}} T^x_{i,j,t} - T^x_{i,j_k,t} \tag{9}$$

where $J_{i,t}$ denotes the set of trade counterparties of country i at time t. The first term captures the aggregate currency invoicing of country i in currency k with direction x. The second term deducts the trade conducted with the countries that have currency k as their home currency, thereby isolating the excessive amount of currency k invoiced. More details on the construction of $y^x_{i,k,t}$ based on the raw datasets is given in appendix A.1.1.

Figure 1 depicts the geographic distribution of the average export-based excessive currency invoicing for the USD and the EUR in our sample. Figure 6 in appendix A.4 depicts the distribution for import-based excessive currency invoicing. In total, we cover 119 countries in our dataset. Focussing on the USD export-based excessive currency invoicing, all countries, except the Bahamas, Niger, and the Republic of Fiji, use the USD in excess of their trade with the United States on average. That is, we find substantial use of the USD as a vehicle currency to conduct export-based trade. Particularly Asian and some Latin American countries have large positive export-based excessive USD invoicing positions on average. Generally, European countries have positive, albeit relatively lower, positions. The USD import-based measure in Figure 6 panel (a) shows similar patterns. Only one country, the Bahamas, has a negative USD import-based excessive currency invoicing position on average. Judging from the magnitude of positions, there is comparable usage of the USD across exports and imports as a vehicle currency. On the import side, Asian and European countries have particularly large positive import-based excessive USD invoicing positions on average.

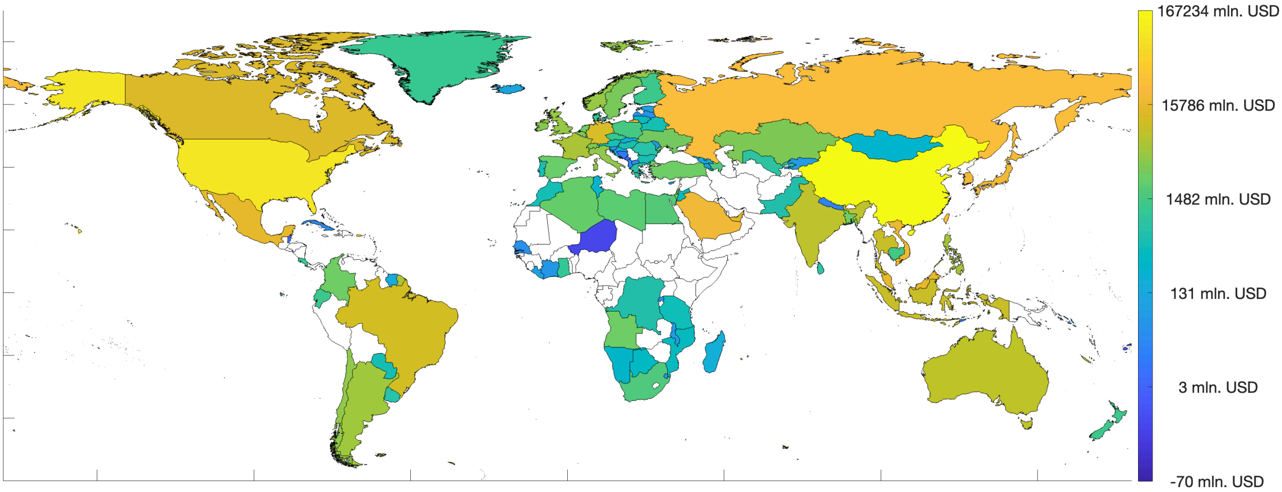
Focussing on the EUR export-based excessive currency invoicing, the majority of countries use less EUR relative to their trade with the Euro Area countries on average, leading to negative excessive currency invoicing positions. Mostly European and their immediate neighbouring countries have large positive export-based excessive EUR invoicing positions. The fact that some European countries on average have large positive EUR export-based excessive currency invoicing positions indicates a form of producer currency pricing. The EUR import-based measure in figure 6 panel (b) again shows similar patterns, in that mostly European and neighbouring countries have large positive import-based excessive EUR invoicing positions. Interestingly, we again observe that European countries on average have a large positive EUR import-based excessive currency invoicing position. This indicates a form of local (destination) currency pricing. Together, these patterns lend support to claims that the EUR is less of a globally, but more of a regionally dominant currency.

V.1 Dataset Construction

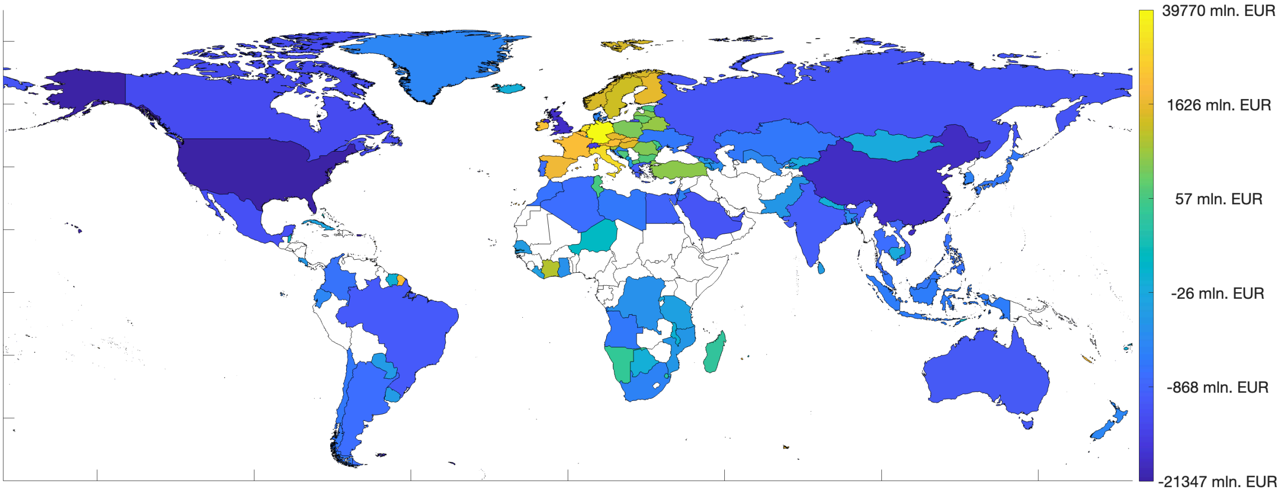
The focus of the empirical study is to investigate the drivers of USD and EUR excessive currency invoicing, and in particular to asses whether network externalities affect the currency invoicing decision. We construct our dependent variable at monthly frequency based in exports and imports and add a large set of country-specific variables, suggested in the previous literature as potential drivers of the currency invoicing decisions, to our dataset.

In particular, the literature has found that exporters might coordinate on a certain invoicing currency to improve their pricing competitiveness in a certain market or hedge against exchange shocks to their inputs (e.g., labor, capital, or intermediate goods) (Gopinath, 2015; Doepke and Schneider, 2017; Mukhin, 2022; Eren and Malamud, 2022). It is important to control for price

Figure 1: Export-Based Excessive Currency Invoicing across Countries



(a) USD Excessive Currency Invoicing



(b) EUR Excessive Currency Invoicing

The figure depicts the average monthly excessive currency invoicing across countries over our sample. All amounts are in USD equivalents. The countries marked in white are not included in our sample due to missing observations. The top ten countries by export-based excessive USD invoicing positions in our sample are: China, the United States, Taiwan, Russia, South Korea, Saudi Arabia, Japan, Vietnam, Singapore, and Mexico. The top ten countries by export-based excessive EUR invoicing positions in our sample are: Germany, the Netherlands, Italy, Ireland, France, Belgium, Austria, Spain, the Slovak Republic, and the Czech Republic. Panel (a): USD excessive currency invoicing. Panel (b): EUR excessive currency invoicing.

volatilities and the size of the market. Hence, among the covariates, we include consumer price index-based inflation and inflation volatility, the change in domestic exchange rates and exchange rate volatility with the USD or EUR and the share of total aggregate imports or exports. Bahaj and Reis (2020) find that currency invoicing decisions of exporters depend on the level of financial services provided to exporting and importing firms denominated in certain currencies. For example, suppose a large share of counterparties of country i have a well developed financial market denominated in EUR instead of USD. Trade and working capital financing as well as currency risk hedging in EUR would be cheaper and readily available. Then, firms in country i would have more incentive to invoice their trades in EUR. Similar ideas are also found in Maggiori (2017), Gourinchas, Rey, and Sauzet (2019), and Gopinath and Stein (2021). In these papers, it is the characteristics of a country's trading partner countries, such as whether these partner countries have a well developed credit or debt market denominated in USD or EUR, that determine whether USD, or EUR, or any other currency is used for invoicing. Motivated by these findings, we also include the aggregate level of firm-level debt denominated in the USD or EUR, dummy variables indicating whether a country has swap lines with the United States Federal Reserve or the European Central Bank, the financial development index, and the foreign direct investment inflows or outflows of a country. For detailed variable definitions, data sources and data-cleaning steps, see Appendix A.1.

To construct the final dataset we lag all independent variables with respect to their original frequency. We then add lagged dependent variables, that is, lags of import- or export-based USD or EUR excessive currency invoicing and time- and country-fixed effects. The final dataset, including explanatory variables for our baseline specification, covers 84 countries from January 2004 to December 2019. These countries cover on average 91% (93%) of worldwide exports (imports) reported in the Direction of Trade Statistics database during the sample period.

Before estimation we standardise our data in two ways. First, we divide our dependent variable by lagged nominal gross domestic product. We also divide our foreign direct investment and aggregate level of firm-level debt variables by contemporaneous nominal gross domestic product. Second, we normalise all variables (independent and covariates), except the swap line dummy variable, by their sample standard deviation.

VI Network Analysis

In this section, our focus is to explore the influence of network externalities on the currency invoicing choices for a broad set of countries in the context of trade-induced transactions. We incorporate a substantial set of covariates, previously suggested in relevant literature, as potential factors driving currency invoicing decisions, and we examine whether the structure of the trade network itself acts as an additional driving force.

First, we start by conducting a comparative analysis between dynamic panel specifications for the invoicing decision and alternative specifications (SLM, SEM, and SDM) that account for potential network spillover effects. The data overwhelmingly indicate that a country's currency invoicing decision is significantly influenced by the currency invoicing choices made by its trade partners. In essence, network externalities emerge as one of the significant drivers impacting the currency invoicing choices. Second, we revisit the evidence on the determinants of the currency invoicing choice through the lenses of spatial dependency across countries. In doing so, we discover that certain findings from previous analyses become more nuanced when we consider both direct and indirect (i.e., effects through the network) effects. Third, employing our estimated structural model, we identify the key players in currency invoicing – countries whose decisions wield the most significant influence on total currency invoicing. Remarkably, countries and regions exhibiting substantial trade network centrality emerge as critical actors in this process. Fourth, we analyse the spillovers between export and import invoicing, to shed light on the *natural hedge* (Doepke and Schneider, 2017; Amiti, Itskhoki, and Konings, 2022) channel of currency invoicing determination, and whether USD and EUR are complementary or substitute in the invoicing decisions. Fifth, we perform a counterfactual analysis to assess the potential fragility of the current dominant currency equilibrium.

VI.1 Are there Trade-Network Spillovers in Currency Invoicing?

The first question we ask the data is whether there are indeed network spillovers driving the currency invoicing decision. We do so by computing the posterior probability of the spatial Durbin model (SDM) implied by our currency invoicing model in equation (3) and the same quantity for the panel specification obtainable by shutting down the trade-network channel (i.e., setting ϕ and the vector θ equal to zero). Furthermore, we consider alternative sources of spatial dependence. In particular, we consider two alternative canonical cases. First, the case in which the invoicing decision of country i depends on the invoicing of other countries in the network, but not directly on the other countries' covariates (i.e., $\phi \neq 0$ but the vector θ equal to zero in equation (3)). This is the so-called spatial lag or spatial autocorrelation model (SLM). Second, we also consider network spillovers purely driven by network propagation of the shocks (as, e.g., in Denbee, Julliard, Li, and Yuan (2021)). That is, the invoicing decision of each country does not depend directly on the invoicing decision of any other countries or on other countries' covariates (i.e., ϕ and the vector θ equal to zero as in a panel specification), but the shocks in each country are linked via the network, i.e. $\mu_{i,t} = \mu_i + z_{i,t}$, where $z_{i,t} = \phi \sum_j g_{i,j,t} z_{j,t} + \nu_{i,t}$, where $\nu_{i,t}$ denotes cross-sectionally uncorrelated shocks.

Posterior model probabilities, that is the likelihood of the various models being the true data generating process, are computed assuming equal prior probabilities for all the models (i.e., assuming that the various specification are ex ante equally likely). That is, the posterior probability of the m-th model is $prob_m = \frac{p_m}{\sum_m p_m}$, where p_m denotes the so-called marginal likelihood of model m (the value of the integrated unnormalized posterior, i.e. likelihood times the prior, over the parameter space).

Log marginal likelihood values and posterior specification probabilities are reported in Table 1. Each column considers a different dependent variable: excessive currency invoicing of exports in USD (column 1) and EUR (column 2), and excess currency invoicing of imports in the same two currencies (respectively, columns 3 and 4). Several observations are in order. First, there is overwhelming evidence of network spillovers: The panel specification with no spatial

Table 1: The Posterior Likelihood of Trade-Network Spillovers

Specification:		ECI^{Ex}_{USD}	ECI^{Ex}_{EUR}	ECI^{Im}_{USD}	ECI^{Im}_{EUR}
Panel	$\ln p_m$	203.701	-1999.739	721.933	-2653.269
	$prob_m$	0.000	0.000	0.000	0.000
SEM	$\ln p_m$	178.036	-1973.738	710.634	-2634.372
	$prob_m$	0.000	0.000	0.000	0.000
SLM	$\ln p_m$	227.448	-2001.040	732.393	-2570.273
	$prob_m$	0.000	0.000	0.000	0.000
SDM	$\ln p_m$	274.748	-1863.344	897.106	-2479.632
	$prob_m$	1.000	1.000	1.000	1.000

The table reports the logarithm of the marginal likelihood ($\ln p_m$) of the data, given the model and the posterior model probabilities ($prob_m$). Note that the marginal likelihoods are adjusted by subtracting the logarithm of the number of observations. The models are separately estimated on each dataset using our baseline specification. Depending on the dataset, the baseline specification uses, respectively, USD or EUR export- or import-based excessive currency invoicing as the dependent variable. As independent variables, we include lags of inward foreign direct investments, a USD SWAP line dummy, exchange rate changes with the USD and EUR, realized exchange rate volatility with the USD and EUR, the share of aggregate exports, CPI-based inflation and CPI-based inflation volatility, USD export-, USD import-, EUR export-, and EUR import-based excessive currency invoicing, and country- and time-fixed effects.

dependency is never preferred by the data. Second, the SDM model – the specification of our theoretical formulation – is always strongly preferred by the data, with posterior probability approaching 1 in all cases considered. Third, even alternative spatial formulations generally dominate the specification with no network dependency with the SLM formulation being almost always strongly preferred to the panel one. Fourth, the SEM model is typically the worst performing among the spatial specifications considered, and it is a less likely data generating process (DGP) than the dynamic panel in all cases: This emphasizes that the measured network spillovers are driven by the effect of a country's invoicing decision on its traded partner's invoicing decisions, rather than being merely the result of common shocks propagated via the trade network. Furthermore, as shown in Table A.3 of the appendix, the above findings hold if we use actual currency invoicing, or aggregate currency invoicing, instead of our preferred measure of *excessive* currency invoicing as the dependent variable.

Overall, Table 1 emphasizes the need to account for network spillovers when analyzing the currency invoicing choice and provides strong support for the formulation (the SDM) adopted in our model.

VI.2 The Drivers of Excessive Currency Invoicing

Having established the presence of network spillovers and empirical support for our SDM formulation, we now turn to analyse the implications of our model for the determinants of currency invoicing suggested in the previous literature.

Direct interpretation of coefficients for spatial models is difficult, as they often do not represent the marginal effects of the explanatory variables. This is because marginal effects in spatial models depend on potentially non-zero cross-derivatives. Intuitively, this is because the change in an explanatory variable for an individual country can potentially affect the dependent variable in all other countries, through, for example, feedback loops. Hence, covariates have both a direct and indirect (through the network dependency) effect on the outcome variables. Furthermore, since we also include among the controls the lagged values of the dependent variables to capture time series autocorrelation, perturbations of any of the covariates have both short- and long-run effects.

Hence, we report direct and total effects – the difference between the two indicating the indirect effect – in both the short-term (i.e., contemporaneously) and the long-term. The total effect, which we define as in LeSage and Pace (2009a), is the time series average of the average row sum of partial derivatives (since, due to time variation in $\mathbf{G_t}$, the partial derivatives are time varying). This corresponds to the average impact on the individual dependent variable $y_{i,t}$ resulting from changing a given explanatory variable by the same amount across all individual countries. It is important to account for changes across multiple countries, as this allows us to trace out the spatial impact. The direct effect, which we also define similarly to LeSage and Pace (2009a), is the time series average of the diagonal partial derivatives. This corresponds to the average impact on individual observation $y_{i,t}$ by changing its own i^{th} observation of a given explanatory variable. This statistic is closely related to the marginal effect in a standard regression model. To see this, suppose ϕ and θ are all zero. We would then find that the direct effect is exactly the β coefficient associated with the given covariate. Finally, the indirect effect is defined as the difference between total and direct effect.

We report these estimated effects in Tables 2 and 3 for excessive and, respectively, aggregate currency invoicing. In each table, panel A and B focus, respectively, on USD and EUR denominated invoicing. We add different groups of regressors, while always including country- and time-fixed effects, and lagged values of inward foreign direct investments, outward foreign direct investments, USD export-, USD import-, EUR export-, and EUR import-based excessive currency invoicing, as control variables. In both tables, long-term and short-term effects are similar in sign and significance. We report both for completeness.

Several observations are in order. First, for both USD and EUR denominated excess currency invoicing, we observe large and highly statistically significant network effects: The ϕ coefficient ranges from 0.245 to 0.296 for USD denominated invoicing and from 0.144 to 0.188 for EUR denominated invoicing. These estimated coefficients are not only statistically significant at any customary confidence level but also very stable across specifications.

Second, being positive, the estimates of ϕ imply strategic complementarity in the currency invoicing decision: If a country increases its invoicing in a given currency, its trade partners are also likely to do so. In particular, the coefficients imply an average amplification of the shocks to currency invoicing of about 17%–42% relative to a world with $\phi = 0$.

Moreover, as shown in Table 3, this strong evidence of network-induced strategic complementarity in the currency invoicing choice is supported by the data even if we use aggregate invoicing values rather than our preferred excessive currency invoicing measure. If anything, in this robustness check, the measured network spillovers are even stronger. This stability of the estimated network effect is extremely reassuring.

Third, albeit most estimates of the direct effects of covariates conform with previous findings in the literature, these are much less stable across specifications and currency denomination, and, most importantly, it is not uncommon to find significant direct effects – akin to those estimated with a panel specification – while the total effects are not statistically significant, and vice versa. This is not too surprising given the strong evidence in Table 1 in favour of spatial modeling, which indicates that evidence produced ignoring the network spillovers is affected by a large degree of misspecification. Hence, reduced-form evidence that ignores the spatial dependency should be taken with a substantial grain of salt.

Tables 2 and 3 further highlight that impacts for USD and EUR invoicing are noticeably different in terms of sign, magnitude, and significance. To a large degree the differences in results across USD and EUR, as well as across excess and aggregate currency invoicing, can be reconciled with explanations treating the USD as a globally dominant currency and the EUR as a regionally dominant currency, i.e. a pecking order of dominant currencies.

For example, we find that the larger a country's share of worldwide exports (TS^{Ex}) is, the smaller is its amount of USD excess and aggregate invoicing. This finding is in line with the theoretical results in Mukhin (2022), predicting that the larger a country's market size the lower is its reliance on vehicle currencies for invoicing. For EUR aggregate invoicing, similar patterns arise, however, for EUR excess invoicing we find that a country's trade size leads to higher EUR excess invoicing. EUR excess currency invoicing proxies for a country's EUR trade conducted with non-Euro Area countries. This indicates that larger countries tend to be more likely to invoice in EUR with non-Euro Area countries. Finally, judging by the marginal likelihoods ($\ln p_m$), a country's trade size is one of the most important determinants across the considered covariates for currency invoicing.

Next, we find that swap lines with the US federal reserve ($SWAP_{USD}$) lead to an increase in USD excess and aggregate invoicing. This corroborates the findings by Bahaj and Reis (2020) for Chinese RMB trade invoicing. The coefficients for aggregate invoicing are overall insignificant, indicating that swap lines typically impact vehicle currency trade invoicing. Further, for USD denominated excess invoicing, only the total effect is significant, while the direct effect remains insignificant. This illustrates that swap lines lead to an increase in USD excess invoicing predominantly through indirect network effects. The significantly negative effect on EUR excess invoicing suggests substitution between EUR and USD when the swap line is activated, consistent with a pecking order and the dominance of the USD. Turning to swap lines with the European Central Bank ($SWAP_{EUR}$), we find only negative effects. Closer examination of the data showed that in total only ten non Euro Area countries had a swap line with the European Central Bank. These became effective during the great financial crisis or European debt crisis, explaining the estimated negative effects of EUR swap lines for both USD and EUR invoicing[8].

Turning to exchange rate related variables, we document that when a country's currency depreciates with respect to the USD or EUR ($FXChng_{USD}$ and $FXChng_{EUR}$ respectively), in general excess and aggregate invoicing in both USD and EUR decrease. The only exception is that for depreciation with respect to the USD ($FXChng_{USD}$), we find a positive statistically significant direct effect for EUR excess invoicing. Note however, the total effect is negative albeit insignificant and for aggregate EUR invoicing the effects are negative and significant. Overall, the estimated effects are more significant for aggregate than for excess currency invoicing, indicating that exchange rate depreciation is relatively less relevant for vehicle currency invoicing. Theoretically, exporting firms invoice in vehicle currency to hedge against exchange rate volatility. We find weak evidence to support that exchange rate volatility increases dominant currency invoicing. In Table 2, we observe that the direct effect of higher EUR exchange rate volatility ($FXVol_{EUR}$) is positive and significant on excess EUR invoicing while the total effect is positive but not significant. By comparison, the direct effect of higher USD exchange rate volatility ($FXVol_{USD}$) on USD excess invoicing is actually negative, whereas the total effect after accounting for network impact is positive as expected, although neither estimate is statistically significant. In Table 3, when we study the driver of aggregate currency invoicing, the impacts of exchange rate volatility are statistically insignificant. We also observe a cross-currency impact: a larger EUR exchange rate volatility lowers both excess and aggregate USD invoicing, and the total effects are statistically significant. This, again, might reflect a substitution effect between the two currencies when exporting firms hedge against relevant exchange rate volatility.

Inflation and inflation volatility have statistically significant but different impacts on excessive currency invoicing decisions for both USD and EUR. For aggregate USD currency invoicing the effects appear similar, however, significance levels change somewhat. The level of domestic inflation (CPI) has negative direct and total effects. This might reflect that domestic inflation

[8]The non Euro Area countries are the United States, the United Kingdom, Denmark, Sweden, Switzerland, Canada, Japan, China, Hungary and Poland. Swap lines were activated in 2007-2011 and kept in place throughout the sample for all countries except Poland and Hungary.

makes exporters more competitive due to reduced local cost and less concerned about price competition in target markets. Interestingly, domestic inflation volatility ($CPIVol$) has positive direct and total effects. Therefore, inflation risk appears to be a more important driver than the level of inflation for dominant currency invoicing. This is intuitive because exporters use currency invoicing to manage balance sheet risks caused by inflation volatility. For excess EUR currency invoicing the signs of the effects are the opposite, however, they change across the two tables. This highlights that the effects are sensitive with respect to EUR invoiced trade conducted with Euro Area countries. The negative effect of inflation volatility for excess rather than aggregate EUR invoicing means that a higher CPI volatility leads to a lower amount of EUR invoicing to non-Euro Area countries, suggesting that the EUR is used as a regional currency.

We also find that foreign debt, which is measured as amount of corporate debt in USD (FD_{USD}) relative to domestic gross domestic product, is positively linked with excess and aggregate USD and EUR invoicing. The variable can be viewed as proxying whether a country has access to international capital markets and hence suggests that countries with more access to international capital markets tend to invoice more of their trade using vehicle currencies. We find that corporate debt in EUR (FD_{EUR}) is not associated with a significant effect. This can be viewed as further evidence of the USD dominance relative to that of the EUR. We further examine the change in corporate debt in USD ($FDChng_{USD}$) or EUR ($FDChng_{EUR}$), which typically lead to effects with plausible signs. Note however that overall the model incorporating data on corporate debt performs worst in terms of its associated marginal likelihood ($\ln p_m$), indicating that corporate debt is a less relevant determinant relative to the other variables considered.

Finally, we do not find that the financial market index (FMI), an index aiming to summarise the broad financial development of a country, has any significant impact on trade invoicing. Together with the previous results, this suggests that only certain financial frictions such as liquidity (captured by swap lines or the level of foreign firm debt relative to gross domestic product) affect trade invoicing decisions.

Tables 5 and 6 in the appendix depict our model baseline specification underlying the subsequent analysis. We included all of the discussed variables except the financial market index and the foreign debt variables. The former was excluded as the overall impact was insignificant. The latter were excluded as judging by the marginal likelihood other model specifications were preferred. Finally, we excluded the swap line with the European Central Bank due to the aforementioned issues. We further dropped outward foreign direct investments, which improved the marginal likelihood of the resulting models.

VI.3 The Network Key Players

With the estimated spatial Durbin we can evaluate which country's shocks are expected to have the largest impact on the overall network – that is, we can identify the key players in the trade network. To see this, note that the SDM, singling out the role of the lagged dependent variables and merging the x covariates into a more compact notation, can be rewritten in vector form as

$$y_t = \alpha y_{t-1} + \eta G_t y_{t-1} + \phi G_t y_t + X_t \beta + G_t X_t \theta + \epsilon_t \tag{10}$$

where $\epsilon_t \sim N(0, \sigma^2 I)$. Define $M_t = (I - \phi G_t)^{-1}$ and $A_t = (\alpha I + \eta G_t)$. Suppose that y_t, as in our empirical implementation, is scaled by the GDP levels for stationarity and normalized to have unit variance. Let $D_t = diag(GDP_{i,t}^{-1})$ and $\Lambda = diag(\sigma_i^{-1})$, where $\sigma_i = Var(y_{i,t}/GDP_{i,t})^{1/2}$. Hence, we have $y_t = \Lambda D_t y_t^{\$}$, where $y_t^{\$}$ is our independent variable in USD units. The above immediately implies that the standard deviation of the errors of the USD unit dependent variable, $\epsilon_t^{\$}$, are heteroskedastic and vary over time. Specifically, $\sigma_{i,t}^{\$} = Var(\epsilon_{i,t}^{\$})^{1/2} = \sigma\sigma_i GDP_{i,t}$. We are mostly interested in computing statistics in terms of USD units from here onward. In what follows, let e be a column vector of ones of size $N \times 1$. Hence, $Y_t = e' y_t^{\$}$ denotes the total USD excess currency invoicing at time t.

Given the presence of lagged independent variables on the right-hand side of equation (10), a country-specific shock affects all other countries both contemporaneously and over time. That is, impulse-response functions (IRFs) of this model have both a spatial (across countries) and

Table 2: The Drivers of Excess Currency Invoicing

		Independent Variables													
		(1)		(2)				(3)	(4)				(5)		(6)
		CPI	$CPIVol$	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	TS^{Ex}	FD_{USD}	$FDChng_{USD}$	FD_{EUR}	$FDChng_{EUR}$	$SWAP_{USD}$	$SWAP_{EUR}$	FMI
Panel A. Dependent Variable: Export Excess Currency Invoicing in USD (ECI^{Ex}_{USD})															
Short-term:	Direct Effect	-0.011**	0.028***	-0.017	-0.004	-0.014	-0.004	-0.097***	0.042***	0.019**	0.012	-0.011	0.048	-0.045	0.006
		(0.092)	(0.000)	(0.182)	(0.668)	(0.210)	(0.687)	(0.000)	(0.000)	(0.017)	(0.106)	(0.148)	(0.129)	(0.208)	(0.317)
	Total Effect	-0.093***	0.019**	-0.083	-0.074***	0.070	-0.072**	-0.136***	0.104***	0.017	0.042	-0.037	0.324***	-0.453***	0.007
		(0.000)	(0.080)	(0.113)	(0.009)	(0.203)	(0.014)	(0.000)	(0.004)	(0.460)	(0.195)	(0.264)	(0.001)	(0.000)	(0.828)
Long-term:	Direct Effect	-0.044**	0.108***	-0.067	-0.017	-0.055	-0.016	-0.434***	0.159***	0.074**	0.044	-0.043	0.192	-0.178	0.025
		(0.086)	(0.000)	(0.176)	(0.651)	(0.219)	(0.668)	(0.000)	(0.000)	(0.017)	(0.105)	(0.147)	(0.123)	(0.199)	(0.319)
	Total Effect	-0.399***	0.084**	-0.363	-0.325**	0.304	-0.317**	-0.749***	0.426***	0.073	0.172	-0.150	1.370***	-1.915***	0.031
		(0.001)	(0.086)	(0.116)	(0.010)	(0.206)	(0.018)	(0.000)	(0.005)	(0.458)	(0.201)	(0.268)	(0.001)	(0.000)	(0.829)
	ϕ	0.252***		0.245***				0.248***	0.296***				0.259***		0.248***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.948		0.948				0.949	0.950				0.948		0.948
	NObs	10812		10835				10835	9303				10835		10835
	log marginal	194.757		198.141				291.295	-75.518				206.735		182.530
Panel B. Dependent Variable: Export Excess Currency Invoicing in EUR (ECI^{Ex}_{EUR})															
Short-term:	Direct Effect	-0.006	-0.009	0.033**	-0.006	-0.005	0.023**	0.046***	-0.005	0.037***	-0.012	0.009	-0.198***	-0.106**	0.000
		(0.459)	(0.252)	(0.028)	(0.609)	(0.740)	(0.044)	(0.000)	(0.637)	(0.000)	(0.165)	(0.367)	(0.000)	(0.013)	(0.962)
	Total Effect	0.079***	-0.042***	-0.025	-0.035	-0.017	0.044	0.060***	0.103***	-0.046**	0.051	-0.103***	-0.047	-0.516***	0.009
		(0.005)	(0.000)	(0.653)	(0.250)	(0.771)	(0.161)	(0.000)	(0.008)	(0.064)	(0.138)	(0.003)	(0.638)	(0.000)	(0.798)
Long-term:	Direct Effect	-0.017	-0.029	0.105**	-0.019	-0.015	0.074**	0.141***	-0.014	0.105***	-0.034	0.024	-0.606***	-0.324**	0.001
		(0.494)	(0.244)	(0.028)	(0.607)	(0.738)	(0.044)	(0.000)	(0.638)	(0.000)	(0.165)	(0.367)	(0.000)	(0.013)	(0.961)
	Total Effect	0.286***	-0.154***	-0.081	-0.112	-0.055	0.142	0.196***	0.296**	-0.131**	0.146	-0.295***	-0.139	-1.528***	0.029
		(0.006)	(0.001)	(0.655)	(0.251)	(0.769)	(0.163)	(0.000)	(0.010)	(0.066)	(0.144)	(0.003)	(0.637)	(0.000)	(0.799)
	ϕ	0.161***		0.144***				0.144***	0.188***				0.144***		0.147***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.963		0.963				0.963	0.966				0.963		0.963
	NObs	10813		10836				10836	9304				10836		10836
	$\ln p_m$	-1864.490		-1872.266				-1867.117	-1910.905				-1845.850		-1884.534

The table reports the posterior means of the estimated effects and their respective p-values in brackets. Coefficient estimates significant at the 10%, 5% and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the listed independent variables, we always include country- and time-fixed effects, lags of inward foreign direct investments, outward foreign direct investments, USD export-, USD import-, EUR export-, and EUR import-based excessive currency invoicing as control variables.

Table 3: The Drivers of Aggregate Currency Invoicing

		Independent Variables													
		(1)		(2)				(3)	(4)				(5)		(6)
		CPI	$CPIVol$	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	TS^{Ex}	FD_{USD}	$FDChng_{USD}$	FD_{EUR}	$FDChng_{EUR}$	$SWAP_{USD}$	$SWAP_{EUR}$	FMI
Panel A. Dependent Variable: Export Aggregate Currency Invoicing in USD (ACI^{Ex}_{USD})															
Short-term	Direct Effect	-0.001	0.021***	-0.021**	0.006	-0.014	-0.008	-0.121***	0.029***	0.020***	0.005	-0.016**	0.039	-0.043	0.007
		(0.858)	(0.000)	(0.049)	(0.447)	(0.163)	(0.367)	(0.000)	(0.000)	(0.004)	(0.368)	(0.012)	(0.160)	(0.175)	(0.201)
	Total Effect	-0.112***	0.017	-0.102**	-0.091***	0.079	-0.093***	-0.194***	0.060	0.012	0.014	-0.128***	0.096	-0.612***	0.003
		(0.000)	(0.149)	(0.074)	(0.005)	(0.183)	(0.004)	(0.000)	(0.171)	(0.674)	(0.700)	(0.001)	(0.403)	(0.000)	(0.932)
Long-term	Direct Effect	-0.001	0.101***	-0.098**	0.033	-0.067	-0.033	-0.651***	0.129***	0.090***	0.024	-0.069**	0.182	-0.182	0.033
		(0.957)	(0.000)	(0.055)	(0.412)	(0.149)	(0.399)	(0.000)	(0.000)	(0.004)	(0.368)	(0.018)	(0.164)	(0.218)	(0.195)
	Total Effect	-0.416***	0.063	-0.388**	-0.348***	0.302	-0.358***	-0.998***	0.172	0.035	0.041	-0.370***	0.349	-2.218***	0.011
		(0.000)	(0.154)	(0.079)	(0.008)	(0.188)	(0.007)	(0.000)	(0.179)	(0.666)	(0.704)	(0.002)	(0.406)	(0.000)	(0.937)
	ϕ	0.387***		0.391***				0.369***	0.450***				0.393***		0.393***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.963		0.963				0.964	0.963				0.963		0.963
	NObs	10812		10835				10835	9271				10835		10835
	$\ln p_m$	1663.108		1663.017				1842.718	1180.256				1677.898		1644.081
Panel B. Dependent Variable: Export Aggregate Currency Invoicing in EUR (ACI^{Ex}_{EUR})															
Short-term	Direct Effect	0.008	0.018***	-0.027***	-0.004	-0.005	0.004	-0.101***	0.016**	0.028***	0.002	-0.014**	-0.015	-0.027	0.001
		(0.133)	(0.001)	(0.007)	(0.634)	(0.567)	(0.581)	(0.000)	(0.018)	(0.000)	(0.741)	(0.015)	(0.560)	(0.357)	(0.854)
	Total Effect	-0.046	0.014	-0.125**	-0.109***	0.026	-0.056	-0.229***	-0.028	0.017	0.027	-0.198***	0.085	-0.792***	-0.042
		(0.143)	(0.282)	(0.048)	(0.002)	(0.695)	(0.123)	(0.000)	(0.555)	(0.568)	(0.493)	(0.000)	(0.505)	(0.000)	(0.285)
Long-term	Direct Effect	0.042	0.094***	-0.141***	-0.018	-0.028	0.023	-0.563***	0.083**	0.142***	0.009	-0.071**	-0.079	-0.109	0.006
		(0.130)	(0.001)	(0.008)	(0.669)	(0.559)	(0.563)	(0.000)	(0.016)	(0.000)	(0.751)	(0.020)	(0.544)	(0.457)	(0.835)
	Total Effect	-0.231	0.069	-0.565**	-0.495***	0.117	-0.254	-1.121***	-0.116	0.077	0.119	-0.860***	0.328	-2.973***	-0.200
		(0.153)	(0.289)	(0.055)	(0.004)	(0.697)	(0.133)	(0.000)	(0.574)	(0.569)	(0.500)	(0.000)	(0.504)	(0.000)	(0.293)
	ϕ	0.499***		0.491***				0.488***	0.543***				0.496***		0.493***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.964		0.965				0.965	0.967				0.964		0.964
	NObs	10813		10836				10836	9272				10836		10836
	$\ln p_m$	2491.015		2493.079				2638.641	2047.666				2515.026		2473.841

The table reports the posterior means of the estimated effects and their respective p-values in brackets. Coefficient estimates significant at the 10%, 5% and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the listed independent variables, we always include country- and time-fixed effects, lags of inward foreign direct investments, outward foreign direct investments, USD export-, USD import-, EUR export-, and EUR import-based aggregate currency invoicing as control variables.

a temporal (across time) dimension. We define the USD unit spatiotemporal impulse-response function (STIRF) of $Y_t = e'y_t^{\$}$, to a one standard deviation shock to country i, as

$$STIRF_{i,t,\tau} = \frac{\partial Y_{t+\tau}}{\partial \epsilon_{i,t}^{\$}} \sigma_{i,t}^{\$} = \begin{cases} e'\{D_t^{-1}\Lambda^{-1}M_t\}_{\cdot,i}\sigma \text{ for } \tau = 0 \\ e'\{D_{t+\tau}^{-1}\Lambda^{-1}\prod_{j=0}^{\tau-1} M_{t+\tau-j}A_{t+\tau-j}M_t\}_{\cdot,i}\sigma \text{ for } \tau \geq 1 \end{cases}$$

where $\{\}_{\cdot,i}$ is the operator returning the ith column of a matrix.

We can also isolate the purely network-driven part of the STIRF – which is the effect in excess of the original shock

$$STIRF_{i,t,\tau}^{e} = \begin{cases} e'\{D_t^{-1}\Lambda^{-1}M_t\}_{\cdot,i}\sigma - \sigma\sigma_i GDP_{i,t} \text{ for } \tau = 0 \\ e'\{D_{t+\tau}^{-1}\Lambda^{-1}\prod_{j=0}^{\tau-1} M_{t+\tau-j}A_{t+\tau-j}M_t\}_{\cdot,i}\sigma - \alpha^{\tau}\sigma\sigma_i GDP_{i,t} \text{ for } \tau \geq 1 \end{cases}$$

Figures 2 and 3 report $STIRF_{i,\tau}$ and $STIRF_{i,\tau}^{e}$ of, respectively, USD and EUR excess currency invoicing evaluated at the average adjacency matrix during the sample and average gross domestic product of each individual country.

Focusing on the USD denominated currency invoicing in Figure 2, China is the key player for USD invoicing: A one standard deviation shock generates a contemporaneous change in total ECI of 15 billion USD with about 10% of the effect driven by trade externalities. The United States follows in second place – this is mostly because China exports almost 1.5 times as much as the United States and invoices 92% of its exports in USD on average. Four other countries stand out: Japan, South Korea, Russia, and Germany. A one standard deviation shock to the ECI of these countries would result in a contemporaneous change (panel a) in total ECI of about 2.7-3.1 billion USD invoicing, i.e. about 0.5% of the total ECI in USD and a total cumulative effect (panel b) after 18 months of 15-21 billions – about 0.2% of total USD ECI over the same period. However, the drivers of these large effects are very different in nature, as outlined by the STIRFs in excess of the original shocks. For Russia, and to a lesser extent South Korea, the effects are almost entirely driven by the direct effect of a change in their USD invoicing, whereas for Germany, and to a lesser extent Japan, more than a third of the effect of a domestic shock is due to the network amplification and the central position that these countries have in the trade network. Furthermore, for countries such as Canada, the UK, Hong Kong, France, and the Netherlands, we also observe that a large share of the total effect is generated by network externalities.

Focusing on the EUR denominated currency invoicing in Figure 3, Germany is a clear outlier: a one standard deviation shock in this country would imply a contemporaneous change (panel a) of about 4 billion EUR (about 11.5% of total EUR ECI), with around 16% of the effect due to the network externalities generated by this country. Similarly, Germany generates the largest cumulative impulse-response after 18 months, with a total effect of about 15 billion EUR (or around 2.3% of EUR ECI over the same period). The second and third largest STIRFs are generated, in order of magnitude, by Italy and the United States (with STIRFs, respectively, about 75% and 50% of the German ones). Interestingly, albeit the effect of a shock to Italian EUR ECI is larger than that of the United States, the shocks arising in the latter are characterised by a larger degree of network amplification. It is worth noticing that Russia, with the ninth largest STIRFs, seems to play an important role also for the EUR denominated ECI but this effect, as in the USD case, is almost entirely direct in nature, rather than being amplified through the network.

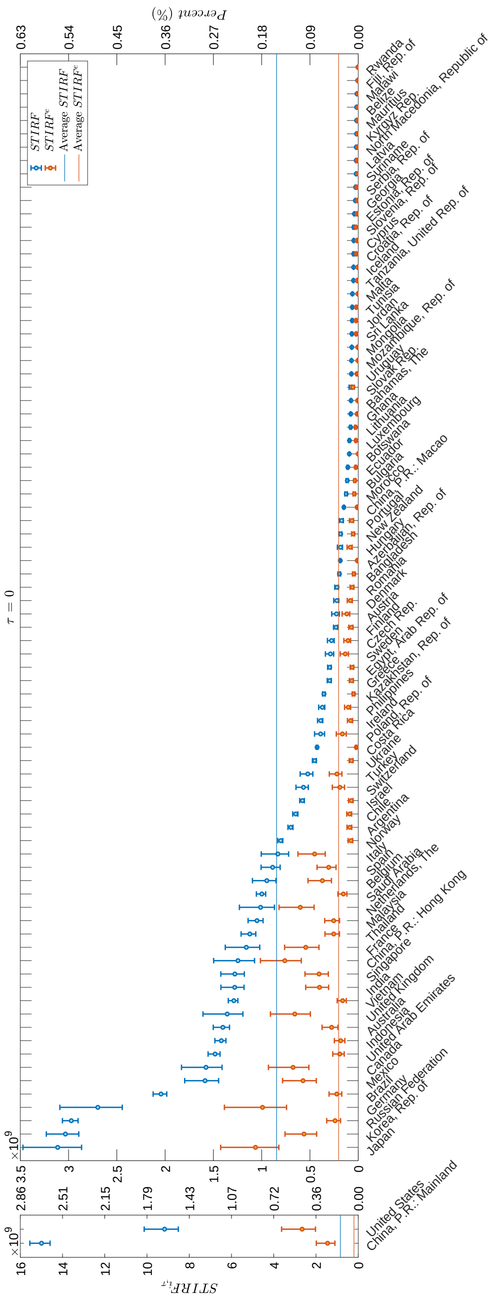
In Figures 7 and 8 of the appendix we report the network impulse-response functions for actual currency invoicing, rather than our excess invoicing measure, and find extremely similar results. Overall, the stability of the estimated effects is extremely reassuring.

VI.4 Cross-Currency and Export-Import Spillovers

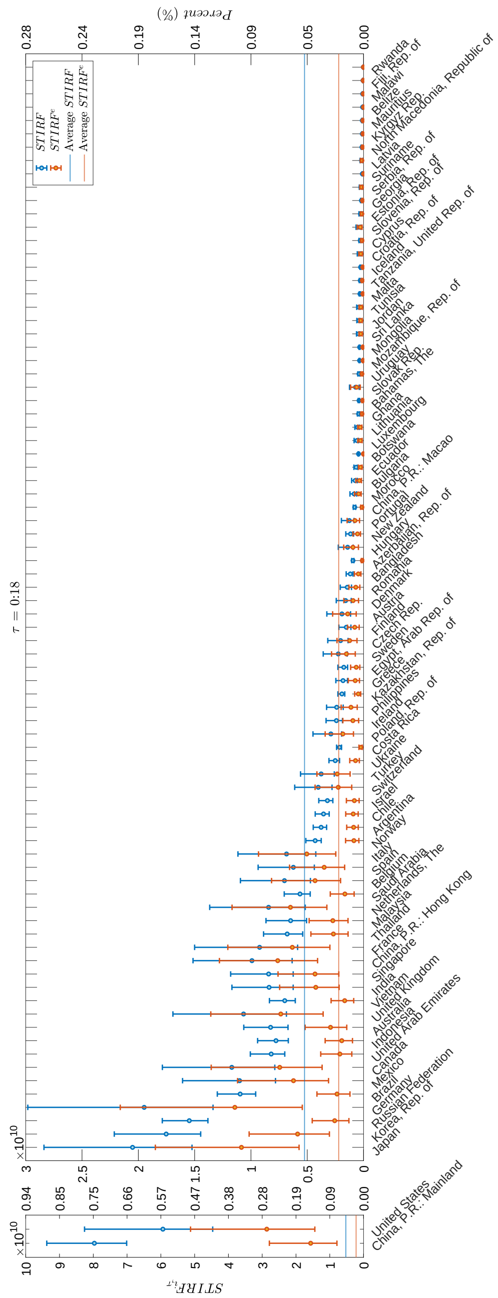
So far we have considered the determination of excess currency invoicing of exports in USD and EUR separately, while including as controls the lagged values of ECI in the currencies for both exports and imports. This allows us to consistently estimate the spatial spillovers in a specific currency export or import pair, but it does not provide an estimate of the *contemporaneous* links *within* a country of the ECI in different currencies and of imports and exports.

Nevertheless, our SDM specification implies that, after accounting for the spatial dependency, the estimation equations for the ECI in EUR and USD have the same structure as the

Figure 2: Impulse-Response Functions of USD Excess Currency Invoicing



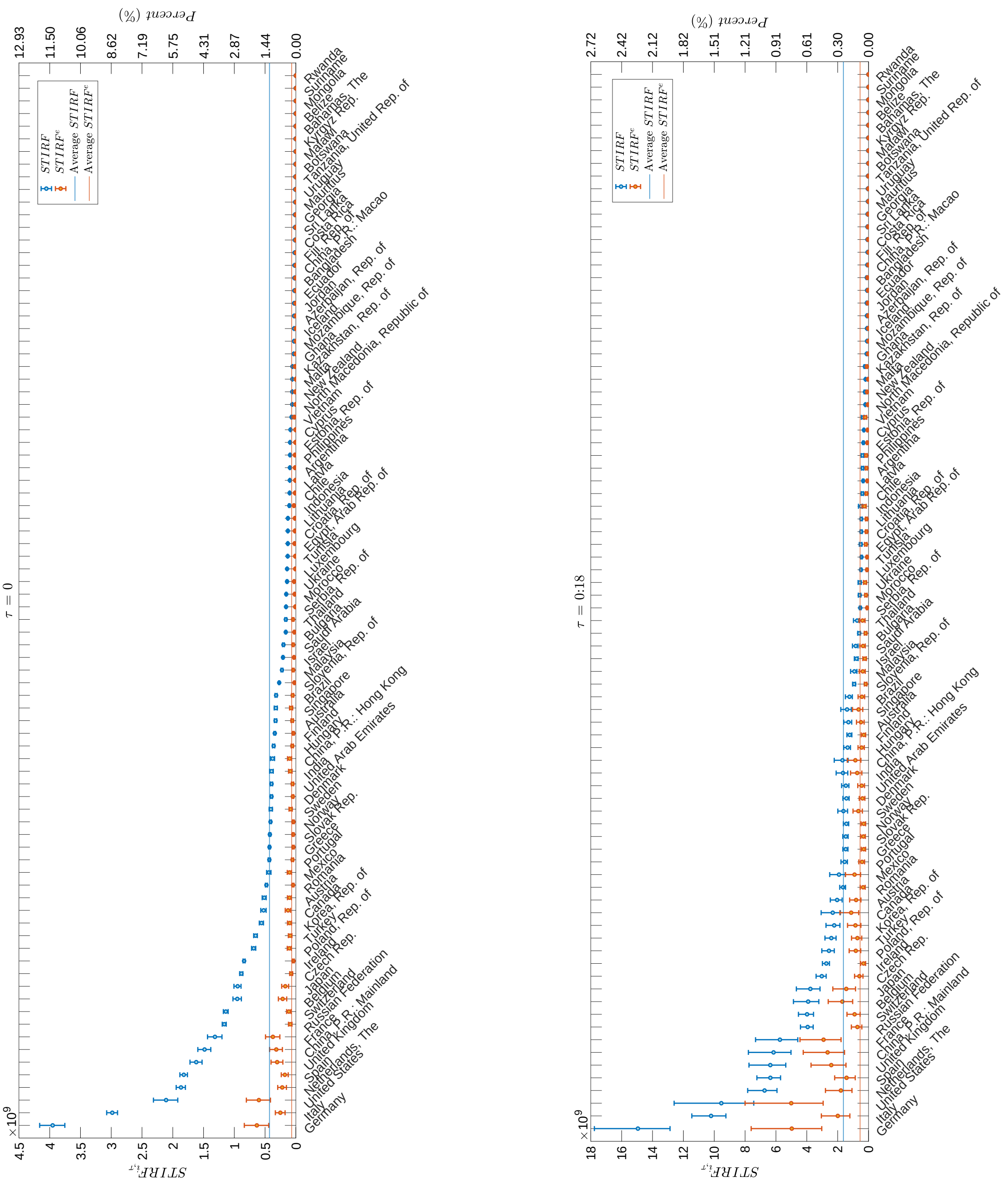
(a) Contemporaneous Effect



(b) Cumulated Effect over 18 Months

Spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = USD. Right axis = percentage of monthly total excess currency invoicing in USD over the same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage.

Figure 3: Impulse-Response Functions of EUR Excess Currency Invoicing



(a) Contemporaneous Effect **(b)** Cumulated Effect over 18 Months

Spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = EUR. Right axis = percentage of monthly total excess currency invoicing in EUR over the same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage.

corresponding equations of a reduced-form Vector Autoregression (VAR) system with four dependent variables (in addition to contemporaneously independent covariates and fixed effects): ECI in EUR and USD for *both* exports and imports. This observation implies that, by also estimating our SDM specification for the ECI of imports, we have a complete reduced-form VAR (with spatial dependencies in the mean processes) for these four variables. Hence, as in the Structural-VAR literature (see, e.g., Sims and Zha (1999)), one can recover the contemporaneous relationship between ECI of imports and exports and of different currencies, that is the matrix Γ, from the covariance matrix of the reduced-form VAR residuals.

Recall from (7) that $\epsilon_{i,t}$ correspond to country-specific shocks, which in our model in (1) is interpreted as shocks to a country's value of excess invoicing. To emphasise, $\epsilon_{i,t}$ measures the shock to a country without propagating it through the network system. It measures an idiosyncratic country-specific shock to the value of a country's excess invoicing. Using our estimates, we can calculate the $N_t \times 1$ vectors $\hat{\epsilon}^x_{k,t,b} = (I - \hat{\phi}^x_{k,b} G^x_t) y^x_{k,t} - (X_t \hat{\beta}^x_{k,b} + G^x_t X_t \hat{\theta}^x_{k,b})$, where k denotes the currency, t denotes the time period, b denotes the posterior sample draw, and x denotes the trade direction. Note that parameter estimates have subscript k and superscript x to emphasise that estimation is carried out separately on the four types of ECI (USD export, EUR export, USD import and EUR import).

For the sake of exposition, let us suppress the dependence on b, the posterior sample draw. We then organise countries residuals as a 4×1 vector $\hat{\epsilon}_{i,t} = [\hat{\epsilon}^{Im}_{\$,i,t}, \hat{\epsilon}^{Im}_{€,i,t}, \hat{\epsilon}^{Ex}_{\$,i,t}, \hat{\epsilon}^{Ex}_{€,i,t}]^\top$. Let Σ_i denote the corresponding covariance matrix of dimension 4×4. The covariance matrices Σ_i can be used to recover the matrix of contemporaneous linkages Γ_i, since $\Sigma_i \equiv \Gamma_i^{-1} \Lambda_i (\Gamma_i^\top)^{-1}$, where Λ_i is a diagonal matrix with entries equal to the country-specific variance of the structural shocks.

Since Σ_i is symmetric, it has only $\frac{4\times(4+1)}{2}$ distinct entries, while the matrix of contemporaneous linkages Γ_i has 4×4 free entries and the matrix of structural variances has 4 free entries, Γ_i and Λ_i cannot be recovered without imposing additional restrictions. To achieve identification, we assume that Γ_i is identical across countries, i.e. $\Gamma_i = \Gamma$. Put differently, we assume that all countries USD/ EUR- export/ import ECI react the same way to structural shocks. Notice that this still allows for cross-sectional heterogeneity in the structural variances, Λ_i. This implies that $\Sigma_i = \Gamma^{-1}\Lambda_i(\Gamma^{-1})^\top \ \forall\ i$. To emphasize, Γ encodes the contemporaneous relationships between ECI of import and export for different currencies for a specific country.

The above identification strategy mimics ideas from identification via time series heteroskedasticity. In these models, time variation in Σ_t is used to identify the structural parameters (see Brunnermeier, Palia, Sastry, and Sims (2021) for a recent example). Instead of time series variation, we utilize cross-sectional heteroskedasticity. That is, we use the variation in Σ_i to identify the structural parameters. The reason we opt for identification via cross-sectional heteroskedasticity is twofold. First, our dataset covers only a relatively short time period from 2004 to 2019. Second, by employing identification via heteroskedasticity, we are not required to take a stance on short-run, long-run, or sign restrictions, allowing us to identify effects under fairly general conditions. As long as the contemporaneous relationship matrix Γ is shared across the countries, identification via cross-sectional heteroskedasticity is possible.

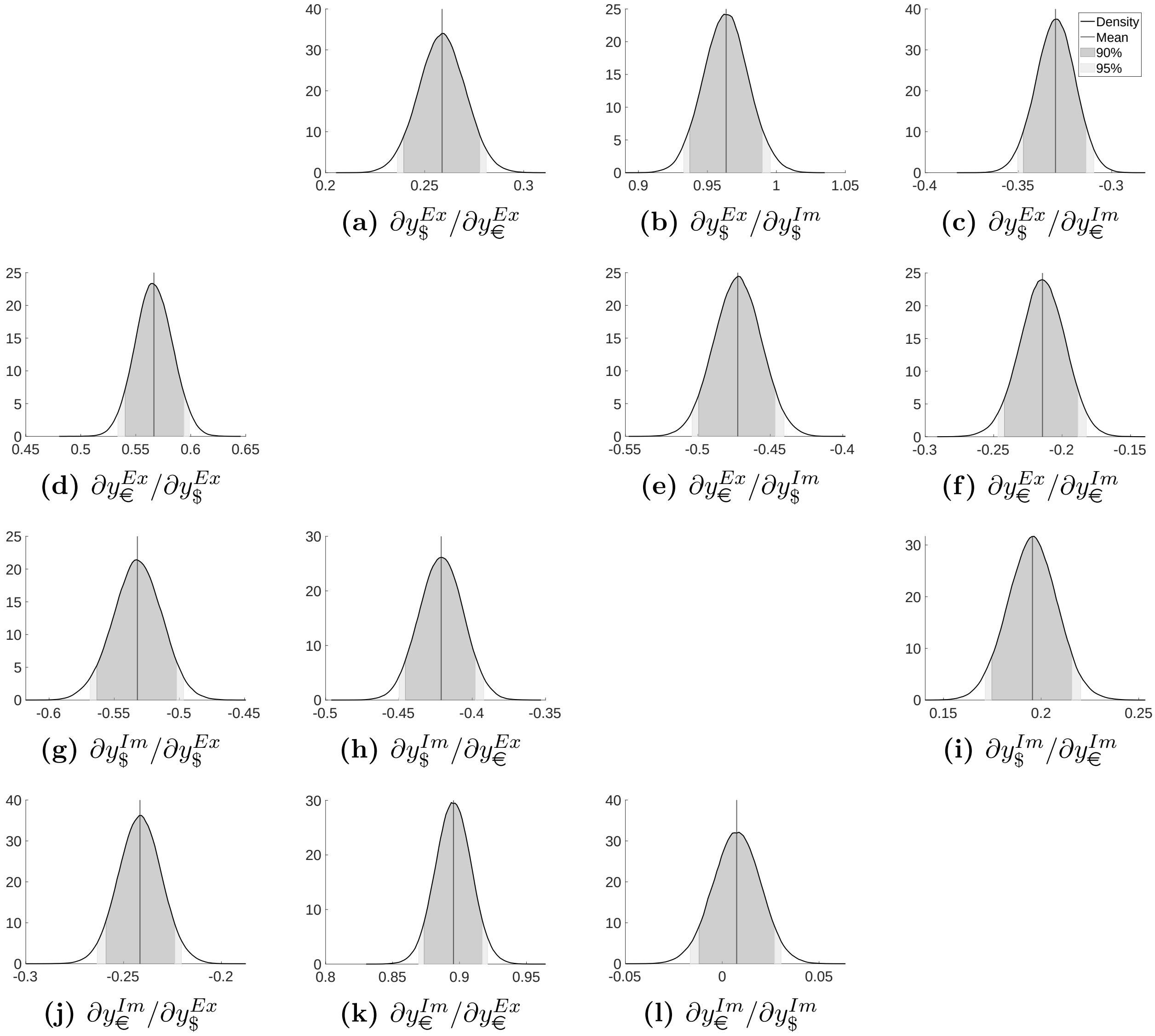
Note that the previous assumptions achieve identification for the different products of Γ and Λ_i, however, similar to Brunnermeier, Palia, Sastry, and Sims (2021), we cannot separate Γ from Λ_i[9]. Therefore, we need to impose one more restriction

$$\frac{1}{N}\sum_{i=1}^{N}\lambda_{k,i}^{x} = 1$$

where $\lambda_{k,i}^{x}$ is one of the diagonal elements of Λ_i. The interpretation of this normalization is that we force the cross-country average structural variance to be one in each equation. This ensures identification of Γ up to flipping the sign of a row and identification of Γ and the set of Λ_i up to permuting the order of rows. We rule out former permutations by requiring Γ to have a positive sign on the diagonal and the latter permutations by selecting the final rows to ensure that Γ has its largest element on the diagonal. We estimate Γ and Λ_i using Bayesian techniques. The estimation procedure yields posterior samples of the 4×4 matrix Γ_b, and details on the estimation are given in appendix A.2.4.

[9]Multiplying the rows of Γ and the set of Λ_i by scale factors leaves the likelihood function unchanged (see appendix A.2.4 equation (11)).

Figure 4: Cross-Currency and Export-Import Spillovers



(a) $\partial y^{Ex}_{\$} / \partial y^{Ex}_{€}$ **(b)** $\partial y^{Ex}_{\$} / \partial y^{Im}_{\$}$ **(c)** $\partial y^{Ex}_{\$} / \partial y^{Im}_{€}$

(d) $\partial y^{Ex}_{€} / \partial y^{Ex}_{\$}$ **(e)** $\partial y^{Ex}_{€} / \partial y^{Im}_{\$}$ **(f)** $\partial y^{Ex}_{€} / \partial y^{Im}_{€}$

(g) $\partial y^{Im}_{\$} / \partial y^{Ex}_{\$}$ **(h)** $\partial y^{Im}_{\$} / \partial y^{Ex}_{€}$ **(i)** $\partial y^{Im}_{\$} / \partial y^{Im}_{€}$

(j) $\partial y^{Im}_{€} / \partial y^{Ex}_{\$}$ **(k)** $\partial y^{Im}_{€} / \partial y^{Ex}_{€}$ **(l)** $\partial y^{Im}_{€} / \partial y^{Im}_{\$}$

The figures depict the posterior distribution of the elements of Γ, identified via cross-sectional heteroskedasticity. For the sake of interpretation, we have scaled the draws of Γ_b such that the diagonal only contains ones and then multiplied each row by negative one. Additionally, the figures depict the posterior mean, as well as 90% and 95% confidence intervals.

The posterior distribution of the off-diagonal elements of Γ – the contemporaneous effects matrix – is reported in Figure 4. Coefficients have been normalized such that contemporaneous partial derivatives between variables can be identified immediately. Several observations are in order.

First, we find some evidence of *natural hedging*, i.e. countries limiting their currency mismatch between imports and exports. Consider an increase in excessive USD denominated imports and focus on panels b and e. As the excessive USD denominated imports increase, USD denominated exports increase and EUR denominated exports decrease. This suggests that countries actively rebalance the currency denomination of their exports as they are faced with higher USD denominated imports. A similar pattern is observed for EUR denominated exports. Panels h and k illustrate that when countries excessive EUR denominated exports increase, in response USD denominated imports decrease and EUR denominated imports increase. These findings are in line with natural hedging and are fairly robust when considering our alternative aggregate currency invoicing measure (see Figure 9 in appendix A.4). Further, the coefficients in b and k are close to one, indicating almost perfect natural hedging for excessive currency invoicing – when considering aggregate currency invoicing these same coefficients are substantially below one. This indicates that the hedging motive is particularly prevalent when counterparties use a vehicle currency to conduct trade, i.e. when the currency does not correspond to the home currency of either involved country.

The responses associated with increases in excessive USD denominated exports and EUR denominated imports are less in line with natural hedging. Specifically, the posterior mean of the relevant coefficients in panel g and, respectively, panel f have the wrong sign. However, these coefficient estimates seem to be less robust as when considering our alternative aggregate currency invoicing measure the coefficient in g becomes insignificant and in f flips sign, i.e. starts to support natural hedging (see Figure 9). Furthermore, evaluating the joint responses associated with increases in excessive USD denominated exports or excessive EUR denominated imports (panels d, g, j and, respectively, c, f, i), could indicate that other currencies play a role not considered in the analysis here. For example, panels d, g, and j suggest that as excessive

USD denominated exports increase, so do excessive EUR denominated exports, but excessive USD and EUR denominated imports decrease. The increase in exports can be reconciled either with additional domestic production or imports denominated in another currency. However, with the data available to us this is difficult to distinguish.

Second, we find evidence of complementarity across currencies used for export and import invoicing. Panels a and d illustrate that generally as a country increases its excessive currency invoicing for exports in either currency, excessive invoicing of exports in the other currency also increases contemporaneously. This suggests that as a country increases its international exports, it tends to do so both in USD and EUR. Panels i and l suggest a similar pattern for imports. However, the response of excessive EUR denominated imports to excessive USD denominated imports is insignificant.

When examining aggregate currency invoicing (see Figure 9) the coefficients for d and l flip signs. This indicates that as a country increases its aggregate USD denominated exports (imports), their EUR denominated exports (imports) decrease. As aggregate EUR denominated exports or imports increase, their USD counterparties still increase. These patterns can be interpreted as confirming the dominant status of the USD over the EUR, at least for exports and imports evaluated in aggregate currency invoicing. The latter indicate that as a country exports or imports more, it does so in either currency, whereas the former stress the special role of the USD: EUR denominated trade is substituted for USD denominated trade.

VI.5 Counter-Factual Analysis

Suppose a country decides to permanently stop using a vehicle currency, and let us focus on the USD for exposition. This would lead to a reduction of $y^x_{i,USD,t+\tau}$ to zero for all τ. Notice that since we focus on excessive currency invoicing, this allows for countries to continue using the USD to trade with the United States but requires countries to use another currency as a vehicle currency, such as the EUR or Renminbi, when trading with other counterparties.

Within our framework, using our previous notation, we can view this as a shock $\epsilon^{\$}_{i,t}$, such that $y^{\$}_{i,t} = 0$ in period t. In period $t+1$, we then seek a shock $\epsilon^{\$}_{i,t+1}$, such that $y^{\$}_{i,t+1} = 0$, taking into account the previous shock $\epsilon^{\$}_{i,t}$. Due to scaling and the network effects, $\epsilon^{\$}_{i,t+\tau}$ is multiplied by a matrix $(D^{-1}_{t+\tau}\Lambda^{-1}M_{t+\tau}\Lambda D_{t+\tau})$, and it is therefore not immediately clear what size the shock must take.

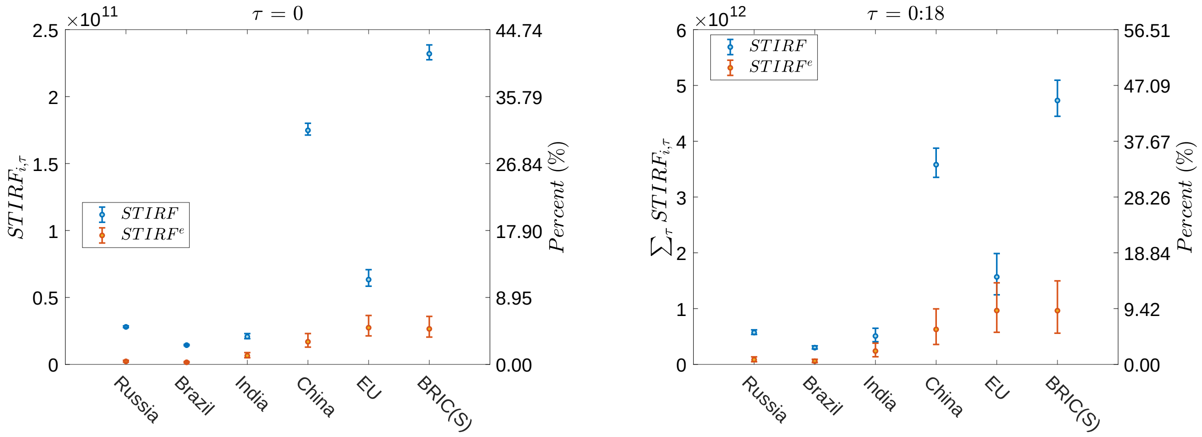
Let S denote a set of countries that we want to shock such that for $i \in S$, we require $y^{\$}_{i,t+\tau} = 0$. Let $|S|$ be the cardinality of set S and let $y^{\$}_{S,t+\tau}$ and $\epsilon^{\$}_{S,t+\tau}$ for $\tau \geq 0$ be the sequence of vectors of size $|S| \times 1$ containing ECI and shocks of countries within the set. Let $\{D^{-1}_{t+\tau}\Lambda^{-1}M_{t+\tau}\Lambda D_{t+\tau}\}_{S,S}$ denote the submatrix corresponding to the countries within the set. Using this notation, we can show that the sequence of shocks $\epsilon^{\$}_{S,t+\tau}$ needs to satisfy

$$0 = y^{\$}_{S,t+\tau} + \underbrace{\{D^{-1}_{t+\tau}\Lambda^{-1}M_{t+\tau}\Lambda D_{t+\tau}\}_{S,S}\epsilon^{\$}_{S,t+\tau}}_{\text{Impact of shock at } t+\tau}$$
$$+ \underbrace{\sum_{j=1}^{\tau}\{D^{-1}_{t+\tau}\Lambda^{-1}\prod_{i=0}^{j-1}M_{t+\tau-i}A_{t+\tau-i}M_{t+\tau-j}\Lambda D_{t+\tau-j}\}_{S,S}\epsilon^{\$}_{S,t+\tau-j}}_{\text{Impact of shocks up until } t+\tau-1}$$

Assuming that $\{D^{-1}_{t+\tau}\Lambda^{-1}M_{t+\tau}\Lambda D_{t+\tau}\}_{S,S}$ is invertible, the above has a unique solution and allows us to solve for $\epsilon^{\$}_{S,t+\tau}$ sequentially. That is, given $\epsilon^{\$}_{S,t}$, we can determine $\epsilon^{\$}_{S,t+1}$. Then given $\epsilon^{\$}_{S,t}$ and $\epsilon^{\$}_{S,t+1}$, we can determine $\epsilon^{\$}_{S,t+2}$, and so forth. Once these shocks are obtained, we can calculate the STIRFs of each shock and aggregate them to assess the impact on total excessive currency invoicing over time.

Figure 5 depicts this counterfactual exercise for Russia, Brazil, India, and China individually, the EU block, and the members of BRICS in our sample (Brazil, Russia, India and China jointly). The calculations are done using average values. The estimated effects are quantitatively large, with the effects of the BRIC(S) block (EU) abandoning the USD for excess invoicing resulting in a 42% (11%) reduction in the overall use of this currency. But the channels through which these large effects arise are quite different. In the case of the BRIC(S) countries, most of the effect is driven by the direct reduction in the use of this currency by these countries, while in the EU case almost half of the effect is due to network externalities. That is, due to the EU

Figure 5: Counterfactual: Abandonment of USD as Vehicle Currency



(a) Contemporaneous Effect

(b) Cumulative Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a shock sequence that sets the excessive currency invoicing of the specified countries to zero permanently. EU contains all 19 Euro Area countries, while BRIC(S) contain the BRICS countries excluding South Africa, due to missing observations. Left axis = USD. Right axis = percentage of monthly total excess currency invoicing in USD. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 month. Box-plots report posterior means and centered 95% posterior coverage.

countries central role in the trade network, and the strategic complementarity in the invoicing currency choice, if the block were to abandon the USD, the consequent reduction in the usage of this currency would almost double the direct effect.

To emphasize, the figures depict the impact on total excessive currency invoicing if the aforementioned sets of countries stop using the USD as vehicle currency permanently. The exercise still allows for countries to continue trading in USD or EUR with the United States or the EU, respectively. In Figures 10 of the appendix we report results on the same exercise using aggregate currency invoicing. The findings are similar.

The above counterfactual stresses the inherent fragility of the dominant currency equilibrium we uncover in the data: In the presence of strategic complementarity in currency choice, the abandonment of the dominant currency by players that are large or central to the trade network can have dramatic effects.

VII Conclusion

In this paper, we examine the drivers of dominant currency invoicing for cross-border trades by constructing and estimating an equilibrium network model. The network externality arises because when choosing in which foreign currency to invoice their trades, besides being affected by its own macro and microeconomic conditions, agents are impacted by their trading partners' invoicing decisions either due to balance sheet hedging, competition, financing considerations or various other reasons.

Our estimation results show strong evidence of strategic complementarity in currency invoicing across countries: Exporting countries tend to invoice more in a given currency when their main trade partners invoice in that same currency. We find that the USD as a dominant currency is less stable than the EUR. The estimated network attenuation factor, ϕ, for the USD export trade is 0.241 and for the EUR export trade is 0.159. This suggests that there is a higher degree of complementarity for USD invoicing than for EUR invoicing. Conversely, this underscores that the USD as a dominant currency is more fragile than for example the EUR – the ϕ coefficients imply an average shock amplification of about 32% for the USD export ECI compared to 19% for the EUR export ECI.

We also identify key players in a given dominant currency, that is, countries that would have a sizeable impact if they were to abandon a certain dominant currency. Some of these key player countries are those that invoice most of their exports in that foreign currency (e.g., China, South Korea, and Russia). Some are countries that are central in the international trade network (e.g., Japan, Germany, and Canada). Furthermore, we find evidence for strategic complementarity between the choices of export and import currencies supporting the balance sheet hedging hypotheses for currency invoicing.

Finally, we conduct counterfactual analyses to examine how the use of dominant currency for trade invoicing were impacted if some countries were to abandon the USD in coordination. We find that if the BRIC(S) block (EU) were to bring their excessive invoicing in USD to zero, there would be a 42% (11%) reduction in the usage of USD in international trade with countries other than the United States.

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A Appendix

A.1 Data

A.1.1 Excessive Currency Invoicing

We define excessive currency invoicing as in (9), that is, as the aggregate exports (imports) per country and currency in excess of exports (imports) to (from) countries that have such currency as their base currency, in USD equivalent amounts. To construct excessive currency invoicing we will rely on data on the value of merchandise imports and exports disaggregated according to a country's trading partners and on data on the shares of aggregate exports (imports) invoiced in USD and EUR by countries.

The data on exports (imports) trades between countries over time is obtained from the Direction of Trade Statistics database of the International Monetary Fund at monthly frequency in USD equivalent amounts. Import trades are quoted as cost, insurance and freight and translated to free-on-board by dividing reported values by 1.1 before January 2000 and by 1.06 thereafter, following IMF (2018). Export trades are quoted as free-on-board. Where possible, missing import (export) values of a country from (to) its counterparty are filled with observed export (import) values of the counterparty to (from) the country. This leaves us with monthly unbalanced import (export) trade data for 216 different countries from January 1960 to January 2022.

The data on the shares of aggregate imports (exports) invoiced by USD and EUR are taken from Boz, Casas, Georgiadis, Gopinath, Le Mezo, Mehl, and Nguyen (2022) and are at annual frequency. We keep only payment share data on the USD and EUR due to data coverage issues. This leaves us with data on payment shares for the USD, EUR, and "*Other excluding EUR and USD*" for imports and exports. We found that in seven cases the last category for exports reported a negative value. In these cases we set the value to zero and renormalize the other shares.

Data for several key countries, such as China, Mexico, and Canada, are missing or poorly covered by the Boz, Casas, Georgiadis, Gopinath, Le Mezo, Mehl, and Nguyen (2022) dataset. For this reason, we augment the dataset with proprietary data obtained from SWIFT on payment settlements across borders. These data are available to us for several countries at monthly frequency, broken down by counterparty country, currency and message type. We focus on message types MT400, which is an advice of payment, and MT700, which is an issue of a documentary credit. Both message types are directly related to trade activity. From this we calculate for each country the shares of aggregate payments sent (imports) or received (exports) in USD and EUR at monthly frequency. To combine the SWIFT payment share data with the annual payment share data by Boz, Casas, Georgiadis, Gopinath, Le Mezo, Mehl, and Nguyen

(2022), we average the SWIFT data for each year. This allows us to augment the payment share dataset with data on eleven countries[10] from 2011 to 2022.

To combine the annual payment share data with the monthly import (export) data, we assume that payment shares are constant throughout the reporting year. This leaves us with annual unbalanced payment share data for 119 different countries from 1989 to 2019.

Following our definition in (9), we first aggregate import (export) trades of a country across counterparties. We then multiply the resulting value by the aggregate import (export) invoicing share for the USD or EUR. Finally, we obtain USD excessive currency invoicing by deducting the import (export) trade with the United States. To obtain EUR excessive currency invoicing, we deduct the import (export) trades with countries that were members of the Euro Area at the respective point in time. This leaves us with monthly unbalanced excessive currency invoicing data for 119 different countries from January 1989 to December 2022.

A.1.2 Consumer Price Index Data

We construct inflation and inflation volatility of the consumer price index (CPI) of a country.

The data on the CPI of each country is obtained from the International Financial Statistics and Consumer Price Index (CPI) database of the International Monetary Fund at monthly frequency. For New Zealand and Australia, the CPI was not available at monthly frequency. Hence, we used CPI data at quarterly frequency. For Argentina no CPI data were available. Hence, consumer price implied inflation was taken from the Instituto Nacional de Estadistica y Censos Republica Argentina at monthly frequency.

We first linearly interpolate the raw data to monthly frequency where necessary. We then calculate the implied inflation rate of a country as the percentage change in the inflation index. To this we add the Argentinian inflation data. This leaves us with monthly unbalanced inflation data for 185 different countries from January 1989 to December 2022.

To obtain inflation volatility, a GARCH(1,1) model is fit to the inflation data. The GARCH(1,1) model is fit in an expanding fashion for each country separately and requires at least 24 initial inflation datapoints. If inflation data are missing within the estimation window, due to the data being unbalanced, we linearly interpolate the inflation data. From the fitted model we then infer the monthly volatility at the end of the estimation window and multiply it by $\sqrt{12}$.

[10]The countries are Mexico, Singapore, the United Arab Emirates, Vietnam, China, Hong Kong, Canada, Taiwan, Libya, Cuba, and Sri Lanka. Data on more countries are available, however, were disregarded due to data quality concerns. Specifically, to add a country, we first calculate the total imports/ exports of a country implied by the SWIFT dataset. We then calculate the correlation of changes in SWIFT-based imports/ exports with changes in imports/ exports reported in the Direction of Trade Statistics database. We keep a country only if the correlation is above 0.2 for both imports and exports. We have made two exceptions to this rule: Canada exhibited a correlation of 0.195 for imports and Mexico exhibited a correlation of 0.12 for exports. Due to the size and role within international trade we kept these in the final dataset.

This leaves us with monthly unbalanced inflation volatility data for 185 different countries from December 1990 to December 2022.

A.1.3 Exchange Rate Data

We construct the change and realised volatility of the exchange rate of a country with the USD and the EUR.

The exchange rate data are obtained from Reuters and the Bank of International Settlement Statistics Warehouse at daily frequency. We use the latter database for Euro Area countries as it in our experience accurately accounts for changes in the home currency of countries, i.e. the adoption of the EUR by some countries. We measure exchange rates as the amount of a country's currency per USD (EUR).

Based on the raw data, we calculate the average exchange rate prevailing within each month. We then calculate the change in monthly average exchange rates with the USD (EUR) for each country. Given how we measure exchange rates, a positive change corresponds to a country's currency depreciating, whilst a negative change corresponds to a countries currency appreciating with respect to the USD (EUR). This leaves us with monthly change in exchange rate data for 149 different countries from February 2000 to August 2022.

To obtain realised exchange rate volatility with the USD (EUR), we calculate the daily log return for each exchange rate. We then calculate realised exchange rate volatility within each month. Finally, we multiply the volatility measure with $\sqrt{252}$. To calculate the volatility measure, we require at least 15 observations within each month. This leaves us with monthly realised exchange rate volatility data for 149 different countries from January 2000 to August 2022.

A.1.4 Trade Share Data

We construct the percentage trade share of a country out of aggregate import (export) trades.

Data on import (export) trades between countries over time is obtained from the Direction of Trade Statistics database of the International Monetary Fund at monthly frequency in USD equivalent amounts. We clean the raw data following the same steps as in section A.1.1 and are left with monthly trade data.

To obtain the import (export) trade share of a country out of total trades, we first calculate the total aggregate imports (exports), aggregated across counterparties and countries, at each point in time. We then aggregate the imports (exports) of a country across counterparties. Finally, we divide a country's aggregate imports (exports) by the total aggregate imports (exports). This leaves us with monthly trade shares for 216 different countries from January 1960 to January 2022.

A.1.5 Foreign Debt by Firms

We use data on the aggregate amount of firm-level debt denominated in USD and the EUR and its change, measured in USD equivalents.

Data on firm-level debt-instruments aggregated by industry are obtained from Mrkaic, Kim, and Mano (2020) at annual frequency. We first aggregate the raw data by industry and debt-instrument type, leaving us with annual data for USD and EUR denominated debt by country. We then linearly interpolate the raw data to monthly frequency. This leaves us with monthly unbalanced aggregate firm-level debt data for 141 different countries from December 2005 to December 2020.

Based on the aggregate firm-level debt data we also calculate its change. This leaves us with monthly unbalanced change in aggregate firm-level debt data for 139 different countries from January 2006 to December 2020.

A.1.6 Swap Line Data

We construct a dummy variable indicating whether a swap line existed between a country and the United States Federal Reserve (FED) or the European Central Bank (ECB).

We obtain data on swap line agreements from Tokuoka, Shin, Rao, and Perks (2021) and from The Yale Program on Financial Stability swap line database. To construct our dummy variable, we checked in both databases whether throughout a month a country had a swap line in place with the FED or ECB. If a swap line was in place, the dummy variable takes value one. We construct the swap line dummy variable at monthly frequency for the 119 countries in our excessive currency invoicing sample from April 1994 to December 2019.

A.1.7 Financial Market Index Data

We construct the change of the financial market index as developed by Svirydzenka (2016). The index aims to summarise the development of financial institutions and financial markets in terms of their depth, access, and efficiency.

Data on the index by country are obtained from the Financial Development Index database of the International Monetary Fund at annual frequency. We first linearly interpolate the index to monthly frequency and then calculate its change. This leaves us with monthly unbalanced change in financial market index data for 187 different countries from January 1981 to December 2019.

A.1.8 Foreign Direct Investment Data

We use foreign direct investment equity flows into or out of the reporting economy, measured in USD equivalents.

Data on foreign direct investment flows by country is obtained from the Balance of Payments database of the World Bank at annual frequency. We linearly interpolate the data to monthly frequency. This leaves us with monthly unbalanced data on foreign direct investment inflows (outflows) for 193 (187) different countries from December 1970 to December 2021.

A.1.9 Gross Domestic Product Data

We use nominal gross domestic product data, measured in USD equivalents.

Data on nominal gross domestic product by country is obtained from the International Financial Statistics database by the International Monetary Fund at annual and quarterly frequencies in local currency. First, we combine the annual and quarterly databases to obtain better country coverage. To do so, we divide the annual figures by four and repeat them throughout the quarters within a year. We then linearly interpolate the data to monthly frequency. Lastly, using our average monthly exchange rate data (see section A.1.3), we translate the gross domestic product to USD equivalents. This leaves us with monthly unbalanced data on nominal gross domestic product for 104 different countries from January 2000 to June 2022.

A.2 Additional Estimation Details

We estimate four different models (Panel, SEM, SLM, and SDM) using Bayesian methods in our empirical analysis. Throughout we assume a flat prior on $\beta := [\delta^\top, \rho^\top]^\top$, θ, and σ^2 and a uniform prior for ϕ over $[-1, 1]$. Below we describe the posterior sampling algorithms for the three spatial model specifications (SDM, SLM and SEM), while we omit for brevity the one of the simple panel model since it is readily available in the literature (see, e.g., Lancaster (2004)).

It will be convenient to define some notation. As we allow for unbalanced samples in our estimation approach, the number of cross-sectional observation available per period, N_t, changes over time. Let $N = \sum_{t=1}^{T} N_t$ denote the total number of observations in our sample. At each point in time, let $y_t = [y_{1,t}, ..., y_{N_t,t}]^\top$ be the $N_t \times 1$ vector containing our dependent variable observations, let $X_t = [x_{1,t}, ..., x_{N_t,t}]^\top$ be the $N_t \times k$ matrix containing our independent variable observations, and let $\mathbf{G}_t$ be the $N_t \times N_t$ matrix containing the row standardized network weights (hence, $\mathbf{G}_t$ is always a right stochastic matrix). Define the $N \times 1$ vector $y = [y_1, ..., y_T]^\top$, the $N \times k$ matrix $X = [X_1^\top, ..., X_T^\top]^\top$, and the block-diagonal $N \times N$ matrix $\mathbf{G}$ containing $\mathbf{G}_t$ $\forall$ t as its diagonal elements. Furthermore, let I be the $N \times N$ identity matrix, $\tilde{y} = (I - \phi\mathbf{G})y$, and $\tilde{X} = (I - \phi\mathbf{G})X$. We will always be conditioning on the matrix of independent variables

X and the network matrix $\mathbf{G}$. Hence, for brevity, we will leave this conditioning implicit in the notation.

A.2.1 Spatial Error Model

The model takes the form $(I - \phi\mathbf{G})y = (I - \phi\mathbf{G})X\beta + \epsilon$, where $\epsilon \sim N(0, \sigma^2 I)$. Conditional on ϕ, a flat prior on β and σ^2 yields the normal-inverse-gamma posterior distribution for β and σ^2 of a linear regression model of $\tilde{y}$ on $\tilde{X}$. That is,

$$p(\beta|y, \sigma^2, \phi) \sim N(\hat{\beta}, (\tilde{X}^\top \tilde{X})^{-1}\sigma^2)$$
$$p(\sigma^2|y, \phi) \sim \text{Inv-}\Gamma((N-k)/2 - 1, N\hat{\sigma}^2/2)$$

where $\hat{\beta}$ is the OLS coefficient of a regression of $\tilde{y}$ on $\tilde{X}$ and $\hat{\sigma}^2$ is the corresponding OLS estimate of the residual variance.

The posterior of ϕ conditional on β and σ^2 is non-standard, but can be readily obtained by writing the likelihood[11] for y and dropping the terms that do not affect the posterior shape. This gives us

$$p(\phi|y, \beta, \sigma^2) \propto |I - \phi\mathbf{G}| exp\Big(-\frac{1}{2\sigma^2}[\tilde{y} - \tilde{X}\beta]^\top [\tilde{y} - \tilde{X}\beta]\Big)$$

The above is a non-standard distribution, but we can take draws from it using a Metropolis-Hastings (MH) approach. To do so, we use a Gaussian proposal distribution. To ensure that $|\phi| < 1$ (see proposition 1), we always discard draws outside of the support $[-1, 1]$ by modifying the acceptance rate.

The Gibbs sampling algorithm, with a nested MH component, to draw from the posterior distribution is then as follows:

1. Initialization:
   - Set $b = 1$ and set a starting value ϕ_0
2. OLS step:
   - Compute $\hat{\beta} = (\tilde{X}^\top \tilde{X})^{-1}\tilde{X}^\top \tilde{y}$ and $\hat{\sigma}^2 = (\hat{\epsilon}^\top \hat{\epsilon})/(N-k)$, where $\hat{\epsilon} = \tilde{y} - \tilde{X}\hat{\beta}$
3. Draw β and σ^2:
   - Draw σ_b^2 from $\text{Inv-}\Gamma((N-k)/2 - 1, N\hat{\sigma}^2/2)$
   - Draw β_b from $N(\hat{\beta}, (\tilde{X}^\top \tilde{X})^{-1}\sigma_b^2)$
4. Draw ϕ using MH:
   - Draw ϕ_c from $N(\phi_{b-1}, c^2)$
   - Calculate the acceptance rate $r = min(1, \frac{p(\phi_c|y,\beta_b,\sigma_b^2)q(\phi_{b-1}|\phi_c)}{p(\phi_{b-1}|y,\beta_b,\sigma_b^2)q(\phi_c|\phi_{b-1})}, \mathbb{1}(|\phi_c| \leq 1))$, where $q(\phi_{b-1}|\phi_c)$ is $N(\phi_c, c^2)$ evaluated at ϕ_{b-1} and $p(\phi_c|y, \beta_b, \sigma_b^2)$ is the derived posterior of ϕ evaluated at ϕ_c, β_b and σ_b^2. $q(\phi_c|\phi_{b-1})$ and $p(\phi_{b-1}|y, \beta_b, \sigma_b^2)$ are defined similarly

[11] This is simply the likelihood of $y = X\beta + \eta$, where $\eta \sim N(0, \sigma^2(I - \phi G)^{-1}[(I - \phi G)^{-1}]^\top)$.

- Set $\phi_b = \phi_c$ with probability r, else set $\phi_b = \phi_{b-1}$. If $\phi_b = \phi_c$, set $ac_b = 1$
- Calculate $acr = \sum_{j=1}^{b} ac_j/b$. If $acr < 0.4$, set $c = c/1.1$. If $acr > 0.6$, set $c = 1.1c$

5. Increase b by one and repeat from point 2 above.

Repeating the above B times, after discarding an initial set of draws, leaves us with a set of parameter draws from the posterior. We always set $B = 50000$, discard the first 5000 draws, set $\phi_0 = 0.5$, and initialize $c = 0.2$.

A.2.2 Spatial Lag Model

The model takes the form $(I - \phi G)y = X\beta + \epsilon$, where $\epsilon \sim N(0, \sigma^2 I)$. Conditional on ϕ, a flat prior on β and σ^2 yields the normal-inverse-gamma posterior distribution for β and σ^2 of a linear regression model of $\tilde{y}$ on X. That is,

$$
\begin{aligned}
p(\beta|y, \sigma^2, \phi) &\sim N(\hat{\beta}, (X^\top X)^{-1}\sigma^2) \\
p(\sigma^2|y, \phi) &\sim \text{Inv-}\Gamma((N-k)/2 - 1, N\hat{\sigma}^2/2)
\end{aligned}
$$

where $\hat{\beta}$ is the OLS coefficient of $\tilde{y}$ on X and $\hat{\sigma}^2$ is the corresponding OLS estimate of the residual variance.

The posterior of ϕ conditional on β and σ^2 is non-standard, but can be readily obtained by writing the likelihood[12] for y and dropping the terms that do not affect the posterior shape. This gives us

$$
p(\phi|y, \beta, \sigma^2) \propto |I - \phi \mathbf{G}| exp\bigg(- \frac{1}{2\sigma^2}[\tilde{y} - X\beta]^\top [\tilde{y} - X\beta] \bigg)
$$

The above is a non-standard distribution, but we can take draws from it using a Metropolis-Hastings (MH) approach. To do so, we use a Gaussian proposal distribution. To ensure that $|\phi| < 1$ (see proposition 1), we always discard draws outside of the support $[-1, 1]$ by modifying the acceptance rate.

The Gibbs sampling algorithm, with a nested MH component, to draw from the posterior distribution is then as follows:

1. Initialization:
    - Set $b = 1$ and set a starting value ϕ_0
2. OLS step:
    - Compute $\hat{\beta} = (X^\top X)^{-1} X^\top \tilde{y}$ and $\hat{\sigma}^2 = (\hat{\epsilon}^\top \hat{\epsilon})/(N-k)$, where $\hat{\epsilon} = \tilde{y} - X\hat{\beta}$
3. Draw β and σ^2:
    - Draw σ_b^2 from Inv-$\Gamma((N-k)/2 - 1, N\hat{\sigma}^2/2)$
    - Draw β_b from $N(\hat{\beta}, (X^\top X)^{-1}\sigma_b^2)$
4. Draw ϕ using MH:

[12] This is simply the likelihood of $y = (I - \phi G)^{-1} X\beta + \eta$, where $\eta \sim N(0, \sigma^2 (I - \phi G)^{-1} [(I - \phi G)^{-1}]^\top)$.

- Draw ϕ_c from $N(\phi_{b-1}, c^2)$
- Calculate the acceptance rate $r = min(1, \frac{p(\phi_c|y,\beta_b,\sigma_b^2)q(\phi_{b-1}|\phi_c)}{p(\phi_{b-1}|y,\beta_b,\sigma_b^2)q(\phi_c|\phi_{b-1})}, \mathbb{1}(|\phi_c| \leq 1))$, where $q(\phi_{b-1}|\phi_c)$ is $N(\phi_c, c^2)$ evaluated at ϕ_{b-1} and $p(\phi_c|y, \beta_b, \sigma_b^2)$ is the derived posterior of ϕ evaluated at ϕ_c, β_b and σ_b^2. $q(\phi_c|\phi_{b-1})$ and $p(\phi_{b-1}|y, \beta_b, \sigma_b^2)$ are defined similarly
- Set $\phi_b = \phi_c$ with probability r, else set $\phi_b = \phi_{b-1}$. If $\phi_b = \phi_c$, set $ac_b = 1$
- Calculate $acr = \sum_{j=1}^{b} ac_j/b$. If $acr < 0.4$, set $c = c/1.1$. If $acr > 0.6$, set $c = 1.1c$

5. Increase b by one and repeat from point 2 above.

Repeating the above B times, after discarding an initial set of draws, leaves us with a set of parameter draws from the posterior. We always set $B = 50000$, discard the first 5000 draws, set $\phi_0 = 0.5$, and initialize $c = 0.2$.

A.2.3 Spatial Durbin Model

The model takes the form $(I - \phi\mathbf{G})y = X\beta + \mathbf{G}X_s\theta + \epsilon$, where $\epsilon \sim N(0, \sigma^2 I)$. The matrix X_s is of dimension $N \times s$ with $s \leq k$ and contains a subset of the matrix X. This allows for spatial lags of some independent variables to enter the model. It will be convenient to define $Z = [X, \mathbf{G}X_s]$ and $\gamma = [\beta^\top, \theta^\top]^\top$. Conditional on ϕ, a flat prior on γ and σ^2 yields the normal-inverse-gamma posterior distribution for γ and σ^2 of a linear regression model of $\tilde{y}$ on X. That is,

$$p(\gamma|y, \sigma^2, \phi) \sim N(\hat{\gamma}, (Z^\top Z)^{-1}\sigma^2)$$
$$p(\sigma^2|y, \phi) \sim \text{Inv-}\Gamma((N - k - s)/2 - 1, N\hat{\sigma}^2/2)$$

where $\hat{\gamma}$ is the OLS coefficient of $\tilde{y}$ on Z and $\hat{\sigma}^2$ is the corresponding OLS estimate of the residual variance.

The posterior of ϕ conditional on γ and σ^2 is non-standard, but can be readily obtained by writing the likelihood[13] for y and dropping the terms that do not affect the posterior shape. This gives us

$$p(\phi|y, \gamma, \sigma^2) \propto |I - \phi G| exp\Big(- \frac{1}{2\sigma^2}[\tilde{y} - Z\gamma]^\top[\tilde{y} - Z\gamma]\Big)$$

The above is a non-standard distribution, but we can take draws from it using a Metropolis-Hastings (MH) approach. To do so, we use a Gaussian proposal distribution. To ensure that $|\phi| < 1$ (see proposition 1), we always discard draws outside of the support $[-1, 1]$ by modifying the acceptance rate.

The Gibbs sampling algorithm, with a nested MH component, to draw from the posterior distribution is then as follows:

1. Initialization:
   - Set $b = 1$ and set a starting value ϕ_0

[13]This is simply the likelihood of $y = (I - \phi G)^{-1}Z\gamma + \eta$ where $\eta \sim N(0, \sigma^2(I - \phi G)^{-1}[(I - \phi G)^{-1}]^\top)$.

2. OLS step:
   - Compute $\hat{\gamma} = (Z^\top Z)^{-1} Z^\top \tilde{y}$ and $\hat{\sigma}^2 = (\hat{\epsilon}^\top \hat{\epsilon})/(N-k-s)$, where $\hat{\epsilon} = \tilde{y} - Z\hat{\gamma}$
3. Draw γ and σ^2:
   - Draw σ_b^2 from Inv-$\Gamma((N-k-s)/2-1, N\hat{\sigma}^2/2)$
   - Draw γ_b from $N(\hat{\gamma}, (Z^\top Z)^{-1}\sigma_b^2)$
4. Draw ϕ using MH:
   - Draw ϕ_c from $N(\phi_{b-1}, c^2)$
   - Calculate the acceptance rate $r = min(1, \frac{p(\phi_c|y,\gamma_b,\sigma_b^2)q(\phi_{b-1}|\phi_c)}{p(\phi_{b-1}|y,\gamma_b,\sigma_b^2)q(\phi_c|\phi_{b-1})}, \mathbb{1}(|\phi_c| \leq 1))$, where $q(\phi_{b-1}|\phi_c)$ is $N(\phi_c, c^2)$ evaluated at ϕ_{b-1} and $p(\phi_c|y, \gamma_b, \sigma_b^2)$ is the derived posterior of ϕ evaluated at ϕ_c, γ_b and σ_b^2. $q(\phi_c|\phi_{b-1})$ and $p(\phi_{b-1}|y, \gamma_b, \sigma_b^2)$ are defined similarly
   - Set $\phi_b = \phi_c$ with probability r, else set $\phi_b = \phi_{b-1}$. If $\phi_b = \phi_c$, set $ac_b = 1$
   - Calculate $acr = \sum_{j=1}^{b} ac_j/b$. If $acr < 0.4$, set $c = c/1.1$. If $acr > 0.6$, set $c = 1.1c$
5. Increase b by one and repeat from point 2 above.

Repeating the above B times, after discarding an initial set of draws, leaves us with a set of parameter draws from the posterior. We always set $B = 50000$, discard the first 5000 draws, set $\phi_0 = 0.5$, and initialize $c = 0.2$.

A.2.4 Γ Estimation via Heterogeneous SVAR

For exposition we consider the SDM case. Let x denote the dataset, i.e. $x \in \{EUR{-}Im, USD{-}Im, EUR-Ex, USD-Ex\}$. Define $Z_t^x = [X_t, G_t^x X_t]$, $\gamma^x = [(\beta^x)^\top, (\theta^x)^\top]^\top$, and $\epsilon_t^x = (I - \phi^x G_t^x) y_t^x - Z_t^x \gamma^x$. Denote by $\boldsymbol{\epsilon_{i,t}} = [\epsilon_{USD,i,t}^{Im}, \epsilon_{EUR,i,t}^{Im}, \epsilon_{USD,i,t}^{Ex}, \epsilon_{EUR,i,t}^{Ex}]^\top$ the 4×1 vector of residuals for a specific country. Let $\boldsymbol{\epsilon_i}$ be the corresponding $4 \times T_i$ matrix of residuals for country i. Define $\tilde{\boldsymbol{y}}_i$ as the $T_i \times 4$, matrix where the element in row t and column x is $\tilde{y}_{i,t}^x = \{(I - \phi^x G_t^x)\}_{i.} y_t^x$. Define $\boldsymbol{Z_i} = [Z_{USD,i}^{Im}, Z_{EUR,i}^{Im}, Z_{USD,i}^{Ex}, Z_{EUR,i}^{Ex}]$ as the $T_i \times 4k$ matrix of independent variables, and define $\boldsymbol{\Psi}$ as a blockdiagonal matrix of dimension $4k \times 4$ with the respective γ^x on its diagonal. Note that we have $\boldsymbol{\epsilon_i}^\top = \tilde{\boldsymbol{y}}_i - \boldsymbol{Z_i}\boldsymbol{\Psi}$. For convenience, we denote the collection of parameters across the different datasets by $\boldsymbol{\alpha} = [\alpha_{USD}^{Im}, \alpha_{EUR}^{Im}, \alpha_{USD}^{Ex}, \alpha_{EUR}^{Ex}]$.

We assume that $\epsilon_{i,t} \sim N(0, \Sigma_i)$, where $\Sigma_i = \Gamma^{-1}\Lambda_i(\Gamma^{-1})^\top$ for all i. Note that the likelihood is proportional to

$$\begin{aligned} q(\{\Sigma_i\}, \boldsymbol{\Psi}, \boldsymbol{\phi}) &\propto \prod_{i=1}^{N} |\Sigma_i|^{-T_i/2} \exp\Bigg(-\frac{1}{2}\sum_{t=1}^{T_i} \epsilon_{i,t}^\top \Sigma_i^{-1} \epsilon_{i,t} \Bigg) \\ &= \prod_{i=1}^{N} |\Sigma_i|^{-T_i/2} \exp\Bigg(-\frac{1}{2} trace(\Sigma_i^{-1}[\hat{\boldsymbol{\epsilon}}_{\boldsymbol{i}}\hat{\boldsymbol{\epsilon}}_{\boldsymbol{i}}^\top + (\boldsymbol{\Psi} - \hat{\boldsymbol{\Psi}})^\top \boldsymbol{Z_i}^\top \boldsymbol{Z_i}(\boldsymbol{\Psi} - \hat{\boldsymbol{\Psi}})]) \Bigg) \end{aligned} \tag{11}$$

where $\hat{\boldsymbol{\Psi}}$ are the OLS estimates of the regression parameters and $\hat{\boldsymbol{\epsilon}}_{\boldsymbol{i}}$ the corresponding OLS residuals.

Similar to Lanne, Lütkepohl, and Maciejowska (2010) and Brunnermeier, Palia, Sastry, and Sims (2021), an identification issue remains. We can multiply Γ and Λ by scale factors without changing the likelihood. Following Brunnermeier, Palia, Sastry, and Sims (2021), we impose the restriction

$$\frac{1}{N}\sum_{i=1}^{N}\lambda_{x,i} = 1 \;\;\forall\;\; x \in 1,...,4$$

where in slight abuse of notation, $\lambda_{x,i}$ is the x^{th} diagonal element of Λ_i. The interpretation of this normalization is that we make the cross-country average structural variance one in each equation. Given the normalization and the technical condition that each pair of equations differs in variance in at least one country, we can uniquely identify Γ, up to the sign of a row. See Lanne, Lütkepohl, and Maciejowska (2010) for details and Brunnermeier, Palia, Sastry, and Sims (2021) for a similar application in the context of time series heteroskedasticity.

Following Brunnermeier, Palia, Sastry, and Sims (2021), we use a Dirichlet prior for $\lambda_{x.}/N$. This restricts each $\lambda_{x,i}$ to lie in $[0, N]$ and enforces our normalization constraint that for each structural shock the $\lambda_{x,i}$ average to one across countries. We further introduce a prior $p(\Gamma) = |\Gamma|^{4k}$ and integrate out $\boldsymbol{\Psi}$ such that the posterior becomes

$$p(\{\Lambda_i\},\Gamma|\boldsymbol{\phi}) \propto \prod_{i=1}^{N}|\Gamma|^{T_i}|\Lambda_i|^{-(T_i-4k)/2}\exp\left(-\frac{1}{2}trace(\Gamma^{\top}\Lambda_i^{-1}\Gamma\hat{\boldsymbol{\epsilon}}_{\boldsymbol{i}}\hat{\boldsymbol{\epsilon}}_{\boldsymbol{i}}^{\top})\right)\prod_{j=1}^{4}\frac{\mathit{\Gamma}(\alpha N)}{\mathit{\Gamma}(\alpha)^N}\prod_{i=1}^{N}\frac{\lambda_{j,i}}{N}^{\alpha-1}$$

where, in slight abuse of notation, $\mathit{\Gamma}(.)$ refers to the Gamma function. The above is a non-standard distribution, but we can take draws from it using a Metropolis-Hastings (MH) approach. To do so we will employ random walks for all parameters[14].

Note that the distribution of $\{\Lambda_i\}$ and Γ is conditional on the $\boldsymbol{\phi}$. Specifically, the $\hat{\boldsymbol{\epsilon}}_{\boldsymbol{i}}$ are OLS residuals computed conditional on the draw of $\boldsymbol{\phi}$. Hence, given draws for $\boldsymbol{\phi}$, we can sample $\{\Lambda_i\}$ and Γ. The draws of $\{\Lambda_i\}$ and Γ do not affect the draws of the other parameters. Hence, to make drawing efficient, we first carry out the estimation of the models on the different ECI datasets and store the corresponding parameter draws, or, equivalently, OLS residuals $\hat{\epsilon}_t^x$. Put differently, we can estimate $\{\Lambda_i\}$ and Γ and the other parameters in two separate stages.

The sampling algorithm to draw $\{\Lambda_i\}$ and Γ from the posterior distribution is as follows:

1. Pre-estimation:
    - Estimate the model on the different ECI datasets and store $\hat{\epsilon}_t^x$ for different draws
2. Initialization:
    - Set $b = 1$ and set a starting value Γ_0 and $\Lambda_{i,0}$ for all i

[14] For Γ this is straightforward. Note that Λ_i needs to be sampled subject to the normalization constraint. We enforce the constraint, by sampling $\lambda_{x,1:N-1}$, using the random walk and set $\lambda_{x,N}$ such that the constraint is satisfied.

3. Draw $\{\Lambda_i\}$ and Γ using MH:
   - Denote the collection of parameters as $\theta = [vec(\Gamma)^\top, diag(\Lambda_1)^\top, ..., diag(\Lambda_{N-1})^\top]^\top$
   - Draw $vec(\theta_c)$ from $N(vec(\theta_{b-1}, cV_\theta)$
   - Determine $\Lambda_{N,c}$ from the constraint
   - Calculate the acceptance rate $r = min(1, \frac{p(\{\Lambda_{i,c}\},\Gamma_c|\boldsymbol{\phi}_{b-1})}{p(\{\Lambda_{i,b-1}\},\Gamma_{b-1}|\boldsymbol{\phi}_{b-1})})$, where $p(\{\Lambda_i\},\Gamma|\boldsymbol{\phi})$ was defined previously
   - Set $\{\Lambda_{i,b}\} = \{\Lambda_{i,c}\}$ and $\Gamma_b = \Gamma_c$ with probability r, else set $\{\Lambda_{i,b}\} = \{\Lambda_{i,b-1}\}$ and $\Gamma_b = \Gamma_{b-1}$. If accepted, set $ac_b = 1$
   - Calculate $acr = \sum_{j=1}^{b} ac_j/b$. If $acr < 0.4$, set $c = max(c/1.1, 10^{-6})$. If $acr > 0.6$, set $c = min(1.1c, 5)$
4. Increase b by one and repeat from point 3 above.

Repeating the above B times, after discarding an initial set of draws, leaves us with a set of parameter draws from the posterior. We always set $B = 50000$ and discard the first 5000 draws. To initialize the algorithm we first compute the posterior mode[15]. We then set Γ_0 and $\Lambda_{i,0}$ to the respective estimates. We start with $c = 0.1$, set V_θ to the inverse Hessian obtained from the estimation of the posterior mode, and set the prior for $\{\Lambda_i\}$ with $\alpha = 2$. We have found that since we use an estimate of the posterior mode satisfying the normalizations, no ex-post normalization (sign-flipping or row permutation) was necessary. To obtain a reliable sample from the posterior distribution, we ran the above algorithm 100 times and pooled the final draws across all MCMC chains.

[15]The posterior mode is obtained from a constrained optimization for $\hat{\boldsymbol{\epsilon}}_{\boldsymbol{i}}$ evaluated at the posterior mean of $\boldsymbol{\phi}$. The constraints ensure that the diagonal elements of Γ are positive. Finally the rows of the resulting estimates for Γ and Λ_i are permuted to ensure that the large elements are on the diagonal of Γ.

A.3 Additional Tables

Table 4: The Posterior Likelihood of Trade-Network Spillovers

Specification:		ACI_{USD}^{Ex}	ACI_{EUR}^{Ex}	ACI_{USD}^{Im}	ACI_{EUR}^{Im}
Panel	$\ln p_m$	1602.892	2260.553	1298.417	163.474
	$prob_m$	0.000	0.000	0.000	0.000
SEM	$\ln p_m$	1612.020	2429.686	1335.039	-27.280
	$prob_m$	0.000	0.000	0.000	0.000
SLM	$\ln p_m$	1626.628	2348.159	1308.943	273.662
	$prob_m$	0.000	0.000	0.000	0.000
SDM	$\ln p_m$	1769.339	2592.921	1543.097	562.501
	$prob_m$	1.000	1.000	1.000	1.000

The table reports the logarithm of the marginal likelihood ($\ln p_m$) of the data, given the model and the posterior model probabilities ($prob_m$). Note that the marginal likelihoods are adjusted by subtracting the logarithm of the number of observations. The models are separately estimated on each dataset using our baseline specification. Depending on the dataset, the baseline specification uses respectively USD or EUR export or import-based aggregate currency invoicing as the dependent variable. As independent variables, we include lags of inward foreign direct investments, a USD SWAP line dummy, exchange rate changes with the USD and EUR, realized exchange rate volatility with the USD and EUR, the share of aggregate exports, CPI-based inflation and CPI-based inflation volatility, USD export-, USD import-, EUR export-, and EUR import-based aggregate currency invoicing, and country- and time-fixed effects.

Table 5: The Baseline Spatial Durbin Model

		Independent Variables												
		ECI^{Im}_{USD}	ECI^{Im}_{EUR}	ECI^{Ex}_{USD}	ECI^{Ex}_{EUR}	FDI^{In}	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	$SWAP_{USD}$	TS^{Ex}	CPI	$CPIVol$
Panel A. Dependent Variable: Export Excess Currency Invoicing in USD (ECI^{Ex}_{USD})														
Short-term	Direct Effect	0.015**	0.027***	0.791***	-0.035***	0.015**	-0.015	-0.013	-0.004	-0.023**	-0.055**	-0.101***	-0.009	0.019***
		(0.059)	(0.000)	(0.000)	(0.000)	(0.023)	(0.243)	(0.264)	(0.658)	(0.020)	(0.074)	(0.000)	(0.188)	(0.004)
	Total Effect	-0.013	0.061***	0.846***	-0.058***	0.053**	-0.075	0.078	-0.111***	-0.103***	0.188**	-0.145***	-0.075***	0.005
		(0.630)	(0.004)	(0.000)	(0.005)	(0.015)	(0.148)	(0.153)	(0.000)	(0.001)	(0.044)	(0.000)	(0.004)	(0.633)
Long-term	Direct Effect	0.065**	0.122***		-0.155***	0.068**	-0.066	-0.054	-0.022	-0.104**	-0.236**	-0.451***	-0.040	0.084***
		(0.060)	(0.000)		(0.000)	(0.022)	(0.228)	(0.288)	(0.603)	(0.018)	(0.084)	(0.000)	(0.165)	(0.005)
	Total Effect	-0.081	0.337***		-0.321***	0.294**	-0.411	0.426	-0.610***	-0.568***	1.031**	-0.798***	-0.411***	0.030
		(0.608)	(0.008)		(0.010)	(0.019)	(0.153)	(0.158)	(0.001)	(0.002)	(0.047)	(0.000)	(0.005)	(0.629)
	ϕ							0.241***						
								(0.000)						
	R^2							0.949						
	NObs							10871						
	log marginal							284.0414						
Panel B. Dependent Variable: Export Excess Currency Invoicing in EUR (ECI^{Ex}_{EUR})														
Short-term	Direct Effect	0.122***	-0.056***	-0.079***	0.668***	-0.010	0.029**	-0.002	-0.001	0.022**	-0.203***	0.038***	-0.007	-0.005
		(0.000)	(0.000)	(0.000)	(0.000)	(0.234)	(0.053)	(0.895)	(0.930)	(0.062)	(0.000)	(0.000)	(0.353)	(0.554)
	Total Effect	0.310***	-0.105***	-0.034	0.738***	-0.076***	-0.026	-0.030	-0.021	0.066**	0.043	0.077***	0.074***	-0.053***
		(0.000)	(0.000)	(0.225)	(0.000)	(0.002)	(0.652)	(0.618)	(0.520)	(0.050)	(0.677)	(0.000)	(0.009)	(0.000)
Long-term	Direct Effect	0.369***	-0.169***	-0.233***		-0.030	0.086**	-0.006	-0.004	0.068**	-0.599***	0.113***	-0.020	-0.015
		(0.000)	(0.000)	(0.000)		(0.212)	(0.056)	(0.881)	(0.920)	(0.058)	(0.000)	(0.000)	(0.395)	(0.523)
	Total Effect	1.147***	-0.395***	-0.126		-0.282***	-0.095	-0.110	-0.076	0.246**	0.158	0.287***	0.273**	-0.197***
		(0.000)	(0.000)	(0.231)		(0.002)	(0.653)	(0.618)	(0.523)	(0.053)	(0.678)	(0.000)	(0.010)	(0.000)
	ϕ							0.159***						
								(0.000)						
	R^2							0.963						
	NObs							10872						
	$\ln p_m$							-1854.050						

The table reports the posterior means of the estimated effects and their respective p-values. Coefficient estimates significant at the 10%, 5%, and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the depicted independent variables, we always include country- and time-fixed effects.

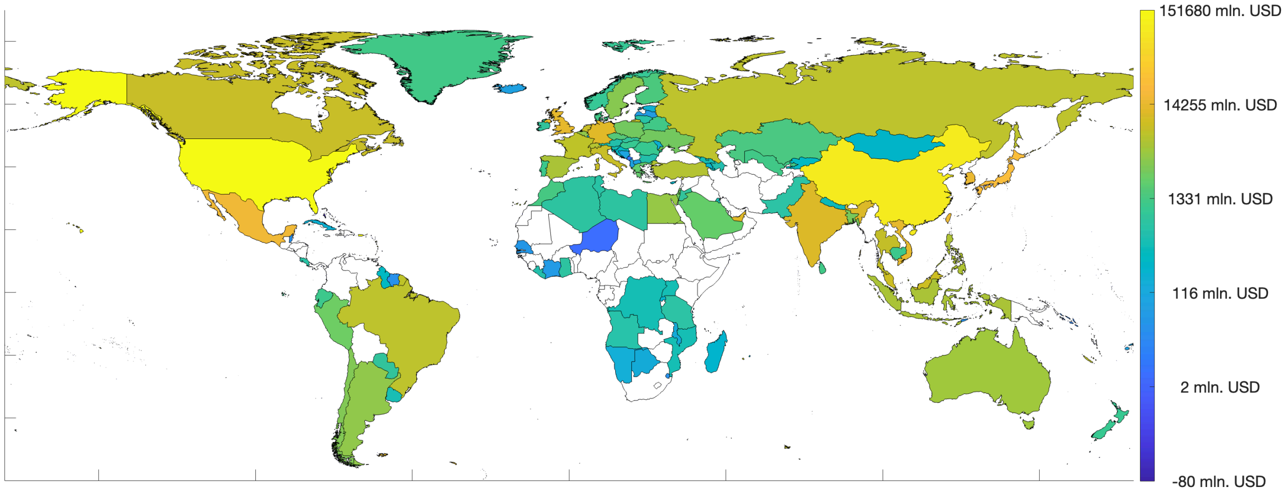
Table 6: The Baseline Spatial Durbin Model

		Independent Variables												
		ACI^{Im}_{USD}	ACI^{Im}_{EUR}	ACI^{Ex}_{USD}	ACI^{Ex}_{EUR}	FDI^{In}	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	$SWAP_{USD}$	TS^{Ex}	CPI	$CPIVol$
Panel A. Dependent Variable: Export Aggregate Currency Invoicing in USD (ACI^{Ex}_{USD})														
Short-term	Direct Effect	0.028***	-0.003	0.861***	-0.055***	0.020***	-0.019**	-0.014	0.005	-0.029***	-0.076***	-0.121***	0.003	0.013**
		(0.000)	(0.711)	(0.000)	(0.000)	(0.001)	(0.081)	(0.167)	(0.553)	(0.001)	(0.004)	(0.000)	(0.617)	(0.029)
	Total Effect	-0.053	-0.020	0.858***	0.009	0.070***	-0.090	0.090	-0.126***	-0.132***	0.063	-0.178***	-0.078***	-0.015
		(0.111)	(0.472)	(0.000)	(0.686)	(0.004)	(0.104)	(0.117)	(0.000)	(0.000)	(0.564)	(0.000)	(0.004)	(0.182)
Long-term	Direct Effect	0.160***	-0.015		-0.323***	0.114***	-0.110**	-0.080	0.029	-0.170***	-0.441***	-0.701***	0.017	0.074**
		(0.000)	(0.715)		(0.000)	(0.001)	(0.082)	(0.167)	(0.552)	(0.001)	(0.005)	(0.000)	(0.615)	(0.030)
	Total Effect	-0.318	-0.115		0.052	0.408***	-0.519	0.522	-0.733***	-0.770***	0.357	-1.030***	-0.453***	-0.088
		(0.142)	(0.481)		(0.700)	(0.008)	(0.110)	(0.123)	(0.000)	(0.001)	(0.571)	(0.000)	(0.007)	(0.189)
	ϕ							0.382***						
								(0.000)						
	R^2							0.964						
	NObs							10871						
	$\ln p_m$							1778.633						
Panel B. Dependent Variable: Export Aggregate Currency Invoicing in EURs (ACI^{Ex}_{EUR})														
Short-term	Direct Effect	0.027***	-0.005	-0.056***	0.870***	0.014**	-0.025**	-0.006	-0.004	-0.017**	-0.094***	-0.102***	0.011**	0.010**
		(0.000)	(0.478)	(0.000)	(0.000)	(0.012)	(0.012)	(0.531)	(0.650)	(0.035)	(0.000)	(0.000)	(0.030)	(0.075)
	Total Effect	-0.030	-0.092***	-0.061**	0.942***	0.003	-0.104**	0.036	-0.179***	-0.120***	0.207**	-0.184***	-0.004	-0.023**
		(0.410)	(0.004)	(0.050)	(0.000)	(0.912)	(0.093)	(0.574)	(0.000)	(0.001)	(0.090)	(0.000)	(0.886)	(0.067)
Long-term	Direct Effect	0.159***	-0.033	-0.338***		0.082**	-0.156**	-0.033	-0.031	-0.106**	-0.548***	-0.620***	0.068**	0.056**
		(0.000)	(0.407)	(0.000)		(0.014)	(0.010)	(0.561)	(0.511)	(0.026)	(0.000)	(0.000)	(0.034)	(0.088)
	Total Effect	-0.254	-0.791**	-0.516**		0.029	-0.873	0.303	-1.497***	-1.005***	1.732**	-1.546***	-0.037	-0.199**
		(0.416)	(0.019)	(0.065)		(0.902)	(0.102)	(0.579)	(0.000)	(0.002)	(0.098)	(0.000)	(0.887)	(0.083)
	ϕ							0.492***						
								(0.000)						
	R^2							0.965						
	NObs							10872						
	$\ln p_m$							2602.215						

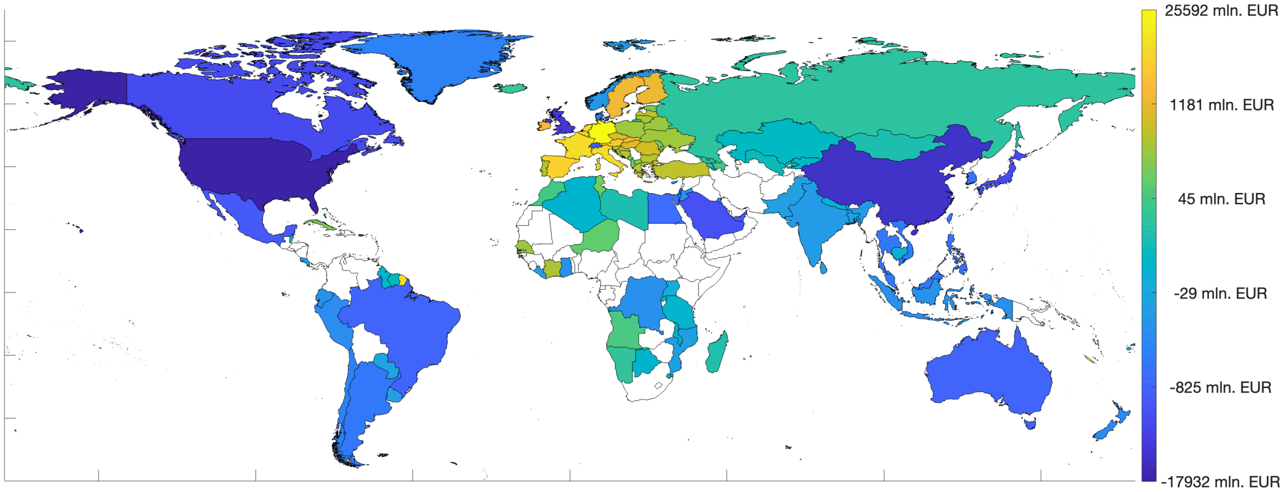
The table reports the posterior means of the estimated effects and their respective p-values. Coefficient estimates significant at the 10%, 5%, and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the depicted independent variables, we always include country- and time-fixed effects.

A.4 Additional Figures

Figure 6: Import-based Excessive Currency Invoicing across Countries



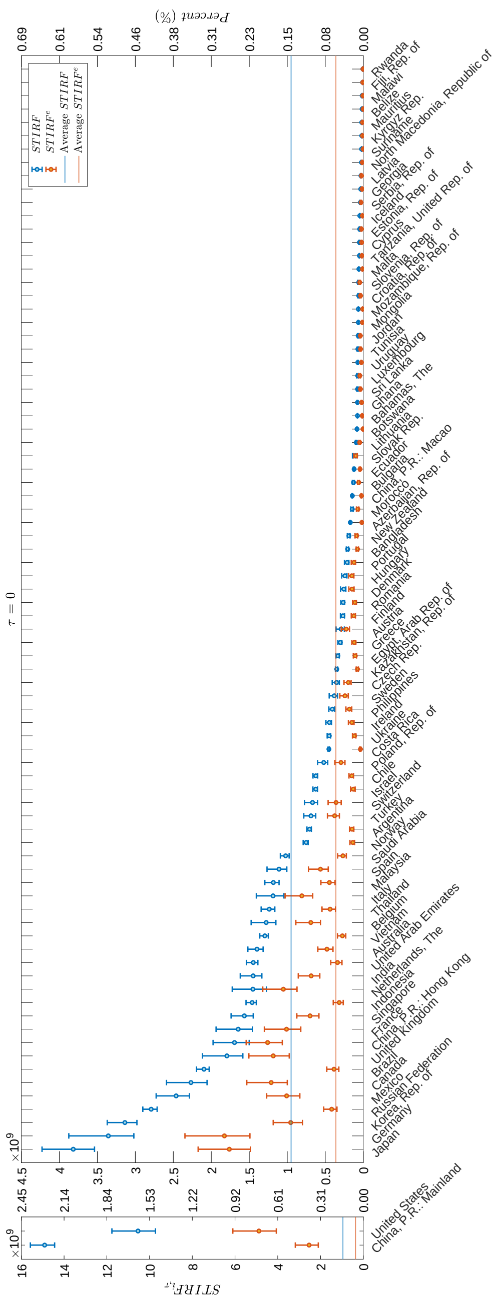
(a) USD Excessive Currency Invoicing



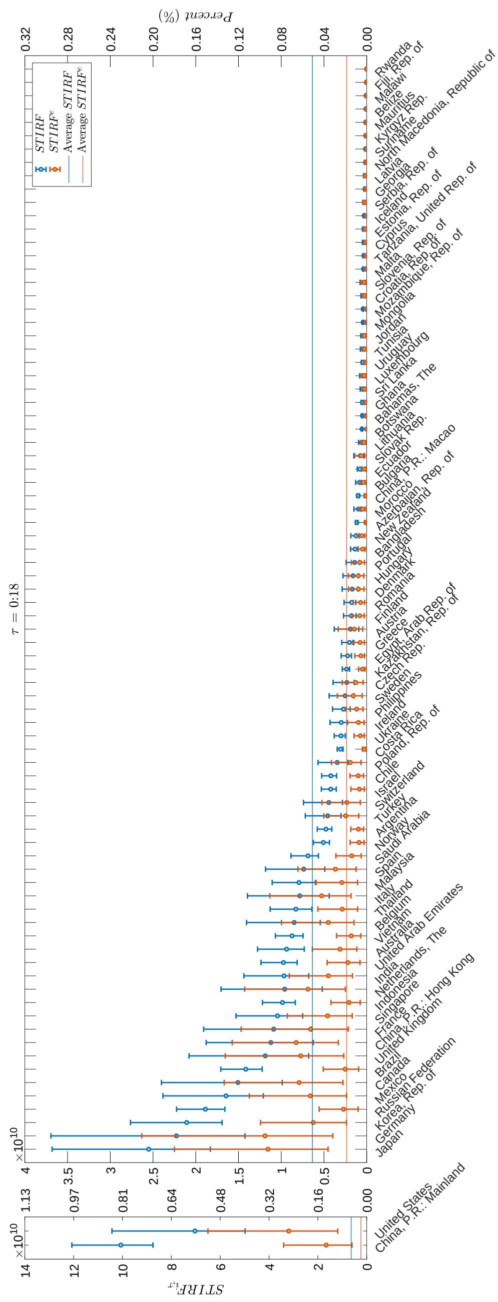
(b) EUR Excessive Currency Invoicing

The figure depicts the average monthly excessive currency invoicing across countries over our sample. All amounts are in USD equivalents. The countries marked in white are not included in our sample due to missing observations. The top ten countries by import-based excessive USD invoicing positions in our sample are: the United States, China, Hong Kong, Japan, Singapore, Mexico, Taiwan, South Korea, Vietnam, and the United Kingdom. The top ten countries by import-based excessive EUR invoicing positions in our sample are: Germany, the Netherlands, Italy, France, Belgium, Spain, Austria, Ireland, the Slovak Republic, and Sweden. Panel (a): USD excessive currency invoicing. Panel (b): EUR excessive currency invoicing.

Figure 7: Impulse-Response Functions of USD Aggregate Currency Invoicing



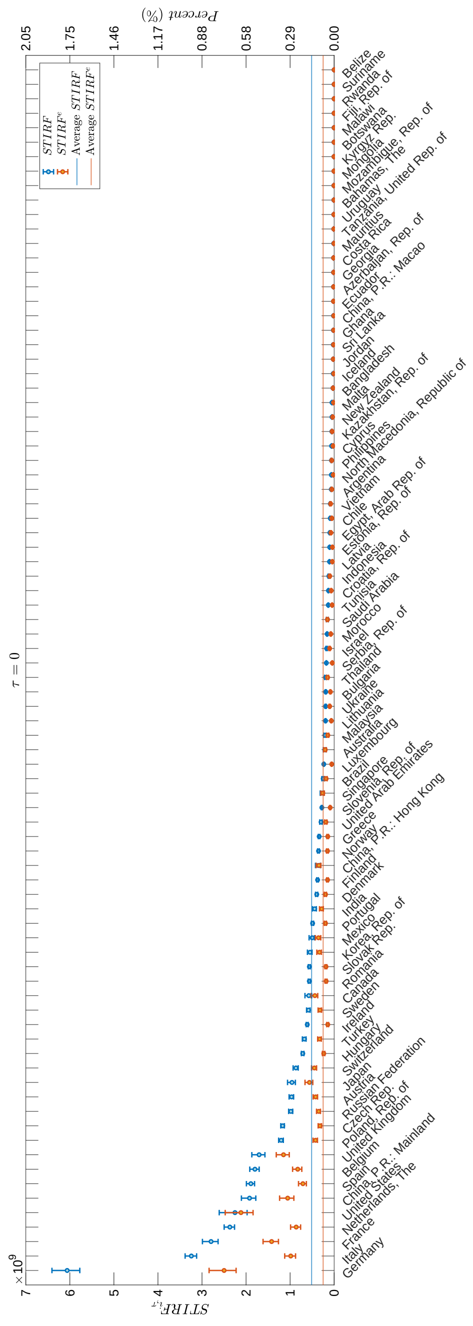
(a) Contemporaneous Effect



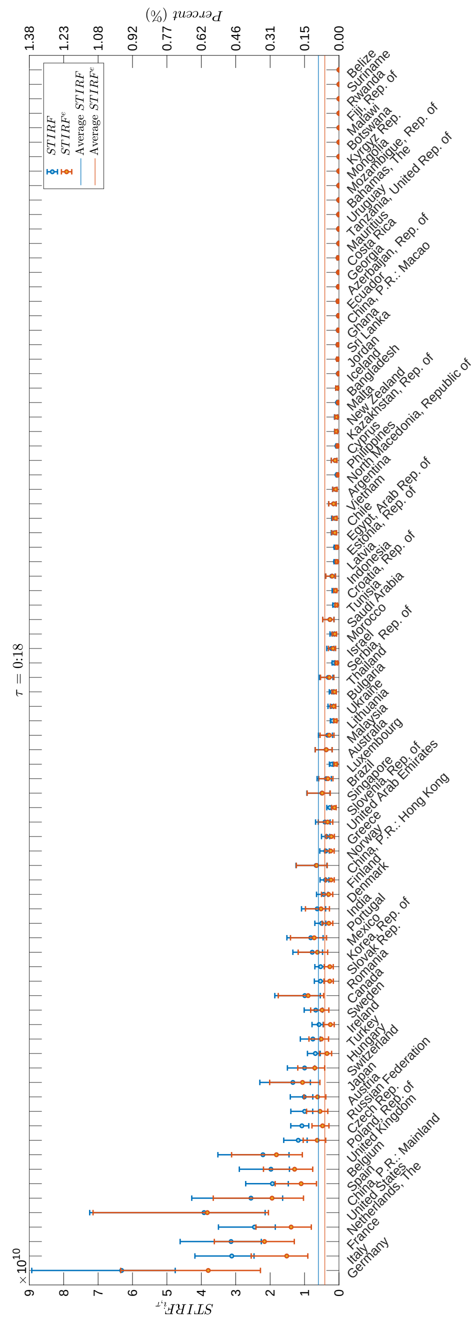
(b) Cumulated Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = USD. Right axis = percentage of monthly total aggregate currency invoicing in USD over same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage.

Figure 8: Impulse-Response Functions of EUR Aggregate Currency Invoicing



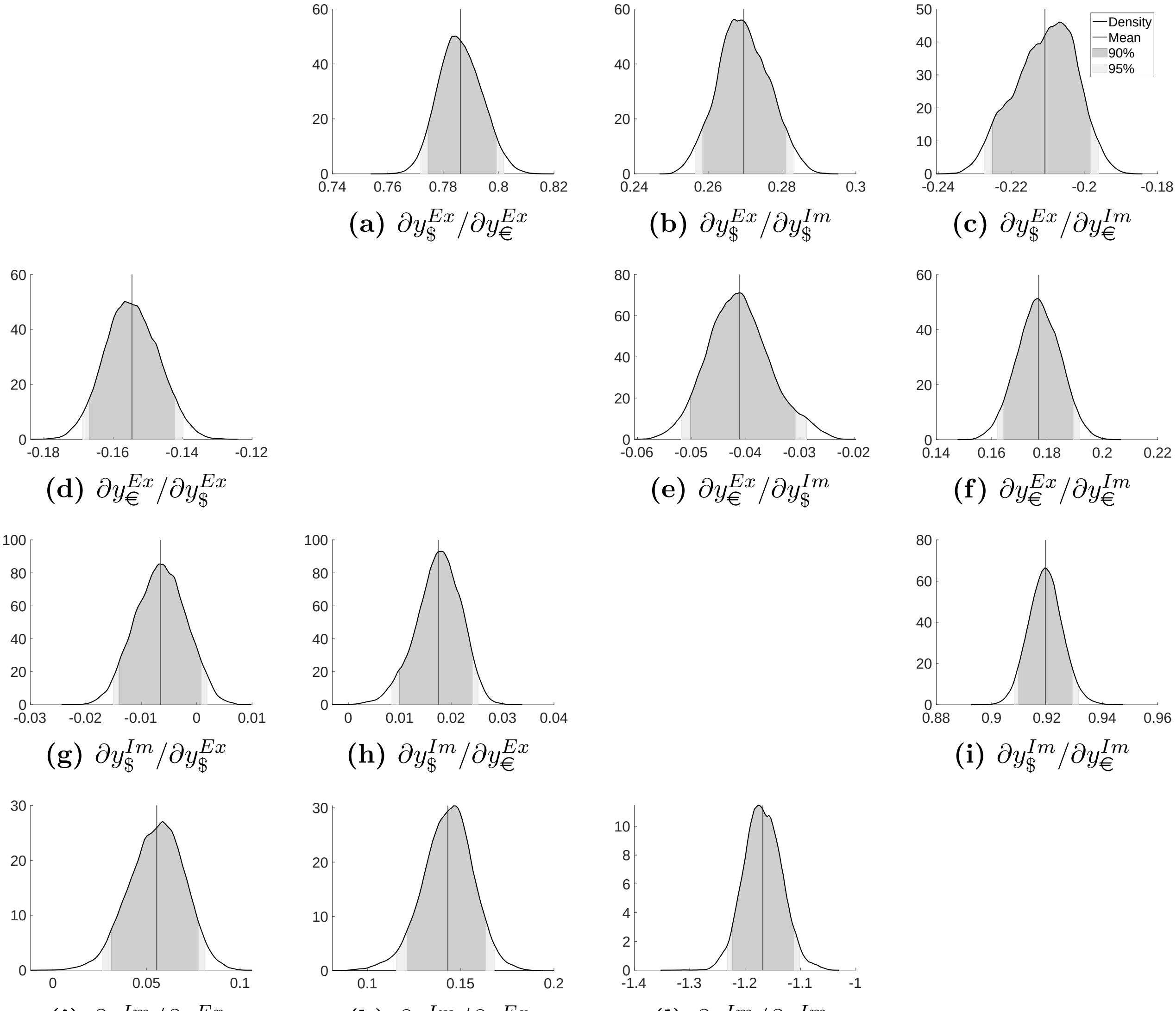
(a) Contemporaneous Effect



(b) Cumulated Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = EUR. Right axis = percentage of monthly total aggregate currency invoicing in EUR over same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage.

Figure 9: Cross-Currency and Export-Import Spillovers – Aggregate Currency Invoicing



(a) $\partial y_{\$}^{Ex}/\partial y_{€}^{Ex}$ **(b)** $\partial y_{\$}^{Ex}/\partial y_{\$}^{Im}$ **(c)** $\partial y_{\$}^{Ex}/\partial y_{€}^{Im}$

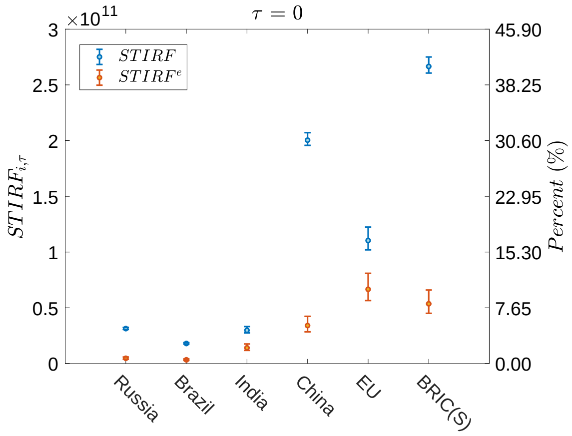
(d) $\partial y_{€}^{Ex}/\partial y_{\$}^{Ex}$ **(e)** $\partial y_{€}^{Ex}/\partial y_{\$}^{Im}$ **(f)** $\partial y_{€}^{Ex}/\partial y_{€}^{Im}$

(g) $\partial y_{\$}^{Im}/\partial y_{\$}^{Ex}$ **(h)** $\partial y_{\$}^{Im}/\partial y_{€}^{Ex}$ **(i)** $\partial y_{\$}^{Im}/\partial y_{€}^{Im}$

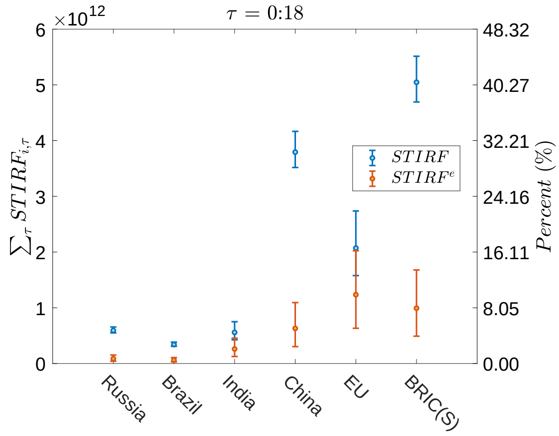
(j) $\partial y_{€}^{Im}/\partial y_{\$}^{Ex}$ **(k)** $\partial y_{€}^{Im}/\partial y_{€}^{Ex}$ **(l)** $\partial y_{€}^{Im}/\partial y_{\$}^{Im}$

The figure depicts the posterior distribution of the elements of Γ, identified via cross-sectional heteroskedasticity. For the sake of interpretation, we scaled the draws of Γ_b such that the diagonal only contains ones and then multiplied each row by negative one. Additionally, the figure depicts the posterior mean, as well as 90% and 95% confidence intervals.

Figure 10: Counterfactual: Abandonment of USD as Vehicle Currency – Aggregate Currency Invoicing



(a) Contemporaneous Effect



(b) Cumulated Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a shock sequence that sets the aggregate currency invoicing of the specified countries to zero permanently. EU contains all 19 Euro Area countries, while BRIC(S) contain the BRICS countries excluding South Africa, due to missing observations. Left axis = USD. Right axis = percentage of monthly total excess currency invoicing in USD. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage.

B Online Appendix

Contents

B.1 Additional Tables

Table 7: The Posterior Likelihood of Trade-Network Spillovers excluding SWIFT

Specification:		ECI^{Ex}_{USD}	ECI^{Ex}_{EUR}	ECI^{Im}_{USD}	ECI^{Im}_{EUR}
Panel	$\ln p_m$	250.883	-1768.196	895.122	-2479.854
	$prob_m$	0.000	0.000	0.000	0.000
SEM	$\ln p_m$	205.359	-1770.185	873.752	-2481.233
	$prob_m$	0.000	0.000	0.000	0.000
SLM	$\ln p_m$	276.069	-1768.911	922.874	-2410.119
	$prob_m$	0.000	0.000	0.000	0.000
SDM	$\ln p_m$	299.697	-1714.356	1016.831	-2372.963
	$prob_m$	1.000	1.000	1.000	1.000

The table reports the logarithm of the marginal likelihood ($\ln p_m$) of the data, given the model and the posterior model probabilities ($prob_m$). Note that the marginal likelihoods are adjusted by subtracting the logarithm of the number of observations. The models are separately estimated on each dataset using our baseline specification. Depending on the dataset, the baseline specification uses respectively USD or EUR export or import-based aggregate currency invoicing as the dependent variable. As independent variables, we include lags of inward foreign direct investments, a USD SWAP line dummy, exchange rate changes with the USD and EUR, realized exchange rate volatility with the USD and EUR, the share of aggregate exports, CPI-based inflation and CPI-based inflation volatility, USD export-, USD import-, EUR export-, and EUR import-based excessive currency invoicing, and country- and time-fixed effects. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

Table 8: The Posterior Likelihood of Trade-Network Spillovers excluding SWIFT

Specification:		ACI_{USD}^{Ex}	ACI_{EUR}^{Ex}	ACI_{USD}^{Im}	ACI_{EUR}^{Im}
Panel	$\ln p_m$	1639.241	2029.045	1570.431	202.190
	$prob_m$	0.000	0.000	0.000	0.000
SEM	$\ln p_m$	1594.445	2085.847	1594.558	255.737
	$prob_m$	0.000	0.000	0.000	0.000
SLM	$\ln p_m$	1662.744	2086.940	1587.294	277.430
	$prob_m$	0.000	0.000	0.000	0.000
SDM	$\ln p_m$	1782.935	2317.868	1748.225	498.804
	$prob_m$	1.000	1.000	1.000	1.000

The table reports the logarithm of the marginal likelihood ($\ln p_m$) of the data, given the model and the posterior model probabilities ($prob_m$). Note that the marginal likelihoods are adjusted by subtracting the logarithm of the number of observations. The models are separately estimated on each dataset using our baseline specification. Depending on the dataset, the baseline specification uses respectively USD or EUR export or import-based aggregate currency invoicing as the dependent variable. As independent variables, we include lags of inward foreign direct investments, a USD SWAP line dummy, exchange rate changes with the USD and EUR, realized exchange rate volatility with the USD and EUR, the share of aggregate exports, CPI-based inflation and CPI-based inflation volatility, USD export-, USD import-, EUR export-, and EUR import-based aggregate currency invoicing, and country- and time-fixed effects. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

Table 9: The Drivers of Excess Currency Invoicing excluding SWIFT

		Independent Variables												
		(1)		(2)				(3)	(4)				(5)		(6)
		CPI	$CPIVol$	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	TS^{Ex}	FD_{USD}	$FDChng_{USD}$	FD_{EUR}	$FDChng_{EUR}$	$SWAP_{USD}$	$SWAP_{EUR}$	FMI
Panel A. Dependent Variable: Export Excess Currency Invoicing in USD (ECI^{Ex}_{USD})															
Short-term:	Direct Effect	-0.007	0.029***	-0.024**	0.000	-0.011	0.003	-0.099***	0.049***	0.024***	0.019**	-0.013	0.046	-0.048	0.004
		(0.334)	(0.000)	(0.074)	(0.985)	(0.349)	(0.688)	(0.000)	(0.000)	(0.005)	(0.012)	(0.128)	(0.152)	(0.198)	(0.560)
	Total Effect	-0.083***	0.021**	-0.157**	-0.104***	0.150**	-0.002	-0.118***	0.094**	-0.015	0.043	-0.064	0.199**	-0.524***	0.034
		(0.002)	(0.047)	(0.050)	(0.002)	(0.044)	(0.946)	(0.000)	(0.012)	(0.574)	(0.198)	(0.100)	(0.032)	(0.000)	(0.309)
Long-term:	Direct Effect	-0.027	0.113***	-0.098**	-0.001	-0.041	0.013	-0.444***	0.188***	0.090***	0.072**	-0.049	0.185	-0.199	0.016
		(0.311)	(0.000)	(0.066)	(0.978)	(0.382)	(0.690)	(0.000)	(0.000)	(0.005)	(0.012)	(0.122)	(0.144)	(0.179)	(0.547)
	Total Effect	-0.373***	0.095**	-0.715**	-0.472***	0.682**	-0.008	-0.662***	0.425**	-0.063	0.195	-0.288	0.906**	-2.361***	0.155
		(0.003)	(0.054)	(0.055)	(0.003)	(0.048)	(0.945)	(0.000)	(0.018)	(0.592)	(0.206)	(0.106)	(0.042)	(0.000)	(0.313)
	ϕ	0.207***		0.240***				0.202***	0.297***				0.208***		0.218***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.946		0.945				0.947	0.949				0.946		0.946
	NObs	9915		9971				9971	8439				9971		9971
	$\ln p_m$	229.730		247.171				333.437	-38.994				241.339		230.386
Panel B. Dependent Variable: Export Excess Currency Invoicing in EUR (ECI^{Ex}_{EUR})															
Short-term:	Direct Effect	-0.006	-0.002	0.047***	0.004	-0.013	0.011	0.046***	-0.010	0.037***	-0.009	0.001	-0.167***	-0.114**	-0.002
		(0.454)	(0.816)	(0.004)	(0.766)	(0.382)	(0.280)	(0.000)	(0.377)	(0.000)	(0.330)	(0.893)	(0.000)	(0.013)	(0.765)
	Total Effect	0.056**	-0.027**	-0.114	-0.087***	0.055	0.004	0.044***	0.016	-0.063**	0.025	-0.198***	0.105	-0.777***	0.006
		(0.057)	(0.022)	(0.163)	(0.010)	(0.471)	(0.886)	(0.001)	(0.670)	(0.016)	(0.458)	(0.000)	(0.289)	(0.000)	(0.863)
Long-term:	Direct Effect	-0.018	-0.007	0.152***	0.011	-0.040	0.036	0.146***	-0.028	0.104***	-0.026	0.002	-0.524***	-0.357**	-0.008
		(0.494)	(0.795)	(0.005)	(0.785)	(0.390)	(0.280)	(0.000)	(0.383)	(0.000)	(0.339)	(0.954)	(0.000)	(0.013)	(0.769)
	Total Effect	0.231**	-0.110**	-0.409	-0.312**	0.196	0.013	0.159***	0.053	-0.206**	0.081	-0.641***	0.334	-2.467***	0.022
		(0.060)	(0.031)	(0.166)	(0.011)	(0.473)	(0.890)	(0.001)	(0.664)	(0.019)	(0.458)	(0.000)	(0.291)	(0.000)	(0.863)
	ϕ	0.116***		0.103***				0.098***	0.133***				0.096***		0.102***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.962		0.962				0.962	0.965				0.962		0.962
	NObs	9916		9972				9972	8440				9972		9972
	log marginal	-1703.531		-1726.374				-1727.051	-1763.841				-1705.720		-1741.567

The table reports the posterior means of the estimated effects and their respective p-values in brackets. Coefficient estimates significant at the 10%, 5% and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the listed independent variables, we always include country- and time-fixed effects, lags of inward foreign direct investments, outward foreign direct investments, USD export-, USD import-, EUR export-, and EUR import-based excessive currency invoicing as control variables. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

Table 10: The Drivers of Aggregate Currency Invoicing excluding SWIFT

		Independent Variables													
		(1)		(2)				(3)	(4)				(5)		(6)
		CPI	$CPIVol$	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	TS^{Ex}	FD_{USD}	$FDChng_{USD}$	FD_{EUR}	$FDChng_{EUR}$	$SWAP_{USD}$	$SWAP_{EUR}$	FMI
Panel A. Dependent Variable: Export Aggregate Currency Invoicing in USD (ACI^{Ex}_{USD})															
Short-term	Direct Effect	-0.001	0.019***	-0.023**	0.012	-0.011	-0.011	-0.117***	0.028***	0.028***	0.010	-0.014**	0.010	-0.023	0.003
		(0.857)	(0.001)	(0.050)	(0.186)	(0.289)	(0.211)	(0.000)	(0.000)	(0.000)	(0.104)	(0.037)	(0.717)	(0.488)	(0.564)
	Total Effect	-0.136***	0.005	-0.200**	-0.092**	0.162**	-0.050	-0.194***	0.005	0.020	0.027	-0.070**	0.158	-0.627***	0.024
		(0.000)	(0.625)	(0.016)	(0.011)	(0.036)	(0.131)	(0.000)	(0.908)	(0.501)	(0.459)	(0.094)	(0.148)	(0.000)	(0.500)
Long-term	Direct Effect	-0.004	0.090***	-0.106**	0.057	-0.052	-0.050	-0.637***	0.128***	0.125***	0.046	-0.064**	0.047	-0.107	0.015
		(0.881)	(0.002)	(0.053)	(0.183)	(0.280)	(0.214)	(0.000)	(0.000)	(0.000)	(0.104)	(0.040)	(0.720)	(0.502)	(0.568)
	Total Effect	-0.620***	0.024	-0.909**	-0.417**	0.733**	-0.228	-1.225***	0.019	0.081	0.103	-0.275	0.734	-2.891***	0.107
		(0.000)	(0.631)	(0.021)	(0.016)	(0.043)	(0.140)	(0.000)	(0.909)	(0.500)	(0.469)	(0.110)	(0.160)	(0.000)	(0.506)
	ϕ	0.341***		0.373***				0.349***	0.421***				0.364***		0.365***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.959		0.958				0.960	0.960				0.958		0.958
	NObs	9915		9971				9971	8384				9971		9971
	$\ln p_m$	1695.128		1706.266				1855.114	1181.749				1695.729		1670.357
Panel B. Dependent Variable: Export Aggregate Currency Invoicing in EUR (ACI^{Ex}_{EUR})															
Short-term	Direct Effect	0.006	0.020***	-0.034***	0.003	-0.000	-0.002	-0.103***	0.015**	0.036***	0.006	-0.014**	-0.031	-0.008	-0.004
		(0.306)	(0.000)	(0.002)	(0.717)	(0.962)	(0.818)	(0.000)	(0.035)	(0.000)	(0.274)	(0.029)	(0.232)	(0.811)	(0.502)
	Total Effect	-0.088**	0.011	-0.282***	-0.120***	0.174**	-0.009	-0.229***	-0.084**	0.024	-0.002	-0.165***	0.211**	-0.956***	-0.054
		(0.011)	(0.398)	(0.004)	(0.005)	(0.055)	(0.816)	(0.000)	(0.074)	(0.492)	(0.970)	(0.001)	(0.096)	(0.000)	(0.198)
Long-term	Direct Effect	0.027	0.098***	-0.166***	0.017	-0.004	-0.009	-0.539***	0.072**	0.171***	0.031	-0.064**	-0.153	-0.008	-0.018
		(0.327)	(0.001)	(0.002)	(0.694)	(0.930)	(0.820)	(0.000)	(0.030)	(0.000)	(0.269)	(0.037)	(0.211)	(0.960)	(0.511)
	Total Effect	-0.477**	0.059	-1.284***	-0.547***	0.794**	-0.042	-1.007***	-0.332**	0.096	-0.008	-0.659***	0.775	-3.499***	-0.253
		(0.019)	(0.412)	(0.008)	(0.010)	(0.066)	(0.815)	(0.000)	(0.072)	(0.500)	(0.961)	(0.002)	(0.106)	(0.000)	(0.210)
	ϕ	0.493***		0.497***				0.497***	0.535***				0.484***		0.491***
		(0.000)		(0.000)				(0.000)	(0.000)				(0.000)		(0.000)
	R^2	0.964		0.964				0.965	0.966				0.964		0.964
	NObs	9916		9972				9972	8385				9972		9972
	$\ln p_m$	2222.893		2262.011				2380.157	1806.976				2266.600		2224.708

The table reports the posterior means of the estimated effects and their respective p-values in brackets. Coefficient estimates significant at the 10%, 5% and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the listed independent variables, we always include country- and time-fixed effects, lags of inward foreign direct investments, outward foreign direct investments, USD export-, USD import-, EUR export-, and EUR import-based aggregate currency invoicing as control variables. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

Table 11: The Baseline Spatial Durbin Model excluding SWIFT

		Independent Variables												
		ECI^{Im}_{USD}	ECI^{Im}_{EUR}	ECI^{Ex}_{USD}	ECI^{Ex}_{EUR}	FDI^{In}	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	$SWAP_{USD}$	TS^{Ex}	CPI	$CPIVol$
Panel A. Dependent Variable: Export Excess Currency Invoicing in USD (ECI^{Ex}_{USD})														
Short-term	Direct Effect	0.015**	0.025***	0.789***	-0.033***	0.007	-0.025**	-0.009	0.002	-0.016**	-0.054**	-0.101***	-0.003	0.018***
		(0.077)	(0.001)	(0.000)	(0.000)	(0.291)	(0.056)	(0.414)	(0.824)	(0.063)	(0.075)	(0.000)	(0.662)	(0.007)
	Total Effect	-0.011	0.058***	0.852***	-0.051**	-0.046**	-0.151**	0.158**	-0.122***	-0.017	0.147	-0.109***	-0.068**	-0.004
		(0.688)	(0.003)	(0.000)	(0.012)	(0.076)	(0.042)	(0.021)	(0.000)	(0.467)	(0.118)	(0.000)	(0.012)	(0.696)
Long-term	Direct Effect	0.063**	0.112***		-0.146***	0.030	-0.117**	-0.035	0.005	-0.071**	-0.229**	-0.448***	-0.016	0.080***
		(0.080)	(0.001)		(0.000)	(0.326)	(0.045)	(0.489)	(0.908)	(0.062)	(0.085)	(0.000)	(0.602)	(0.008)
	Total Effect	-0.074	0.330***		-0.292**	-0.258**	-0.851**	0.892**	-0.687***	-0.098	0.838	-0.615***	-0.382**	-0.024
		(0.657)	(0.006)		(0.019)	(0.081)	(0.048)	(0.026)	(0.000)	(0.470)	(0.130)	(0.000)	(0.014)	(0.702)
	ϕ							0.193***						
								(0.000)						
	R^2							0.947						
	NObs							9974						
	$\ln p_m$							308.905						
Panel B. Dependent Variable: Export Excess Currency Invoicing in EUR (ECI^{Ex}_{EUR})														
Short-term	Direct Effect	0.136***	-0.058***	-0.086***	0.686***	-0.012	0.040**	-0.010	0.007	0.012	-0.163***	0.034***	-0.008	0.004
		(0.000)	(0.000)	(0.000)	(0.000)	(0.147)	(0.015)	(0.502)	(0.594)	(0.251)	(0.000)	(0.000)	(0.311)	(0.673)
	Total Effect	0.279***	-0.134***	-0.041	0.775***	-0.067**	-0.097	0.030	-0.092***	0.011	0.219**	0.050***	0.062**	-0.028**
		(0.000)	(0.000)	(0.155)	(0.000)	(0.018)	(0.238)	(0.693)	(0.008)	(0.675)	(0.037)	(0.001)	(0.038)	(0.021)
Long-term	Direct Effect	0.435***	-0.186***	-0.269***		-0.040	0.120**	-0.029	0.017	0.038	-0.500***	0.109***	-0.024	0.010
		(0.000)	(0.000)	(0.000)		(0.130)	(0.019)	(0.518)	(0.654)	(0.248)	(0.000)	(0.000)	(0.357)	(0.707)
	Total Effect	1.169***	-0.569***	-0.174		-0.283**	-0.407	0.125	-0.387***	0.046	0.919**	0.208***	0.262**	-0.119**
		(0.000)	(0.000)	(0.162)		(0.020)	(0.242)	(0.696)	(0.009)	(0.678)	(0.042)	(0.002)	(0.040)	(0.031)
	ϕ							0.111***						
								(0.000)						
	R^2							0.962						
	NObs							9975						
	$\ln p_m$							-1705.148						

The table reports the posterior means of the estimated effects and their respective p-values. Coefficient estimates significant at the 10%, 5%, and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the depicted independent variables, we always include country- and time-fixed effects. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

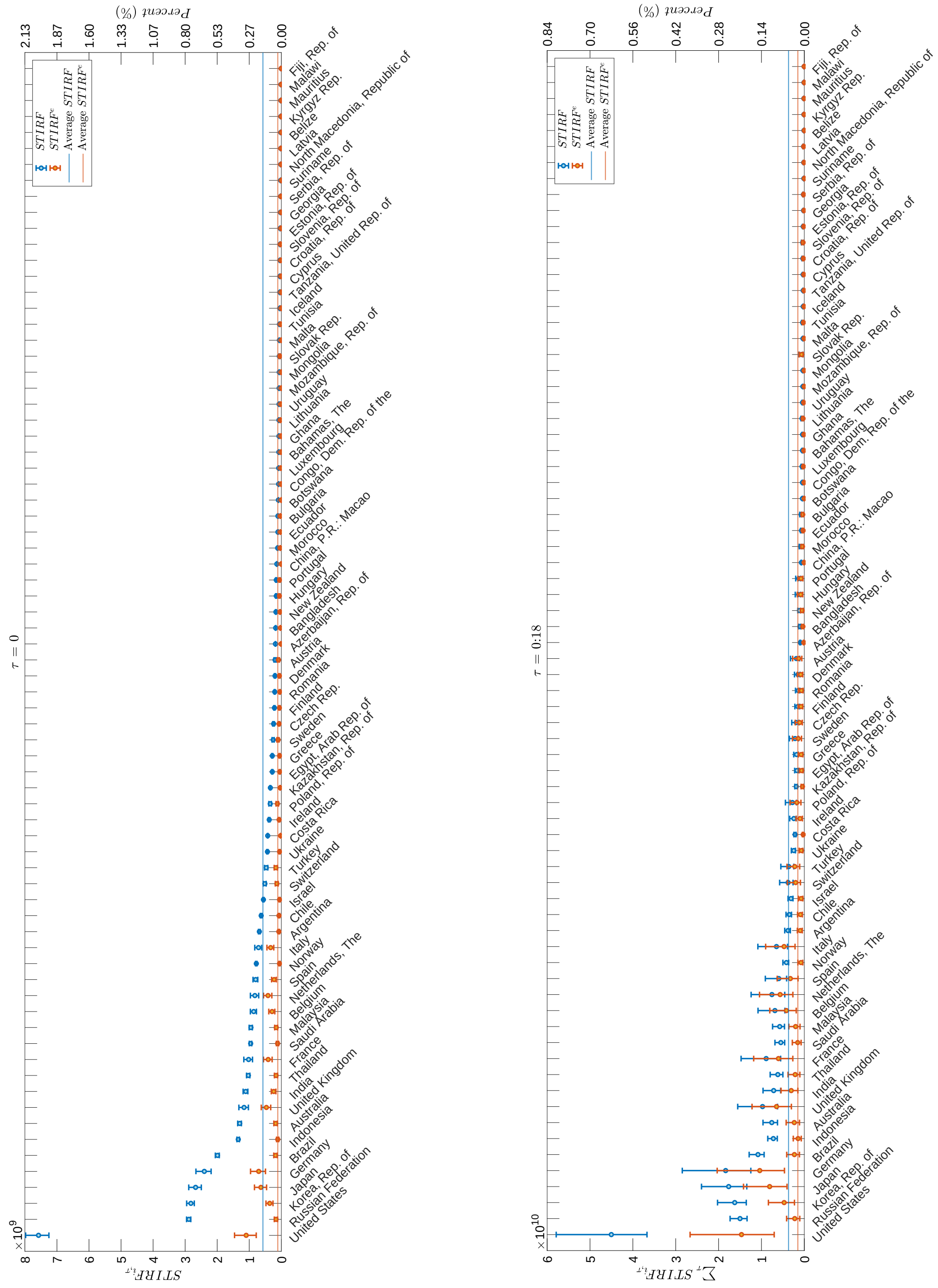
Table 12: The Baseline Spatial Durbin Model excluding SWIFT

		Independent Variables													
		ACI^{Im}_{USD}	ACI^{Im}_{EUR}	ACI^{Ex}_{USD}	ACI^{Ex}_{EUR}	FDI^{In}	$FXChng_{USD}$	$FXChng_{EUR}$	$FXVol_{USD}$	$FXVol_{EUR}$	$SWAP_{USD}$	TS^{Ex}	CPI	$CPIVol$	
Panel A. Dependent Variable: Export Aggregate Currency Invoicing in USD (ACI^{Ex}_{USD})															
Short-term	Direct Effect	0.037***	-0.004	0.861***	-0.065***	0.013**	-0.023**	-0.010	0.012	-0.034***	-0.092***	-0.115***	0.004	0.010**	
		(0.000)	(0.584)	(0.000)	(0.000)	(0.036)	(0.045)	(0.325)	(0.168)	(0.000)	(0.000)	(0.000)	(0.446)	(0.083)	
	Total Effect	0.021	-0.137***	0.897***	0.035	-0.030	-0.173**	0.167**	-0.123***	-0.116***	0.149	-0.155***	-0.110***	-0.028***	
		(0.510)	(0.000)	(0.000)	(0.117)	(0.274)	(0.028)	(0.021)	(0.000)	(0.000)	(0.150)	(0.000)	(0.000)	(0.009)	
Long-term	Direct Effect	0.217***	-0.027		-0.375***	0.072**	-0.138**	-0.053	0.068	-0.202***	-0.529***	-0.672***	0.022	0.058**	
		(0.000)	(0.525)		(0.000)	(0.041)	(0.039)	(0.371)	(0.193)	(0.000)	(0.001)	(0.000)	(0.510)	(0.091)	
	Total Effect	0.128	-0.938***		0.238	-0.206	-1.181**	1.144**	-0.844***	-0.798***	1.029	-1.064***	-0.755***	-0.194**	
		(0.540)	(0.000)		(0.123)	(0.281)	(0.034)	(0.027)	(0.001)	(0.001)	(0.161)	(0.000)	(0.000)	(0.015)	
	ϕ							0.338***							
								(0.000)							
	R^2							0.960							
	NObs							9974							
	$\ln p_m$							1792.143							
Panel B. Dependent Variable: Export Aggregate Currency Invoicing in EURs (ACI^{Ex}_{EUR})															
Short-term	Direct Effect	0.033***	0.032***	-0.004	-0.065***	0.869***	0.010**	-0.033***	-0.001	0.006	-0.024***	-0.100***	-0.101***	0.011**	0.011**
		(0.000)	(0.529)	(0.000)	(0.000)	(0.097)	(0.002)	(0.955)	(0.511)	(0.003)	(0.000)	(0.000)	(0.039)	(0.049)	
	Total Effect	-0.006	-0.185***	-0.020	0.984***	-0.079**	-0.266***	0.186**	-0.172***	-0.088**	0.328***	-0.167***	-0.050	-0.032**	
		(0.871)	(0.000)	(0.526)	(0.000)	(0.016)	(0.004)	(0.030)	(0.000)	(0.017)	(0.008)	(0.000)	(0.134)	(0.014)	
Long-term	Direct Effect	0.192***	-0.046	-0.386***		0.048	-0.223***	0.016	0.015	-0.154***	-0.559***	-0.615***	0.062**	0.062**	
		(0.000)	(0.302)	(0.000)		(0.173)	(0.001)	(0.782)	(0.768)	(0.002)	(0.000)	(0.000)	(0.068)	(0.071)	
	Total Effect	-0.068	-1.916***	-0.210		-0.799**	-2.723***	1.904**	-1.754***	-0.907**	3.350**	-1.717***	-0.513	-0.329**	
		(0.860)	(0.000)	(0.528)		(0.018)	(0.008)	(0.037)	(0.000)	(0.024)	(0.010)	(0.000)	(0.146)	(0.028)	
	ϕ							0.472***							
								(0.000)							
	R^2							0.965							
	NObs							9975							
	$\ln p_m$							2327.076							

The table reports the posterior means of the estimated effects and their respective p-values. Coefficient estimates significant at the 10%, 5%, and 1% levels are indicated by *, **, and *** respectively. Estimation is carried out separately for the two different datasets. In addition to the depicted independent variables, we always include country- and time-fixed effects. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

B.2 Additional Figures

Figure 11: Impulse-Response Functions of USD Excess Currency Invoicing excluding SWIFT

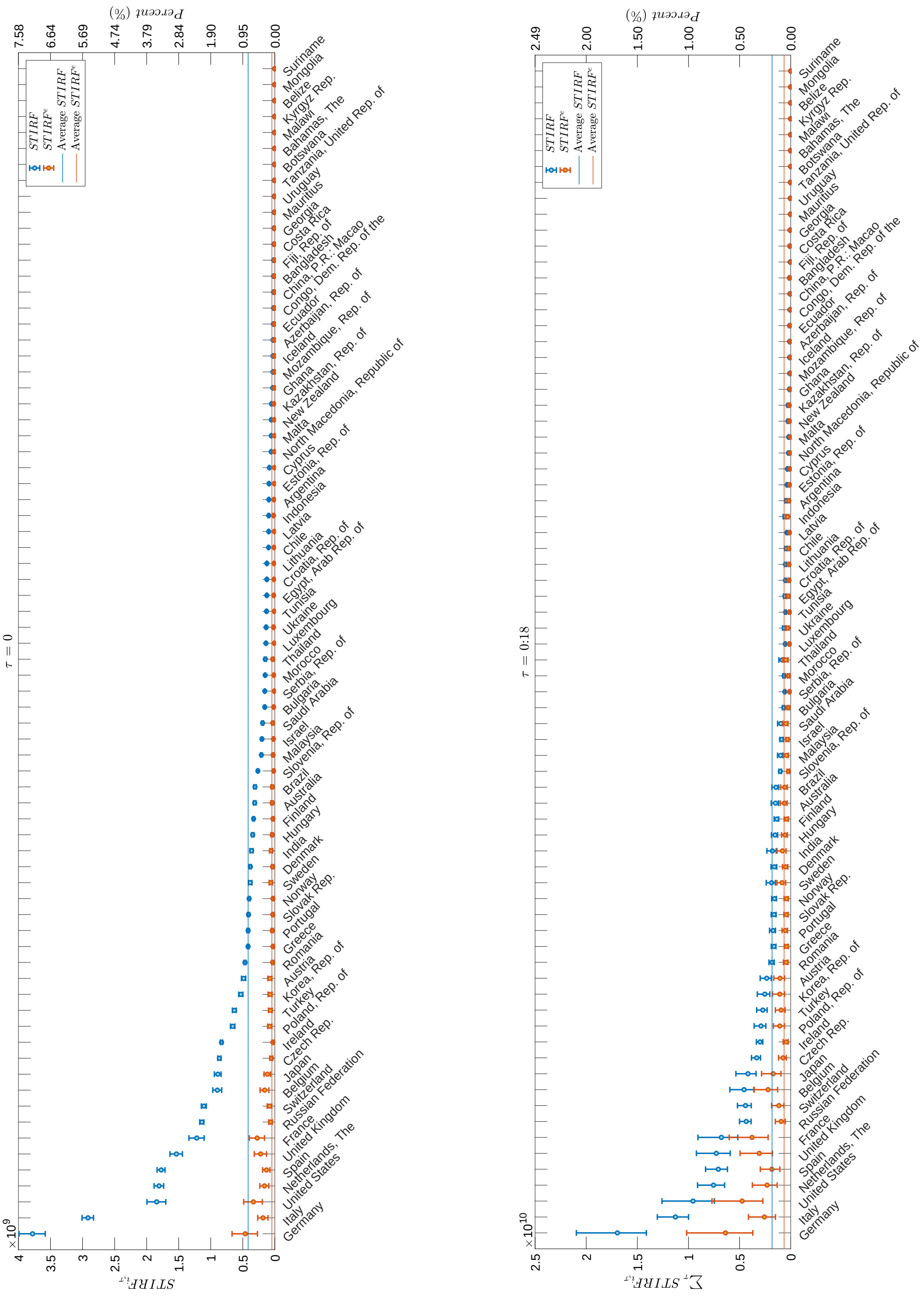


(a) Contemporaneous Effect

(b) Cumulated Effect over 18 Months

Spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = USD. Right axis = percentage of monthly total excess currency invoicing in USD over the same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

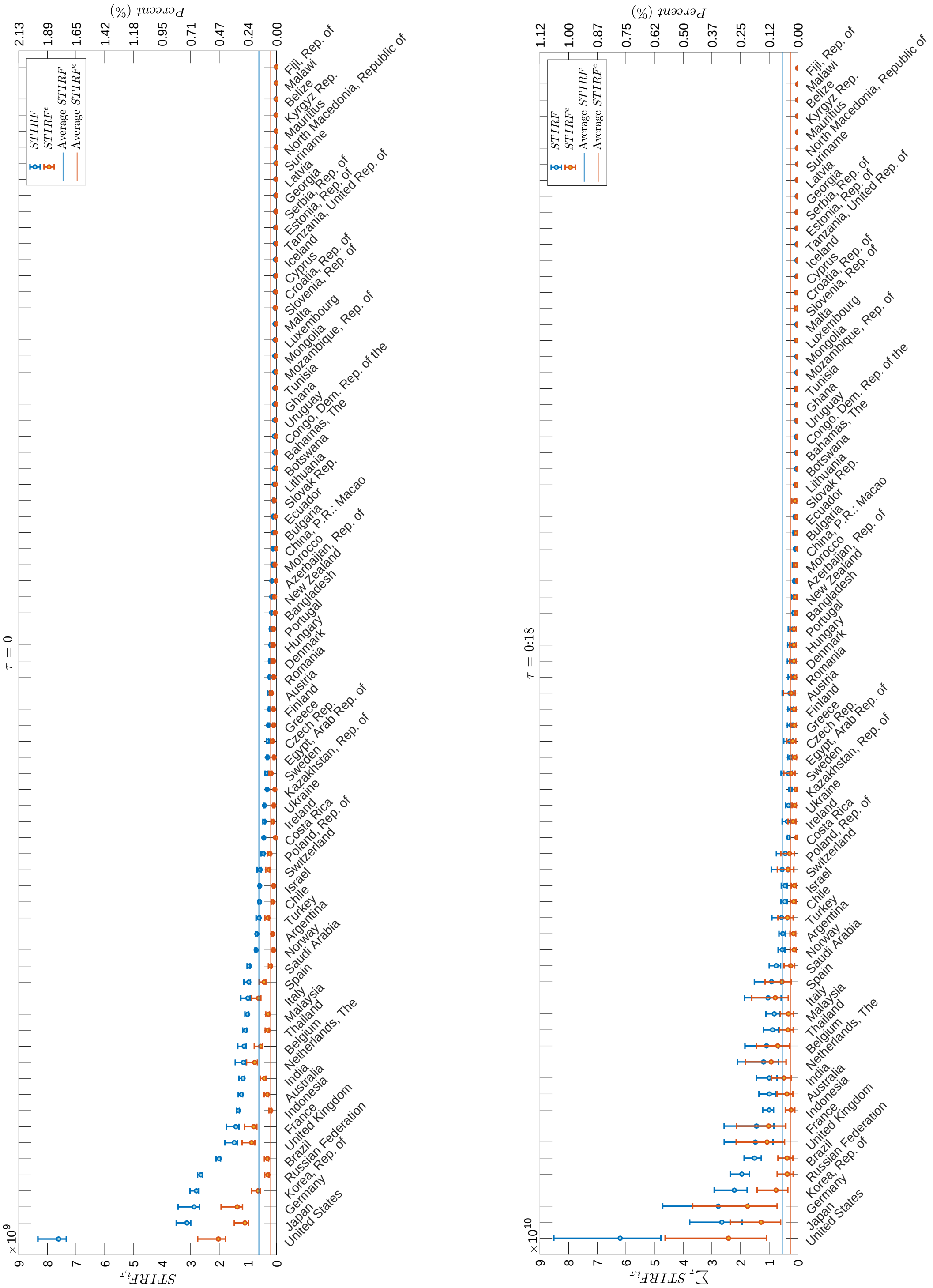
Figure 12: Impulse-Response Functions of EUR Excess Currency Invoicing excluding SWIFT



(a) Contemporaneous Effect **(b)** Cumulated Effect over 18 Months

Spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = EUR. Right axis = percentage of monthly total excess currency invoicing in EUR over the same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

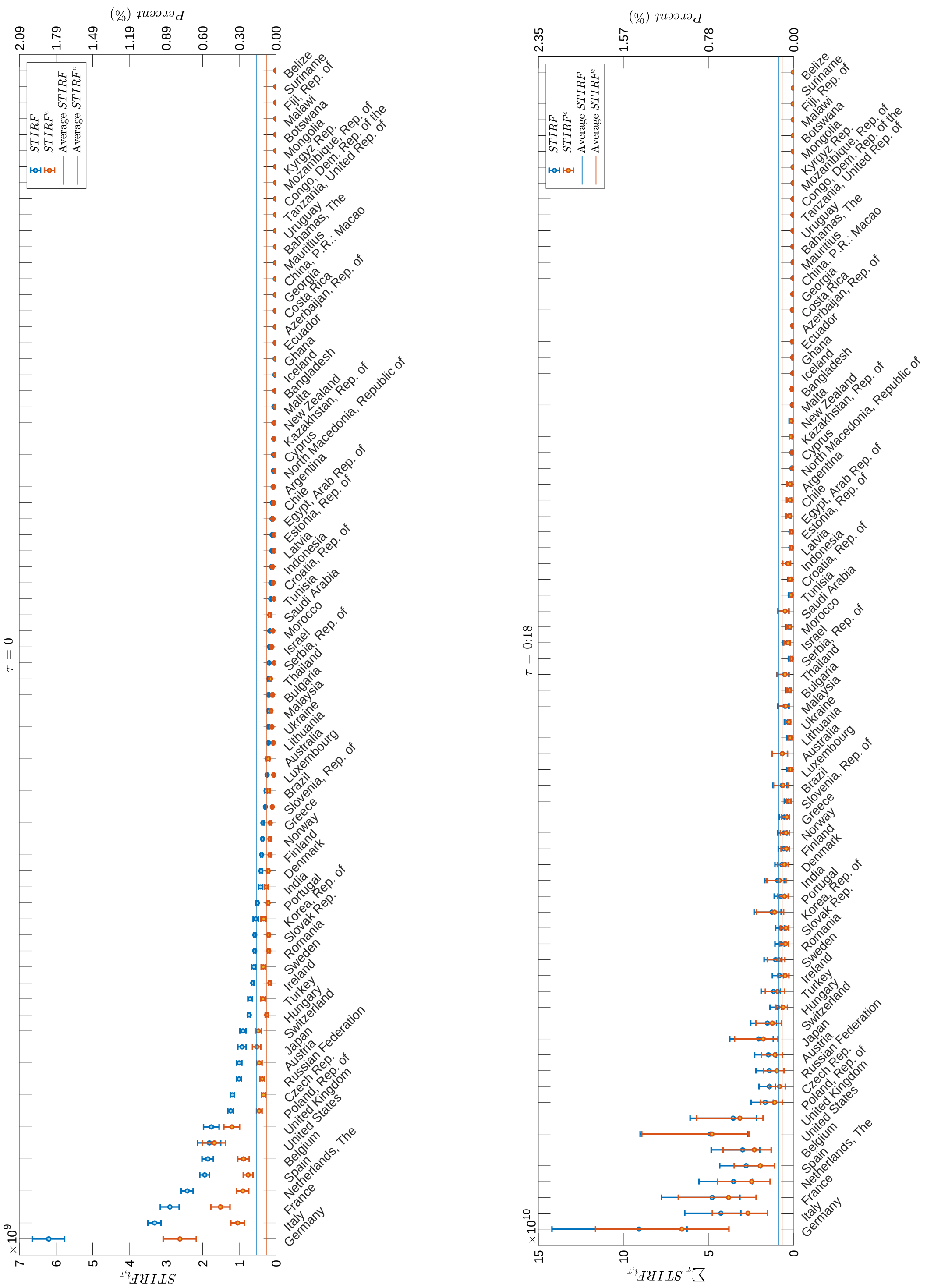
Figure 13: Impulse-Response Functions of USD Aggregate Currency Invoicing excluding SWIFT



(a) Contemporaneous Effect **(b)** Cumulated Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = USD. Right axis = percentage of monthly total aggregate currency invoicing in USD over same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

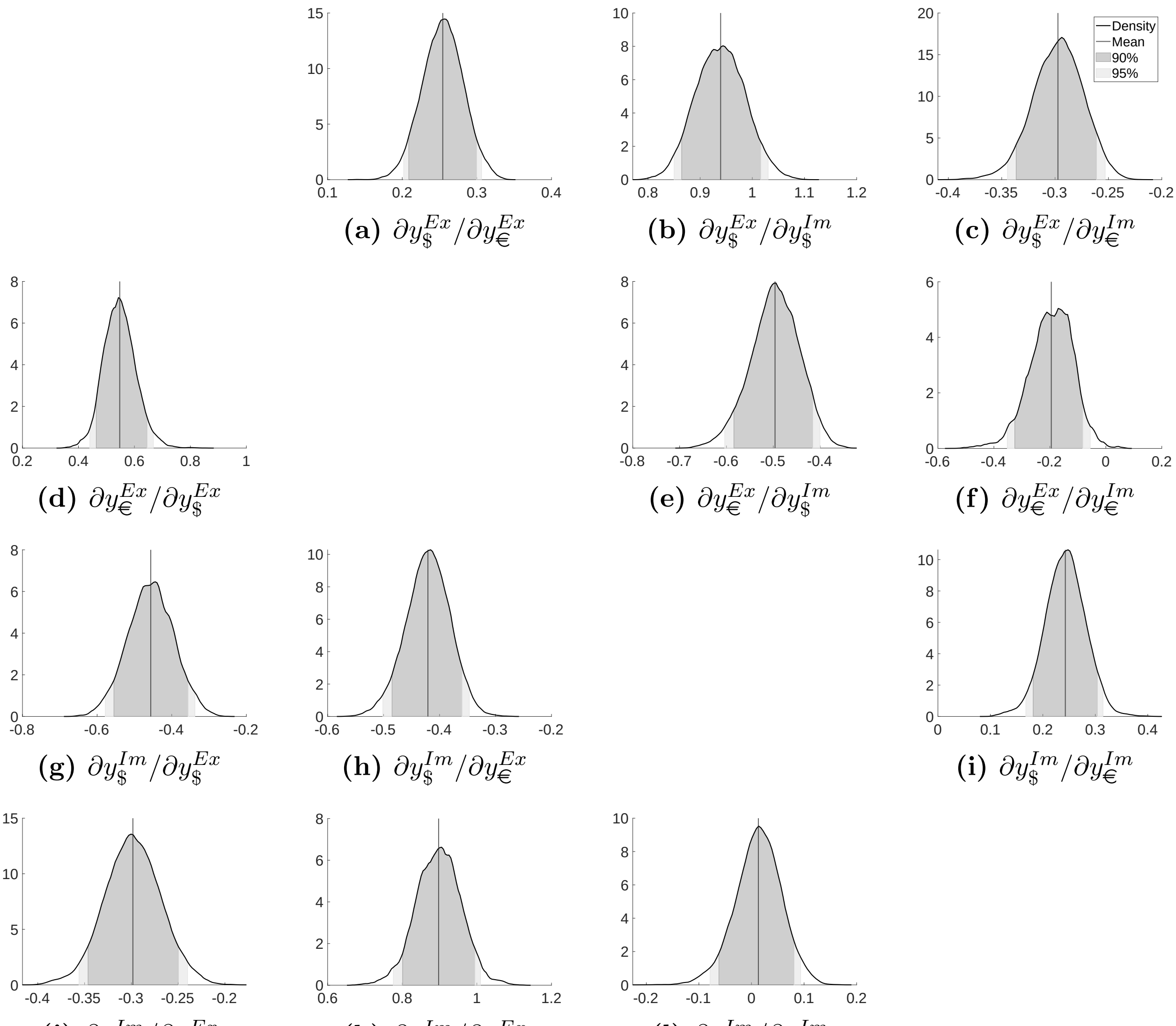
Figure 14: Impulse-Response Functions of EUR Aggregate Currency Invoicing excluding SWIFT



(a) Contemporaneous Effect　　**(b)** Cumulated Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a domestic one standard deviation shock. Left axis = EUR. Right axis = percentage of monthly total aggregate currency invoicing in EUR over same horizon. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

Figure 15: Cross-Currency and Export-Import Spillovers – Excessive Currency Invoicing excluding SWIFT



(a) $\partial y^{Ex}_{\$}/\partial y^{Ex}_{€}$ (b) $\partial y^{Ex}_{\$}/\partial y^{Im}_{\$}$ (c) $\partial y^{Ex}_{\$}/\partial y^{Im}_{€}$

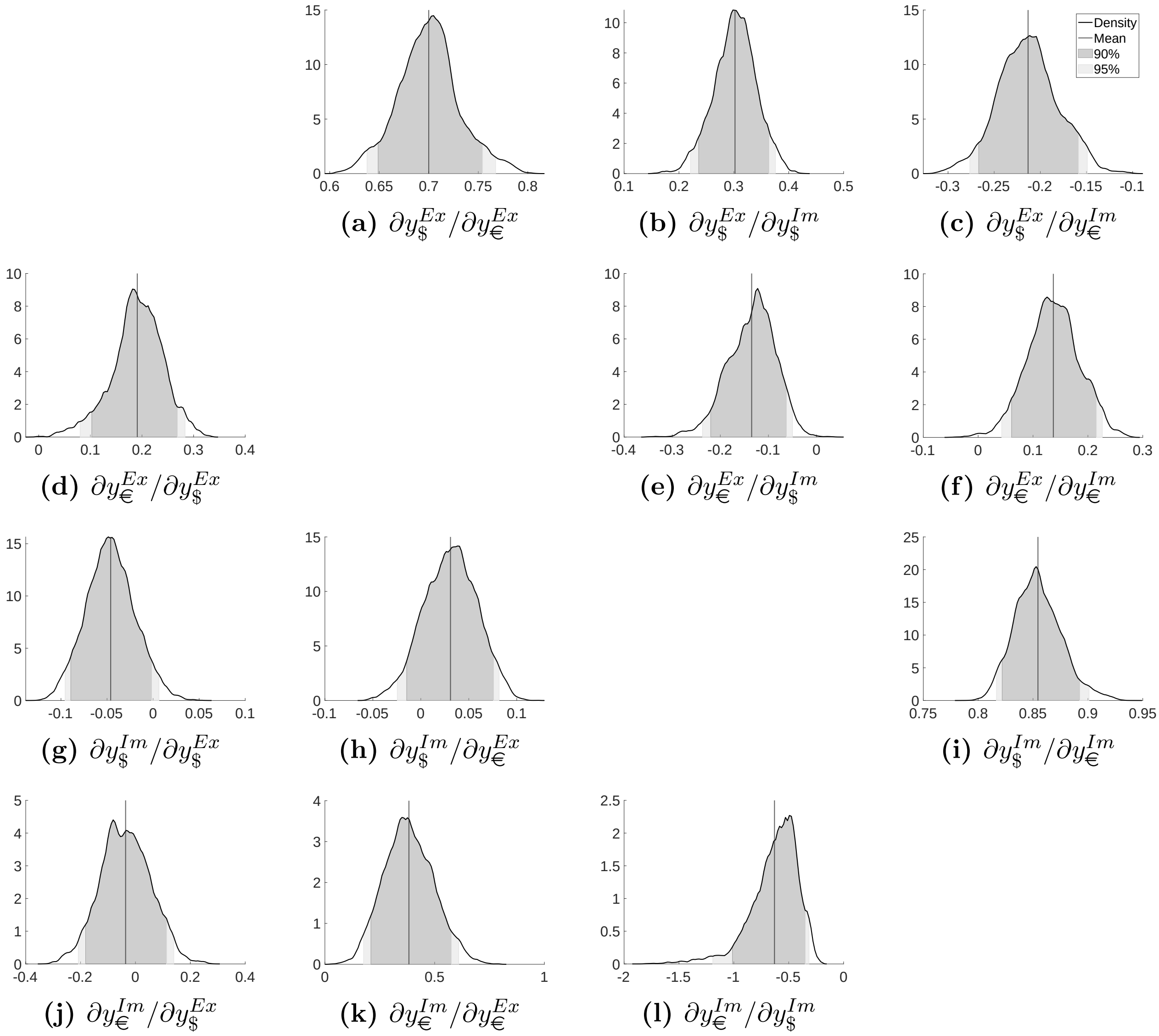
(d) $\partial y^{Ex}_{€}/\partial y^{Ex}_{\$}$ (e) $\partial y^{Ex}_{€}/\partial y^{Im}_{\$}$ (f) $\partial y^{Ex}_{€}/\partial y^{Im}_{€}$

(g) $\partial y^{Im}_{\$}/\partial y^{Ex}_{\$}$ (h) $\partial y^{Im}_{\$}/\partial y^{Ex}_{€}$ (i) $\partial y^{Im}_{\$}/\partial y^{Im}_{€}$

(j) $\partial y^{Im}_{€}/\partial y^{Ex}_{\$}$ (k) $\partial y^{Im}_{€}/\partial y^{Ex}_{€}$ (l) $\partial y^{Im}_{€}/\partial y^{Im}_{\$}$

The figures depict the posterior distribution of the elements of Γ, identified via cross-sectional heteroskedasticity. For the sake of interpretation, we have scaled the draws of Γ_b such that the diagonal only contains ones and then multiplied each row by negative one. Additionally, the figures depict the posterior mean, as well as 90% and 95% confidence intervals. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

Figure 16: Cross-Currency and Export-Import Spillovers – Aggregate Currency Invoicing excluding SWIFT



(a) $\partial y_{\$}^{Ex}/\partial y_{\euro}^{Ex}$ **(b)** $\partial y_{\$}^{Ex}/\partial y_{\$}^{Im}$ **(c)** $\partial y_{\$}^{Ex}/\partial y_{\euro}^{Im}$

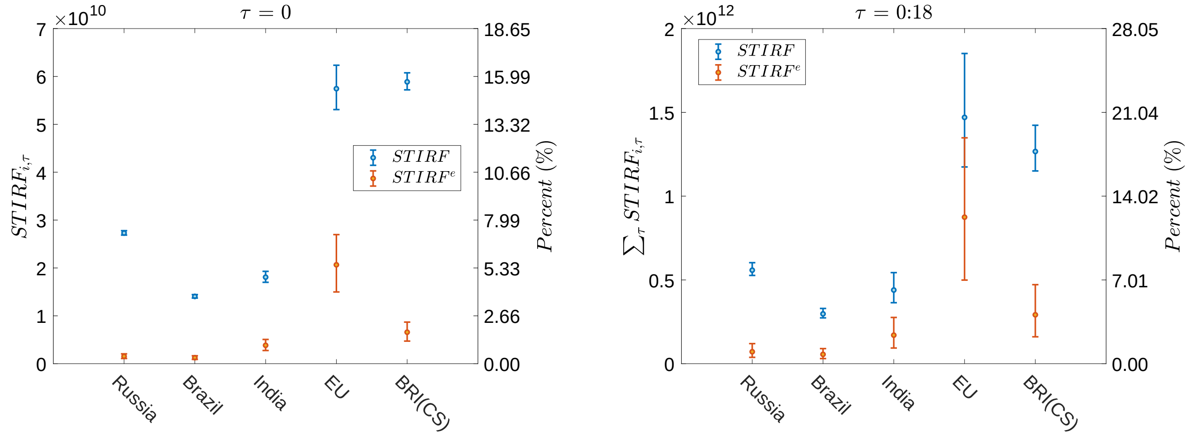
(d) $\partial y_{\euro}^{Ex}/\partial y_{\$}^{Ex}$ **(e)** $\partial y_{\euro}^{Ex}/\partial y_{\$}^{Im}$ **(f)** $\partial y_{\euro}^{Ex}/\partial y_{\euro}^{Im}$

(g) $\partial y_{\$}^{Im}/\partial y_{\$}^{Ex}$ **(h)** $\partial y_{\$}^{Im}/\partial y_{\euro}^{Ex}$ **(i)** $\partial y_{\$}^{Im}/\partial y_{\euro}^{Im}$

(j) $\partial y_{\euro}^{Im}/\partial y_{\$}^{Ex}$ **(k)** $\partial y_{\euro}^{Im}/\partial y_{\euro}^{Ex}$ **(l)** $\partial y_{\euro}^{Im}/\partial y_{\$}^{Im}$

The figure depicts the posterior distribution of the elements of Γ, identified via cross-sectional heteroskedasticity. For the sake of interpretation, we scaled the draws of Γ_b such that the diagonal only contains ones and then multiplied each row by negative one. Additionally, the figure depicts the posterior mean, as well as 90% and 95% confidence intervals. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

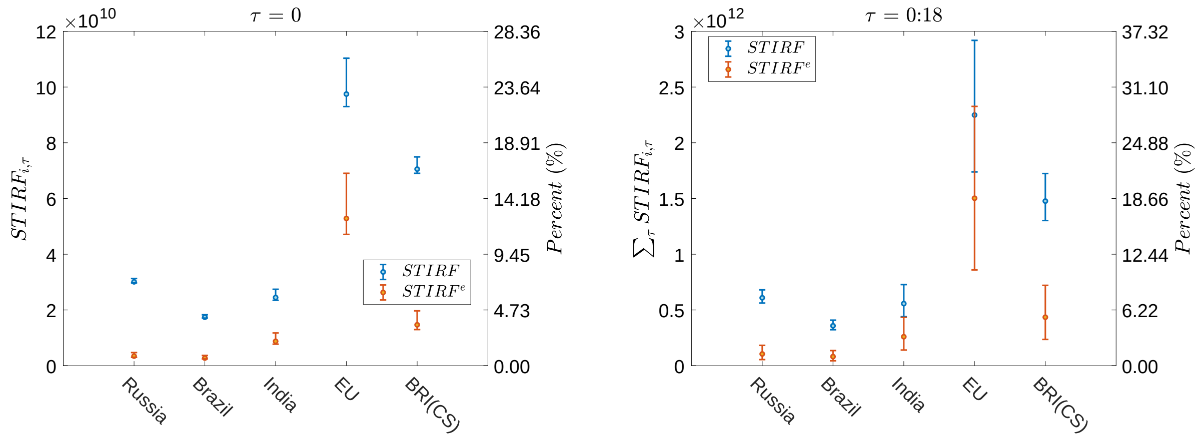
Figure 17: Counterfactual: Abandonment of USD as Vehicle Currency – Excessive Currency Invoicing excluding SWIFT



(a) Contemporaneous Effect **(b)** Cumulative Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a shock sequence that sets the excessive currency invoicing of the specified countries to zero permanently. EU contains all 19 Euro Area countries, while BRI(CS) contain the BRICS countries excluding China, and South Africa, due to missing observations. Left axis = USD. Right axis = percentage of monthly total excess currency invoicing in USD. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 month. Box-plots report posterior means and centered 95% posterior coverage. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.

Figure 18: Counterfactual: Abandonment of USD as Vehicle Currency – Aggregate Currency Invoicing excluding SWIFT



(a) Contemporaneous Effect **(b)** Cumulated Effect over 18 Months

The figure depicts spatiotemporal impulse-response functions to a shock sequence that sets the aggregate currency invoicing of the specified countries to zero permanently. EU contains all 19 Euro Area countries, while BRI(CS) contain the BRICS countries excluding China, and South Africa, due to missing observations. Left axis = USD. Right axis = percentage of monthly total excess currency invoicing in USD. Panel (a): Contemporaneous effect. Panel (b): Cumulative effect after 18 months. Box-plots report posterior means and centered 95% posterior coverage. Data on payment shares from SWIFT is excluded, which effectively decreases the coverage of the dataset by 8 countries, including Mexico, Canada and China.