

Global Trade and the Dollar*

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Abstract: We document that it is not bilateral exchange rates but the dollar exchange rate that drives global trade prices and volumes. Using a newly constructed data set of bilateral price and volume indices for more than 2,500 country pairs, we establish the following facts: 1) The dollar exchange rate quantitatively dominates the bilateral exchange rate in price pass-through and trade elasticity regressions. U.S. monetary policy induced dollar fluctuations have high pass-through into bilateral import prices. 2) Bilateral non-commodities terms of trade are essentially uncorrelated with bilateral exchange rates. 3) The cross-sectional heterogeneity in pass-through/elasticity across country pairs is related to the share of imports invoiced in dollars. Our results derive from fixed effects panel regressions as well as a Bayesian semiparametric hierarchical panel data model. Unlike standard panel regressions, the Bayesian approach allows us to quantify the cross-sectional heterogeneity of exchange rate pass-through/elasticities and the relation of this heterogeneity to dollar invoicing. Our findings strongly support the dominant currency paradigm as opposed to the traditional Mundell-Fleming pricing paradigms.

Keywords: Bayesian semiparametrics, bilateral trade, dominant currency, exchange rate pass-through, hierarchical Bayes, panel data, trade elasticity, U.S. dollar.

JEL codes: C11, C33, F14, F31.

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1 Introduction

Exchange rate fluctuations impact a country's trade competitiveness, inflation, and output and therefore have important consequences for its welfare and economic policy. It is common practice to estimate this impact by examining the pass-through of *bilateral* exchange rates into export and import prices and volumes. This practice follows naturally from the classic Mundell-Fleming paradigm of sticky prices and producer currency pricing whereby exporting firms infrequently change prices denominated in their home currency. In this model, the price an importing country faces when expressed in the importing country's currency fluctuates closely with the bilateral exchange rate. Accordingly, most existing studies of exchange rate pass-through focus on trade-weighted bilateral exchange rate changes.

Recent evidence by [Goldberg and Tille \(2008\)](#) and [Gopinath \(2015\)](#) question the Mundell-Fleming assumption of producer currency pricing, as the vast majority of trade is invoiced in a small number of "dominant currencies", with the U.S. dollar playing an outsize role. Accordingly [Casas et al. \(2016\)](#) develop a "dominant currency paradigm" where trade prices are sticky in dollars and demonstrate that the value of a country's currency relative to the dollar is a primary driver of a country's import prices and quantities *regardless* of where the good originates from. They provide empirical evidence supporting these predictions using customs data for Colombia. However, no evidence exists on the impact of dominant currencies on global trade.

In this paper we examine the implications of the dominant currency paradigm for a large number of countries using a newly constructed dataset as well as econometric methods suited to analyzing the cross-sectional heterogeneity of international trade. We construct harmonized annual *bilateral* import and export unit value and volume indices for 55 countries (yielding more than 2,500 dyads, i.e., trading pairs) from highly disaggregated UN Comtrade data starting as early as 1989, depending on the country, and covering through 2015. In this process we use the methodology developed by [Boz and Cerutti \(2017\)](#), who (in contrast to us) construct country-level indices. Our bilateral indices are broken down by commodities/noncommodities. We then merge this dataset with the invoicing data from [Gopinath \(2015\)](#) to relate the degree of sensitivity of a country's import prices to the share of trade invoiced in dollars. In order to characterize the cross-sectional heterogeneity of pass-through and its relation to dollar invoicing, we employ a novel Bayesian semiparametric hierarchical panel data model.

Our empirical results forcefully reject the Mundell-Fleming benchmark in favor of the dominant currency paradigm by establishing the following facts: 1) The dollar exchange rate quantitatively dominates the bilateral exchange rate in price pass-through and trade elasticity regressions. U.S. monetary policy induced exchange rate changes have high pass-through into bilateral import

prices. 2) Bilateral non-commodities terms of trade are essentially uncorrelated with bilateral exchange rates. 3) The cross-sectional heterogeneity in pass-through/elasticity across country pairs is related to the share of imports invoiced in dollars. These results derive from fixed effects panel regressions as well as a novel Bayesian semiparametric hierarchical panel data model.

We elaborate further on each of these findings. First, using standard pass-through regressions, we document that when country j 's currency depreciates relative to country i by 10%, import prices in country j for goods imported from country i rise by 8%, suggestive of close to complete pass-through at the one year horizon. However, when we augment this standard regression with the dollar exchange rate, we find that the relevance of the bilateral exchange rate is sharply reduced and almost all of the effect is absorbed by the dollar, consistent with the findings of Casas et al. (2016) for Colombia. Specifically, the dollar knocks the coefficient on the bilateral exchange rate from 0.80 down to 0.32 in the case when exporter-reported prices are used, and from 0.76 to 0.16 when importer-reported prices are used. The coefficient on the dollar exchange rate of 0.66 (0.78) dominates that of the bilateral exchange rate. Similarly, adding the dollar exchange rate to the bilateral volume regressions knocks down the coefficient on the bilateral exchange rate by a substantial amount. The contemporaneous volume elasticity for the dollar exchange rate is around -0.20 across specifications and data sources, while the elasticity for the bilateral exchange rate is an order of magnitude smaller at -0.03 . We also show that the dollar's role as an invoicing currency is indeed special as it handily beats the explanatory power of the euro in price and volume regressions.

To evaluate the impact of U.S. monetary policy shocks on bilateral trade, we isolate daily dollar exchange rate changes on scheduled U.S. monetary policy announcement dates. As theory predicts, we document that a tightening of U.S. monetary policy is associated with a nominal appreciation of the dollar. Using only this subset of exchange rate changes in our regressions, we estimate a high pass-through of the dollar exchange rate into bilateral import prices. The impact of U.S. monetary shocks also significantly increases with the share of a country's imports invoiced in dollars.

Second, the previous finding that prices respond to the dollar exchange rate but not the bilateral exchange rate would imply that the terms of trade should not be sensitive to the bilateral exchange rate (Gopinath, 2015; Casas et al., 2016), in sharp contrast to the Mundell-Fleming paradigm. More generally, if bilateral trade is invoiced in a dominant currency (for some countries this could be the euro), we should obtain low sensitivity to bilateral exchange rate changes. We indeed find this to be the case. In a regression of changes in the bilateral non-commodities terms of trade on changes in the bilateral exchange rate and the bilateral PPI, the coefficient

on the exchange rate is indistinguishable from zero, with the 95% confidence interval equal to $[-0.013, 0.037]$ for data reported by exporters, and $[-0.017, 0.035]$ for data reported by importers.

Third, we demonstrate that the cross-dyad heterogeneity in pass-through coefficients is well explained by the propensity to invoice imports in dollars. For this we use the importer's country-level dollar invoicing share from [Gopinath \(2015\)](#) as a proxy for the invoicing share of bilateral imports.¹ Using standard panel regressions with interactions, we estimate that increasing the dollar invoicing share by 10 percentage points causes the contemporaneous dollar pass-through to increase by about 3 percentage points. The import invoicing share therefore plays an economically and statistically significant role for the dollar pass-through.

To quantify the economic significance of dollar invoicing relative to unobserved factors in accounting for the heterogeneity in the pass-through rates across trade dyads, we employ a Bayesian semiparametric hierarchical panel data model. Unlike standard panel regressions that can be informative about the *average* pass-through and the statistical significance of the determinants of pass-through heterogeneity, the Bayesian approach allows us to quantify the cross-sectional heterogeneity of exchange rate pass-through/elasticities and the relation of this heterogeneity to dollar invoicing. Specifically, we employ a linear panel data model with the twist that the slope parameters on exchange rates are allowed to vary across dyads. We adopt a flexible specification for the cross-sectional distribution of pass-through coefficients, and in particular allow the distribution to depend non-parametrically on the importer's dollar invoicing share. The hierarchical aspect allows the parameters of the cross-sectional distribution to be inferred from the data, and it provides a unified framework for uncertainty assessment and model selection. Loosely, the Bayesian model can be thought of as striking an optimal bias-variance balance between two extreme approaches: (1) constrained but precisely estimated panel regressions with cross-sectionally constant parameters and (2) unconstrained but noisily estimated dyad-by-dyad time series regressions.

The Bayesian analysis shows that there is substantial heterogeneity in dollar pass-through into prices and quantities across trade dyads, and this heterogeneity is well explained by the differential propensity to invoice in dollars by the importing country. While the cross-dyad distribution of the contemporaneous dollar price pass-through coefficient is centered at 0.76 (similar to the panel regressions), the cross-dyad distribution has high variance and fat tails. The importer's dollar invoicing share accounts for a substantial part of the heterogeneity: Going from a dollar invoicing share of 0.13 (Switzerland) to 0.88 (Argentina) shifts upward the entire cross-sectional

¹[Casas et al. \(2016\)](#) use customs data to calculate export invoicing shares for Colombia at the bilateral level and find small heterogeneity, implying that a country's average should serve as a good proxy for some countries.

distribution of dollar pass-through by about 0.10, a shift comparable to the estimated overall cross-dyad interquartile range for dollar pass-through of 0.13. The cross-dyad Spearman rank correlation coefficient between dollar pass-through and the importer's dollar invoicing share is estimated to be 0.39, with 95% credible interval [0.27, 0.47], strongly indicating that the dyads with the highest dollar invoicing shares also tend to have the highest dollar pass-through. For the quantity specification, we similarly find high cross-dyad heterogeneity of elasticities with respect to the dollar, and point estimates indicate that the invoicing share is an economically important driver of the heterogeneity. However, the posterior uncertainty is larger in the quantity specification.

The magnitudes of our results and the global nature of our data set point to the dominant currency paradigm as being a more empirically relevant starting point for analysis than traditional modeling approaches. It explains why shocks that cause the dollar exchange rate to fluctuate, including U.S. monetary policy shocks, have a greater impact on global trade than other countries' monetary policy shocks do. It also helps rationalize why countries may choose to stabilize the value of their currencies relative to the dollar even when their trade with the U.S. is a small share of their overall trade.

Literature review. Our exchange rate pass-through analysis appears to be among the first to exploit a globally representative data set on bilateral trade volumes in addition to values. This allows us to distinguish the effects of exchange rates on volumes and prices (more precisely, unit values) at the level of country pairs. We use the cross-sectional richness of our data set to investigate the determinants of differential pass-through, especially as it relates to currency of invoicing. Our analysis appears to be the first attempt in the literature at quantifying the overall extent and determinants of the heterogeneity of exchange rate pass-through and elasticity across trade dyads.

To our knowledge, the only other work that utilizes a similarly rich data set is [Bussière et al. \(2016\)](#), who analyze trade prices and quantities at the product level. The goal of that paper is to quantify the elasticity of prices and quantities to the bilateral exchange rate and check if Marshall-Lerner conditions hold. In contrast, our goal is to understand the prominence of dominant currencies in international trade by comparing the importance of dollar and bilateral exchange rates and by exploiting data on currency invoicing.

The remaining literature on exchange rate pass-through falls into two main camps.² First,

²The trade gravity equation literature frequently uses extensive bilateral data sets, but the data is on trade values without distinguishing between prices and volumes (see the review by [Head and Mayer, 2015](#)).

many papers have used unilateral/country-level time series, which limits the ability to analyze cross-sectional heterogeneity and necessitates the use of trade-weighted rather than truly bilateral exchange rates (e.g., [Leigh et al., 2015](#)). Second, a recent literature has estimated pass-through of bilateral exchange rates into product-level prices (as opposed to unit values), but these micro data sets are only available for a small number of countries (see the review by [Burstein and Gopinath, 2014](#)).

Our paper is closely related to [Casas et al. \(2016\)](#) who model the dominant currency paradigm and test its implications for the dollar's role in pass-through regressions and for the terms of trade using product level data for Colombia. We build on this work by providing evidence for the dominant currency paradigm using newly constructed import and export price index data for 55 countries and over 2,500 country-pairs. In addition, and separate from [Casas et al. \(2016\)](#), we relate the heterogeneity in pass-through estimates to the dollar invoicing shares of countries and estimate the impact of U.S. monetary policy shocks on bilateral import price pass-through.

From a methodological perspective, our paper's contribution is to introduce a semiparametric Bayesian panel data model with cross-sectionally heterogeneous slope coefficients. Our specification of the cross-sectional distribution of slope coefficients relies on the class of Mixture of Gaussian Linear Regression nonparametric conditional density priors in [Pati et al. \(2013\)](#), who derive high-level posterior concentration results. The MGLR prior class extends the much-used Dirichlet Process Mixture density prior class to *conditional* density estimation.³ [Liu \(2017\)](#) uses the MGLR prior specification but places it on the unit-specific panel intercepts (rather than slopes), and she focuses on forecasting rather than characterizing cross-sectional heterogeneity. Although our linear-in-parameters specification is more restrictive than the frequentist non-parametric approaches of [Evdokimov \(2010\)](#) and [Chernozhukov et al. \(2013\)](#), our Bayesian framework facilitates visualization of the entire conditional pass-through distribution, uncertainty assessment, and model selection. For posterior sampling, we rely on the Stan software package ([Stan Development Team, 2016](#)), which we show achieves robust and rapid mixing in our application despite the thousands of parameters and non-conjugate priors. A caveat to our analysis is that identification of the full distribution of random slopes in linear panel data models is only possible under *a priori* restrictions on the persistence of the idiosyncratic regressions errors ([Chamberlain, 1992](#); [Arellano and Bonhomme, 2012](#)).

Outline. The paper is organized as follows. [Section 2](#) discusses a simple conceptual framework that motivates our empirical analysis. [Section 3](#) describes our data set of bilateral trade unit values

³[Hirano \(2002\)](#) imposes the DPM prior on the distribution of idiosyncratic errors in a panel data model.

and quantities, exchange rates, dollar invoicing shares, and U.S. monetary shocks. [Section 4](#) presents panel regression evidence on the average pass-through from bilateral, dollar, and euro exchange rates (or monetary shocks) into prices, quantities, and terms of trade. In [Section 5](#), we employ the Bayesian model to characterize the cross-sectional heterogeneity of dollar pass-through and its relation to invoicing shares. The [Appendix](#) contains details on the data set, the Bayesian approach, and supplementary empirical results.

2 Conceptual framework

In this section we provide a simple conceptual framework along the lines of Proposition 2 in [Casas et al. \(2016\)](#) to motivate the empirical analysis that follows. Define p_{ij} to be the log price of goods exported from country i to country j measured in currency j , e_{ij} to be the log bilateral exchange rate between country i and country j expressed as the price of currency i in terms of currency j , and $e_{\$j}$ to be the log price of a U.S. dollar in currency j . Suppose a fraction θ_i of these exports are invoiced in the producer's (country i) currency, a fraction θ_j in the local (destination country j) currency and a fraction θ_u in the dominant currency (dollar) with $\sum_{k \in \{i,j,u\}} \theta_k = 1$. Import price inflation for country j for goods originating from country i is then,

$$\Delta p_{ij,t} = \theta_j \Delta p_{ij,t}^j + \theta_i [\Delta p_{ij,t}^i + \Delta e_{ij,t}] + \theta_u [\Delta p_{ij,t}^u + \Delta e_{uj,t}]$$

where $p_{ij,t}^k$ stands for the price of goods imported by country j from i that are invoiced in the currency k . Under Calvo pricing we have, $\Delta p_{ij,t}^k = (1 - \delta_p) (\bar{p}_{ij,t}^k - p_{ij,t-1}^k)$ where $\bar{p}_{ij,t}^k$ is the reset-price for (ij) in currency k . Through substitution we can express import price inflation as

$$\Delta p_{ij,t} = \theta_i \Delta e_{ij,t} + \theta_u \Delta e_{uj,t} + (1 - \delta_p) \sum_k \theta_k \Delta \bar{p}_{ij,t}^k,$$

where $\Delta \bar{p}_{ij,t}^k \equiv \bar{p}_{ij,t}^k - p_{ij,t-1}^k$. In the very short-run when $\delta_p \rightarrow 1$, we have the following benchmarks for the changes in import prices and the terms of trade (TOT).

- In the case of producer currency pricing (PCP), $\theta_i = 1$ and $\theta_j = \theta_u = 0$,

$$\begin{aligned} \Delta p_{ij,t} &= 1 \cdot \Delta e_{ij,t} + 0 \cdot \Delta e_{uj,t}, & \Delta p_{ji,t} &= -1 \cdot \Delta e_{ij,t} + 0 \cdot \Delta e_{uj,t}, \\ \text{tot}_{ij,t} &= \Delta p_{ij,t} - (\Delta p_{ji,t} + \Delta e_{ij,t}) = 1 \cdot \Delta e_{ij,t}. \end{aligned}$$

- In the case of local currency pricing (*LCP*), $\theta_j = 1$ and $\theta_i = \theta_u = 0$,

$$\begin{aligned}\Delta p_{ij,t} &= 0 \cdot \Delta e_{ij,t} + 0 \cdot \Delta e_{uj \neq i,t}, & \Delta p_{ji,t} &= 0 \cdot \Delta e_{ij,t} + 0 \cdot \Delta e_{uj \neq i,t}, \\ \text{tot}_{ij,t} &= \Delta p_{ij,t} - (\Delta p_{ji,t} + \Delta e_{ij,t}) = -1 \cdot \Delta e_{ij,t}.\end{aligned}$$

- In the case of dominant currency pricing (*DCP*), $\theta_u = 1$ and $\theta_i = \theta_j = 0$,

$$\begin{aligned}\Delta p_{ij,t} &= 0 \cdot \Delta e_{ij,t} + 1 \cdot \Delta e_{uj,t}, & \Delta p_{ji,t} &= 0 \cdot \Delta e_{ij,t} + 1 \cdot \Delta e_{ui,t}, \\ \text{tot}_{ij,t} &= \Delta p_{ij,t} - (\Delta p_{ji,t} + \Delta e_{ij,t}) = 0 \cdot \Delta e_{ij,t}.\end{aligned}$$

In summary, the predicted coefficients from a regression of (log) changes in import prices on (log) changes in bilateral and dollar exchange rates differ qualitatively across the *PCP*, *LCP*, and *DCP* benchmarks, as do the implications for the terms of trade.

At longer horizons, some prices do adjust and the predictions depend on the response of reset prices $\bar{p}_{ij,t}^k$ to changes in $e_{ij,t}$. With endogenous currency choice and Calvo timing, [Gopinath et al. \(2010\)](#) demonstrate that firms choose to price in currencies in which its reset price is most stable, that is its desired pass-through conditional on a price change is low. Consequently, even at longer (annual) horizons, we should expect the divergent predictions across *PCP*, *LCP*, and *DCP* to hold.

3 Data

The core of our data set consists of panel data on bilateral trade values and volumes from Comtrade. To this global data set we append macroeconomic country aggregates from the World Bank's World Development Indicators, financial variables from the Federal Reserve Bank of St. Louis's FRED database, and currency invoicing shares from [Gopinath \(2015\)](#). Finally, we construct an annual series of U.S. monetary policy induced exchange rate changes.

Comtrade. UN Comtrade provides detailed customs data for a large set of countries at HS 6-digit product level with information about the USD value, quantity, and weight of imports and exports. This dataset makes it possible to compute volume changes over time for each product, and use the value data to infer unit values. Once unit values are calculated, we compute Laspeyres, Paasche and Fisher indices, both in their fixed base and chained forms to aggregate up from the product level. We do various aggregations, the main one being across products we classify

as commodities and one for noncommodities. Given the inherent difficulty in drawing a line between commodities and noncommodities, we define commodities fairly broadly as HS chapters 1–27 and 72–83 which comprises animal, vegetable, food, mineral, and metal products. We use chained Fisher indices in the analysis that follows.⁴

We conduct this exercise at annual frequency, and for exporter and importer reported data separately. Coverage of Comtrade at annual frequency over time and across countries is good. The longest time span of the data is 1989–2015, although the coverage varies by dyad. [Appendix A.1](#) breaks down the coverage by country. For each reporting country, we construct indices for both imports and exports. This gives us two sets of numbers for each bilateral trade flow, one as reported by the importer and one as reported by the exporter and allows us to do robustness checks by comparing our empirical results across the two sets.

The biggest challenge for constructing price and volume indices using customs data is the so-called unit value bias, as argued by [Silver \(2007\)](#). Unit values, calculated simply by dividing observed values by quantities, are not actual prices. Even at the narrowly defined product categories at 6-digit product level, there is likely to be a wide range of products whose prices may not be moving proportionately. The implication is that if there are shifts in quantities traded within the narrowly defined product categories, unit values would be influenced even when there may not be any price movement. This creates a bias that the employed methodology takes a stab at correcting for by eliminating products whose unit values have a variance higher than a threshold and hence are more likely to suffer from the unit value bias.

Another challenge that arises from using Comtrade data is related to the use of different HS vintages over time. HS classification is updated about every five years to ensure that the available codings accurately reflect the variety of products being traded. This involves introducing codes for new products, eliminating the old ones, and often regrouping existing products. While concordances are readily available to facilitate the matching of HS codes across different HS vintages, this process inevitably leads to a loss of information especially in the case of data on quantities because the mapping of products across vintages is rarely one-to-one. To get around this problem, for the years in which there is a transition to a new HS vintage, we compute the indices twice, once under the old vintage (using concordances) and once under the new one. This way, only these transition years would be effected by the loss of information due to matching across vintages. After that year, we switch to working with the new vintage. This method not only minimizes the loss of information but also allows us to include new products in the construction

⁴The Fisher price index satisfies a number of tests laid out in index number theory and is flexible enough to provide a good proxy for a large set of functional forms ([Gaulier et al., 2008](#); [IMF, 2009](#)).

of the indices. Further details of this method, including the strategy for dealing with outliers and missing values, and the comparison with a similar dataset constructed by [Gaulier et al. \(2008\)](#) is discussed in ongoing work by [Boz and Cerutti \(2017\)](#).

In the final stage, we compare our unit value indices to those provided by the BLS for the U.S., the only country, to our knowledge, that collects import price indices based on price surveys by origin. As shown in [Appendix A.1](#), this comparison for the U.S. suggests that working with unit values is acceptable as the growth rates of the two series are broadly aligned for most trading partners. Additionally, [Boz and Cerutti \(2017\)](#) find favorable results when comparing country-level indices with those from the WTO and IMF World Economic Outlook.

Dollar invoicing share. For currency invoicing shares we use the data set constructed by [Gopinath \(2015\)](#). The export and import invoicing share for a country is a simple average of the respective shares for the years in which it is reported over the period 1999–2014. For all countries the invoicing shares tend to be fairly stable over time. [Appendix A.1](#) lists the USD import invoicing share for the 39 countries in our sample with available invoicing data.

U.S. monetary shocks. We compute currency-specific annual U.S. monetary policy induced exchange rate changes by summing across daily exchange rate changes on U.S. Federal Open Market Committee (FOMC) announcement dates. We use the *scheduled* FOMC announcement dates for 1990–2004 from [Gürkaynak et al. \(2005\)](#), supplemented with dates for 2005–2013 from [Nakamura and Steinsson \(2016\)](#), as well as dates for 2014–2015 from the FOMC meeting calendar on the website of the Board of Governors. There are a total of 219 scheduled announcement dates from 1990–2015. On each of these dates, we compute the daily log change (relative to the previous weekday) in the exchange rate vis-à-vis the U.S. dollar for each country in the Comtrade sample. Daily exchange rate series were obtained from FactSet (close mid price).⁵ To obtain an annual series for each country, we compute the unweighted sum of the log exchange rate changes on FOMC dates in a given year.

Country-level and global macro data. We obtain annual exchange rates and macroeconomic data for the countries in our sample from the World Bank’s World Development Indicators (WDI) database. We obtain the WTI oil price, 1-year Treasury bill rate, and VIX from the St. Louis Fed’s FRED database. See [Appendix A.1](#) for details.

⁵FactSet corrects exchange rates for redenomination and currency substitution. We only use data on FOMC dates.

4 Bilateral pass-through, terms of trade, and the dollar

In this section we show that our global trade dataset is consistent with the dominant currency paradigm: The U.S. dollar plays an outside role in driving international trade prices and quantities. We run fixed effects panel regressions at the dyad (country pair) level with exchange rates as the independent variable, and either prices, terms of trade, or volumes as the dependent variables. In all cases we find that bilateral (importer vs. exporter) exchange rates matter substantially less than the exchange rate vis-à-vis the U.S. dollar. The effects of the dollar are stronger when the importing country has a higher fraction of trade invoiced in dollars. The pass-through of the subset of dollar exchange rate fluctuations that are due to U.S. monetary policy actions is high. Finally, we show that the dollar's quantitative dominance holds up in specifications that control also for the euro exchange rate.

All specifications below rely on Comtrade series that use Fisher price indices, data for non-commodities goods only, and the preferred outlier truncation technique of [Boz and Cerutti \(2017\)](#). In [Appendix A.2](#) we show that our results are robust to alternative choices.

4.1 Exchange rate pass-through into prices

We first examine the pass-through of bilateral and dollar exchange rates to bilateral trade price indices. Define p_{ij} to be the log price of goods exported from country i to country j measured in currency j , e_{ij} to be the log bilateral exchange rate between country i and country j expressed as the price of currency i in terms of currency j , and $e_{\$j}$ to be the log price of a U.S. dollar in currency j . We estimate the following specifications,

$$\Delta p_{ij,t} = \lambda_{ij} + \delta_t + \sum_{k=0}^2 \alpha_k \Delta e_{ij,t-k} + \theta' X_{i,t} + \varepsilon_{ij,t} \quad (1)$$

$$\Delta p_{ij,t} = \lambda_{ij} + \delta_t + \sum_{k=0}^2 \alpha_k \Delta e_{ij,t-k} + \sum_{k=0}^2 \beta_k \Delta e_{\$j,t-k} + \theta' X_{i,t} + \varepsilon_{ij,t} \quad (2)$$

$$\begin{aligned} \Delta p_{ij,t} = & \lambda_{ij} + \delta_t + \sum_{k=0}^2 \alpha_k \Delta e_{ij,t-k} + \sum_{k=0}^2 \eta_k \Delta e_{ij,t-k} \times S_j \\ & + \sum_{k=0}^2 \beta_k \Delta e_{\$j,t-k} + \sum_{k=0}^2 \psi_k \Delta e_{\$j,t-k} \times S_j + \theta' X_{i,t} + \varepsilon_{ij,t} \end{aligned} \quad (3)$$

where λ_{ij} and δ_t are dyadic and time fixed effects, respectively. $X_{i,t}$ are other controls, namely the change in the log producer price index of the exporting country i measured in currency i (and two lags).

For reference, we first consider the specification without the dollar exchange rate as an explanatory variable. Regression Eq. (1) is a standard pass-through regression where bilateral import prices are regressed on bilateral exchange rates. The estimates from such a regression are reported in columns (1) and (4) of Table 1. Column (1) uses import prices of country j originating from country i as reported by country i , and column (4) uses prices reported by country j . Under perfect construction, these two should be the same, but that is not the case in practice. However, we obtain similar estimates for pass-through. According to these estimates, when country j 's currency depreciates relative to country i by 10%, import prices in country j rise by 8%, suggestive of close to complete pass-through at the one year horizon.⁶ The second and third lags are economically less important.

Our main result in this section establishes the dominance of the dollar over bilateral exchange rates in predicting trade price movements. Columns (2) and (5) report estimates from regression Eq. (2). As is evident, including the dollar exchange rate sharply reduces the relevance of the bilateral exchange rate. It knocks the coefficient on the bilateral exchange rate from 0.80 down to 0.32 in the case when exporter-reported prices are used, and from 0.76 to 0.16 when importer-reported prices are used. Instead, almost all of the effect is absorbed by the dollar exchange rate. Notice that, due to our inclusion of time fixed effects, the apparent dominance of the dollar cannot be an artifact of special conditions that may apply in times when the dollar appreciates or depreciates against *all* other currencies, for example due to global recessions or flight to safety in asset markets. Appendix A.2 shows that our results are robust to the choice of time sample.

The cross-dyad heterogeneity in pass-through coefficients is related to the propensity to invoice imports in dollars. Columns (3) and (6) interact the dollar and bilateral exchange rates with the share of invoicing in dollars at the importer country level, as in regression Eq. (3). Notice that we do not have data on the fraction of *bilateral* trade invoiced in dollars, so we use the importer's country-level share as a proxy. As expected, the import invoicing share plays an economically and statistically significant role for the dollar pass-through. Depending on whether we use prices reported by exporters or importers, the regression results indicate that increasing the dollar invoicing share by 10 percentage points causes the contemporaneous dollar pass-through to increase by about 3 percentage points. In Section 5 below we further quantify the importance of the dollar invoicing share for explaining the cross-sectional variation in pass-through.

⁶With year fixed effects this should be interpreted as fluctuations in excess of world annual fluctuations.

EXCHANGE RATE PASS-THROUGH INTO PRICES

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	export $\Delta p_{ij,t}$	export $\Delta p_{ij,t}$	export $\Delta p_{ij,t}$	import $\Delta p_{ij,t}$	import $\Delta p_{ij,t}$	import $\Delta p_{ij,t}$
$\Delta e_{ij,t}$	0.801*** (0.0113)	0.315*** (0.0127)	0.318*** (0.0177)	0.757*** (0.0132)	0.164*** (0.0126)	0.209*** (0.0169)
$\Delta e_{ij,t-1}$	0.0762*** (0.00675)	0.115*** (0.0133)	0.126*** (0.0206)	0.0674*** (0.00818)	0.0521*** (0.0123)	0.0270* (0.0154)
$\Delta e_{ij,t-2}$	0.0113** (0.00489)	-0.0656*** (0.0114)	-0.0863*** (0.0147)	0.0306*** (0.00608)	-0.0727*** (0.0127)	-0.0721*** (0.0167)
$\Delta e_{ij,t} \times S_j$			-0.0152 (0.0230)			-0.0841*** (0.0240)
$\Delta e_{ij,t-1} \times S_j$			-0.0156 (0.0260)			0.0319 (0.0232)
$\Delta e_{ij,t-2} \times S_j$			0.0205 (0.0156)			-0.000922 (0.0164)
$\Delta e_{\$j,t}$		0.656*** (0.0142)	0.522*** (0.0274)		0.781*** (0.0143)	0.565*** (0.0283)
$\Delta e_{\$j,t-1}$		-0.128*** (0.0146)	-0.118*** (0.0290)		-0.0737*** (0.0157)	0.0844*** (0.0276)
$\Delta e_{\$j,t-2}$		0.0857*** (0.0124)	0.143*** (0.0227)		0.104*** (0.0146)	0.117*** (0.0259)
$\Delta e_{\$j,t} \times S_j$			0.196*** (0.0320)			0.348*** (0.0326)
$\Delta e_{\$j,t-1} \times S_j$			-0.0145 (0.0353)			-0.185*** (0.0358)
$\Delta e_{\$j,t-2} \times S_j$			-0.0716*** (0.0261)			-0.0495* (0.0290)
Exp. PPI	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
R-squared	0.411	0.447	0.507	0.356	0.398	0.515
Observations	45,945	45,945	33,291	46,820	46,820	34,513
Dyads	2,611	2,611	1,867	2,647	2,647	1,900

Table 1: The first (resp., last) three columns use Comtrade data reported by exporting (resp., importing) countries. S.e. clustered by dyad. *** p<0.01, ** p<0.05, * p<0.1.

AVERAGE PRICE PASS-THROUGH

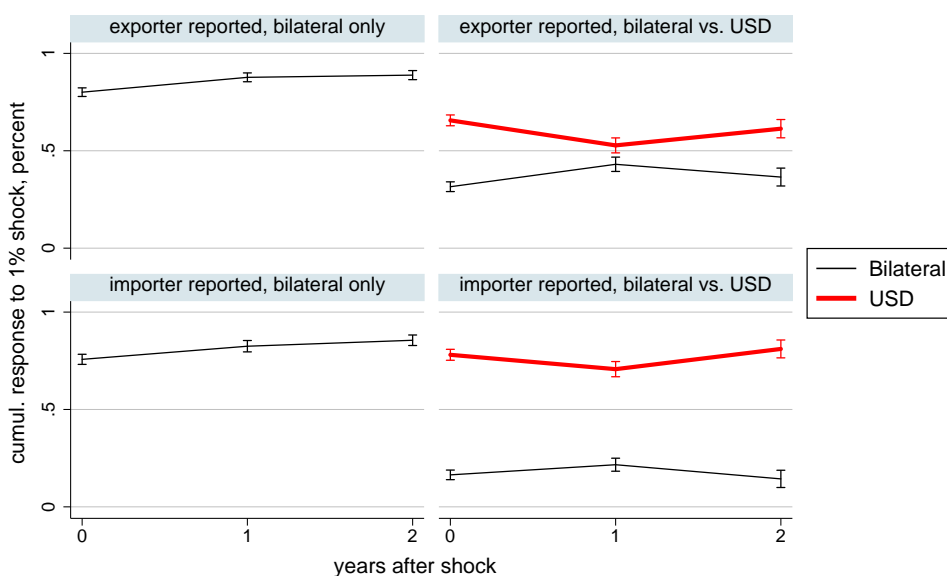


Figure 1: Impulse responses of bilateral price level to bilateral $e_{ij,t}$ and USD $e_{\$j,t}$ exchange rates. Based on the regressions in Table 1 without interactions. Top row: exporter reported data, bottom row: importer reported. Left column: specifications (1) and (4), right column: specifications (2) and (5). Error bars: 95% confidence intervals, clustering by dyad.

PRICE PASS-THROUGH AS A FUNCTION OF INVOICING SHARE

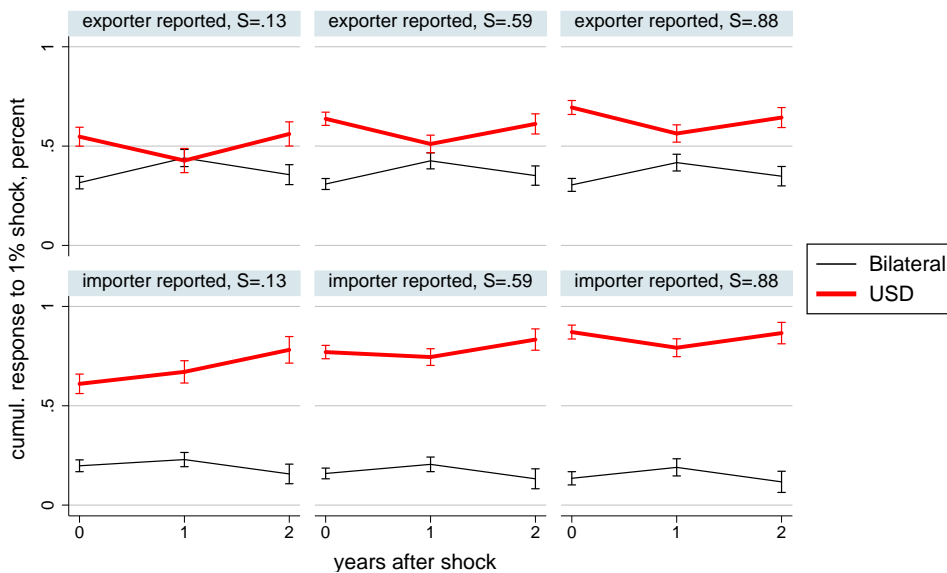


Figure 2: Impulse responses of bilateral price level to bilateral $e_{ij,t}$ and USD $e_{\$j,t}$ exchange rates, as a function of importer's dollar invoicing share S_j . Based on regression specifications (3) and (6) in Table 1 with interactions. Top row: exporter reported data, bottom row: importer reported. Error bars: 95% confidence intervals, clustering by dyad.

Figs. 1 and 2 depict the regression results visually in the form of impulse response functions. Fig. 1 shows the impulse responses of the bilateral import price *level*. The top row uses exporter reported data, the bottom row importer reported data. The left column shows the bilateral pass-through in the specifications without the dollar exchange rate, while the right column compares the bilateral and dollar pass-throughs in specifications with both exchange rates. Fig. 2 illustrates the pass-through heterogeneity as a function of the invoicing share S_j , as implied by the regression specifications with interactions. The figure focuses on three representative countries: Switzerland ($S_j = 0.13$), Turkey ($S_j = 0.59$), and Argentina ($S_j = 0.88$).

4.2 Terms of trade and exchange rates

The previously established fact that prices respond to the dollar exchange rate but not the bilateral exchange rate implies that the terms of trade should not respond to the bilateral exchange rate (Gopinath, 2015; Casas et al., 2016). We now test this hypothesis directly in our data by relating bilateral terms of trade to bilateral exchange rates. In this subsection, a cross-sectional unit is defined to be an *unordered* country pair, so that all trade flows between two countries i and j are associated with the cross-sectional unit $\{i, j\}$. Define the bilateral log terms of trade $tot_{ij} = p_{ij} - p_{ji} - e_{ij}$, a unitless quantity (i.e., export and import price indices measured in the same currency). Moreover, let ppi_{ij} denote the log ratio of PPI in country i divided by PPI in country j , with indices expressed in the same currency.

We consider the following regressions:

$$\Delta tot_{ij,t} = \lambda_{ij} + \delta_t + \sum_{k=0}^2 \alpha_k \Delta e_{ij,t-k} + \varepsilon_{ij,t}, \quad (4)$$

$$\Delta tot_{ij,t} = \lambda_{ij} + \delta_t + \sum_{k=0}^2 \alpha_k \Delta e_{ij,t-k} + \sum_{k=0}^2 \beta_k \Delta ppi_{ij,t-k} + \varepsilon_{ij,t}, \quad (5)$$

where λ_{ij} and δ_t are dyadic and time fixed effects. Regression Eq. (4) relates the growth rate of the bilateral terms of trade to the growth rate of the bilateral nominal exchange rate (and two lags). As discussed in Section 2, if exporting firms set prices in their local currencies (producer currency pricing, PCP) and prices are sticky, the contemporaneous exchange rate coefficient α_0 should equal 1. On the other hand, if exporting firms set prices in the destination currency (local currency pricing, LCP) and prices are sticky, the contemporaneous exchange rate coefficient should be -1 . However, if most prices are invoiced in U.S. dollars and are sticky in nominal terms, the coefficients α_k should be close to zero. Regression Eq. (5) controls for lags 0–2 of the growth rate

TERMS OF TRADE AND EXCHANGE RATES

VARIABLES	(1)	(2)	(3)	(4)
	export $\Delta tot_{ij,t}$	export $\Delta tot_{ij,t}$	import $\Delta tot_{ij,t}$	import $\Delta tot_{ij,t}$
$\Delta e_{ij,t}$	-0.0881*** (0.00941)	0.0121 (0.0127)	-0.0369*** (0.00863)	0.00938 (0.0130)
$\Delta e_{ij,t-1}$	0.0157 (0.0102)	-0.0126 (0.0169)	0.0447*** (0.0104)	-0.0167 (0.0157)
$\Delta e_{ij,t-2}$	0.0269*** (0.00875)	-0.00807 (0.0105)	0.00174 (0.00788)	0.00710 (0.00877)
$\Delta ppi_{ij,t}$		0.239*** (0.0246)		0.0340 (0.0260)
$\Delta ppi_{ij,t-1}$		0.0605** (0.0257)		-0.131*** (0.0263)
$\Delta ppi_{ij,t-2}$		-0.0687*** (0.0195)		-0.0511** (0.0212)
Time FE	yes	yes	yes	yes
R-squared	0.007	0.015	0.008	0.011
Observations	22,928	18,757	24,270	19,847
Dyads	1,322	1,172	1,347	1,200

Table 2: The first (resp., last) two columns use Comtrade data reported by exporting (resp., importing) countries. S.e. clustered by dyad. The number of dyads is about half that in [Table 1](#) since here the two ordered country tuples (i, j) and (j, i) are collapsed into one cross-sectional unit $\{i, j\}$. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

of the ratio of PPI in the two countries, since firms' optimal reset prices should fluctuate with domestic cost conditions.

In line with the dominant currency paradigm, we find that bilateral exchange rates are virtually uncorrelated with bilateral terms of trade. The results of the panel regressions are shown in [Table 2](#). If we do not control for relative PPI, the regression results indicate that the contemporaneous effect of the exchange rate on the terms of trade is negative, in direct contradiction of PCP. While the negative sign is consistent with LCP, the magnitude is not, as the 95% confidence interval equals $[-0.11, -0.07]$ for data reported by exporters, and $[-0.05, -0.02]$ for data

reported by importers.⁷ The coefficients on the first and second lags have opposite sign of the contemporaneous coefficient but are very small in magnitude. When controlling for relative PPI, the point estimates of the coefficients on the bilateral exchange rate shrink further toward zero, and confidence intervals on these coefficients remain narrow. Hence, the results lend strong support to the prediction of the dominant currency paradigm: Terms of trade are unresponsive to bilateral exchange rates.

4.3 Trade volume elasticity

Having demonstrated the outsize role of the U.S. dollar in determining international relative prices, we now investigate the relative importance of bilateral and dollar exchange rates in predicting bilateral trade volumes.

Table 3 shows the results from panel regressions of trade volume on bilateral and dollar exchange rates. Let y_{ij} denote the log volume of goods exported from country i to country j . Our volume regressions take the same form as in the price pass-through regressions Eqs. (1) to (3), except that the dependent variable is now the log growth rate $\Delta y_{ij,t}$ of bilateral trade volumes, and the extra controls $X_{j,t}$ (here indexed by j rather than i) consist of the log growth rate of real GDP (and two lags) for the importing country j . These regressions do not capture structural demand elasticity parameters, since we do not attempt to control for all relevant relative prices, and the importer’s GDP growth is an imperfect proxy for the level of import demand. In particular, our results will invariably conflate expenditure switching and shifts in aggregate import demand (for example due to valuation effects on net foreign assets). We view these regressions as predictive relationships that may inform future structural estimation exercises. Nevertheless, we will refer to the coefficients on exchange rates as “trade elasticities” for simplicity.

The volume regressions underline the dominant role played by the U.S. dollar. As in the case of the price pass-through regressions, adding the dollar exchange rate to the volume regressions knocks down the coefficient on the bilateral exchange rate by a substantial amount. The contemporaneous elasticity for the dollar exchange rate is around -0.2 across specifications and data sources, while the elasticity for the bilateral exchange rate is an order of magnitude smaller. The data point to an interesting reversal in the years following the contemporaneous effect, whereby import volumes tend to increase one year after a *ceteris paribus* depreciation of the importer currency rate vis-à-vis the dollar. We discuss these lag dynamics below. Unlike the price pass-through regressions, the interactions of exchange rate changes with the importer’s

⁷Attenuation bias is not a worry in this context, since the explanatory variables of interest (exchange rates) are precisely measured, except perhaps for time aggregation issues at the annual frequency.

TRADE ELASTICITY WITH RESPECT TO EXCHANGE RATE

VARIABLES	(1)	(2)	(3)	(4)	(5)	(6)
	export $\Delta y_{ij,t}$	export $\Delta y_{ij,t}$	export $\Delta y_{ij,t}$	import $\Delta y_{ij,t}$	import $\Delta y_{ij,t}$	import $\Delta y_{ij,t}$
$\Delta e_{ij,t}$	-0.148*** (0.0148)	-0.0384** (0.0180)	0.0171 (0.0403)	-0.119*** (0.0139)	-0.0310* (0.0160)	-0.0765* (0.0403)
$\Delta e_{ij,t-1}$	0.0755*** (0.0148)	0.00728 (0.0198)	-0.0682 (0.0485)	0.0757*** (0.0126)	-0.00245 (0.0165)	0.00742 (0.0354)
$\Delta e_{ij,t-2}$	0.0416*** (0.0102)	0.0128 (0.0141)	0.0495 (0.0311)	0.0393*** (0.00919)	0.0235** (0.0115)	0.00410 (0.0241)
$\Delta e_{ij,t} \times S_j$			-0.0606 (0.0655)			0.118* (0.0684)
$\Delta e_{ij,t-1} \times S_j$			0.0976 (0.0746)			-0.0433 (0.0640)
$\Delta e_{ij,t-2} \times S_j$			-0.0441 (0.0494)			0.0419 (0.0428)
$\Delta e_{\$j,t}$		-0.237*** (0.0294)	-0.188*** (0.0587)		-0.186*** (0.0250)	-0.140** (0.0600)
$\Delta e_{\$j,t-1}$		0.148*** (0.0278)	0.359*** (0.0666)		0.168*** (0.0248)	0.221*** (0.0635)
$\Delta e_{\$j,t-2}$		0.0542*** (0.0201)	-0.114** (0.0580)		0.0365* (0.0198)	0.111** (0.0525)
$\Delta e_{\$j,t} \times S_j$			-0.0104 (0.0906)			-0.0903 (0.0871)
$\Delta e_{\$j,t-1} \times S_j$			-0.244** (0.100)			-0.0465 (0.0922)
$\Delta e_{\$j,t-2} \times S_j$			0.192** (0.0797)			-0.0952 (0.0706)
Imp. GDP	yes	yes	yes	yes	yes	yes
Time FE	yes	yes	yes	yes	yes	yes
R-squared	0.073	0.075	0.084	0.069	0.071	0.074
Observations	50,761	50,761	36,757	52,272	52,272	38,582
Dyads	2,773	2,773	1,982	2,807	2,807	2,014

Table 3: The first (resp., last) three columns use Comtrade data reported by exporting (resp., importing) countries. S.e. clustered by dyad. *** p<0.01, ** p<0.05, * p<0.1.

dollar invoicing share are mostly imprecisely estimated here.

Fig. 3 visually depicts the regression results in the form of impulse responses. The figure shows the response of the level of bilateral trade volume to exchange rate shocks. The right column shows results from regression specifications with both bilateral and dollar exchange rates. It is apparent from the figure that the dollar exchange rate has a much more negative impact effect than the bilateral exchange rate. Yet, the figure also shows that the effect of either exchange rate on the level is essentially neutral at horizons of 1–2 years, due to the negative lagged terms in Table 3. One potential explanation is that the ratio of import prices and domestic prices adjust with a lag to exchange rate changes, implying that a year after the initial shock, relative prices faced by consumers are mostly unchanged compared to the period before the shock. However, we show in Appendix A.2 that this particular finding is driven by the early years in our sample, as results on the 2002–2015 subsample point toward a large, permanent negative effect of dollar appreciations on the volume of bilateral trade.

Fig. 4 illustrates the trade elasticity heterogeneity as a function of the dollar invoicing share, similar to Fig. 2. The point estimates of the impulse responses point toward an association between higher dollar invoicing shares and more negative trade elasticities, but the confidence intervals are wider than in our earlier price pass-through regressions. Section 5 provides further quantitative evidence on trade elasticity heterogeneity and its determinants.

4.4 Effects of U.S. monetary policy shocks

We now directly estimate the effects of U.S. monetary policy induced exchange rate changes on bilateral trade. The dominant role played by the dollar in our earlier price and volume regressions suggests that U.S. monetary policy actions that cause the dollar to fluctuate could have large spillover effects on trade prices and volumes. In this section we directly measure the impulse responses with respect to U.S. monetary shocks.

As described in Section 3, for each country we construct an annual measure of U.S. monetary policy induced exchange rate fluctuations by summing daily log exchange rate changes on dates with scheduled FOMC announcements. Let $z_{j,t}$ be the sum of these daily log changes in year t for country j , where the exchange rate is measured in units of country j currency per U.S. dollar. The use of daily exchange rate changes on FOMC announcement dates allows for a specific interpretation of the shocks $z_{j,t}$, whereas the overall exchange rate change $\Delta e_{\$,j,t}$ arguably is an amalgam of the effects of several distinct shocks. However, we do not claim that $z_{j,t}$ is solely driven by U.S. monetary policy actions, or that all fluctuations in $z_{j,t}$ are necessarily “surprises”. Because we are interested in a large number of currencies for a sample going back to 1990, we

AVERAGE TRADE ELASTICITY

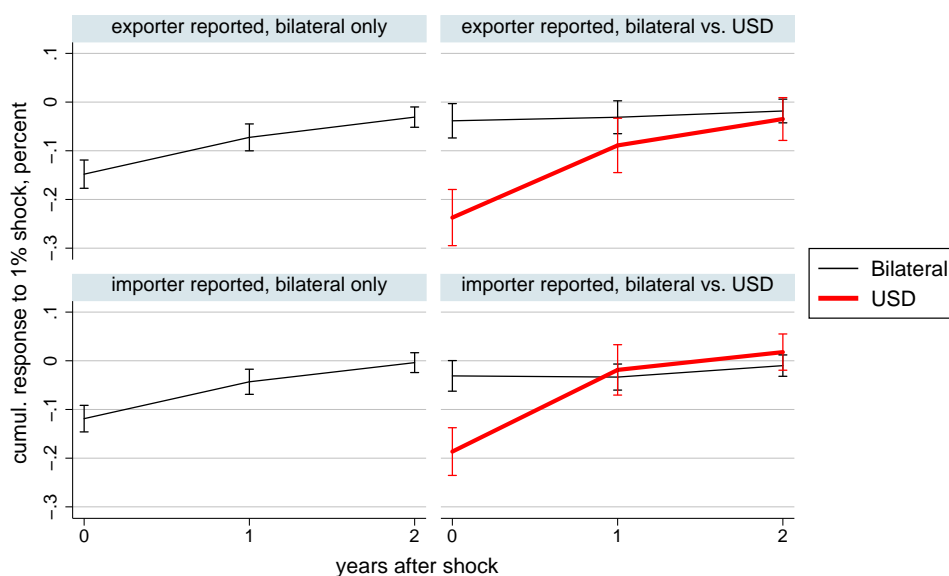


Figure 3: Impulse responses of bilateral volume to bilateral $e_{ij,t}$ and USD $e_{\$j,t}$ exchange rates. Based on regressions in Table 3 without interactions. Top row: exporter reported data, bottom row: importer reported. Left column: specifications (1) and (4), right column: specifications (2) and (5). Error bars: 95% confidence intervals, clustering by dyad.

TRADE ELASTICITY AS A FUNCTION OF INVOICING SHARE

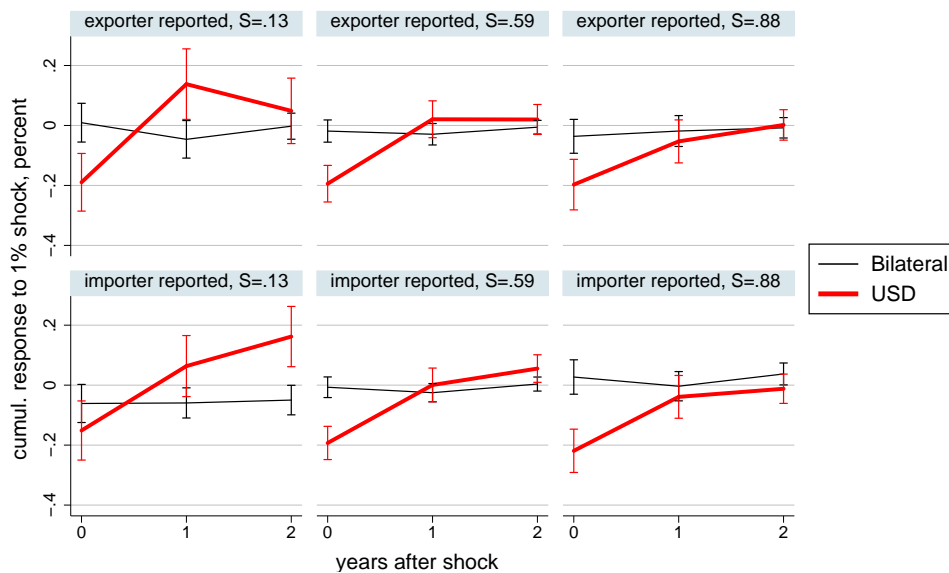


Figure 4: Impulse responses of bilateral volume to bilateral $e_{ij,t}$ and USD $e_{\$j,t}$ exchange rates, as a function of importer's dollar invoicing share S_j . Based on regression specifications (3) and (6) in Table 1 with interactions. Top row: exporter reported data, bottom row: importer reported. Error bars: 95% confidence intervals, clustering by dyad.

cannot use high-frequency intra-day data as in Andersen et al. (2003), Gürkaynak et al. (2005), and Nakamura and Steinsson (2016), for example.

Daily and annual data are consistent with our interpretation of the U.S. monetary shock series. U.S. monetary tightenings are associated with appreciations of the dollar against the currencies in our sample: The daily correlation of log exchange rate changes (across all currencies) and changes in the U.S. 1-year Treasury bill rate is 0.064 on FOMC dates in the period 1990–2007 (i.e., excluding the zero lower bound period). The standard deviation of daily log exchange rate changes across all currencies is 0.72% on FOMC dates; it is 0.92% across all days in the 1990–2015 sample. The standard deviation of the *annual* (i.e., summed) monetary shock series $z_{j,t}$ is 2.6%, compared to an annual standard deviation of 31.6% for overall log exchange rate changes $\Delta e_{\$j,t}$ on the same 1990–2015 sample. The annual correlation of $z_{j,t}$ and $\Delta e_{\$j,t}$ is 0.17. We conclude that our monetary shock series captures a small but nontrivial fraction of shocks to exchange rates vis-à-vis the dollar.

We measure the effect of U.S. monetary policy actions on bilateral trade prices using panel fixed effects regressions as in Eqs. (1) to (3) in Section 4.1, except here we replace exchange rate changes with our U.S. monetary shock series. Specifically, we replace the log change in the bilateral exchange rate $\Delta e_{ij,t}$ with the U.S. monetary policy induced change in the bilateral exchange rate, $z_{j,t} - z_{i,t}$, and we replace the log change in the dollar exchange rate $\Delta e_{\$j,t}$ with the dollar exchange rate shock $z_{j,t}$. We include lags 0–6 of the exchange rate shocks on the right-hand side of our regression specifications, as our results below suggest that the pass-through of U.S. monetary shocks is more gradual than the pass-through of raw exchange rate changes. We continue to control for dyad and time fixed effects, as well as lags 0–2 of exporter PPI log growth.

Fig. 5 shows that the average pass-through of U.S. monetary policy induced exchange rate changes into bilateral import prices is high in the long run. The figure depicts the impulse response functions of the bilateral price level to shocks.⁸ The left column is based on specifications with only shocks $z_{j,t} - z_{i,t}$ to the bilateral exchange rate, while the right column is based on specifications that add shocks $z_{j,t}$ to the dollar exchange rate. We split the results by exporter (top row) and importer (bottom row) reported data. The *impact* effect of shocks to both bilateral and dollar exchange rates is about 0.3. However, in specifications with both bilateral and dollar exchange rate shocks, the dollar pass-through rises to about 0.6–1.0 in years 4–6, depending on specification, whereas the bilateral pass-through is negligible in the long run.

Fig. 6 shows that the pass-through of shocks to the dollar exchange rate is strongly positively

⁸For brevity, we do not report to underlying regression results in table form. These results are available from the authors upon request.

AVERAGE PRICE PASS-THROUGH FROM U.S. MONETARY SHOCKS

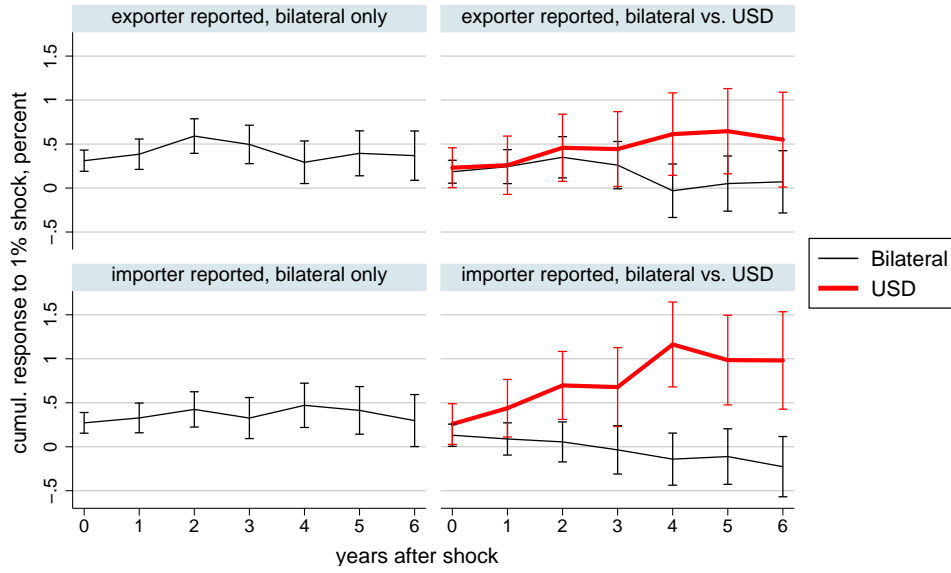


Figure 5: Impulse responses of bilateral price level to bilateral $z_{j,t} - z_{i,t}$ and USD $z_{j,t}$ U.S. monetary policy induced exchange rate shocks. Based on regression specifications without interactions. Top row: exporter reported data, bottom row: importer reported. Left column: specifications with only bilateral shock, right column: specifications with bilateral and USD shocks. Error bars: 95% confidence intervals, clustering by dyad.

PRICE PASS-THROUGH FROM U.S. MONETARY SHOCKS GIVEN INVOICING SHARE

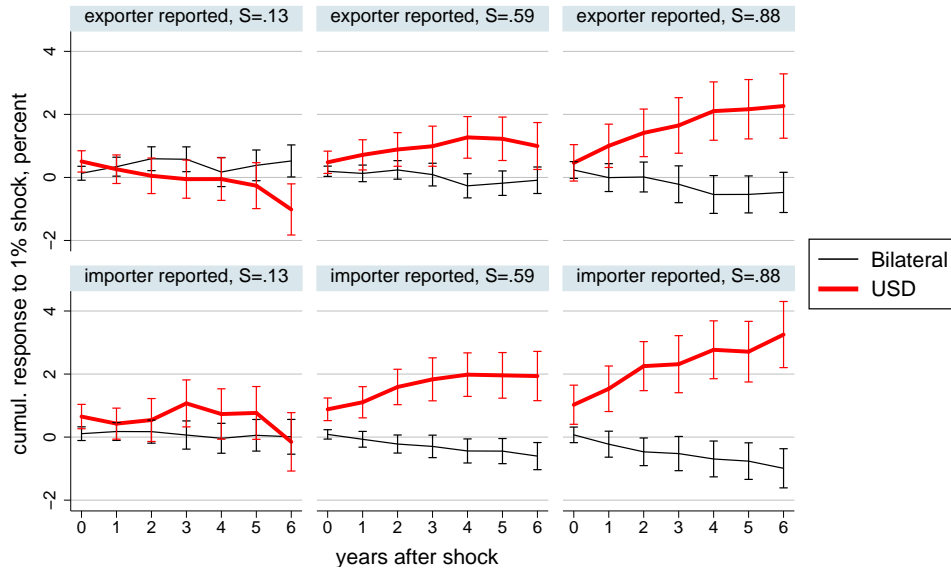


Figure 6: Impulse responses of bilateral price level to bilateral $z_{j,t} - z_{i,t}$ and USD $z_{j,t}$ U.S. monetary policy induced exchange rate shocks, as a function of importer's dollar invoicing share S_j . Based on regression specifications with interactions. Top row: exporter reported data, bottom row: importer reported. Error bars: 95% confidence intervals, clustering by dyad.

associated with the importer’s dollar invoicing share S_j . As in [Section 4.1](#), we report impulse response functions for low, medium, and high levels of dollar invoicing, where the point estimates and confidence intervals are computed from regressions with interactions. The association between pass-through and dollar invoicing is even stronger for the U.S. monetary policy induced shocks than for the overall exchange rate changes analyzed in [Section 4.1](#). While the estimated long-run pass-through of shocks to the dollar exchange rate is close to zero for a country like Switzerland with $S_j = 0.13$, it is about 2.0–3.5 for a country like Argentina with $S_j = 0.88$, depending on specification. These magnitudes are not directly comparable with the pass-through magnitudes in [Section 4.1](#), since a 1% monetary shock $z_{j,t}$ represents a much rarer occurrence than a 1% appreciation of the dollar exchange rate $e_{\$,t}$, as discussed above.

Unlike for price pass-through, regressions of trade volumes on U.S. monetary shocks yield very noisy results. This is a consequence of relatively low R^2 values for volume regressions, which we also found in [Section 4.3](#), coupled with the limited variation in measured monetary shocks relative to the variation in overall exchange rates. We therefore refrain from reporting volume regression results here. It is an interesting topic for future research to develop more comprehensive (and thus more volatile) measures of U.S. monetary policy shocks that can be related directly to trade volumes.

4.5 The dollar versus the euro

We conclude this section by comparing the explanatory power of the dollar exchange rate with that of the euro. We show that the dollar dominates both the bilateral exchange rate and the euro in regression specifications that include all three exchange rates.

The preceding panel regressions do not directly imply that the U.S. dollar is a uniquely important vehicle currency. In our regression specifications *without* interactions, we would have obtained exactly the same coefficient estimates if we had used the euro exchange rate in place of the dollar exchange rate, say, due to the fact that we control for time fixed effects. Nevertheless, our specifications *with* interactions indicated that the dollar may play a special role. Now we directly compare the explanatory power of the dollar against that of the euro in panel regressions that do not control for time fixed effects but instead control for observed global real and financial variables.

To measure bilateral price pass-through, we run panel regressions of the form

$$\Delta p_{ij,t} = \lambda_{ij} + \sum_{k=0}^2 \alpha_k \Delta e_{ij,t-k} + \sum_{k=0}^2 \beta_k \Delta e_{\$,t-k} + \sum_{k=0}^2 \xi_k \Delta e_{\text{€},t-k} + \theta' X_{ij,t} + \varepsilon_{ij,t}, \quad (6)$$

where $e_{\in j,t}$ denotes the log euro exchange rate in units of currency j per euro. Notice that we omit time fixed effects, as is necessary to identify β_k and ξ_k separately. In addition to lags 0–2 of exporter PPI log growth, the controls $X_{ij,t}$ consist of the contemporaneous values of global real GDP growth, global GDP deflator inflation, global export volume growth, growth in the WTI oil price deflated by the global GDP deflator, and the log VIX. The time sample for regressions in this subsection is 2002–2015 due to the introduction of the euro in 1999 and our use of lagged exchange rate changes.

Fig. 7 shows that the euro pass-through into prices is negligible on average, while the dollar pass-through remains high when we control for the euro. The figure displays the regression results in the form of impulse responses of the bilateral price level; corresponding regression tables are available in Appendix A.2. We split by exporter (top) and importer (bottom) reported data. The left column shows results for specifications that do not include the dollar exchange rate, i.e., restricting $\beta_k = 0$ in Eq. (6). The right column displays estimates of bilateral, dollar, and euro pass-through from regressions with all three exchange rates. In the latter specifications, the dollar pass-through is quantitatively much larger than the euro pass-through; indeed, the results are close to those of Section 4.1 where we did not consider the euro at all. The euro pass-through is quantitatively small at all horizons, and it is in fact estimated to be slightly negative. The difference between the dollar and euro pass-through is statistically significant at conventional significance levels. In Appendix A.2 we show through regressions with interactions that the importer’s dollar and euro invoicing shares help explain the heterogeneity in pass-through.

Similarly, we find that the dollar exchange rate has the largest predictive power for trade volumes. We run panel regressions similar to Eq. (6), except with volume growth $\Delta y_{ij,t}$ on the left-hand side, and we replace exporter PPI with lags 0–2 of importer real GDP growth in the list of controls $X_{ij,t}$. Fig. 8 shows impulse responses of the level of bilateral trade volume to the bilateral, dollar, and euro exchange rates. The dollar exchange rate is the only one of the three that has a quantitatively large negative association with trade volumes.⁹ Curiously, the trade elasticity of the euro exchange rate is estimated to be positive both in the short and long run, although the confidence intervals are consistent with economically small magnitudes.¹⁰ The difference between the dollar and euro trade elasticities is significant at conventional significance levels.

⁹The different long-run level effect of the dollar in Figs. 3 and 8 is due to the difference in time sample, as discussed in Appendix A.2.

¹⁰It is an interesting topic for future research to investigate whether the positive predictive effect of euro appreciations on bilateral import volume can be ascribed to valuation effects on net foreign assets that shift the overall level of import demand.

PRICE PASS-THROUGH FROM DOLLAR AND EURO EXCHANGE RATES

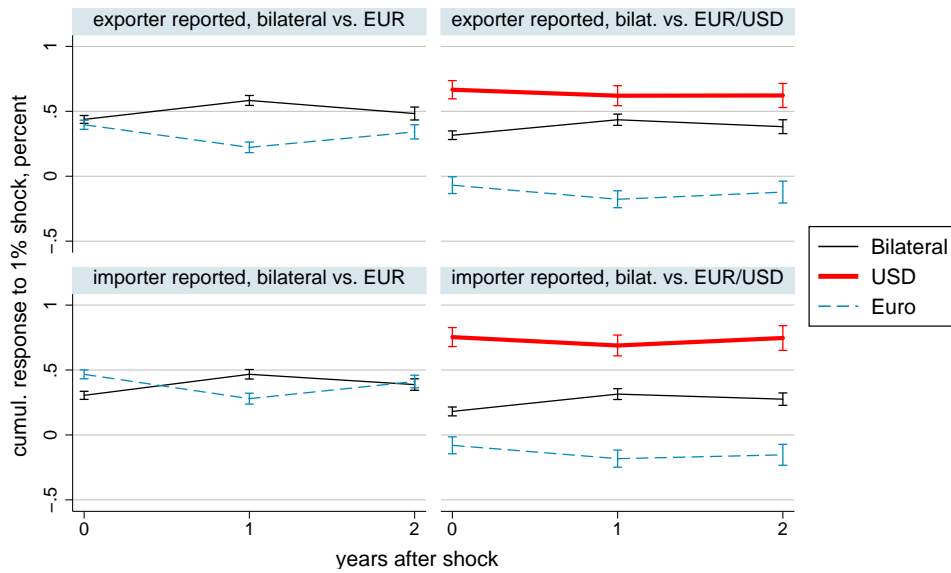


Figure 7: Impulse responses of bilateral price level to bilateral $e_{ij,t}$, USD $e_{\$j,t}$, and euro $e_{\text{€}j,t}$ exchange rates. Based on regressions in Table 6, Appendix A.2. Top row: exporter reported data, bottom row: importer reported. Left column: specifications with only bilateral and euro ER, right column: specifications adding USD. Error bars: 95% confidence intervals, clustering by dyad.

TRADE ELASTICITY FOR DOLLAR AND EURO EXCHANGE RATES

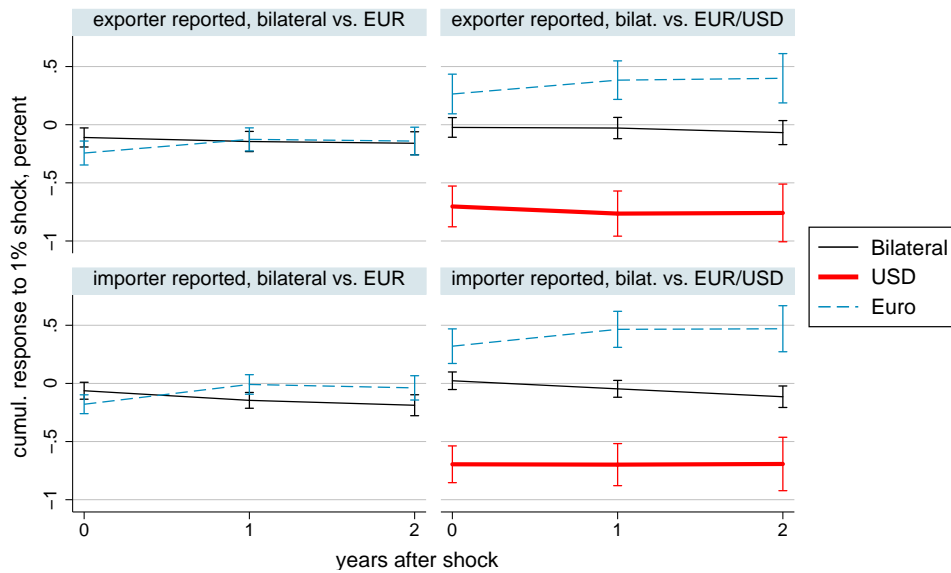


Figure 8: Impulse responses of bilateral volume to bilateral $e_{ij,t}$, USD $e_{\$j,t}$, and euro $e_{\text{€}j,t}$ exchange rates. Based on regressions in Table 7, Appendix A.2. Top row: exporter reported data, bottom row: importer reported. Left column: specifications with bilateral and euro ER, right column: specifications adding USD. Error bars: 95% confidence intervals, clustering by dyad.

5 Determinants of pass-through heterogeneity

In this section we show that the cross-dyad variation in exchange rate price pass-through and trade elasticity is well explained by the U.S. dollar’s dominance as invoicing currency. The theoretical framework underlying the dominant currency paradigm predicts that pass-through from bilateral exchange rates to prices or quantities should vary across countries depending on the share of imports invoiced in U.S. dollars. The panel regressions in the previous section indicate that this interaction effect is statistically and economically significant for price pass-through. In this section we directly estimate how important the interaction effect is relative to unobserved factors affecting the cross-sectional heterogeneity of price pass-through and trade elasticities.

5.1 Bayesian model of pass-through heterogeneity

We employ a Bayesian hierarchical panel data model with cross-sectionally varying slopes. This model optimally exploits the geographical and temporal richness of our data set. By explicitly modeling the cross-sectional heterogeneity of pass-through, we are able to quantify how much of this heterogeneity can be explained by the share of trade invoiced in U.S. dollars (for brevity, here we use the term “pass-through” to describe the relationship between exchange rates and prices or quantities). Such questions cannot be answered by linear panel models with interactions, as these common-coefficients panel models are unable to quantify the overall cross-sectional heterogeneity of pass-through. We use a hierarchical Bayes framework with a semiparametric specification for the distribution of pass-through coefficients conditional on the dollar invoicing share.

The hierarchical approach lets the data determine how much pass-through varies across trade dyads.¹¹ This approach can roughly be thought of as striking a balance between two extreme but standard econometric methods. In one extreme, we could run dyad-by-dyad time series regressions to determine dyad-specific pass-through coefficients. However, these pass-through estimates would be highly noisy due to the availability of on average about 20 annual data points per dyad, especially given the need to control for other covariates. In the other extreme, we could run constant-coefficient panel regressions as in [Section 4](#). While these are informative about average pass-through as well as interaction terms, they are useless for estimating the extent and nature of the overall cross-sectional heterogeneity of pass-through. Our hierarchical Bayes approach

¹¹At an abstract level, hierarchical Bayes methods treat certain prior parameters as unknown model parameters, which themselves are endowed with prior distributions that get updated by the data. This approach is similar to “empirical Bayes” or classical “random effects” methods, which in effect estimate the prior distribution (here: the distribution of pass-through coefficients) from the data.

models this heterogeneity directly and flexibly, allowing the entire panel data set to inform the estimates of the distribution of pass-through as well as individual pass-through coefficients. Being a fully Bayesian method, uncertainty assessment and model selection is straight-forward.

Model. The outcome equation of the model is a linear panel data model with dyad and time fixed effects, except some of the coefficients are allowed to vary across dyads:

$$Y_{ij,t} = \lambda_{ij} + \delta_t + \gamma'_{ij} R_{ij,t} + \theta' X_{ij,t} + \varepsilon_{ij,t}. \quad (7)$$

In our applications, the outcome $Y_{ij,t}$ will be price or quantity log growth, while the covariates $R_{ij,t}$ with cross-sectionally varying coefficients γ_{ij} will be the contemporaneous log growth rates of the bilateral and U.S. dollar exchange rates, $R_{ij,t} = (\Delta e_{ij,t}, \Delta e_{\$j,t})'$. The covariates $X_{ij,t}$ include lags of the exchange rates as well as the other exogenous controls used in [Section 4](#). We impose a standard random effects assumption on the dyad-specific effects, $\lambda_{ij} \sim N(\alpha, \tau^2)$ (i.i.d. across dyads), and assume Gaussian errors $\varepsilon_{ij,t} \sim N(0, \sigma^2)$ (i.i.d. across dyads and time).¹² We place independent diffuse half-Cauchy priors on τ and σ and independent diffuse Cauchy priors on the intercept α , the time fixed effects δ_t , and the cross-sectionally constant coefficients θ . See [Appendix A.3.1](#) for details on the prior specification.

To economize on the number of parameters, we impose the assumption that the *sum* of the pass-through coefficients on the bilateral and dollar exchange rates is constant across dyads: $\gamma_{ij,1} + \gamma_{ij,2} = \bar{\gamma}$ for all (i, j) . This restriction is motivated by the institutional fact that, in most countries in our sample, trade that is not invoiced in dollars is instead invoiced in local currency, so dyads with high dollar pass-through should exhibit low bilateral pass-through, and vice versa.¹³ The restriction on the vector γ_{ij} implies that the outcome equation can be written

$$Y_{ij,t} = \lambda_{ij} + \delta_t + \gamma_{ij,1}(\Delta e_{\$j,t} - \Delta e_{ij,t}) + \bar{\gamma} \Delta e_{ij,t} + \theta' X_{ij,t} + \varepsilon_{ij,t}. \quad (8)$$

This restricted outcome equation can be written in the general form (7), with γ_{ij} a scalar, $R_{ij,t} = \Delta e_{\$j,t} - \Delta e_{ij,t}$, and subsuming the term $\bar{\gamma} \Delta e_{ij,t}$ in the covariate terms $\theta' X_{ij,t}$. We assume this notation in the following.

A key part of the model is the cross-sectional distribution of dollar pass-through conditional on the dollar invoicing share. As above, we denote the importer's observed dollar invoicing share

¹²In the panel regressions in [Section 4](#) we do not find evidence of economically significant serial correlation in the idiosyncratic errors.

¹³We hope to relax the restriction in future work.

by S_j . For maximal flexibility, we use a semiparametric specification of the conditional distribution $\gamma_{ij} \mid S_j$, while letting the hyperparameters of the prior be updated by the data. Specifically, we follow [Pati et al. \(2013\)](#) and [Liu \(2017\)](#) and assume that, conditional on the importer’s dollar invoicing share, the dollar pass-through coefficient is drawn from a Mixture of Gaussian Linear Regressions (MGLR):

$$(\gamma_{ij} \mid S_j) \sim \begin{cases} N(\mu_{0,1} + \mu_{1,1}S_j, \omega_1^2) & \text{with prob. } \pi_1(S_j), \\ N(\mu_{0,2} + \mu_{1,2}S_j, \omega_2^2) & \text{with prob. } \pi_2(S_j), \\ \vdots & \\ N(\mu_{0,K} + \mu_{1,K}S_j, \omega_K^2) & \text{with prob. } \pi_K(S_j), \end{cases}$$

independent across dyads (i, j) . Thus, the dollar pass-through γ_{ij} is drawn from one of K normal distributions, each with possibly different mean and variance parameters. The priors on the hyperparameters $\mu_{0,k}$, $\mu_{1,k}$, and ω_k are described in [Appendix A.3.1](#). The mixture probabilities $\pi_k(S_j)$ are allowed to depend flexibly on the dollar share. We adopt the “probit stick-breaking” specification of [Pati et al. \(2013\)](#),

$$\pi_k(s) = \begin{cases} \Phi(\zeta_k(s)) \prod_{j=1}^{k-1} (1 - \Phi(\zeta_j(s))) & \text{for } k = 1, \dots, K - 1, \\ 1 - \sum_{j=1}^{K-1} \pi_j(s) & \text{for } k = K, \end{cases}, \quad s \in [0, 1],$$

where $\Phi(\cdot)$ is the standard normal CDF. As in [Liu \(2017\)](#), we place independent nonparametric Gaussian process priors on the functions $\zeta_k(\cdot)$ for $k = 1, \dots, K - 1$. See [Appendix A.3.1](#).

The semiparametric prior on the cross-sectionally varying dollar pass-through coefficients allows the data to speak flexibly about our key question of interest, the extent to which the dollar invoicing share can explain pass-through heterogeneity. MGLR priors, as defined above, can accommodate a wide variety of shapes of the conditional density of $\gamma_{ij} \mid S_j$, including heavy-tailed, skewed, and multimodal conditional distributions. Since the mixture probabilities $\pi_k(S_j)$ depend on S_j , the functional form of the conditional distribution is allowed to change as the dollar invoicing share S_j varies, and in particular we do not impose that the distribution of γ_{ij} shifts linearly with S_j .¹⁴ [Pati et al. \(2013\)](#) show that, if $K = \infty$, MGLR priors lead to posterior consistency in nonparametric conditional density estimation problems under weak assumptions. We instead allow the data to inform us about the choice of the number K of mixture component, using the Bayesian Leave-One-Out (LOO) cross-validation model selection criterion of [Gelfand et al. \(1992\)](#), cf. [Appendix A.3.2](#).

¹⁴It is only the distribution *conditional on a mixture component k* that is assumed to shift linearly.

Posterior sampling. We use the Bayesian statistics software package Stan to draw from the posterior distribution of the model parameters (Stan Development Team, 2016). Stan produces samples from the posterior using the No U-Turn Sampler of Hoffman and Gelman (2014), a variant of the Markov Chain Monte Carlo (MCMC) procedure Hamiltonian Monte Carlo (Neal, 2011). From an applied user’s perspective, Stan has the advantage that it only requires the probability model to be specified in “natural” mathematical language (like the equations above). The software then automatically determines how to execute and tune the MCMC procedure. Stan often achieves rapid mixing even in high-dimensional hierarchical models like ours, without requiring priors to be conjugate. Appendix A.3 details the performance of the MCMC routine in our empirical applications.

5.2 Results: price pass-through

We find support for our hypothesis that the importer’s share of dollar invoicing can explain a substantial fraction of the heterogeneity in dollar pass-through into prices. Below we summarize the most important features of the posterior distribution for our purposes, while Appendix A.3.4 provides additional details on other parameters.

Our empirical specification broadly follows Section 4. In terms of the general Bayesian model in Eq. (7), we set $Y_{ij,t} = \Delta p_{ij,t}$. As extra covariates in $X_{ij,t}$, we use the exporter’s log PPI growth and one lag each of log PPI growth, bilateral exchange rate log growth, and dollar exchange rate log growth (second lags were found to be unimportant in Section 4). Here we focus on results that use Comtrade data reported by importers, as Section 4 found only minor differences between results from the exporter and importer reported data. We remove a few dyads whose data have gaps in the middle of the sample. Since we require data on the importer’s dollar invoicing share, our final sample consists of 1856 dyads for a total of 35,398 observations (average of 19.1 years per dyad).

Our preferred specification uses $K = 2$ mixture components for the conditional distribution of dollar pass-through coefficients given the dollar invoicing share. The LOO model selection criterion indicates strong support for $K \geq 2$ against $K = 1$, but the criterion is practically flat for $K = 2, 3, \dots, 8$. Because the posterior summaries below are virtually unchanged across these values of K , we prefer to show results for the more parsimonious model $K = 2$ here. Appendix A.3.5 provides results for the $K = 8$ specification.

Fig. 9 shows that a higher importer (country-aggregate) dollar invoicing share is associated with a right-ward shift in the cross-sectional density of dollar pass-through. The figure focuses on three invoicing shares: a low one (Switzerland), a medium one (Turkey), and a high one (Ar-

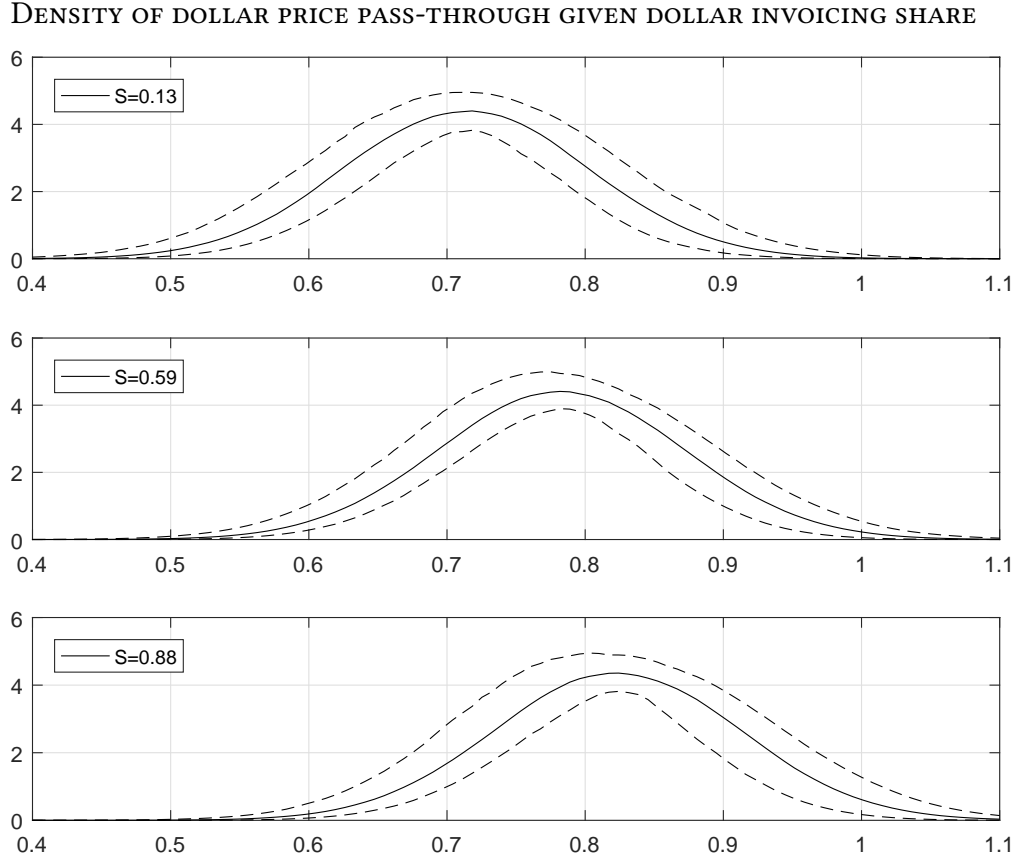


Figure 9: Model-implied conditional density $f(\gamma_{ij} | S_j)$ plotted at the dollar import invoicing shares S_j of Switzerland (top), Turkey (middle), and Argentina (bottom). Solid lines are posterior medians, dashed lines are 95% equal-tailed pointwise posterior credible intervals.

gentina). While the cross-sectional heterogeneity in pass-through is large, there is a noticeable overall right-ward shift in dollar pass-through when going from a low- S_j country to a high- S_j country. Based on posterior median estimates, the mode of the γ_{ij} distribution shifts by about 0.10 when the dollar invoicing share increases from Switzerland to Argentina levels. This is a substantial shift when compared to the estimated cross-dyad interquartile range of γ_{ij} of 0.13 (see below).¹⁵

Fig. 10 plots the conditional mean and standard deviation of the conditional distribution $\gamma_{ij} | S_j$ across all observed values of S_j . The figure confirms that the three conditional densities plotted in Fig. 9 are representative of the entire observed distribution of S_j values. Although not

¹⁵Recall that our data set is limited to using *country-level* dollar invoicing shares for the importer, S_j , as opposed to the ideal of dyad-specific invoicing shares. We conjecture that the quantitative importance of the importer's country-level dollar invoicing share is a lower bound for the importance of the (unobserved) dyad-level invoicing share.

CONDITIONAL MEAN AND STANDARD DEVIATION OF DOLLAR PRICE PASS-THROUGH

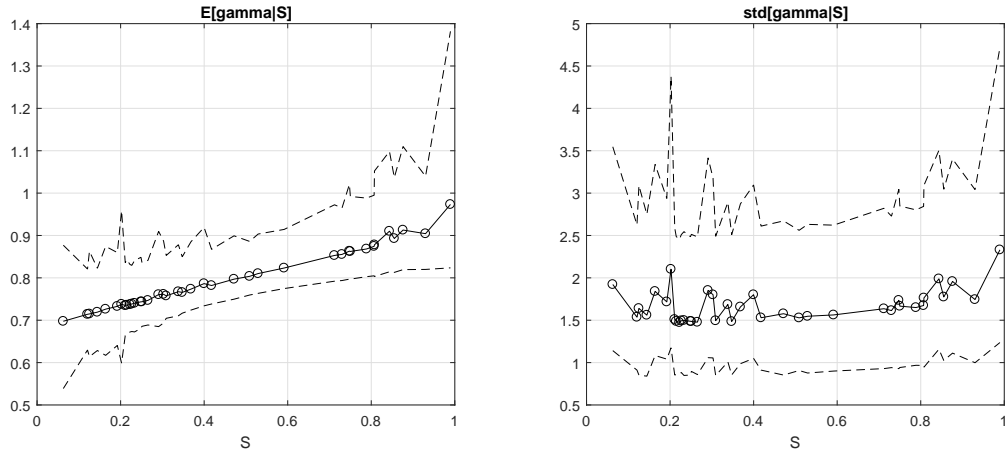


Figure 10: Model-implied conditional mean (left) and standard deviation (right) of γ_{ij} given S_j . Solid lines are posterior medians, dashes lines are 95% equal-tailed pointwise posterior credible intervals. Circles indicate observed S_j values.

SAMPLE DISTRIBUTION OF DOLLAR PRICE PASS-THROUGH

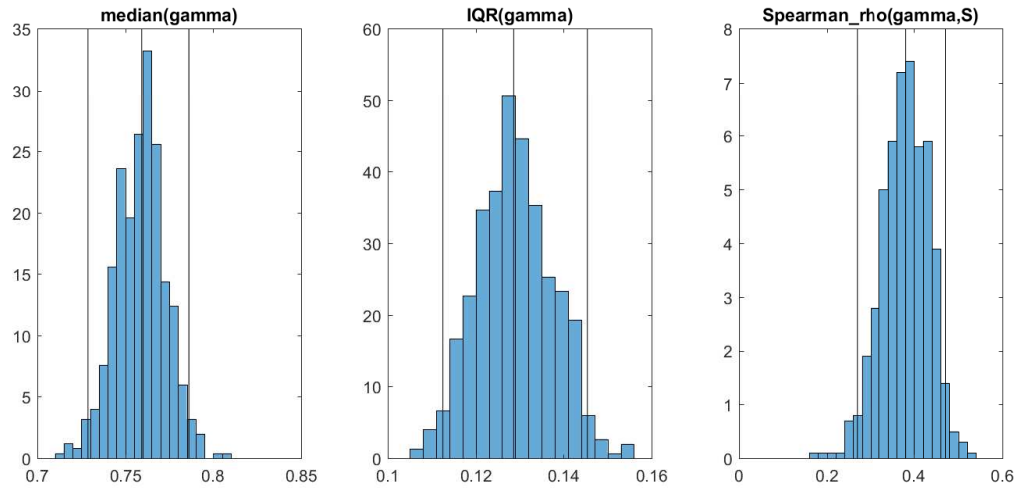


Figure 11: Histogram of posterior draws of the sample median of γ_{ij} (left), the sample interquartile range of γ_{ij} (middle), and the sample Spearman correlation of γ_{ij} and S_j (right). That is, for each posterior draw, we compute the sample median, IQR, and Spearman correlation across the 1856 dyads in our sample. Vertical lines mark the 2.5, 50, and 97.5 posterior percentiles.

assumed *a priori* by our model, the conditional mean $E[\gamma_{ij} \mid S_j]$ appears approximately linear, with a slope that is broadly consistent with the linear model with interactions in [Section 4](#). The conditional standard deviation appears to be fairly constant across S_j values, although the posterior uncertainty is large. However, the conditional distributions are heavy-tailed, as evidenced by the fact that the LOO criterion strongly prefers the $K = 2$ mixture model to the $K = 1$ model with normally distributed heterogeneity.

[Fig. 11](#) provides further evidence that dollar pass-through is high on average but highly heterogeneous, and the heterogeneity is associated with the dollar invoicing share. The figure shows histograms of the posterior draws of the cross-dyad median and interquartile range of γ_{ij} for the 1856 dyads in the sample. The median dollar pass-through is very consistent with the panel regressions in [Section 4](#) (median median 0.76), but there is clearly substantial heterogeneity in pass-through across dyads (median IQR 0.13), a fact we would not have been able to establish using the panel regression framework. The figure also plots the histogram of posterior draws of the cross-sectional Spearman correlation coefficient of γ_{ij} and S_j . We use the Spearman correlation coefficient instead of the usual (Pearson) correlation, as the former is more robust to the presence of outlier dyads.¹⁶ There is a clear positive correlation (median correlation 0.38), again demonstrating that dyads with high dollar pass-through also tend to have a high importer dollar invoicing share.

5.3 Results: trade elasticity

Similar to the price pass-through results, we find that the cross-dyad heterogeneity of the elasticity of trade quantities with respect to the dollar exchange rate is related to the dollar invoicing share. However, the results in this subsection generally come attached with higher posterior uncertainty. [Appendix A.3.4](#) provides additional results on parameters not highlighted below.

Our empirical specification again follows [Section 4](#). We set $Y_{ij,t} = \Delta y_{ij,t}$ in [Eq. \(7\)](#). We control for one lag of bilateral and dollar exchange rates, as well as the contemporaneous value and lag of importer log real GDP growth. The sample of dyad-year observations is the same as for the price pass-through results.

We report results for $K = 4$ mixture components. The LOO model selection criterion strongly favors $K = 3, 4, 5$ against either $K \leq 2$ or $K = 6, 7, 8$. $K = 4$ has a slightly higher LOO score

¹⁶Since the estimated pass-through distribution is heavy-tailed, we do not wish our results to be driven by a few dyads with very large or very small estimated pass-through. The Spearman correlation coefficient equals the Pearson correlation of the *ranks* of γ_{ij} and S_j . We calculate the rank of S_j across the 39 countries in our sample for which this statistic is available (not across the 1856 dyads).

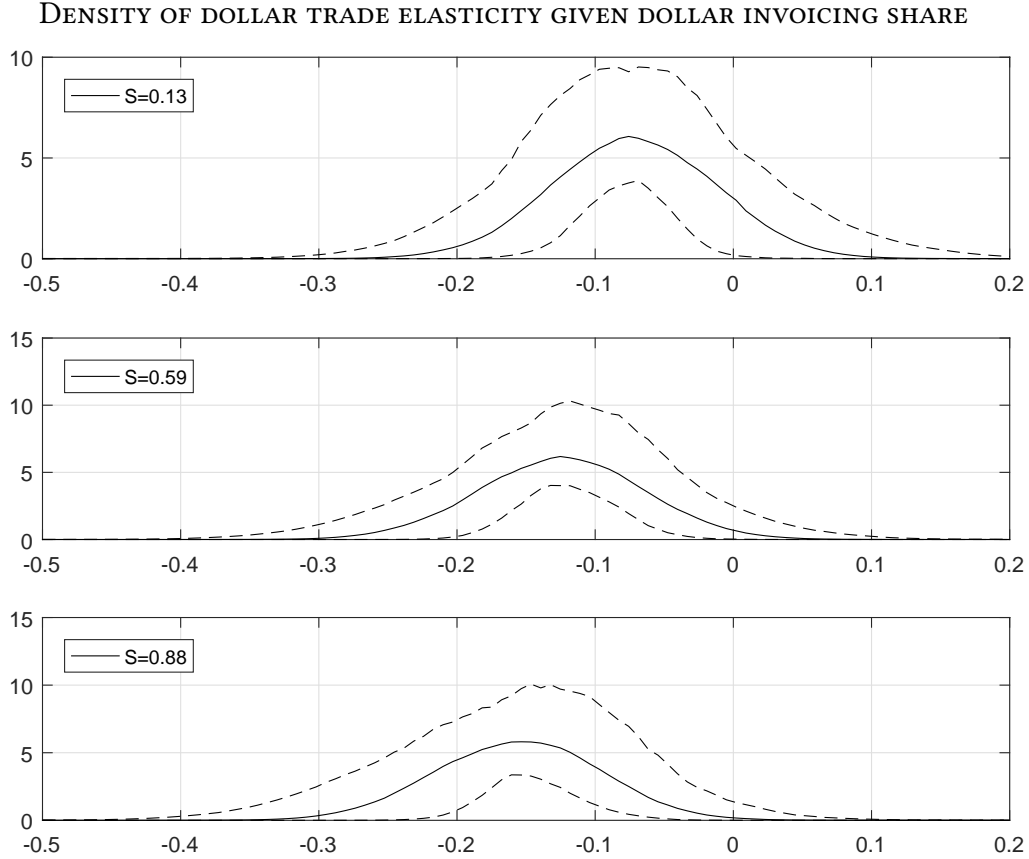


Figure 12: See caption for Fig. 9.

than $K = 3, 5$. However, we remark again that the results presented below are little changed across these specifications. We report results for $K = 8$ in [Appendix A.3.5](#).

[Fig. 12](#) shows that the conditional density of the dollar trade elasticity (expected to be a negative number, as also estimated in [Section 4](#)) shifts leftward when the importer's (country-aggregate) dollar invoicing share increases. That is, the higher the dollar invoicing share, the larger in magnitude is the dollar trade elasticity, on average. Notice, however, that the credible bands are much wider here than for the price pass-through results. This is consistent with the larger standard errors on the interaction terms in the trade elasticity panel regressions in [Section 4](#). [Fig. 13](#) shows the conditional mean and standard deviation. While the posterior medians indicate that the conditional mean function is downward-sloping over most of the range of S_j , the function is estimated with substantial uncertainty.

[Fig. 14](#) summarizes the posterior of the sample distribution of γ_{ij} . The median γ_{ij} (median median -0.11) is in line with the panel regression results in [Section 4](#), but the heterogeneity is substantial (median IQR 0.09). Again we find a strong (here: negative, as expected) Spearman

CONDITIONAL MEAN AND STANDARD DEVIATION OF DOLLAR TRADE ELASTICITY

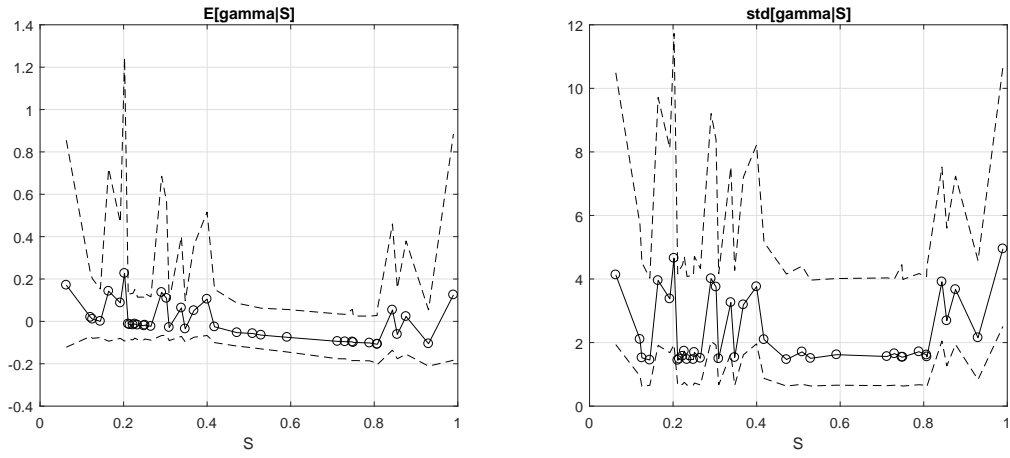


Figure 13: See caption for Fig. 10.

SAMPLE DISTRIBUTION OF DOLLAR TRADE ELASTICITY

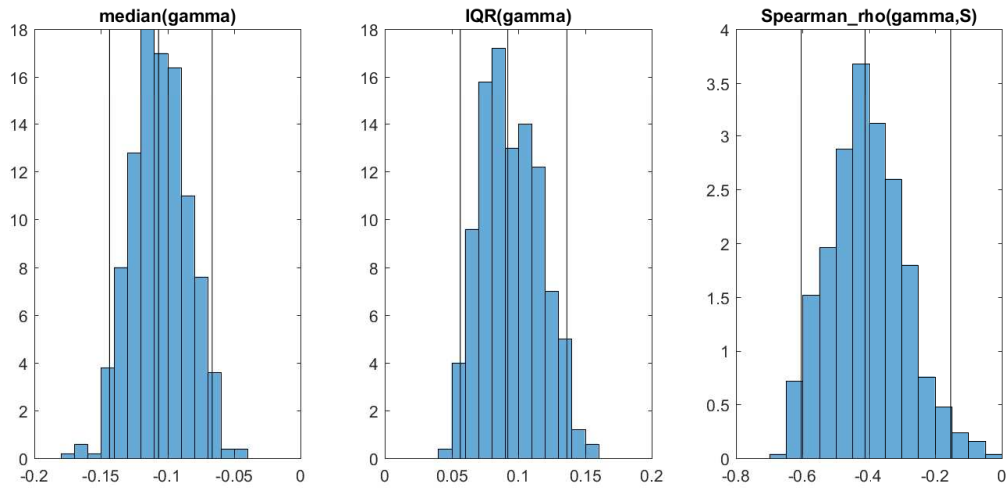


Figure 14: See caption for Fig. 11.

correlation between γ_{ij} and S_j (median correlation -0.41). Thus, trade elasticities with respect to the dollar are highly heterogeneous, but dyads with the largest-in-magnitude dollar elasticities tend to be the dyads with the highest importer dollar invoicing share.

A Appendix

A.1 Data

Here we provide further details on the Comtrade, WDI, and FRED data.

Comtrade country summary statistics. [Table 4](#) lists summary statistics on the number of observations for the 55 countries in our merged Comtrade/WDI dataset. The table also lists the share of imports invoiced in U.S. dollars for the 39 countries for which we observe this measure (cf. [Gopinath, 2015](#)).

Comparison of Comtrade and BLS price series for the U.S. We now compare our unit value indices to survey price indices from the U.S. Bureau of Labor Statistics. The BLS provides U.S. import price indices by locality of origin for Canada, E.U., France, Germany, U.K, Latin America, Mexico, Pacific Rim, China, Japan, ASEAN, Asia Near East, and Asian Newly Industrialized countries. As these price indices are constructed from surveys, their comparison with our unit value based indices can help gauge the effectiveness of our techniques to deal with the unit value bias and other potential mismeasurement inherent in customs data.

To arrive at comparable series, in this subsection we follow BLS in using *Laspeyres* indices of *total* (commodities and non-commodities) goods prices from our data set. For regions with multiple countries, we aggregate country level growth rates using Comtrade import values with a two year lag. Still, the series are not fully comparable because BLS' preferred price basis is f.o.b. (free on board) while import values recorded at customs are c.i.f. (cost, insurance and freight), and not all countries included in BLS regions are in our database.

Our indices constructed from Comtrade unit values track the BLS import price indices fairly well, as shown in [Figs. 15](#) and [16](#). These figures compare the linearly detrended logged indices, since our regressions use log growth rates and absorb any disparity in average growth rates in the intercept. The growth rates of our indices for Canada, Japan, Mexico, and the aggregated Latin America and Asia Near East match those of BLS remarkably well. The comparison with some Asian countries suggests that a unit value bias may still be present, causing the unit value series to be somewhat more volatile than the BLS price series. Nevertheless, for every country group and individual country except Germany, the correlation coefficient between the Comtrade and BLS growth rates is high. Finally, the match for European countries seems acceptable, with the year 2008 being an exception. A closer inspection of the case of Germany reveals that a couple of products (transport vehicles) with large import shares experienced substantial unit

COUNTRY SUMMARY STATISTICS

Country	As exporter		As importer		
	#dyads	avg T	#dyads	avg T	InvS
<i>Africa</i>					
Algeria	20	14.2	49	21.1	
Egypt	54	20.4	52	21.6	
South Africa	54	15.0	53	14.7	
<i>Americas</i>					
Argentina	54	21.8	52	21.8	0.88
Brazil	54	24.2	53	23.1	0.84
Canada	54	24.4	54	24.1	0.75
Chile	52	20.9	50	22.0	
Colombia	53	19.5	52	21.4	0.99
Mexico	54	23.4	52	23.3	
United States	54	24.0	54	23.5	0.93
Venezuela	21	10.9	48	19.9	
<i>Asia</i>					
China	54	23.7	54	22.6	
Hong Kong	54	23.2	52	22.5	
India	54	25.3	53	24.4	0.86
Indonesia	54	23.9	52	23.0	0.81
Israel	53	21.5	51	21.3	0.73
Japan	54	25.6	52	25.5	0.71
Kazakhstan	39	14.6	52	18.2	
Malaysia	54	24.1	53	23.4	
Philippines	54	22.1	50	21.5	
Saudi Arabia	50	20.1	53	21.2	
Singapore	54	24.7	51	24.0	
South Korea	54	25.0	52	24.6	0.81
Thailand	54	24.5	53	24.5	0.79
Turkey	54	24.4	54	23.9	0.59
Vietnam	54	19.3	49	19.0	

(continued on next page)

COUNTRY SUMMARY STATISTICS (CONTINUED)

Country	As exporter		As importer		
	#dyads	avg T	#dyads	avg T	InvS
<i>Europe</i>					
Austria	54	23.1	52	23.0	0.06
Belgium	54	15.9	53	15.9	0.14
Czech Republic	54	20.6	53	21.3	0.19
Denmark	54	22.3	52	24.4	0.25
Estonia	47	17.9	52	19.3	0.34
Finland	54	25.6	52	25.0	0.42
France	54	23.1	54	22.7	0.21
Germany	54	23.3	54	23.0	0.23
Greece	54	23.0	51	23.6	0.40
Hungary	54	23.6	52	22.6	0.27
Ireland	54	23.4	53	22.5	0.23
Italy	54	23.1	54	22.5	0.29
Lithuania	53	17.3	50	18.9	0.51
Luxembourg	54	15.8	51	14.0	0.16
Netherlands	54	23.7	54	23.2	0.37
Norway	54	23.1	52	23.0	0.21
Poland	54	22.9	52	22.3	0.30
Portugal	54	24.9	53	24.8	0.22
Romania	54	22.6	52	21.4	0.31
Russia	54	21.4	52	21.0	
Slovak Republic	54	20.7	51	20.4	0.12
Slovenia	54	21.1	52	20.7	0.20
Spain	54	24.8	54	24.9	0.35
Sweden	54	23.7	54	23.1	0.25
Switzerland	54	25.6	54	25.1	0.13
Ukraine	53	19.3	52	19.8	0.75
United Kingdom	54	23.4	54	23.3	0.47
<i>Oceania</i>					
Australia	54	25.1	52	25.2	0.53
New Zealand	54	22.7	50	24.0	

Table 4: Summary statistics for countries in the merged Comtrade/WDI sample. #dyads: number of non-missing dyads that the country appears in. avg T : average number of years per dyad that the country appears in; a dyad-year observation is counted if at least one UVI or volume observation is reported by the exporter or importer, and exchange rate data exists for both countries. InvS: share of imports invoiced in U.S. dollars.

BLS COUNTRY GROUPS

BLS group	Country ISO codes
ASEAN	BRN* IDN KHM* LAO* MMR* MYS PHL SGP THA VNM*
Asia Near East	ARE* BHR* IRN* IRQ* ISR JOR* KWT* LBN* OMN* QAT* SAU SYR* YEM*
European Union	AUT BEL BGR* CYP* CZE DEU DNK ESP EST FIN FRA GBR GRC HRV* HUN IRL ITA LTU LUX LVA* MLT* NLD POL PRT ROU SVK SVN SWE
Latin America	ARG BRA CHL COL MEX VEN (plus other unspecified Central American, South American, and Caribbean countries*)
Asian New. Ind.	HKG KOR SGP TWN
Pacific Rim	AUS BRN* CHN HKG IDN JPN KOR MAC* MYS NZL PHL PNG* SGP TWN

Table 5: Definition of BLS country groups in Fig. 15. Countries marked with an asterisk (*) are not available in the Comtrade sample.

value decreases that year according to Comtrade, leading our indices to decline while the BLS index shows an increase.

World Development Indicator data. The exchange rate is the World Bank’s “alternative conversion factor” series (PA.NUS.ATLS), which corrects for redenominations and currency substitution, and is measured as an annual average of daily rates. Producer prices are given by the wholesale price index (FP.WPI.TOTL). Real GDP is measured at market prices in constant U.S. dollars (NY.GDP.MKTP.KD). The GDP deflator is given by the ratio of nominal GDP (NY.GDP.MKTP.CD) and real GDP. We use data for 1989–2015 only.

FRED data. We obtain the WTI oil price (POILWTIUSDA), VIX (VIXCLS), and 1-year Treasury bill rate (DTB1YR) from the St. Louis Fed’s FRED database. Annual series are averages of daily indices.

COMTRADE AND BLS IMPORT PRICE INDICES FOR U.S.: COUNTRY GROUPS

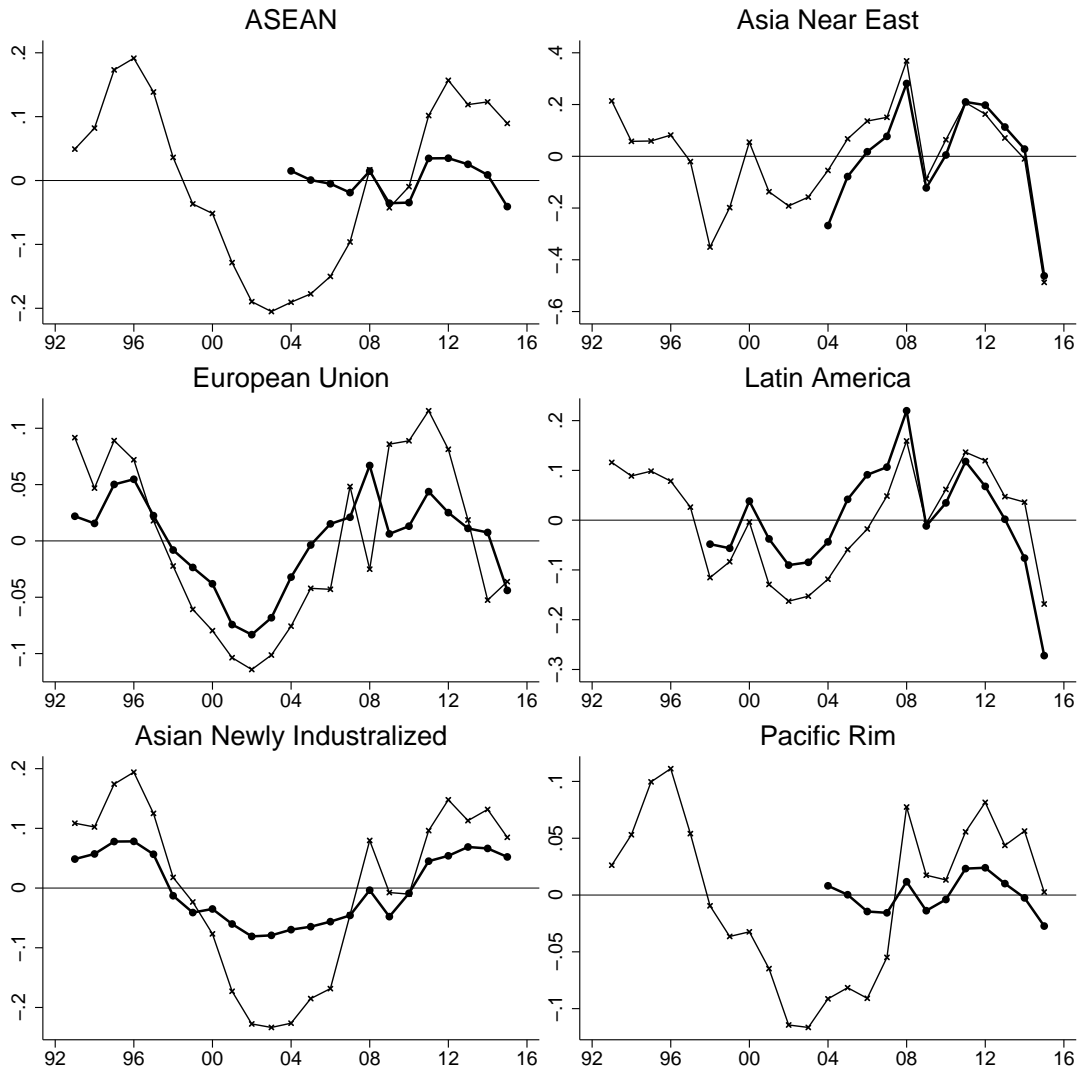


Figure 15: Comparison of BLS Locality of Origin import price indices (thick lines, circles) with our constructed Comtrade analogues (thin lines, crosses). Plotted indices are logged and linearly detrended. The Comtrade sample does not cover all countries in the BLS country groups, cf. [Table 5](#).

COMTRADE AND BLS IMPORT PRICE INDICES FOR U.S.: INDIVIDUAL COUNTRIES

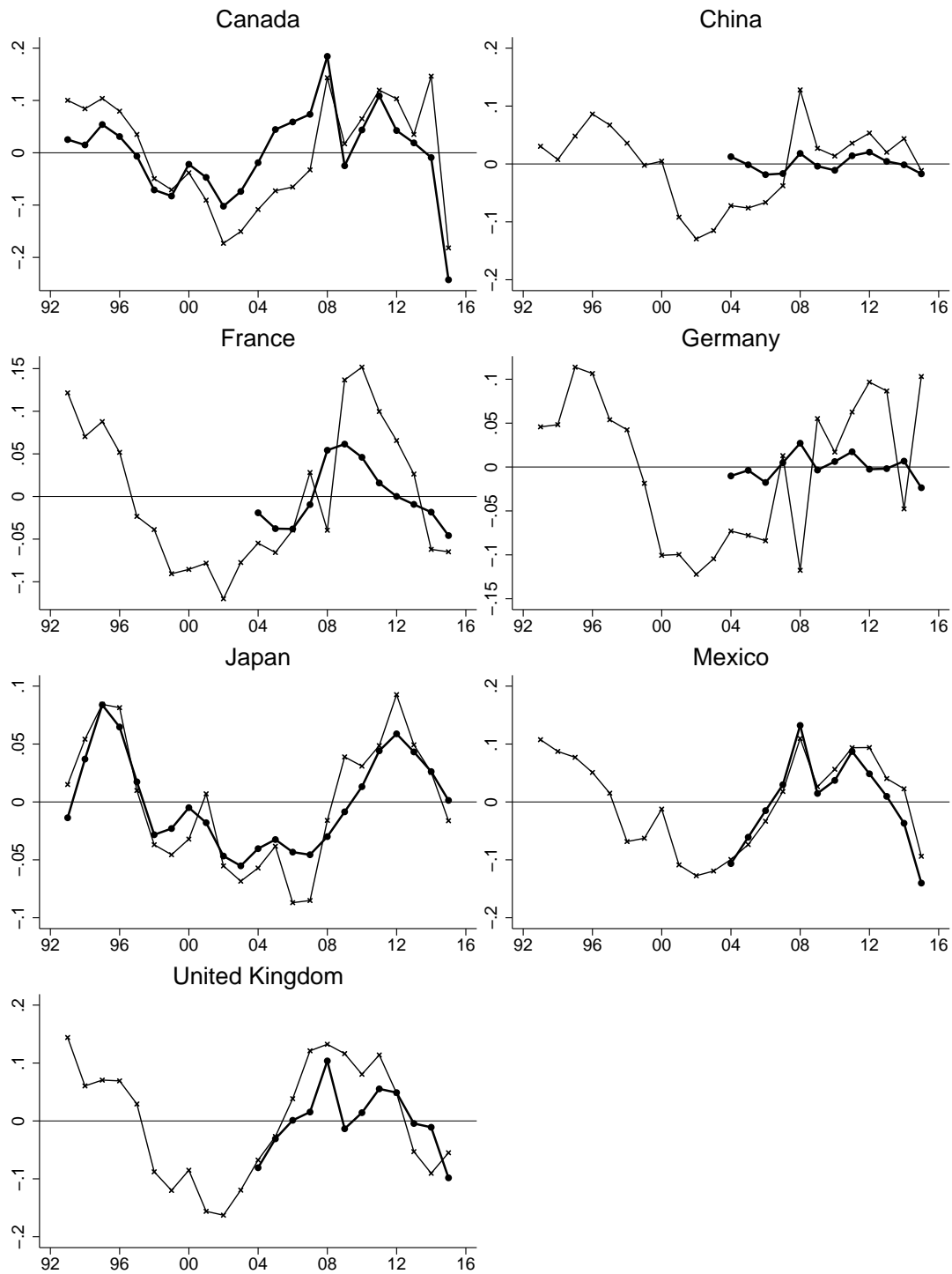


Figure 16: Comparison of BLS Locality of Origin import price indices (thick lines, circles) with our constructed Comtrade analogues (thin lines, crosses). Plotted indices are logged and linearly detrended.

A.2 Supplementary results: panel regressions

This section provides supplementary panel regression results.

Post-2002 results. Exchange rate pass-through into prices has been stable over our sample period, while trade elasticities may have become larger in absolute value in the latter part of the sample. We compute results for the subsample 2002–2015, roughly corresponding to the second half of our data set, and also corresponding to the sample used for the euro regressions in [Section 4.5](#). [Figs. 17](#) and [18](#) show price and volume impulse responses for the 2002–2015 subsample that correspond to the full-sample results in [Figs. 1](#) and [3](#) in [Section 4](#). The price pass-through impulse responses of bilateral and dollar exchange rates are similar to the full-sample results. However, the post-2002 USD cumulative trade elasticity is substantially negative at lags of 1 and 2 years, whereas the level effect is close to zero at lags 1 and 2 on the full sample.

Euro regressions. [Tables 6](#) and [7](#) display the results of the price pass-through and trade elasticity regressions in [Section 4.5](#) involving the euro exchange rate. The regressions do not control for time fixed effects but do include the aggregate control variables listed in [Section 4.5](#). Specifications (1) and (4) focus on the bilateral and euro exchange rates, specifications (2) and (5) add the dollar exchange rate, and specifications (3) and (6) include interactions with the dollar and euro import invoicing shares. S_j^ϵ is the importing country's share of imports invoiced in euros from [Gopinath \(2015\)](#). The interactions are statistically and economically significant and mostly have the expected signs in the price pass-through regressions: A higher share of euro (resp., dollar) invoicing implies a higher pass-through from the euro (resp, dollar) exchange rate. In contrast, the interaction terms are imprecisely estimated in the trade elasticity regressions.

Robustness to data choices. In this section we show that our panel regression results are robust to a number of deviations from the baseline specifications in [Section 4](#): the price index definition, the outlier truncation technique, and using total goods indices rather than non-commodities. [To be completed.]

AVERAGE PRICE PASS-THROUGH, 2002–2015

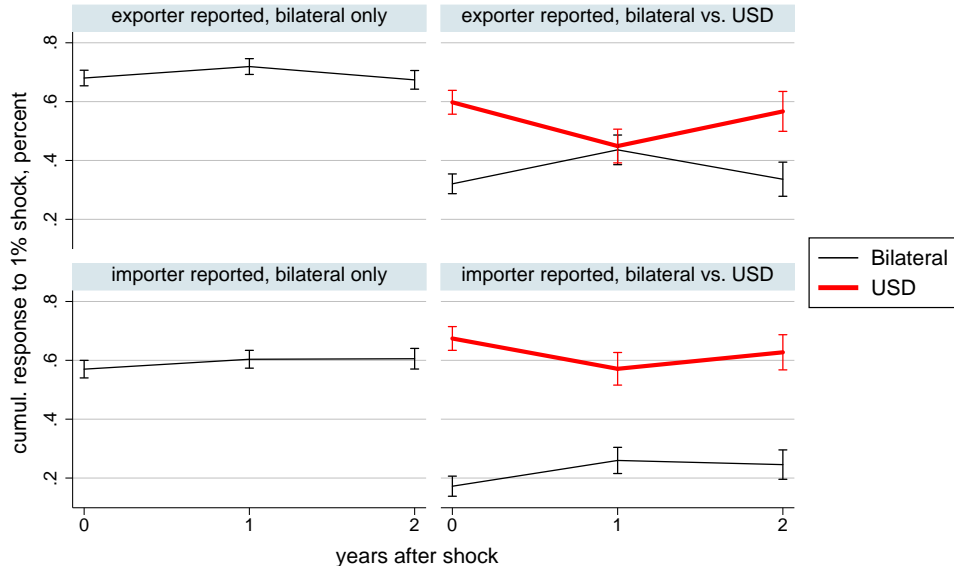


Figure 17: Fig. 1 computed on post-2002 data.

AVERAGE TRADE ELASTICITY, 2002–2015

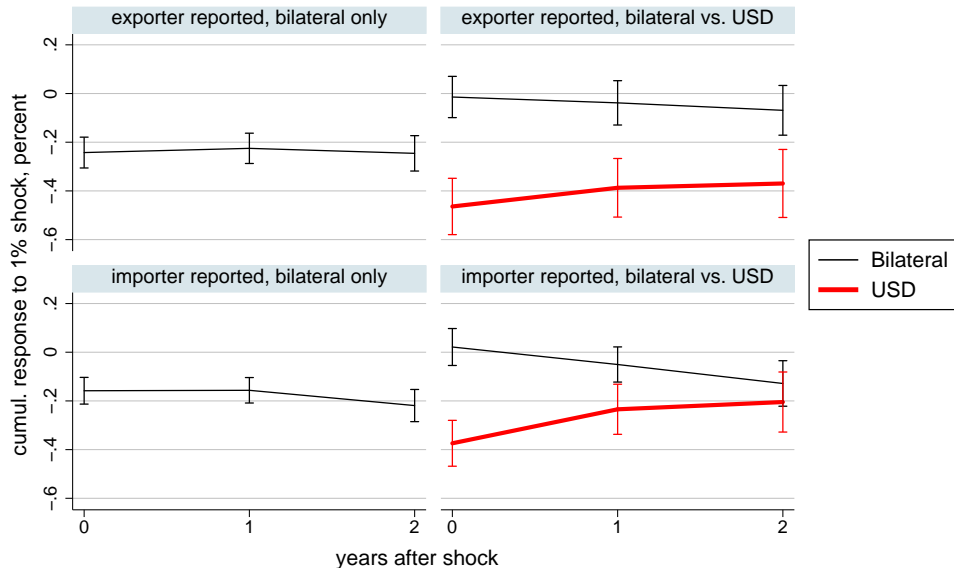


Figure 18: Fig. 3 computed on post-2002 data.

EURO VS. DOLLAR EXCHANGE RATE PASS-THROUGH INTO PRICES

VARIABLES	(1) $\Delta p_{ij,t}$	(2) $\Delta p_{ij,t}$	(3) $\Delta p_{ij,t}$	(4) $\Delta p_{ij,t}$	(5) $\Delta p_{ij,t}$	(6) $\Delta p_{ij,t}$
$\Delta e_{ij,t}$	0.438*** (0.0154)	0.316*** (0.0169)	0.286*** (0.0702)	0.305*** (0.0159)	0.181*** (0.0174)	0.207*** (0.0695)
$\Delta e_{ij,t-1}$	0.146*** (0.0151)	0.119*** (0.0157)	0.276*** (0.0821)	0.162*** (0.0133)	0.134*** (0.0140)	0.0277 (0.0621)
$\Delta e_{ij,t-2}$	-0.101*** (0.0148)	-0.0533*** (0.0151)	-0.0898 (0.0744)	-0.0793*** (0.0123)	-0.0389*** (0.0129)	-0.0723 (0.0666)
$\Delta e_{ij,t} \times (S_j + S_j^\epsilon)$			0.0449 (0.0834)			-0.0357 (0.0784)
$\Delta e_{ij,t-1} \times (S_j + S_j^\epsilon)$			-0.178* (0.0919)			0.0814 (0.0720)
$\Delta e_{ij,t-2} \times (S_j + S_j^\epsilon)$			0.0311 (0.0827)			0.0640 (0.0745)
$\Delta e_{\$j,t}$		0.666*** (0.0358)	0.512*** (0.0448)		0.754*** (0.0373)	0.614*** (0.0405)
$\Delta e_{\$j,t-1}$		-0.0459*** (0.0161)	-0.0121 (0.0311)		-0.0646*** (0.0161)	0.155*** (0.0252)
$\Delta e_{\$j,t-2}$		0.00180 (0.0158)	0.0456 (0.0299)		0.0576*** (0.0148)	0.0154 (0.0228)
$\Delta e_{\$j,t} \times S_j$			0.216*** (0.0470)			0.510*** (0.0439)
$\Delta e_{\$j,t-1} \times S_j$			-0.0841 (0.0613)			-0.447*** (0.0555)
$\Delta e_{\$j,t-2} \times S_j$			-0.0817 (0.0499)			0.101** (0.0465)
$\Delta e_{\epsilon j,t}$	0.396*** (0.0179)	-0.0688** (0.0330)	-0.108** (0.0434)	0.467*** (0.0175)	-0.0800** (0.0332)	-0.347*** (0.0430)
$\Delta e_{\epsilon j,t-1}$	-0.174*** (0.0168)	-0.109*** (0.0201)	-0.0923*** (0.0346)	-0.187*** (0.0166)	-0.103*** (0.0209)	0.0450 (0.0398)
$\Delta e_{\epsilon j,t-2}$	0.119*** (0.0168)	0.0552*** (0.0204)	0.0867*** (0.0295)	0.132*** (0.0156)	0.0294 (0.0188)	-0.0982*** (0.0284)
$\Delta e_{\epsilon j,t} \times S_j^\epsilon$			0.285*** (0.0860)			0.694*** (0.0821)
$\Delta e_{\epsilon j,t-1} \times S_j^\epsilon$			0.000 (0.0893)			-0.203** (0.0982)
$\Delta e_{\epsilon j,t-2} \times S_j^\epsilon$			-0.0615 (0.0819)			0.295*** (0.0851)
Exp. PPI	yes	yes	yes	yes	yes	yes
Agg. controls	yes	yes	yes	yes	yes	yes
Time FE	no	no	no	no	no	no
R-squared	0.185	0.197	0.211	0.131	0.143	0.210
Observations	32,825	32,825	23,668	33,802	33,802	24,463
Dyads	2,611	2,611	1,867	2,647	2,647	1,900

Table 6: The first (resp., last) three columns use Comtrade data reported by exporting (resp., importing) countries. S.e. clustered by dyad. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

EURO VS. DOLLAR TRADE ELASTICITY

VARIABLES	(1) $\Delta y_{ij,t}$	(2) $\Delta y_{ij,t}$	(3) $\Delta y_{ij,t}$	(4) $\Delta y_{ij,t}$	(5) $\Delta y_{ij,t}$	(6) $\Delta y_{ij,t}$
$\Delta e_{ij,t}$	-0.110*** (0.0418)	-0.0234 (0.0432)	0.581*** (0.224)	-0.0631* (0.0371)	0.0229 (0.0386)	0.619*** (0.229)
$\Delta e_{ij,t-1}$	-0.0349 (0.0339)	-0.00530 (0.0354)	-0.177 (0.184)	-0.0827** (0.0343)	-0.0694* (0.0367)	-0.366* (0.188)
$\Delta e_{ij,t-2}$	-0.0151 (0.0307)	-0.0393 (0.0318)	0.167 (0.190)	-0.0419 (0.0270)	-0.0679** (0.0277)	0.121 (0.165)
$\Delta e_{ij,t} \times (S_j + S_j^\epsilon)$			-0.629** (0.260)			-0.668*** (0.253)
$\Delta e_{ij,t-1} \times (S_j + S_j^\epsilon)$			0.160 (0.218)			0.348* (0.207)
$\Delta e_{ij,t-2} \times (S_j + S_j^\epsilon)$			-0.207 (0.221)			-0.203 (0.196)
$\Delta e_{\$j,t}$		-0.703*** (0.0894)	-0.663*** (0.115)		-0.695*** (0.0806)	-0.316*** (0.103)
$\Delta e_{\$j,t-1}$		-0.0615 (0.0441)	0.116 (0.0822)		-0.00291 (0.0410)	-0.120* (0.0693)
$\Delta e_{\$j,t-2}$		0.00568 (0.0441)	-0.257*** (0.0797)		0.00554 (0.0400)	0.0595 (0.0613)
$\Delta e_{\$j,t} \times S_j$			-0.243* (0.131)			-0.760*** (0.121)
$\Delta e_{\$j,t-1} \times S_j$			-0.221 (0.159)			0.357** (0.145)
$\Delta e_{\$j,t-2} \times S_j$			0.446*** (0.131)			0.00131 (0.108)
$\Delta e_{\epsilon j,t}$	-0.244*** (0.0525)	0.264*** (0.0870)	0.302*** (0.110)	-0.179*** (0.0413)	0.320*** (0.0759)	0.427*** (0.0960)
$\Delta e_{\epsilon j,t-1}$	0.117*** (0.0416)	0.119*** (0.0454)	0.218*** (0.0741)	0.170*** (0.0374)	0.145*** (0.0406)	0.00391 (0.0779)
$\Delta e_{\epsilon j,t-2}$	-0.0147 (0.0377)	0.0161 (0.0460)	-0.116* (0.0661)	-0.0295 (0.0333)	0.00521 (0.0406)	0.0250 (0.0639)
$\Delta e_{\epsilon j,t} \times S_j^\epsilon$			0.0101 (0.214)			-0.313* (0.185)
$\Delta e_{\epsilon j,t-1} \times S_j^\epsilon$			-0.115 (0.229)			0.194 (0.197)
$\Delta e_{\epsilon j,t-2} \times S_j^\epsilon$			0.560*** (0.200)			0.0756 (0.201)
Imp. GDP	yes	yes	yes	yes	yes	yes
Agg. controls	yes	yes	yes	yes	yes	yes
Time FE	no	no	no	no	no	no
R-squared	0.072	0.075	0.085	0.068	0.071	0.078
Observations	36,269	36,269	26,129	37,437	37,437	27,109
Dyads	2,773	2,773	1,982	2,807	2,807	2,014

Table 7: The first (resp., last) three columns use Comtrade data reported by exporting (resp., importing) countries. S.e. clustered by dyad. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

A.3 Details of Bayesian analysis

A.3.1 Hyper-priors

Here we describe the remaining parts of the prior not specified in the main text. We incorporate time fixed effects δ_t by adding $T - 1$ dummies in the covariate vector X_t , so the parameter vector θ includes these parameters. We impose the following priors, all mutually independent:

$$\alpha \sim \text{Cauchy}(0, 5), \quad \theta_j \sim \text{Cauchy}(0, 5),$$

$$\sigma \sim \text{HalfCauchy}(0, 1), \quad \tau \sim \text{HalfCauchy}(0, 1).$$

$\text{Cauchy}(0, a)$ is the centered Cauchy distribution with interquartile range $2a$. $\text{HalfCauchy}(0, a)$ is the restriction of the $\text{Cauchy}(0, a)$ distribution to the positive real line. Since the units of our outcome variables $Y_{ij,t}$ are decimals, the above priors are highly diffuse. As for the MGLR prior, we assume¹⁷

$$\omega_k \sim \text{HalfCauchy}(0, 2), \quad \begin{pmatrix} \mu_{0,k} \\ \mu_{1,k} \end{pmatrix} \mid \omega_k \sim N \left(0, \begin{pmatrix} \omega_k^2 & 0 \\ 0 & \omega_k^2 \end{pmatrix} \right), \quad k = 1, \dots, K,$$

$$\zeta_k(\cdot) \sim GP(0, C(\cdot; A_k)), \quad A_k \sim \text{Exponential}(1), \quad k = 1, \dots, K - 1,$$

independently across k . Here $GP(0, C(\cdot; A))$ denotes a Gaussian process with Gaussian radial covariance kernel

$$C(s_1, s_2; A) = \exp\{-A(s_1 - s_2)^2\} + 0.0001 \times \mathbb{1}(s_1 = s_2), \quad s_1, s_2 \in [0, 1].$$

The second term on the right-hand side helps avoid numerical issues in the warm-up phase of the MCMC algorithm, but it is small enough to negligibly affect the final output (the dollar invoicing share S_j is measured in decimals).

¹⁷Because the mixture component labels are not identified, we additionally impose the normalization $\mu_{0,1} < \mu_{0,2} < \dots < \mu_{0,K}$. Stan accomplishes this by reparametrizing the vector $(\mu_{0,1}, \dots, \mu_{0,K})'$ into an unconstrained parameter, while adjusting for the Jacobian of the transformation in the posterior density.

A.3.2 Bayesian leave-one-out cross-validation

The Bayesian Leave-One-Out (LOO) cross-validation criterion of [Gelfand et al. \(1992\)](#) is given by the cross-sectional sum of leave-one-out predictive densities

$$\begin{aligned} LOO &= \sum_{ij} \log f(Y_{ij} \mid R_{ij}, X_{ij}, Y_{-(ij)}, R_{-(ij)}, X_{-(ij)}) \\ &= \sum_{ij} \log \int f(Y_{ij} \mid R_{ij}, X_{ij}, \vartheta) f(\vartheta \mid R_{ij}, X_{ij}, Y_{-(ij)}, R_{-(ij)}, X_{-(ij)}) d\vartheta. \end{aligned}$$

Here ϑ collects all model parameters. $Y_{ij} = (Y_{ij,1}, \dots, Y_{ij,T})$ collects all observed outcomes for dyad (i, j) across time, and similarly for the covariates R_{ij} and X_{ij} .¹⁸ The notation $Y_{-(ij)}$ means all observed outcomes for dyads other than (i, j) , and similarly for $R_{-(ij)}$ and $X_{-(ij)}$. The LOO criterion is large when the model yields good (leave-one-out) out-of-sample fit, given knowledge of the covariates. This is similar in spirit to the well-known non-Bayesian leave-one-out cross-validation criterion. We use a Pareto-smoothed importance sampling estimate of LOO, as developed by [Vehtari et al. \(2016\)](#) and implemented in Stan.

A.3.3 MCMC settings and diagnostics

We execute Stan through Matlab R2016b using MatlabStan 2.7.0.0, which in turn calls CmdStan 2.14.0. For each model specification, we run Stan’s No U-Turn Sampler for 2,500 iterations after discarding 1,000 warm-up iterations, storing every 5th draw. The MCMC routine is initialized at parameter values drawn uniformly at random (after the parameters have been transformed to unconstrained support). We use Stan’s default settings for adaptively tuning the MCMC routine in the warm-up phase. Our results are completely insensitive to the initialization.

The sampler robustly delivers near-independent draws from the posterior distribution in reasonable time. The stored posterior draws of most model parameters exhibit essentially zero serial correlation after a handful of lags. The only parameters that do not exhibit rapid mixing are those MGLR parameters $\mu_{0,k}, \mu_{1,k}, \omega_k, A_k$ that correspond to mixture components k with low posterior probability $\pi_k(\cdot)$ in model specifications with large K , but these parameters negligibly influence the features of the posterior that we care about. Depending on K and the random initial parameter draw, it takes from 2 to 60 hours to run the MCMC routine for each specification on Harvard University’s research computing cluster (CPU: AMD Opteron “Abu Dhabi” with 3 GB RAM allocated). In our experience, it is typically sufficient to run the algorithm for 2–4 hours to get a

¹⁸Since we have an unbalanced panel, the dimension of Y_{ij}, R_{ij}, X_{ij} actually varies across dyads.

rough sense of the final results.

A.3.4 Further empirical results

For completeness, we now report posterior summaries of the model parameters that are not of primary interest to us.

First we report results for the price pass-through model with $K = 2$. Fig. 19 reports the posterior distribution of the cross-sectionally constant regression coefficients. The results are consistent with the panel regressions in Section 4. In particular, the lagged exchange rate changes are economically insignificant. The posterior for the parameter $\bar{\gamma}$ (the sum of the dollar and bilateral pass-throughs) is concentrated close to 1, indicating near-complete *total* pass-through within a year. Fig. 20 reports the posterior of the mean α and standard deviation τ of the random effects distribution for the dyad-specific effects λ_{ij} , as well as the idiosyncratic standard error σ .

Figs. 21 and 22 provide the same posterior summaries for the trade elasticity model with $K = 4$. Again, these results are consistent with the panel regressions from Section 4.

A.3.5 Robustness to number of mixture components

Here we show that the results in Section 5 are robust to varying the number K of components in the MGLR prior for the cross-sectional distribution of dollar pass-through. Specifically, we here report results for $K = 8$. Figs. 23 and 24 are the $K = 8$ analogues of the price pass-through Figs. 9 and 11 (which had $K = 2$), while Figs. 25 and 26 are the $K = 8$ analogues of the trade elasticity Figs. 12 and 14 (which had $K = 4$). Clearly, the additional mixture components in the $K = 8$ specifications receive very low posterior probability.

POSTERIOR OF CONSTANT REGRESSION COEFFICIENTS, PRICE PASS-THROUGH

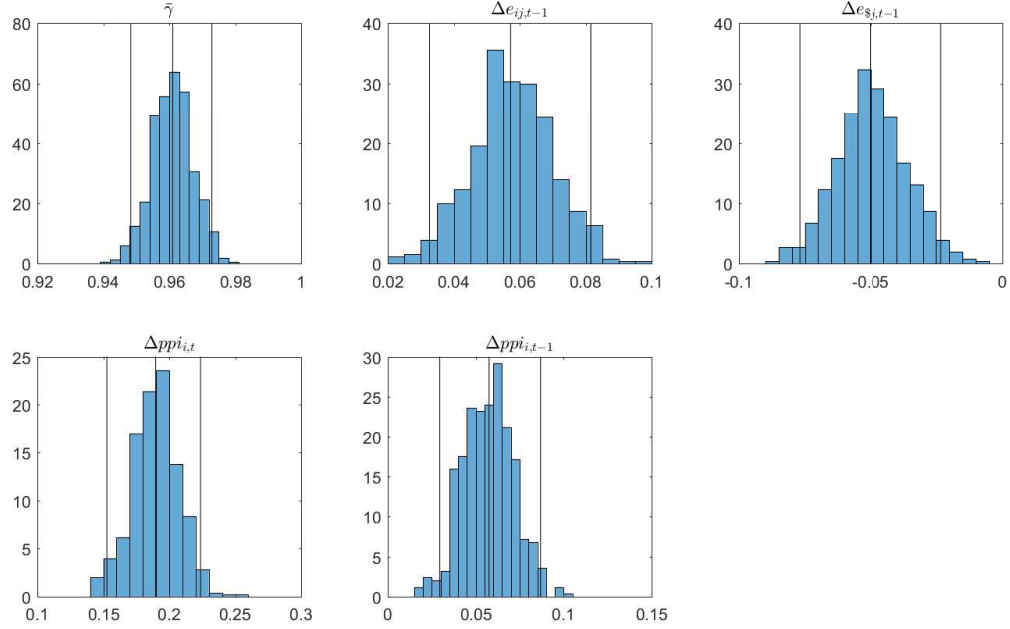


Figure 19: Histogram of posterior draws of elements in θ , the regression coefficients that are assumed constant across dyads. The top left display shows the parameter $\bar{\gamma}$ in Eq. (8). The remaining displays show the coefficients on the indicated exogenous covariates. Vertical lines mark the 2.5, 50, and 97.5 percentiles. For brevity, we do not show the time fixed effects.

POSTERIOR OF OTHER PARAMETERS, PRICE PASS-THROUGH

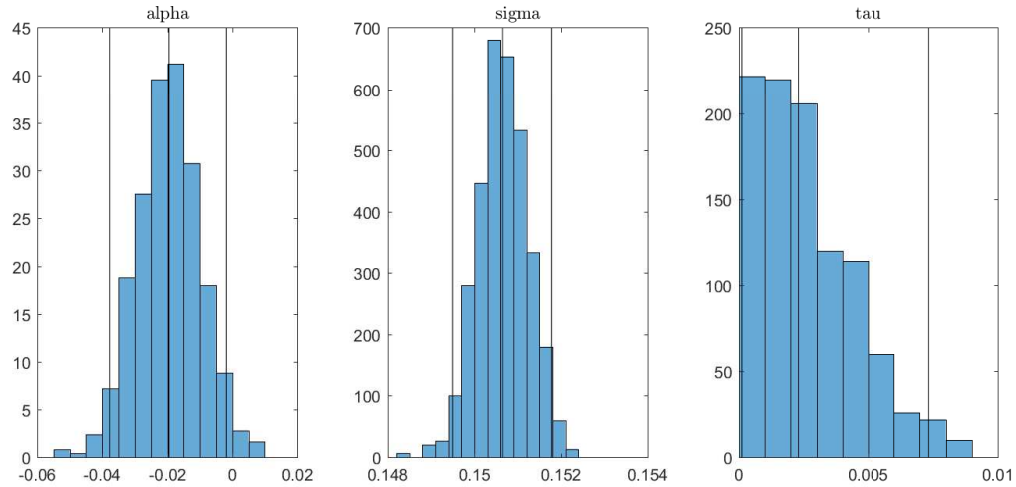


Figure 20: Histogram of posterior draws of α (left), σ (middle), and τ (right). Vertical lines mark the 2.5, 50, and 97.5 percentiles.

POSTERIOR OF CONSTANT REGRESSION COEFFICIENTS, TRADE ELASTICITY

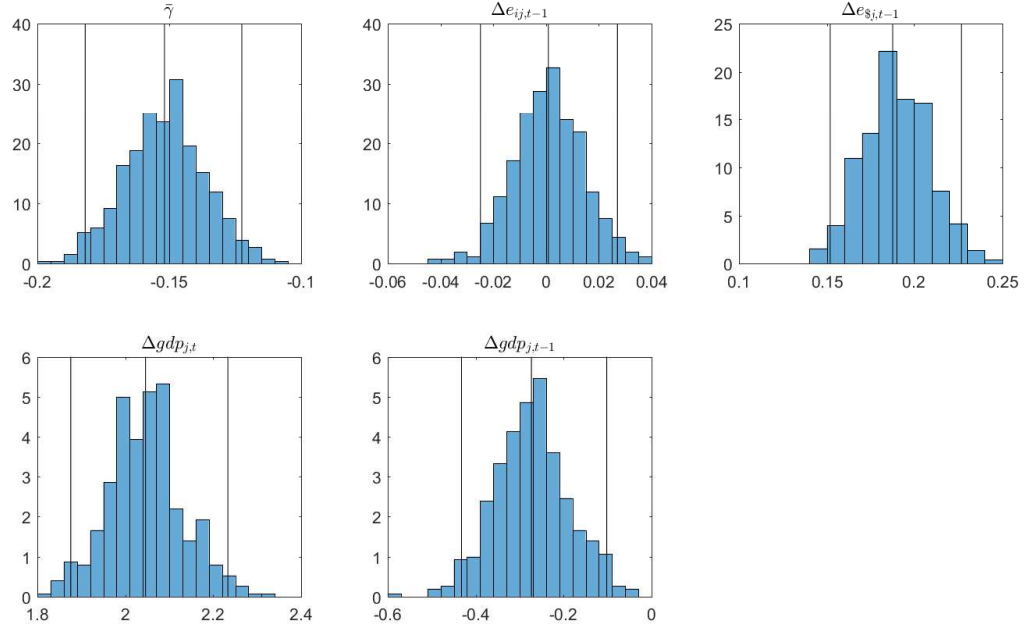


Figure 21: See caption for Fig. 19.

POSTERIOR OF OTHER PARAMETERS, TRADE ELASTICITY

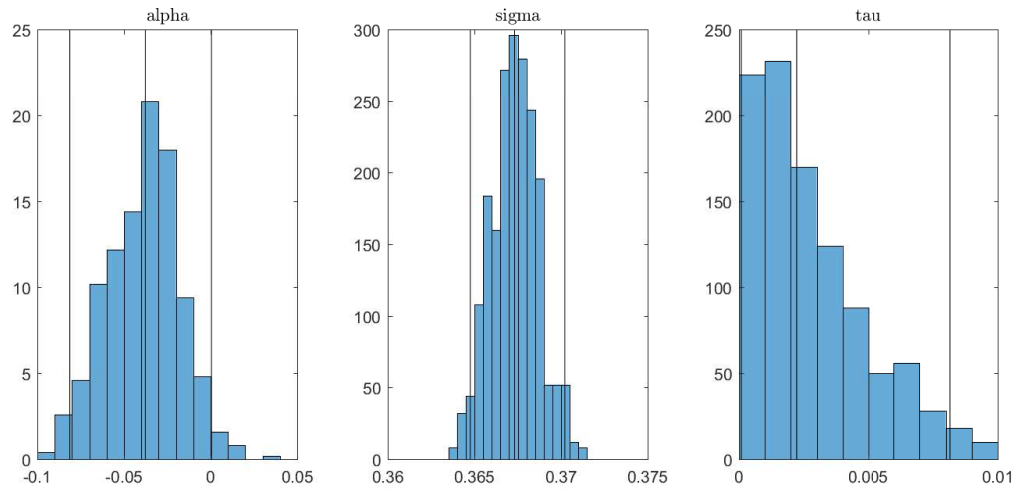


Figure 22: See caption for Fig. 20.

DENSITY OF DOLLAR PRICE PASS-THROUGH GIVEN DOLLAR INVOICING SHARE, $K = 8$

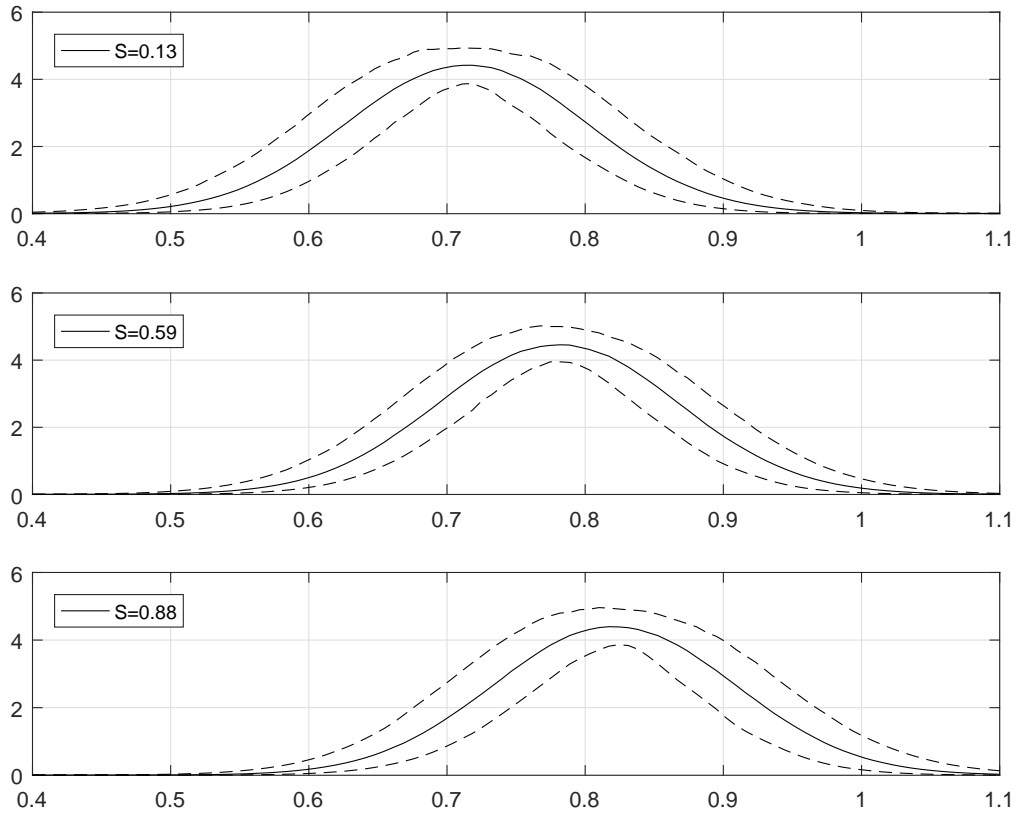


Figure 23: See caption for Fig. 9.

SAMPLE DISTRIBUTION OF DOLLAR PRICE PASS-THROUGH, $K = 8$

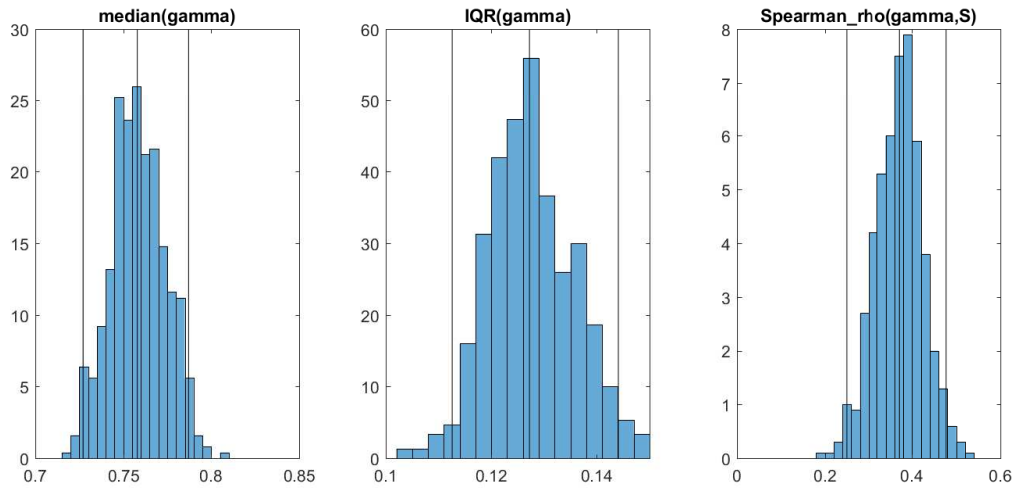


Figure 24: See caption for Fig. 11.

DENSITY OF DOLLAR TRADE ELASTICITY GIVEN DOLLAR INVOICING SHARE, $K = 8$

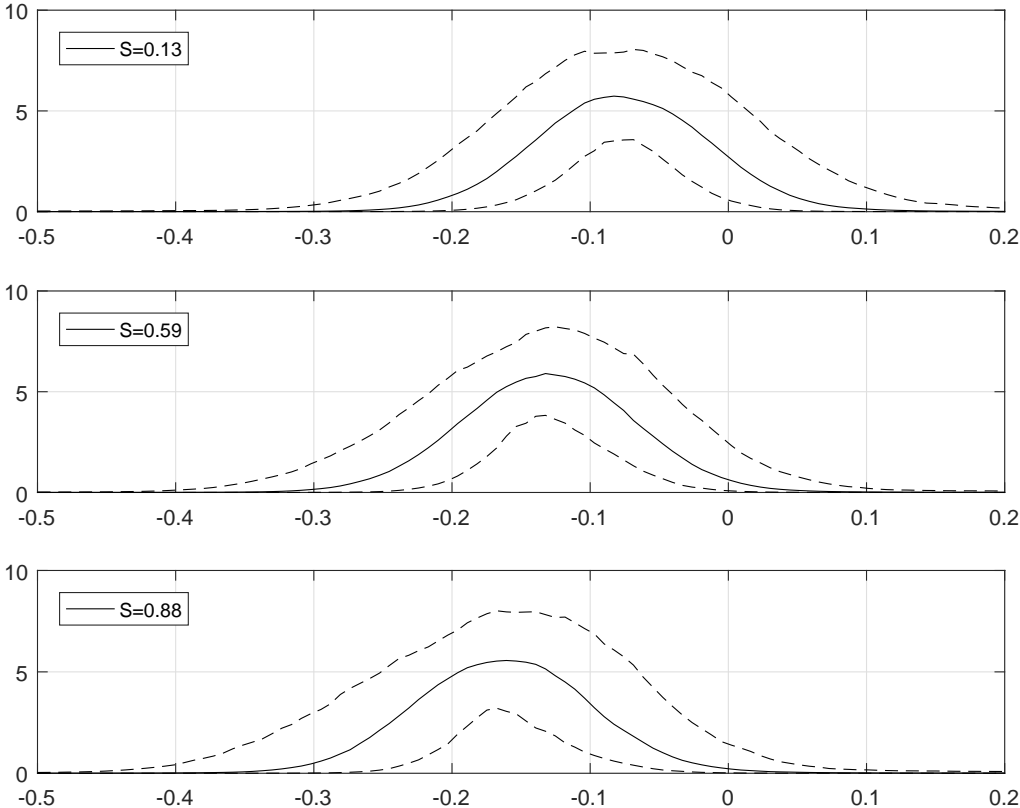


Figure 25: See caption for Fig. 12.

SAMPLE DISTRIBUTION OF DOLLAR TRADE ELASTICITY, $K = 8$

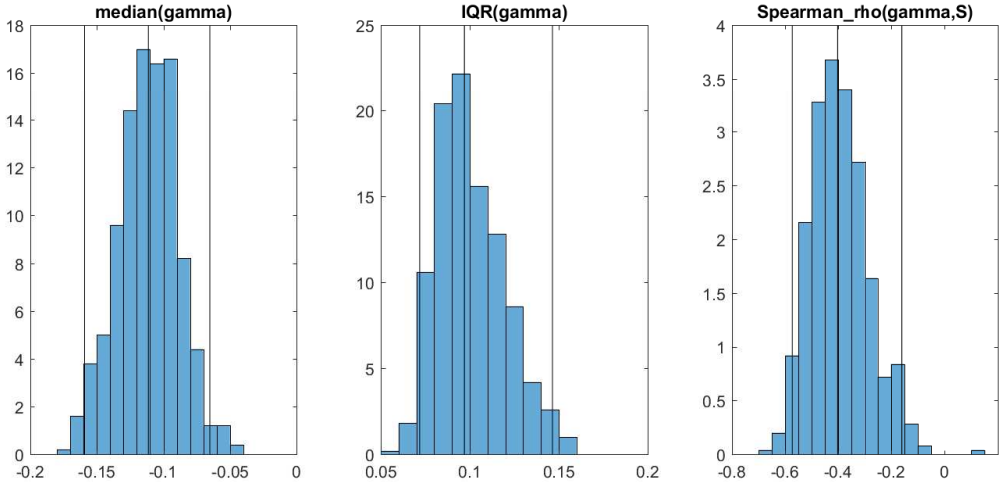


Figure 26: See caption for Fig. 14.

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