

Online Appendix

Gravity and Heterogeneous Trade Cost Elasticities*

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July 27, 2021

Abstract

How do trade costs affect international trade? This paper offers a new approach. We rely on a flexible gravity equation that predicts variable trade cost elasticities, both across and within country pairs. We apply this framework to popular trade cost variables such as currency unions, trade agreements, and WTO membership. While we estimate that these variables are associated with increased bilateral trade on average, we find substantial heterogeneity. Consistent with the predictions of our framework, trade cost effects are strong for ‘thin’ bilateral relationships characterised by small import shares, and weak or even zero for ‘thick’ relationships.

JEL Classification: F14, F15, F33.

Keywords: Currency Unions; Euro; Gravity; Heterogeneity; RTA; Trade Costs; Trade Elasticity; Translog; WTO.

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A Data

Bilateral Exports The International Monetary Fund’s Direction of Trade Statistics (DOTS) is the most widely used data set for studying the effect of currency unions on international trade. For more than 200 countries between 1948 and 2014, it reports bilateral FOB merchandise exports (in US dollars) of which 46% are recorded as zero. Head *et al.* (2010) argue that the true value of many of the zero export flows reported by the DOTS is likely to be positive. Relying on alternative data sources, they identify a number of problematic zeros and replace them by positive values or set them as missing entries. They also fix a number of typos due to incorrect reporting between FOB and CIF values. We rely on the data set cleaned by Head *et al.* (2010) for our analysis. As their data set only spans the period from 1948 to 2006, we update their series up to 2014 using the growth rates of positive exports reported by the DOTS.

GDPs and Populations Nominal GDPs (in US dollars) and populations between 1949 and 2006 are from the Centre d’Etudes Prospectives et d’Informations Internationales (CEPII). We update them up to 2013 using the growth rates of GDPs and populations from the World Bank’s World Development Indicators (WDI).

Gravity Gravity controls are from CEPII. These include bilateral (population weighted) distances (in kilometres), and dummies for sharing a common land border (contiguity), a common (official) language, a common coloniser post-1945, pairs in a colonial relationship post-1945, and for pairs that were, or are, the same country. Dummy variables for membership with the OECD, IMF, and WTO are constructed using online sources (the dummies are equal to one if both countries in a pair are members in each year, and zero otherwise).

We create a dummy variable for country pairs in an RTA using two different sources: CEPII between 1948 and 2006 and De Sousa (2012) between 1958 and 2014. As it contains a larger number of observations for pairs in an RTA between 1958 and 2006 (for instance, it reports the RTA between Thailand and Laos since 1991), we rely on the CEPII series and carry forward the RTA observations up to 2014. Based on De Sousa (2012), we then update the CEPII series in three ways: 1) we add the RTAs created after 2006 (for instance, between the EU and Peru and Colombia since 2013), 2) we identify countries that left an RTA after 2006 (for instance, Angola left the COMESA in 2007), and 3) we add a few missing RTAs prior to 2007 (for instance, the RTA between the EU and the Faroe Islands since 1997).

Currency Unions De Sousa (2012) provides information on currency union membership between 1948 and 2014. He identifies three types of currency unions: 1) *bilateral* currency unions, which ‘commonly occur when a small and/or poor country unilaterally adopts the money of a larger, richer ‘anchor’ country’ (Rose, 2006), 2) *multilateral* currency unions ‘between countries of more or less equal size and wealth’ (Rose, 2006), and 3) cases where ‘money was interchangeable between the two countries at a 1:1 par for an extended period of time, so that there was

no need to convert prices when trading between a pair of countries.’

The data set of De Sousa (2012) covers 230 countries between 1948 and 2014 and includes 58,534 currency union observations. Between 1949 and 2013, which is the time period we focus on in our paper, this number drops to 54,648. In our sample, we only observe 19,514 currency union observations (see Table A1 below).¹ There are several reasons for this discrepancy. First, a number of currency union countries are omitted from the Head *et al.* (2010) data set. These include American Samoa, Belgium, Guam, Monaco, Luxembourg, and Montenegro (De Sousa, 2012, reports data for Belgium and Luxembourg both separately and as a single entity while we merge them over the entire period). Second, for other currency union countries the import shares per good cannot be calculated if either bilateral exports, the importer’s GDP, or the extensive margin are missing: Montserrat, San Marino, and Wallis and Futuna have no trade data; the Falkland Islands, Gibraltar, Nauru, and Saint Helena have no extensive margin and GDP data; Guadeloupe, French Guiana, Martinique, Réunion, and Saint Pierre et Miquelon are omitted as importers as they have no GDP data; Andorra is excluded as an importer because in the sample it only imports from Taiwan which is missing extensive margin data; Equatorial Guinea is omitted as an exporter because it lacks extensive margin data.

Other countries which never belonged to a currency union are also excluded from our data set: Anguilla, British Virgin Islands, Cocos Islands, Cook Islands, Christmas Island, Cayman Islands, Micronesia, Marshall Islands, Northern Mariana Islands, Norfolk Island, Niue, the Palestinian Territory, Pitcairn, Puerto Rico, Turks and Caicos Islands, Tokelau, and Western Sahara have no trade data; North Korea, Taiwan, and Uzbekistan are excluded as exporters because of missing extensive margin data; Timor-Leste is excluded as an importer because in the sample it only imports from Taiwan which has no extensive margin data.

Descriptive Statistics As the pre-1997 trade flows for Belgium and Luxembourg are reported jointly, we merge the two countries into a single entity over the entire period (and we count the two countries as one). Our sample therefore includes 199 countries between 1949 and 2013. Bilateral import shares are given by the ratio between bilateral exports and the importing country’s GDP, and we discard outliers by excluding the highest import shares that represent 0.05% of the sample size. Bilateral import shares *per good* are then obtained by dividing the import shares by the average over time of the number of product categories exported by each country as a share of the total number of categories exported by all countries in each year (from United Nations Comtrade). See Section 3.1.1 for more details.

As shown in Table A1, our full sample includes 1,203,583 observations of which 782,469 import shares (and import shares per good) are positive, and 421,114 are equal to zero (i.e., 35%

¹Togo has been using the CFA franc since 1945. In De Sousa’s (2012) data set, the currency union dummy for Togo with the other countries using the CFA franc is equal to one in all years except 1962. As this dummy is equal to one in 1962 in the data set of Glick and Rose (2016), we switched its value from zero to one in 1962.

Table A1. *Descriptive Statistics.*

	Full sample	Positive import shares
Number of observations	1,203,583	782,469
Number of zero import shares	421,114	0
Number of positive import shares	782,469	782,469
Import shares		
Minimum	0.000%	0.001%
Maximum	41.264%	41.264%
Mean	0.290%	0.447%
Standard deviation	1.522%	1.869%
Number of observations for currency unions	19,514	13,085
Number of pairs in a currency union (directional)	1,255	924
Number of switches into currency unions (directional)	379	342
Number of switches out of currency unions (directional)	782	459

Source: Authors' calculations.

of the sample).² The lowest positive import share is close to zero (from Angola to Colombia), and the largest is equal to 41.3% (from Singapore to the Maldives). The mean and standard deviation of import shares are equal to 0.3% and 1.5% (0.4% and 1.9% in the sample of positive shares). As the import shares per good are given by the import shares over the extensive margin, they do not have any meaningful units and are therefore not described in the table. In the full sample, 1,255 country pairs (directional) share a common currency at some point (amounting to 19,514 observations, or about 1.6% of the sample). There are 379 and 782 country pairs (directional) that switched into or out of currency unions.

Table A2. *Currency Unions and Non-Unions.*

	Currency Unions	Non-Unions
Import share (%)	1.061 (3.897)	0.278 (1.447)
RTA	0.292 (0.454)	0.048 (0.214)
WTO	0.564 (0.496)	0.419 (0.493)
OECD	0.099 (0.298)	0.025 (0.157)
IMF	0.690 (0.462)	0.731 (0.443)
ln Distance	7.645 (0.972)	8.720 (0.768)
Contiguity	0.144 (0.351)	0.019 (0.138)
Shared language	0.712 (0.453)	0.164 (0.370)
Common coloniser	0.597 (0.490)	0.094 (0.292)
Colonial relationship	0.057 (0.232)	0.009 (0.097)
Same country	0.174 (0.379)	0.007 (0.086)
Observations	19,514	1,184,069

Notes: The table reports the mean and standard deviation (in parentheses) of each variable.

²Note that in the empirical analysis, for instance in column (3) of Table 1, the sample size may be reduced as singleton observations are dropped due to the inclusion of fixed effects.

Table A2 provides descriptive statistics for currency unions and non-unions in the full sample (including the zero import shares). For most variables, the sample means are similar for the two groups of countries (standard deviations are reported between parentheses). Still, countries in a currency union have higher import shares, are closer, are more likely to be in a colonial relationship and to belong to the OECD and WTO, and are less likely to belong to the IMF.

B Theory and Monte Carlo Analysis

In Section B.1 we outline the derivation of the translog gravity equation. In Section B.2 we carry out a Monte Carlo simulation under the assumption that the translog gravity model with variable trade cost elasticities is the data generating process. The aim is to confirm that our two-step procedure in Section 3 is able to detect the heterogeneity of trade cost effects implied by variable trade cost elasticities. In Section B.3 we carry out a Monte Carlo simulation under the assumption that the standard log-linear gravity model with a constant trade cost elasticity is the data generating process. This is a placebo check in the sense that under this assumption, we should not find heterogeneous trade cost effects with our two-step procedure. In Section B.4 we compute general equilibrium effects to rule out that those might explain the heterogeneity patterns we find in the data.

B.1 Derivation of the Translog Gravity Equation

We derive the translog gravity equation (1). We refer to Novy (2013) for further details. The translog expenditure function for country j is given by:

$$\ln(E_j) = \ln(U_j) + \alpha_{0j} + \sum_{m=1}^N \alpha_m \ln(p_{mj}) + \frac{1}{2} \sum_{m=1}^N \sum_{k=1}^N \theta_{km} \ln(p_{mj}) \ln(p_{kj}),$$

where E_j is expenditure, U_j is the utility level, with m and k indexing goods and $\theta_{km} = \theta_{mk}$. The price of good m when delivered in country j is denoted by p_{mj} , where $p_{mj} = t_{mj}p_m$ and p_m denotes the price of good m net of trade costs. We assume symmetry across goods from the same origin country i in the sense that $p_m = p_i$ for all goods m originating in country i , and the corresponding bilateral trade costs to country j are also symmetric, i.e., $t_{mj} = t_{ij}$.

As in Feenstra (2003) we impose the following parameter restrictions to ensure homogeneity of degree one:

$$\sum_{m=1}^N \alpha_m = 1 \quad \text{and} \quad \sum_{k=1}^N \theta_{km} = 0.$$

We further impose that goods enter symmetrically:

$$\theta_{mm} = -\frac{\theta}{N}(N-1) \quad \text{and} \quad \theta_{km} = \frac{\theta}{N} \text{ for } k \neq m,$$

with $\theta > 0$.

The expenditure share s_{mj} of country j on good m can be obtained by differentiating the expenditure function with respect to $\ln(p_{mj})$:

$$s_{mj} = \alpha_m + \sum_{k=1}^N \theta_{km} \ln(p_{kj}).$$

The import share corresponding to bilateral trade x_{ij} from country i to country j follows as:

$$\frac{x_{ij}}{y_j} = \sum_{m \in i} s_{mj},$$

where the individual import shares s_{mj} are summed up over all goods m originating in country i . To close the model we impose market clearing:

$$y_i = \sum_{j=1}^S x_{ij},$$

where S denotes the number of countries in the world.

To obtain the translog gravity equation we substitute the import shares into the market clearing condition. Using $p_{kj} = t_{kj}p_k$ we solve for the net prices p_k and substitute them back into the expenditure shares and import shares. This yields the translog gravity equation (1).

B.2 Analysis of the Two-Step Procedure

When running PPML gravity regressions in Section 3, we adopt a two-step procedure to estimate heterogeneous currency union effects. In the first step, we predict the import shares per good. In the second step, we interact the currency union dummy with the log predicted shares. In this section we carry out Monte Carlo simulations to verify the validity of this two-step procedure.

As our trade cost function, we assume:

$$\ln(t_{ij,t}) = \kappa CU_{ij,t} + \zeta W_{ij,t}, \tag{B.1}$$

where $W_{ij,t}$ contains bilateral trade cost variables used in our analysis other than currency unions, i.e., time-invariant geography-related variables (logarithmic bilateral distance and a contiguity dummy) as well as time-varying policy variables (dummies for RTAs and membership of the WTO, OECD, and IMF). We choose values for the trade cost parameters that are derived from our baseline regression in column (3) of Table 1.³ We then compute trade costs on the basis of equation (B.1) using the actual observations for our trade cost variables.

³Assuming an elasticity of substitution of $\sigma = 5$ for the constant elasticity gravity framework implied by

We assume that the data generating process is given by the translog gravity model in Section 2. We choose the translog parameter value as $\theta = 0.095$.⁴ Based on equations (1) to (3), we first compute the import shares in a deterministic way (i.e., without an error term). We use a balanced sample of observed data for the GDP variables $(y_{i,t}, y_{j,t})$, the extensive margin measure n_i , and the trade cost variables underlying equation (B.1) for 120 origin and destination countries over the period from 1990 to 2013.⁵

Then we include an additive error term in the translog gravity equation (1). We choose its standard deviation to match the share of zero observations in the sample (Santos Silva and Tenreyro, 2006).⁶ We then run first-step and second-step regressions as in column (5) of Table 1. In the first step we predict import shares per good, and in the second step we interact the currency union dummy with the log predicted shares. Standard errors are clustered at the non-directional country pair level. We run 100 iterations of this procedure, drawing a new set of errors for every iteration.

We report the results in Table B1. For reference, column (1) shows the true currency union estimates, evaluated at the mean, the 10th, and the 90th percentiles of log predicted import shares (as in Section 3, calculated for non-zero import shares only). The reported coefficients and standard errors in columns (2) and (3) are averaged over all iterations. Analogous to specification (7), the first-step regression in column (2) simply includes distance and a contiguity dummy in addition to time-varying exporter and importer fixed effects. Distance and contiguity have the expected signs. The second-step regression in column (3) includes the currency union dummy and an interaction term with the log predicted import share, as well as the additional time-varying policy variables and fixed effects. Consistent with column (5) of Table 1, we obtain negative and highly significant coefficients on the currency union dummy and the interaction term. The lower panel of column (3) reports the implied currency union estimates, evaluated at the mean, the 10th, and the 90th percentiles of log predicted import shares. We find a mean estimate of 0.384, implying that evaluated at the average import share, two countries trade 46.8% more bilaterally if they are in a currency union. Consistent with the theoretical framework, we find a larger estimate of 0.533 at the 10th percentile (i.e., for relatively small import shares), implying 70.4% more bilateral trade *ceteris paribus*. At the 90th percentile (i.e., for relatively large import shares) we find an estimate of 0.187, implying increased bilateral

column (3) of Table 1, the κ parameter for the currency union dummy in equation (B.1) follows as the estimated coefficient of 0.252 in column (3) of Table 1 divided by $(1 - \sigma)$, i.e., $\kappa = 0.252 / (1 - 5) = -0.063$. The parameters for the RTA, WTO, OECD, and IMF variables follow analogously as -0.032 , 0.001 , -0.148 , and -0.051 . To obtain parameter values for distance and contiguity in (B.1), we run a regression as in equation (7) based on the observed import shares per good, with estimated coefficients of -0.747 and 0.881 (both significant at the 1% level). The parameters thus follow as 0.187 and -0.220 .

⁴In the translog regression in column (1) of Table 6, we obtain a currency union coefficient of 0.006. Assuming the same currency union coefficient as above, it therefore follows $\theta = -0.006 / \kappa = 0.095$.

⁵To reduce computing time we use a subset of data starting in 1990.

⁶Similar to Santos Silva and Tenreyro (2006), we round values to zero (the nearest integer), in this case for sufficiently negative errors that would otherwise imply negative trade shares. The share of zero observations is around 17% in the simulation sample.

Table B1. *Monte Carlo Simulation.*

	(1)	(2)	(3)
		First step	Second step
CU		–	–0.498*** (0.118)
CU × ln predicted share		–	–0.221*** (0.035)
RTA		–	0.074*** (0.007)
WTO		–	0.021 (0.017)
OECD		–	0.492*** (0.030)
IMF		–	0.117* (0.066)
ln Distance		–0.537*** (0.011)	–
Contiguity		0.276*** (0.031)	–
CU estimates	True		Estimated
Mean	0.326	–	0.384*** (0.032)
10 th percentile	0.643	–	0.533*** (0.053)
90 th percentile	0.134	–	0.187*** (0.021)
Observations		223,095	222,937
Corresponding table (column)		–	Table 1 (column 5)

Notes: Exporter-year and importer-year fixed effects are included. Directional country pair fixed effects are further included in (3). The regressions are estimated with PPML for data from 1990 to 2013 with the import share per good as the dependent variable. Translog gravity is the data generating process (with the true currency union estimates reported in the first column). The reported coefficients are averages over 100 iterations. Robust standard errors clustered at the (non-directional) country pair level are reported in parentheses (not bootstrapped), also averaged over 100 iterations. *** and * indicate significance at the 1% and 10% levels, respectively. ‘predicted share’ is the predicted import share.

trade by 20.6%. These estimates can be compared to the true values underlying the simulation indicated in column (1).

Overall, the simulation in Table B1 confirms the validity of our two-step procedure in the sense that qualitatively, it yields heterogeneous currency union estimates as in the underlying model. Quantitatively, the heterogeneity profile is not quite as steep as suggested by the theoretical model, with our results slightly undershooting the true effect at the 10th percentile and slightly overshooting at the 90th percentile. Figure 1 visually compares the true values against the estimates across all deciles of (predicted) import shares. 95% confidence intervals are indicated as dashed lines. The true values lie within the confidence intervals, except for smallest and largest percentiles. The reason for the relatively steeper heterogeneity profile of the true values is the functional form of the translog specification. As equation (4) shows, the translog elasticity is given by the translog preference parameter divided by the import share. This can generate a hyperbolic shape with very large elasticities for the smallest import shares.⁷

⁷Also see the discussion in Section 3.2.

As an additional check, we also investigate the consequences of ignoring the first step altogether by erroneously interacting the currency union dummy with log *actual* import shares (as opposed to log predicted import shares). Since in that case the interacted regressor is by construction positively correlated with the dependent variable, this leads to an upward endogeneity bias on the interaction coefficient. In fact, it even turns positive with high significance. The resulting estimates at the mean, the 10th, and the 90th percentiles follow as -0.540 , -1.422 , and 0.244 (all significant at the 1% level). Thus, they exhibit the opposite pattern of the true values in Table B1 in that they *rise* with the import share.⁸ This is incorrect and we strongly advise against such a specification. This check therefore underlines the importance of predicting shares in the first step.

B.3 Placebo Check

We also carry out a placebo check that is based on the assumption that the standard log-linear gravity model represents the data generating process. We construct the import shares for the standard gravity model using the relationship:

$$\frac{x_{ij,t}}{y_{j,t}} = \frac{y_{i,t}}{y_t^W} \left(\frac{t_{ij,t}}{P_{i,t}P_{j,t}} \right)^{1-\sigma}, \quad (\text{B.2})$$

which is derived by Anderson and van Wincoop (2003). $P_{i,t}$ and $P_{j,t}$ denote the price indices of the origin and destination countries, or multilateral resistance terms, given by:

$$P_{i,t}^{1-\sigma} = \sum_{s=1}^S P_{s,t}^{\sigma-1} \frac{y_{s,t}}{y_t^W} t_{si,t}^{1-\sigma}, \quad (\text{B.3})$$

where S is the number of countries in the world. We assume $\sigma = 5$. We use equations (B.2) and (B.3) as well as trade cost function (B.1) to construct the deterministic import shares, based on the same sample of GDP and trade cost variables for 120 countries as above. We solve for the price indices numerically through iteration. Similarly as above, we include an additive error term in the gravity equation, choosing its standard deviation to match the share of zero observations in the sample. We then run first-step and second-step regressions estimated with PPML, iterating the procedure 100 times with fresh error terms.

We report the results of the placebo check in Table B2. Column (1) shows the true currency union estimates. By construction they are the same when evaluated at different percentiles of simulated import shares. The first-step regression in column (2) includes coefficients on distance and contiguity with the expected signs. The second-step regression in column (3) exhibits a currency union interaction term that is only marginally significant but with the opposite (positive) sign compared to our findings in Section 3. The positive sign would imply a heterogeneity profile that rises with the import share. In any case, the estimated currency

⁸See column (4) in Table 1 where currency union estimates also (erroneously) rise with the import share.

Table B2. *Monte Carlo Simulation (Placebo Check)*.

	(1)	(2)	(3)
		First step	Second step
CU		–	0.269*** (0.008)
CU × ln predicted share		–	0.006* (0.003)
RTA		–	0.124*** (0.002)
WTO		–	–0.006* (0.004)
OECD		–	0.576*** (0.007)
IMF		–	0.200*** (0.011)
ln Distance		–0.795*** (0.005)	–
Contiguity		0.978*** (0.015)	–
CU estimates	True		Estimated
Mean	0.252	–	0.235*** (0.010)
10 th percentile	0.252	–	0.222*** (0.016)
90 th percentile	0.252	–	0.249*** (0.003)
Observations		223,095	223,002
Corresponding table (column)		–	Table 1 (column 5)

Notes: Exporter-year and importer-year fixed effects are included. Directional country pair fixed effects are further included in (3). The regressions are estimated with PPML for data from 1990 to 2013 with the import share as the dependent variable. Standard gravity is the data generating process (with the true currency union estimates reported in the first column). The reported coefficients are averages over 100 iterations. Robust standard errors clustered at the (non-directional) country pair level are reported in parentheses (not bootstrapped), also averaged over 100 iterations. *** and * indicate significance at the 1% and 10% levels, respectively. ‘predicted share’ is the predicted import share.

union effects reported in the lower panel are quantitatively very close and not significantly different from the true effects in column (1).

Overall, the placebo results confirm that if standard gravity is the underlying model, our two-step procedure does not give rise to currency union effects that vary across import shares in a meaningful way.

B.4 General Equilibrium Effects

Our results on the heterogeneity of currency union effects reported in Section 3 refer to the *direct* effect of trade costs on trade (also see our discussion of the trade cost elasticity in Section 2). However, a change in trade costs also has an *indirect* effect on trade through changes in multilateral resistance in general equilibrium, a point famously made by Anderson and van Wincoop (2003). The aim of this appendix is to trace out these general equilibrium effects in response to a change in trade costs. We show that they cannot explain the heterogeneity

patterns in Section 3.

First, we base our analysis on the standard gravity model as in equation (B.2). Similar to Novy (2013) we take logarithms and first differences to arrive at:

$$\Delta \ln \left(\frac{x_{ij,t}}{y_{j,t}} \right) = (1 - \sigma) \Delta \ln (t_{ij,t}) + (\sigma - 1) \Delta \ln (P_{i,t} P_{j,t}) + \Delta \ln \left(\frac{y_{i,t}}{y_t^W} \right). \quad (\text{B.4})$$

The left-hand side represents the percentage change in the import share. The first term on the right-hand side represents the direct effect of the change in trade costs. The second and third terms indicate the indirect general equilibrium effects, consisting of changes in multilateral resistance and the change in the exporting country's income share.

With the help of decomposition (B.4) we analyse a counterfactual change in trade costs. As in Online Appendix B.2 we draw on a sample of 120 origin and destination countries, using the observed data for the GDP variables ($y_{i,t}, y_{j,t}$) and the trade cost variables underlying equation (B.1) with the same parameter values as in that section. In particular, the value of the currency union dummy coefficient κ is chosen such that it matches the 0.252 coefficient in column (3) of Table 1, and as previously we assume $\sigma = 5$. Based on those data we numerically compute an initial equilibrium under the assumption of no currency unions (i.e., we set $CU_{ij,t}$ to zero for all pairs). As our counterfactual exercise, we then compute a new equilibrium under the assumption that a currency union is formed for a particular pair (i.e., we set $CU_{ij,t}$ to one such that $t_{ij,t}$ changes for that particular pair). We then compute the terms in decomposition (B.4), assuming that the exporting country's income share is constant.⁹ We compute such a counterfactual equilibrium for each of the currency union pairs in our sample. We use data for a single-cross section (for the year 2000), in which the data indicate 244 currency union pairs. Thus, we compute 244 counterfactual equilibria.

We present the results in Table B3. Since we are interested in variation across import shares, we report the results as averages across import share intervals for currency union pairs. Specifically, we choose three import share intervals in ascending order based on the initial equilibrium. For example, the first row of Table B3 reports the average changes for currency union pairs that fall in the tercile of the smallest import shares in the initial equilibrium. By construction the direct effect in column (2) reflects the 0.252 currency union dummy coefficient from column (3) of Table 1. That is, entering into a currency union is associated with an increase in bilateral trade of 29% (equal to $\exp(0.252) - 1$). The indirect effect operating through changes in multilateral resistance in column (3) is quantitatively small. The intuition is that currency unions are relatively rare at the bilateral level (see Online Appendix A), and they constitute only one out of several trade cost components. Therefore, the total effect in column (1) is similar to the direct effect, with indirect effects being negligible.

⁹That is, $\Delta \ln (y_{i,t}/y_t^W) = 0$. The effect operating through a changing income share is typically negligibly small. Since we hold income shares fixed, our results can be described as ‘modular trade impact’ in the terminology of Head and Mayer (2014).

Table B3. *General Equilibrium Effects (Standard Gravity).*

	Total effect	=	Direct effect	+	Indirect GE effect
	$\Delta \ln(x_{ij,t}/y_{j,t})$		$(1 - \sigma) \Delta \ln(t_{ij,t})$		$(\sigma - 1) \Delta \ln(P_{i,t}P_{j,t})$
Import share interval	(1)		(2)		(3)
First interval	0.246	=	0.252	+	-0.006
Second interval	0.251	=	0.252	+	-0.001
Third interval	0.242	=	0.252	+	-0.010

Notes: This table is based on the decomposition in equation (B.4). It reports logarithmic differences between the initial equilibrium and counterfactual equilibria (computed numerically). The initial equilibrium assumes no currency unions. In the counterfactual equilibria the currency unions are activated separately for each pair. The results are reported as averages over currency union pairs by terciles of their import shares, where intervals are formed in ascending order of import shares based on the initial equilibrium. Data are for 120 origin and destination countries in the year 2000 consisting of 244 currency union pairs (see Online Appendix B.2 for details including underlying parameter values). Column (1) reports the change in import shares, (2) reports the direct effect of entering a currency union, and (3) reports the indirect general equilibrium (GE) effect operating through multilateral resistance. Income shares are held constant.

We note that the indirect effect does not vary systematically across import share intervals. Intuitively, in response to a change in bilateral trade costs multilateral resistance typically shifts more strongly for small countries as they tend to be more open. But currency union pairs in the data are associated with a mix of both small and large countries across all intervals. Therefore, multilateral resistance effects do not vary systematically across intervals.¹⁰

We conclude that indirect trade cost effects in our setting tend to be quantitatively weak. Most importantly, they do not vary systematically across import share intervals. We also refer to Novy (2013, Section 3.5) who shows formally in Monte Carlo simulations that general equilibrium effects would in any case be absorbed by exporter and importer fixed effects in gravity regressions. Thus, the heterogeneity patterns we find in Section 3 are not related to general equilibrium effects.

Second, we also compute general equilibrium effects based on the translog gravity equation (1). We take first differences to arrive at:

$$\Delta \left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}} \right) = -\theta \Delta \ln(t_{ij,t}) + \Delta D_{i,t} + \theta \Delta \ln(T_{j,t}). \quad (\text{B.5})$$

The left-hand side represents the change in the level of the import share per good. The first term on the right-hand side is the direct effect of the trade cost change. The second and third terms indicate the indirect general equilibrium effects. Thus, this decomposition is similar to

¹⁰In a second counterfactual experiment (not reported here), we assume that the currency union dummy is set to one for *all* pairs at the same time. Quantitatively, the indirect general equilibrium effects are larger than in column (3) of Table B3 since this counterfactual experiment involves multiple trade cost changes in one go. But as in Table B3, there is no systematic variation across import share intervals.

equation (B.4) with the main difference being that on the left-hand side we have a change in levels, not a change in logarithms.

As before, we use the decomposition (B.5) to analyse a counterfactual change in trade costs. We draw on the same data sample, computing an initial equilibrium under the assumption of no currency unions (i.e., we set $CU_{ij,t}$ to zero for all pairs). As our counterfactual exercise, we then compute a new equilibrium under the assumption that a currency union is formed for a particular pair (i.e., we set $CU_{ij,t}$ to one such that $t_{ij,t}$ changes for that particular pair). We then compute the terms in decomposition (B.5). We can further use equations (2) and (3) to derive:

$$\Delta D_{i,t} + \theta \Delta \ln(T_{j,t}) = \theta \left(\frac{y_{j,t}}{y_t^W} + \left(1 - \frac{y_{j,t}}{y_t^W} \right) \frac{n_{i,t}}{N_t} \right) \Delta \ln(t_{ij,t}),$$

where we again assume that countries' income shares are constant, and also that the extensive margin measure is not affected by the trade cost change.¹¹ The parameter values for κ and θ are the same as above. We compute 244 counterfactual equilibria, switching on the currency union dummy for each of the currency union pairs in our sample for the year 2000.

Table B4. *General Equilibrium Effects (Translog Gravity)*.

	Total effect	=	Direct effect	+	Indirect GE effect
	$\Delta \left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}} \right)$		$-\theta \Delta \ln(t_{ij,t})$		$\Delta D_{i,t} + \theta \Delta \ln(T_{j,t})$
Import share interval	(1)		(2)		(3)
First interval	0.0058	=	0.0060	+	-0.0002
Second interval	0.0059	=	0.0060	+	-0.0001
Third interval	0.0059	=	0.0060	+	-0.0001

Notes: This table is based on the decomposition in equation (B.5). It reports differences between the initial equilibrium and counterfactual equilibria (computed numerically). The initial equilibrium assumes no currency unions. In the counterfactual equilibria the currency unions are activated separately for each pair. The results are reported as averages over currency union pairs by terciles of their import shares, where intervals are formed in ascending order of import shares based on the initial equilibrium. Data are for 120 origin and destination countries in the year 2000 consisting of 244 currency union pairs (see Online Appendix B.2 for details including underlying parameter values). Column (1) reports the change in import shares, (2) reports the direct effect of entering a currency union, and (3) reports the indirect general equilibrium (GE) effect. Income shares and extensive margin measures are held constant.

We present the results in Table B4. As in the previous table, we construct three import share intervals for currency union pairs in ascending order based on the initial equilibrium. By construction the direct effect in column (2) reflects the 0.006 currency union dummy coefficient from column (1) of Table 6. That is, entering into a currency union is associated with an increase in the bilateral import share per good by 0.006. The indirect general equilibrium effect operating through changes in the $D_{i,t}$ and $T_{j,t}$ terms in column (3) is quantitatively

¹¹That is, $\Delta (y_{i,t}/y_t^W) = 0$ and $\Delta n_{i,t} = 0$.

minor, and it does not vary systematically across import share intervals. Overall, the total effect in column (1) is therefore similar to the direct effect.

C Robustness

To ensure the robustness of our findings, this appendix provides a number of sensitivity checks.

Selection on Observables Persson (2001) claims that the trade impact of common currencies can be mismeasured if the countries in a currency union are systematically different from those outside (Rose, 2001; Baldwin, 2006; Baldwin *et al.*, 2008). He therefore applies a matching technique to identify non-currency union country pairs that are most similar to currency union pairs. Comparing bilateral trade flows between the two groups, he finds that the trade effect of currency unions is insignificant. To control for non-random selection, we apply the nearest matching estimator of Persson (2001). We run a probit regression to generate the propensity score, and we match the currency union observations with the non-currency union observations that deviate by no more than a small distance from the propensity score.¹²

Table C1. *Robustness: Non-Random Selection.*

	(1)	(2)
CU	0.245*** (0.051)	-0.410*** (0.157)
CU × ln predicted share	–	-0.209*** (0.044)
CU estimates		
Mean	–	1.056*** (0.169)
10 th percentile	–	1.632*** (0.287)
90 th percentile	–	0.507*** (0.069)
Observations	713,552	713,552

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Robust standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses in (1). Standard errors are bootstrapped in (2). *** indicates significance at the 1% level. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. Dummy variables for RTAs, WTO, OECD, and IMF membership are included but not reported.

Based on the matched sample, column (1) of Table C1 shows that currency unions are associated with 28% more trade on average. In column (2), the trade effect of currency unions is heterogeneous across predicted import shares. Our findings thus remain robust to non-random selection on observables.

¹²As in Persson (2001), the probit regresses the currency union indicator on the product of the GDPs and GDPs per capita, the log of distance, and dummy variables for sharing a common border, a common language, the same country, colonial relationships, and RTAs. The value chosen for the maximum distance between the non-currency union observations and the propensity score is equal to 0.0001.

Geopolitical Events, Decolonisation, and Missing Data Campbell (2013) and Campbell and Chentsov (2020) argue that omitted variables and missing data are driving the positive effect of currency unions on trade. First, they argue that the collapse in trade attributed to several currency union dissolutions was driven by major geopolitical events or hostile colonial separations.¹³ Second, to account for the slow and steady decline of former colonial trade ties over time (Head *et al.*, 2010), they include a time trend for bilateral colonial relationships and show that it significantly reduces the trade impact of currency unions. Finally, as trade data are often missing after currency union breakups, they recommend excluding those country pairs from the sample as they may otherwise bias currency union estimates.

Table C2. *Robustness: Geopolitical Events, Decolonisation, and Missing Data.*

	(1)	(2)	(3)	(4)	(5)	(6)
CU	0.173*** (0.050)	0.134*** (0.049)	0.135*** (0.049)	-0.400*** (0.139)	-0.417*** (0.135)	-0.419*** (0.132)
CU × ln predicted share	—	—	—	-0.179*** (0.033)	-0.179*** (0.037)	-0.180*** (0.034)
Trend colonial relationships	-0.023*** (0.002)	-0.022*** (0.002)	-0.022*** (0.002)	-0.022*** (0.002)	-0.022*** (0.002)	-0.022*** (0.003)
CU estimates						
Mean	—	—	—	0.841*** (0.123)	0.824*** (0.143)	0.831*** (0.128)
10 th percentile	—	—	—	1.320*** (0.205)	1.297*** (0.237)	1.307*** (0.214)
90 th percentile	—	—	—	0.383*** (0.064)	0.366*** (0.065)	0.370*** (0.059)
Observations	1,131,641	1,127,743	1,126,275	1,131,641	1,127,743	1,126,275
Geopolitical events	Yes	No	No	Yes	No	No
Hostile colonial separations	Yes	No	No	Yes	No	No
Missing data after CU switch	Yes	Yes	No	Yes	Yes	No

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Robust standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses in (1) to (3). Bootstrapped standard errors in (4) to (6). *** indicates significance at the 1% level. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. Dummy variables for RTAs, WTO, OECD, and IMF membership are included but not reported.

To address those issues, in column (1) of Table C2 we estimate equation (6) and add a time trend for past colonial relationships.¹⁴ Column (2) removes 32 (non-directional) country pairs from the sample whose currency union switches were simultaneous to wars or hostile colonial breakups, while column (3) also excludes 18 country pairs with missing data following a currency union dissolution (Campbell, 2013; Campbell and Chentsov, 2020).¹⁵ The negative coefficient on the trend indicates that former colonial trade ties gradually decay over time. In addition, the trend reduces the magnitude of the currency union coefficient from 0.252 (column 3 of Table 1) to 0.173 (column 1). The currency union coefficient further falls to 0.134 once we

¹³Examples include the breakup in 1965 of the currency union between India and Pakistan that coincided with a border war, or decolonisation after major conflicts of former French and Portuguese colonies.

¹⁴The results are similar with a trend for UK colonies only (Campbell, 2013; Campbell and Chentsov, 2020).

¹⁵Due to the country pair fixed effects, we cannot separately control for these pairs in the regression. We therefore follow Campbell (2013) and Campbell and Chentsov (2020) and remove them from the sample.

drop the country pairs that exited from a currency union at the same time as wars or hostile colonial breakups took place (column 2), and to 0.135 once we also exclude the country pairs with missing data (column 3). Wars and decolonisation therefore matter in explaining the magnitude of the trade effect of currency unions, but sharing a common currency continues to be associated with more trade (14% more trade on average according to column 3).

Columns (4) to (6) report the same regressions as in columns (1) to (3) but the currency union indicator is interacted with log predicted shares. As shown in the lower part of the table, currency unions are associated with more trade, and their effects are heterogeneous and smaller in magnitude for country pairs with larger import shares. We therefore conclude that our results remain robust to controlling for wars, decolonisation, and missing data.

Currency Union Types De Sousa (2012) identifies three types of currency unions: *multilateral* (i.e., between countries of similar size and wealth), *bilateral* (i.e., when a small or poor country adopts the currency of a larger and richer country), and currency unions where money is ‘interchangeable’ between two countries at 1:1 parity.

Table C3. *Robustness: Currency Union Types.*

	(1)	
CU multilateral	−0.166 (0.178)	
CU multilateral × ln predicted share	−0.104** (0.042)	
CU bilateral	−0.483** (0.235)	
CU bilateral × ln predicted share	−0.246*** (0.056)	
CU estimates	Multilateral	Bilateral
Mean	0.551*** (0.154)	1.222*** (0.208)
10 th percentile	0.828*** (0.255)	1.879*** (0.346)
90 th percentile	0.287*** (0.086)	0.593*** (0.110)
Observations	1,131,641	

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. Dummy variables for RTAs, WTO, OECD, and IMF membership are included but not reported.

We broadly split currency unions into two groups, i.e., multilateral versus bilateral.¹⁶ We estimate equation (8) and allow for heterogeneity in the trade impact of both multilateral and bilateral unions. For both types of unions, Table C3 shows that our results continue to hold.

¹⁶The currencies used in multilateral unions include the British West Indies dollar, the Central America and the Caribbean currency, the CFA and CFP francs, the East African shilling, and the euro. The currencies circulating in bilateral unions are the Australian, Malaysian, and US dollars, the Indian, Mauritian, and Pakistani rupees, the Belgian and French francs, the South African rand, the Danish krone, the Portuguese escudo, the Saudi riyal, the Spanish peseta, and the British pound sterling.

Currency Union Entry and Exit Our sample includes 379 and 782 (directional) switches into and out of currency unions. Among the 379 entries, 251 correspond to the euro.¹⁷ We classify our currency union observations into three categories: *entry* (i.e., currency unions created during our sample period), *exit* (i.e., unions that were dissolved), and *continuous* (i.e., they existed over the whole sample period). Some bilateral pairs are therefore classified as both entry and exit if they entered and subsequently left a currency union during our sample period.

Table C4. *Robustness: Currency Union Entry and Exit.*

	(1)	(2)			
CU entry	-0.053 (0.237)	—			
CU entry× ln predicted share	-0.052 (0.068)	—			
CU non-EURO entry	—	-0.226 (0.857)			
CU non-EURO entry× ln predicted share	—	-0.027 (0.191)			
EURO entry	—	-0.565*** (0.153)			
EURO entry× ln predicted share	—	-0.118*** (0.036)			
CU exit	-0.346* (0.190)	-0.238 (0.183)			
CU exit× ln predicted share	-0.204*** (0.044)	-0.181*** (0.041)			
CU continuous× ln predicted share	-0.622*** (0.098)	-0.630*** (0.088)			
Trend EU countries	—	0.027*** (0.003)			
CU estimates	Entry	Exit	Non-EURO entry	EURO entry	Exit
Mean	0.307 (0.248)	1.064*** (0.160)	-0.037 (0.563)	0.250* (0.129)	1.015*** (0.154)
10 th percentile	0.446 (0.425)	1.607*** (0.265)	0.036 (1.042)	0.564** (0.219)	1.498*** (0.252)
90 th percentile	0.174* (0.093)	0.544*** (0.090)	-0.107 (0.254)	-0.051 (0.066)	0.553*** (0.092)
Observations	1,131,641		1,131,641		

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. Dummy variables for RTAs, WTO, OECD, and IMF membership are included but not reported.

Distinguishing between the three types of unions, we estimate equation (8) and report the results in column (1) of Table C4 (for the continuous unions, the currency union dummy is omitted due to collinearity with the pair fixed effects and only its interaction with the log predicted shares is included). The interactions between the currency union dummy and the log predicted shares are negative for the continuous and exit unions only. In column (2), we split the entry currency unions between euro and non-euro currencies (and include a trend for EU

¹⁷Belgium and Luxembourg are merged into a single entity, while Latvia and Lithuania only adopted the euro in 2014 and 2015. Our sample thus includes 16 countries that switched to the euro, accounting for $16 \times 15 = 240$ directional switches. The 11 other switches occurred between Saint Pierre et Miquelon and Eurozone countries.

countries), and the interaction is negative for the euro only. With the exception of non-euro entry currency unions, all other unions are thus associated with heterogeneous trade effects.

Import Shares per Good Our findings remain robust to using alternative proxies for the extensive margin n_i in measuring the bilateral import shares per good. In column (1) of Table C5 the import shares per good are computed using the Hummels and Klenow (2005) measure. In column (2) we assume that the extensive margin is unity for all exporters in which case the dependent variable is simply the bilateral import share.

Table C5. *Robustness: Import Shares per Good.*

	(1)	(2)	(3)	(4)
CU	0.180 (0.165)	-0.389*** (0.114)	-0.704 (0.447)	-0.422 (0.331)
CU × ln predicted share	-0.101* (0.052)	-0.186*** (0.028)	-0.178* (0.096)	-0.178* (0.096)
CU estimates				
Mean	0.771*** (0.182)	1.034*** (0.119)	0.736** (0.353)	0.760** (0.336)
10 th percentile	1.002*** (0.293)	1.647*** (0.205)	1.476** (0.749)	1.499** (0.724)
90 th percentile	0.542*** (0.094)	0.477*** (0.055)	-0.086 (0.135)	-0.057 (0.158)
Observations	854,082	1,157,168	81,807	100,301
Exporter extensive margin	HK (2005)	Unity	OECD STAN	OECD STAN
Importer output	GDP	GDP	Total output	Manuf. output

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. In (1), HK (2005) stands for Hummels and Klenow (2005). Dummy variables for RTAs, IMF, OECD, and WTO membership are included but not reported.

Instead of using the importing country’s GDP to compute the import shares per good, we experiment using total (column 3) or manufacturing (column 4) gross output from the OECD STAN database (available in domestic currency and converted to US dollars using bilateral exchange rates from the International Monetary Fund’s International Financial Statistics). As the data are only available for OECD nations our sample is reduced to 19 importing countries.

Specifications In Table C6 we consider three alternative specifications for the first-step regression (7). In column (1), in addition to bilateral distance and contiguity we include indicator variables for sharing a common language, a common coloniser post-1945, pairs in a colonial relationship post-1945, and for territories that were, or are, the same country. In column (2) we replace bilateral distance and contiguity with a full set of (directional) country pair fixed effects. In column (3) we let the distance and contiguity elasticities vary over time (by interacting the two variables with year dummy variables).

In column (4) we include time-varying distance and contiguity controls in the second-step

regression (8). We also estimate the second-step regression with a lagged dependent variable (column 5), a trend for EU countries (column 6), and a trend for all countries in a currency union in our sample (column 7).

Table C6. *Robustness: Specifications.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Lagged dep. var.	–	–	–	–	3.964*** (0.432)	–	–
CU	–0.275** (0.135)	–0.240* (0.139)	–0.368** (0.149)	–0.335** (0.151)	–0.327*** (0.106)	–0.498*** (0.143)	–0.176 (0.168)
CU × ln predicted share	–0.173*** (0.034)	–0.173*** (0.037)	–0.191*** (0.037)	–0.188*** (0.035)	–0.163*** (0.030)	–0.201*** (0.034)	–0.187*** (0.035)
Trend EU countries	–	–	–	–	–	0.021*** (0.003)	–
Trend CU pairs	–	–	–	–	–	–	–0.013*** (0.004)
CU estimates							
Mean	0.924*** (0.129)	1.104*** (0.177)	0.961*** (0.134)	0.965*** (0.125)	0.798*** (0.119)	0.892*** (0.130)	1.117*** (0.129)
10 th percentile	1.383*** (0.212)	1.742*** (0.310)	1.478*** (0.229)	1.465*** (0.212)	1.231*** (0.197)	1.427*** (0.214)	1.615*** (0.210)
90 th percentile	0.489*** (0.068)	0.528*** (0.075)	0.468*** (0.063)	0.485*** (0.067)	0.383*** (0.053)	0.379*** (0.070)	0.640*** (0.083)
Observations	1,131,641	1,131,641	1,131,641	1,131,641	1,087,964	1,131,641	1,131,641
First-step controls	Gravity controls	Pair effects	Dist. × D_t , contig. × D_t	Dist., contig.	Dist., contig.	Dist., contig.	Dist., contig.

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. In (4), the second-step regression (8) includes time-varying distance and contiguity controls. Dummy variables for RTAs, WTO, OECD, and IMF membership are included but not reported.

Samples In Table C7 we verify the robustness of our findings using alternative data samples. In column (1) we use the exports and GDP data between 1949 and 2006 from Head *et al.* (2010). In column (2) we use exports from the International Monetary Fund’s DOTS combined with GDPs from the World Bank’s WDI between 1960 and 2013. In column (3) we use a balanced sample between 1994 and 2013. We exclude (in column 4) the countries (mostly island nations) omitted from the analysis of Glick and Rose (2016), smaller nations with a nominal GDP below 500 million US dollars in 2013 (column 5), poorer countries with an annual GDP per capita below 500 US dollars in 2013 (column 6), and post-Soviet states (column 7).¹⁸

¹⁸The post-Soviet states are Armenia, Azerbaijan, Belarus, Estonia, Georgia, Kazakhstan, Kyrgyzstan, Latvia, Lithuania, Moldova, the Russian Federation, Tajikistan, Turkmenistan, Ukraine, and Uzbekistan.

Table C7. *Robustness: Samples.*

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
CU	-0.146 (0.163)	-0.360*** (0.135)	-0.472*** (0.139)	-0.394** (0.157)	-0.419*** (0.138)	-0.485*** (0.135)	-0.359** (0.163)
CU × ln predicted share	-0.130*** (0.038)	-0.180*** (0.033)	-0.156*** (0.039)	-0.208*** (0.038)	-0.195*** (0.035)	-0.215*** (0.034)	-0.195*** (0.040)
CU estimates							
Mean	0.768*** (0.133)	0.942*** (0.137)	0.547*** (0.133)	1.046*** (0.140)	0.933*** (0.127)	0.998*** (0.124)	0.990*** (0.138)
10 th percentile	1.117*** (0.229)	1.453*** (0.225)	0.934*** (0.224)	1.606*** (0.236)	1.445*** (0.212)	1.558*** (0.206)	1.511*** (0.239)
90 th percentile	0.432*** (0.065)	0.457*** (0.071)	0.180*** (0.061)	0.510*** (0.071)	0.439*** (0.061)	0.453*** (0.061)	0.490*** (0.062)
Observations	986,961	970,993	310,080	992,368	1,102,783	1,012,463	1,053,636
Sample	Head <i>et al.</i> (2010)	IMF/World Bank	Balanced 1994–2013	Excl. islands	Excl. small countries	Excl. poor countries	Excl. Soviet countries

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. *** and ** indicate significance at the 1% and 5% levels, respectively. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. Dummy variables for RTAs, WTO, OECD, and IMF membership are included but not reported.

Feedback Effects Finally, in Table C8 we test for ‘feedback effects’ of currency unions as discussed in Baier and Bergstrand (2007). As in their paper, we restrict our sample to five-year intervals from 1953 to 2013. Based on equation (8) we add one lead (i.e., values five years ahead, denoted as $t + 1$) of the currency union dummy variable and its interaction with log predicted shares. In column (1) we first show that our results continue to hold based on the sample with five-year intervals. In column (2) we add the future currency union status and its interaction with log predicted shares. These coefficients are insignificant. The coefficient on the future currency union status remains insignificant in column (3) where we do not allow for heterogeneity across country pairs. Similar to Baier and Bergstrand (2007) we therefore do not find evidence of feedback effects.

Table C8. *Feedback Effects as in Baier and Bergstrand (2007).*

	(1)	(2)	(3)
CU (t)	-0.440** (0.218)	-0.356 (0.317)	0.248*** (0.083)
CU × ln predicted share (t)	-0.210*** (0.054)	-0.180** (0.082)	—
CU (t+1)	—	0.021 (0.216)	0.047 (0.069)
CU × ln predicted share (t+1)	—	-0.014 (0.052)	—
CU estimates (t)			
Mean	1.001*** (0.175)	0.877*** (0.266)	—
10 th percentile	1.550*** (0.308)	1.345*** (0.475)	—
90 th percentile	0.472*** (0.075)	0.426*** (0.091)	—
Observations	217,026	183,977	183,977

Notes: PPML estimation. Exporter-year, importer-year, and (directional) country pair fixed effects are included. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses in (1) and (2). Robust standard errors in (3). *** and ** indicate significance at the 1% and 5% levels, respectively. The dependent variable is the import share per good. ‘predicted share’ is the predicted import share per good. Dummy variables for RTAs, WTO, OECD, and IMF membership are included but not reported.

References

- Anderson, J. and van Wincoop, E. (2003). ‘Gravity with gravitas: a solution to the border puzzle’, *American Economic Review*, vol. 93(1), pp. 170–92.
- Baier, S.L. and Bergstrand, J.H. (2007). ‘Do free trade agreements actually increase members’ international trade?’, *Journal of International Economics*, vol. 71(1), pp. 72–95.
- Baldwin, R. (2006). ‘In or out: does it matter? An evidence-based analysis of the euro’s trade effect’, *Centre for Economic Policy Research*, London.

- Baldwin, R., Di Nino, V., Fontagné, L., De Santis, R.A. and Taglioni, D. (2008). ‘Study on the impact of the euro on trade and foreign direct investment’, European Economy Economic Paper 321, European Commission.
- Campbell, D.L. (2013). ‘Estimating the impact of currency unions on trade: solving the Glick and Rose puzzle’, *The World Economy*, vol. 36(10), pp. 1278–93.
- Campbell, D.L. and Chentsov, A. (2020). ‘Breaking badly: the currency union effect on trade’, New Economic School Working Paper 265.
- De Sousa, J. (2012). ‘The currency union effect on trade is decreasing over time’, *Economics Letters*, vol. 117(3), pp. 917–20.
- De Sousa, J. (2012). ‘The currency union effect on trade is decreasing over time – Replication package.’ *Economics Letters*, data deposited at <http://jdesousa.univ.free.fr/data.htm#Regional%20trade%20agreements>.
- Feenstra, R.C. (2003). ‘A homothetic utility function for monopolistic competition models, without constant price elasticity’, *Economics Letters*, vol. 78(1), pp. 79–86.
- Glick, R. and Rose, A.K. (2016). ‘Currency unions and trade: a post-EMU reassessment’, *European Economic Review*, vol. 87, pp. 78–91.
- Glick, R. and Rose, A.K. (2016). ‘Currency unions and trade: a post-EMU reassessment – Replication package.’ *European Economic Review*, data deposited at <http://faculty.haas.berkeley.edu/arose/RecRes.htm#CUTrade>.
- Head, K. and Mayer, T. (2014). ‘Gravity equations: workhorse, toolkit, and cookbook’, in (G. Gopinath, E. Helpman and K. Rogoff, eds.), *Handbook of International Economics*, Chapter 3, pp. 131–95.
- Head, K. and Mayer, T. (2014). ‘Gravity equations: workhorse, toolkit, and cookbook – Replication package.’ *Handbook of International Economics*, data deposited at http://www.cepii.fr/cepii/en/bdd_modele/bdd.asp.
- Head, K., Mayer, T. and Ries, J. (2010). ‘The erosion of colonial linkages after independence’, *Journal of International Economics*, vol. 81(1), pp. 1–14.
- Head, K., Mayer, T. and Ries, J. (2010). ‘The erosion of colonial linkages after independence – Replication package.’ *Journal of International Economics*, data deposited at http://www.cepii.fr/cepii/en/bdd_modele/bdd.asp.
- Hummels, D. and Klenow, P.J. (2005). ‘The variety and quality of a nation’s exports’, *American Economic Review*, vol. 95(3), pp. 704–23.

International Monetary Fund (2021). ‘IMF Direction of Trade Statistics, 1948-2020’, 98th Edition [data collection]. UK Data Service. SN: 4745, <http://doi.org/10.5257/imf/dots/2021-01>.

International Monetary Fund (2021). ‘IMF International Financial Statistics, 1920-2021’, 102nd Edition [data collection]. UK Data Service. SN: 4772, <http://doi.org/10.5257/imf/ifs/20-21-01>.

Mayer, T. and Zignago, S. (2011). ‘Notes on CEPII’s distances measures: the GeoDist Database’, CEPII Working Paper 2011-25.

Mayer, T. and Zignago, S. (2011). ‘Notes on CEPII’s distances measures: the GeoDist Database – Replication package.’ CEPII Working Paper, data deposited at http://www.cepii.fr/cepii/en/-bdd_modele/bdd.

Novy, D. (2013). ‘International trade without CES: estimating translog gravity’, *Journal of International Economics*, vol. 89(2), pp. 271–82.

Organisation for Economic Co-operation and Development (2020). ‘OECD Structural Analysis (STAN), 1970-2017’, 3rd Edition [data collection]. UK Data Service. SN: 5541, <http://doi.org/10.5257/oecd/stan/2018-11>.

Persson, T. (2001). ‘Currency unions and trade: how large is the treatment effect?’, *Economic Policy*, vol. 33(16), pp. 434–48.

Rose, A.K. (2001). ‘Currency unions and trade: the effect is large’, *Economic Policy*, vol. 16(33), pp. 449–61.

Rose, A.K. (2006). ‘Currency unions’, in (S.N. Durlauf and L.E. Blume, eds.), *The New Palgrave Dictionary of Economics*, Second Edition, Palgrave Macmillan, 2008.

Santos Silva, J.M.C. and Tenreyro, S. (2006). ‘The log of gravity’, *Review of Economics and Statistics*, vol. 88(4), pp. 641–58.

United Nations (2021). ‘UN Commodities Trade Statistics Database (COMTRADE)’, <http://comtrade.un.org/>.

World Bank Group (2021). ‘World Bank World Development Indicators, 1960-2020’, 27th Edition [data collection]. UK Data Service. SN: 4814, <http://doi.org/10.5257/wb/wdi/2020Q4>.