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Gravity and heterogeneous trade cost elasticities

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Heterogeneous Trade Cost Elasticities

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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.

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1 Introduction

A key research topic in international trade is to understand the link between trade costs and trade flows. In this paper, we propose a new approach that is built on the idea that trade costs may not affect all trade flows in the same way. Instead, trade costs might have a strong influence on trade between some countries but not between others.

To evaluate the effect of trade costs, researchers typically rely on a standard gravity equation framework and insert trade cost proxies as right-hand side regressors (e.g., bilateral distance, dummy variables for regional trade agreements, currency union status, etc.) This yields single coefficients to assess the trade effects of these variables. By construction, their effects are homogeneous across all country pairs in the sample.[1]

In this paper, we challenge the view that trade costs have a homogeneous 'one-size-fits-all' effect on bilateral trade flows. The core of our paper is to offer an easy-to-implement alternative to the traditional gravity equation that allows us to estimate heterogeneous trade cost effects. Our contribution is to empirically demonstrate in a systematic and comprehensive way that trade cost effects are heterogeneous across country pairs, and also within country pairs by direction of trade.

As a prominent example, consider the trade effect of currency unions. Currency unions are arguably an important institutional arrangement to reduce trade costs. In the period since World War II, a total of 123 countries have been involved in a currency union at some point. By the year 2015, 83 countries continued to do so. In addition, various countries are currently considering to form new currency unions or to join existing ones.[2] But does that mean all currency union member pairs experience an equal increase in international trade? We provide an empirical framework showing that the trade effects associated with currency union membership are heterogeneous across member pairs, even within specific currency unions such as the euro.

We also apply this framework of flexible trade cost effects to a host of other trade cost-related variables popular in the international trade literature. We provide evidence of heterogeneous effects for regional trade agreements (RTAs), World Trade Organization (WTO) membership, bilateral distance, sharing a common border, a common language, and tariffs.

As our theoretical framework, we introduce heterogeneous trade cost effects by taking guidance from a translog gravity equation that predicts variable trade cost elasticities (Novy, 2013).

[1] To be precise, the direct (partial equilibrium) trade effects are homogeneous. We discuss general equilibrium effects in Appendix B.

[2] Currency unions, or monetary unions, 'are groups of countries that share a single money' (Rose, 2006). See Data Appendix A for details. Areas currently considering the creation of a common currency include the economies of the West African Monetary Zone, the Southern African Development Community, the East African Community, and the Gulf Cooperation Council (although in the latter case, talks have stalled).

In this framework, 'thin' bilateral trade relationships (characterised by small bilateral import shares) are more sensitive to trade cost changes compared to 'thick' trade relationships (characterised by large bilateral import shares). The intuition is that small import shares are high up on the demand curve where sales are very sensitive to trade cost changes. Large import shares are further down on the demand curve where sales are more buffered. As a result, smaller import shares have a larger trade cost elasticity in absolute magnitude. The prediction is that a given change in trade costs (induced by a change in currency union status or other trade cost changes) generates heterogeneous effects on trade flows. We should expect larger trade effects for country pairs associated with smaller import shares. This implies a heterogeneous effect even within country pairs since bilateral import shares typically differ depending on the direction of trade.

We start by laying out the flexible gravity framework and relate it to trade cost effects in international trade. This forms the basis for our empirical specifications. We then construct our key variable of interest – the bilateral import shares of 199 countries between 1949 and 2013 – and bring the framework to the data.[3] We adopt two main approaches to test whether the effect of trade costs on trade is heterogeneous across import shares. The first approach is a modification of the standard gravity specification familiar from the literature. Instead of estimating a single trade cost coefficient that is constant over the entire sample, we propose a flexible gravity framework that allows for heterogeneous trade cost effects across import shares.[4] The second approach is to estimate the translog gravity equation directly, which also implies variable trade cost elasticities.

In the first approach, our aim is to examine whether trade cost effects are heterogeneous across bilateral import shares. In principle, this could be attempted by interacting trade cost regressors with import shares. However, this would create an immediate simultaneity bias problem since trade cost effects would vary with the values taken by the dependent variable. We address this issue by letting trade cost effects vary across *predicted* import shares. We propose a two-step methodology for this purpose. In the first step we generate predicted shares by regressing import shares on time-invariant geography-related variables such as distance and contiguity. In the second step we assess how the trade cost effects vary across predicted import shares. To deal with heteroskedasticity and to include the zero import shares in the sample, we estimate our regressions by Poisson Pseudo Maximum Likelihood (PPML), as is typical in the recent gravity literature.

We carry out Monte Carlo simulations to verify the validity of our two-step procedure of estimating heterogeneous trade cost effects. When we assume that the data generating process is driven by variable trade cost elasticities, we show that our two-step procedure produces

[3] As explained in Section 2, the dependent variable is actually the bilateral import share per good of the exporting country. But for simplicity we refer to it as the bilateral 'import share.'

[4] It is well known that the gravity model fits the data very well. The main point of adopting the flexible gravity framework is not necessarily to improve overall fit but to introduce variable trade cost elasticities.

heterogeneous results that match those implied by the model, both qualitatively and quantitatively. Also, when we assume that standard gravity with a constant trade cost elasticity is the data generating process, we demonstrate that our two-step procedure does not spuriously generate heterogeneous trade cost effects.

To illustrate our procedure we initially focus on the effect of currency unions on international trade, and we turn to other trade cost variables later. Empirically, we find that when we estimate a standard gravity regression without heterogeneous effects (i.e., imposing a constant trade cost elasticity), a common currency is associated with 29% more trade on average. Our contribution with the help of the flexible gravity framework is to demonstrate that this average hides a significant amount of heterogeneity *across country pairs*. Bilateral trade effects tend to be particularly strong between countries where at least one partner is relatively small so that import shares can be small. For example, we find a strong currency union effect for trade from Chad to Côte d'Ivoire (141% more bilateral trade) and from Austria to Germany (62%). Conversely, bilateral trade effects tend to be relatively weak or even zero between countries with large import shares, for example from Côte d'Ivoire to Togo (22%) and from France to Belgium-Luxembourg (insignificant).

We also find that the trade effect of currency unions is heterogeneous *within country pairs* and therefore asymmetric by direction of trade. For example, as just mentioned, the effect is large (62%) for trade from Austria to Germany (a low bilateral import share). But it is insignificant for trade from Germany to Austria (a large bilateral import share).

Given the enormous academic and policy interest in the euro, we also focus more specifically on the trade effect of the European single currency. Consistent with evidence reported in the literature, we confirm that the average trade effect of the euro is more modest compared to other common currencies.[5] This is consistent with relatively large import shares on average in the euro area. Still, we find that the effect is heterogeneous across country pairs within the Eurozone. Examples of country pairs with small import shares which are associated with large euro effects include Ireland importing from Cyprus (70%) and Finland importing from Malta (50%). Conversely, country pairs with large import shares not generating any additional trade from the common currency include Cyprus importing from Greece and Germany importing from Italy.

Recent contributions show that estimating a gravity equation by PPML as opposed to log-linear Ordinary Least Squares (OLS) reduces the size and significance of the estimated trade effect of currency unions, and in particular of the euro.[6] Our framework contributes to explaining this finding. As is well known, OLS and PPML estimators have different first-order

[5] See Micco *et al.* (2003), Baldwin (2006), Baldwin and Taglioni (2007), Baldwin *et al.* (2008), Berger and Nitsch (2008), Santos Silva and Tenreyro (2010), Eicher and Henn (2011), Glick and Rose (2016), Mika and Zymek (2018), Larch *et al.* (2019), Mayer *et al.* (2019), or Campbell and Chentsov (2020).

[6] For instance, Santos Silva and Tenreyro (2010), Mika and Zymek (2018), Larch *et al.* (2019), and Mayer *et al.* (2019) find that PPML estimates of the euro trade effect are insignificant.

conditions (Eaton *et al.*, 2013; Head and Mayer, 2014; Mayer *et al.*, 2019). While the OLS conditions involve logarithmic deviations of trade from its expected value, the PPML conditions involve level deviations and therefore tend to give more weight to country pairs with high levels of trade. By highlighting that country pairs with higher trade intensity have a smaller trade cost elasticity, our framework therefore predicts that the PPML currency union estimate should be smaller than its OLS counterpart.

In the second approach, we explore the predictions of our model by estimating the translog gravity equation directly. Our regressions confirm that a common currency is associated with more bilateral trade, and that the magnitude of the effect falls with bilateral import shares.

One concern about our estimations relates to the potentially endogenous nature of trade cost variables. For example, reverse causality may arise because countries that trade intensively with each other are more likely to join a currency union, leading to an overestimation of the trade effect of common currencies.[7] Attempts in the literature to instrument the currency union dummy variable prove disappointing as the instrumentation tends to increase, rather than decrease, the magnitude of currency union estimates (Rose, 2000; Alesina *et al.*, 2002; Barro and Tenreyro, 2007). This has led the profession to conclude that appropriate instruments for currency union membership are not available (see Baldwin, 2006, for a discussion).

In this paper, we do not attempt to instrument the currency union indicator. But in simulation results we show that correcting for endogeneity bias (to the extent that it exists) should strengthen, rather than weaken, the heterogeneity patterns in our results. The intuition is that bilateral trade and currency unions are positively related. This would result in positive endogeneity bias, pushing up the modest currency union effects associated with large import shares. Thus, removing this potential bias would lead to even stronger heterogeneity patterns. Endogeneity can therefore not overturn our heterogeneity results.

As they improve our understanding of how trade costs shape trade flows between trading partners, our results have important policy implications. Most importantly, they help to evaluate the potential changes in bilateral trade flows that countries can expect when their trade costs change. For instance, suppose Bulgaria, Croatia, the Czech Republic, Hungary, Poland, Romania, and Sweden were to join the euro over the next few years. As these countries are relatively small compared to some members of the Eurozone such as France and Germany, they have relatively large import shares. Our results suggest that these import shares will grow only modestly (Baldwin, 2006; Glick, 2017; Mika and Zymek, 2018). However, trade shares in the opposite direction are smaller and can therefore be expected to grow more strongly.

[7] Trading firms hurt by exchange rate fluctuations may lobby to keep the exchange rate with the country's major trading partners fixed (Baldwin, 2006). Reverse causality could also arise if currency unions capture unobserved characteristics that affect trade flows. For evidence that greater bilateral trade reduces bilateral exchange rate volatility, see Devereux and Lane (2003) and Broda and Romalis (2010). Mundell (1961) suggests that by reducing real exchange rate fluctuations, trade reduces the costs of forming a currency union. Alesina and Barro (2002) show that countries trading more with each other are more likely to form currency unions.

Our approach is by no means the only one to explore heterogeneous trade cost elasticities. Novy (2013) concentrates on the theoretical derivation of the translog gravity framework, and he only explores its empirical implications based on bilateral distance and contiguity using a single cross-section of 28 OECD countries with fewer than a thousand observations. By contrast, we use more than 1.1 million observations and explore the empirical importance of heterogeneous trade cost effects in a more comprehensive way using a broad range of trade cost variables popular in the literature including time-varying components such as currency union status, regional trade agreements, and WTO membership. Bas *et al.* (2017) derive country pair aggregate trade cost elasticities from a monopolistic competition model with CES demand and log-normal firm-level heterogeneity. Consistent with our predictions, they find that the trade cost elasticity is smaller in magnitude for country pairs with large trade volumes. Guided by monopolistic competition models with CES demand and truncated Pareto firm-level productivity, Helpman *et al.* (2008) find that bilateral trade cost elasticities are larger for less developed countries, while Melitz and Redding (2015) document that those elasticities vary across markets and levels of trade costs. Spearot (2013) relies on the Melitz and Ottaviano (2008) model with firm-level heterogeneity and linear demand to show that tariff liberalisation disproportionately increases the imports of low revenue varieties. Carrère *et al.* (2020) also stress the importance of non-constant trade elasticities, focusing on the effect of distance in particular.[8]

More specifically, our paper also contributes to a large and growing literature that explores whether currency unions promote trade. In his seminal work, Rose (2000) shows that sharing a common currency more than triples bilateral trade flows. Subsequent work by Rose and co-authors shows that the currency union effect is smaller than initially found but remains large (Rose and van Wincoop, 2001; Frankel and Rose, 2002; Glick and Rose, 2002). Various authors argue that these findings are plagued by omitted variables, econometric errors, and self-selection, may be driven by currency unions between small or poor countries, and that the trade effect of currency unions is small or insignificant.[9] We rely on state-of-the-art PPML techniques which allow us to include zero trade observations in the sample and control for country pair and time-varying exporter and importer fixed effects. In addition, our results remain robust to endogeneity, self-selection, omitted variables such as wars and political conflicts, and to excluding small and poor countries as well as post-Soviet states from the sample.

Nevertheless, there is empirical evidence to suggest that heterogeneity in the trade impact

[8]Also see Atkeson and Burstein (2008) who derive heterogeneous trade cost elasticities from a model with nested CES demand and oligopolistic competition.

[9]See Persson (2001), Nitsch (2002), De Nardis and Vicarelli (2003), López-Córdova and Meissner (2003), Micco *et al.* (2003), Klein (2005), Baldwin (2006), Klein and Shambaugh (2006), Bun and Klaassen (2007), Baldwin *et al.* (2008), Berger and Nitsch (2008), Broda and Romalis (2010), Frankel (2010), Santos Silva and Tenreyro (2010), Eicher and Henn (2011), De Sousa (2012), Campbell (2013), Glick and Rose (2016), Glick (2017), Saia (2017), Mika and Zymek (2018), Larch *et al.* (2019), and Campbell and Chentsov (2020). Baldwin *et al.* (2008) claim that the empirical literature on the trade effect of currency unions 'is a disaster' as the estimates range from 0% (e.g., Berger and Nitsch, 2008) to 1,387% (Alesina *et al.*, 2002), most of them being 'fatally flawed by misspecification and/or econometric errors.'

of currency unions exists along several dimensions.[10] For instance, the effect is larger for developing economies (Santos Silva and Tenreyro, 2010), smaller countries (Micco *et al.*, 2003; Baldwin, 2006), and falls over time (De Sousa, 2012). The effect also varies across currency unions (Nitsch, 2002; Klein, 2005; Eicher and Henn, 2011; Glick and Rose, 2016). Consensus estimates for the euro tend to be more modest than those for broader samples, falling between 5% and 15% (Baldwin, 2006; Baldwin *et al.*, 2008). The trade effect is stronger for industries producing differentiated goods (Flam and Nordström, 2007), and for larger and more productive firms that adjust both at the intensive and extensive margins (Berthou and Fontagné, 2008). In contrast to these papers where the various sources of heterogeneity are explored without theoretical motivation and often across different samples, we are guided by a gravity framework with flexible trade cost elasticities to derive our empirical specifications.

The remainder of the paper is organised as follows. In Section 2 we build on the translog gravity framework to motivate why we might find heterogeneous trade cost effects in the data. In Section 3 we present our main estimation results. When introducing our empirical methodology, we initially focus on currency unions as a well-known trade cost variable to demonstrate the heterogeneity of trade effects. Then in Section 4 we extend the heterogeneity analysis to other prominent trade cost variables popular in the gravity literature such as RTAs, WTO membership, tariffs, bilateral distance, and a shared border and language between trading partners. In Section 5 we carry out Monte Carlo simulations that explore the endogeneity of currency unions. In Section 6 we summarise an extensive battery of robustness checks. We conclude in Section 7. Appendix A summarises our data and sources. In Appendix B we outline the derivation of the translog gravity equation. We also carry out Monte Carlo simulations that validate our estimation strategy, and we discuss general equilibrium effects. Appendix C provides details on the robustness checks.

2 Theoretical Motivation

The conventional gravity framework in the literature is characterised by a constant trade cost elasticity. This means that the direct effect of a trade cost change is common across country pairs.[11] In this paper, we employ a gravity framework that does not feature a constant trade cost elasticity. Instead, we build on a gravity framework with variable trade cost elasticities. It follows that the effect of a trade cost change is no longer common across country pairs. It becomes heterogeneous.

As a framework that accommodates the crucial feature of variable trade cost elasticities, we

[10] On the heterogeneous trade effects of FTAs, see Glick (2017) and Baier *et al.* (2019). Spearot (2013) studies the heterogeneous trade effects of tariff liberalisation. Subramanian and Wei (2007) and Felbermayr *et al.* (2020) explore the heterogeneous trade effects of WTO membership. Mayer *et al.* (2019) find that the trade effects of belonging to the EU are heterogeneous across member states, and the countries gaining the most are small, open, and centrally located.

[11] See Head and Mayer (2014) for an overview.

use translog gravity to motivate our analysis. As in Novy (2013), the model features multiple countries in general equilibrium that are endowed with an arbitrary number of differentiated goods. Demand is derived from a translog expenditure function using the parameterisation in Feenstra (2003). Trade costs follow the iceberg form where $t_{ij} \geq 1$ denotes the bilateral trade cost factor between countries i and j. Trade costs may be bilaterally asymmetric such that $t_{ij} \neq t_{ji}$.

As outlined in Appendix B.1, imposing market clearing and solving for the general equilibrium results in the translog gravity equation:

$$\frac{x_{ij}/y_j}{n_i} = -\theta \ln(t_{ij}) + D_i + \theta \ln(T_j), \tag{1}$$

where x_{ij} is the bilateral trade flow between exporting country i and importing country j, y_j is the importer's income, and n_i denotes the number of goods of country i (we ignore time indices for now). The dependent variable is the bilateral import share x_{ij}/y_j per good n_i of the exporting country. On the right-hand side, $\theta > 0$ is a translog preference parameter. D_i and T_j denote exporter and importer-specific terms given by:

$$D_i = \frac{y_i/y^W}{n_i} + \theta \sum_{s=1}^{S} \frac{y_s}{y^W} \ln\left(\frac{t_{is}}{T_s}\right), \tag{2}$$

$$\ln(T_j) = \sum_{s=1}^{S} \frac{n_s}{N} \ln(t_{sj}), \tag{3}$$

where y^W denotes world income, S is the number of countries, and N is the number of products in the world with $N \geq S$. T_j is akin to a multilateral resistance term since it represents a weighted average of bilateral trade costs.

The translog gravity equation (1) differs in two key respects from standard gravity equations as in Eaton and Kortum (2002) and Anderson and van Wincoop (2003). The dependent variable is the import share per good, which means an empirical measure of n_i is required. In addition, the dependent variable is in levels. It is not the logarithmic bilateral trade flow. The gravity relationship is therefore not log-linear in trade costs. This implies a variable trade cost elasticity. This is the crucial feature we focus on in this paper.

More specifically, define the trade cost elasticity as $\eta \equiv \partial \ln(x_{ij}) / \partial \ln(t_{ij})$. This is meant as the direct trade cost elasticity in the sense that indirect general equilibrium price effects are omitted here (we discuss those general equilibrium effects in detail in Appendix B.4). In standard gravity equations this elasticity would be constant.[12] In the translog gravity model,

[12]For instance, in Anderson and van Wincoop (2003) the elasticity would be equal to $1 - \sigma$ where σ is the CES elasticity of substitution. In Eaton and Kortum (2002) it would be equal to the Fréchet shape parameter. In Chaney (2008) it would be equal to the Pareto shape parameter.

however, this elasticity is variable. It follows from equation (1) as:

$$\eta_{ij} = -\frac{\theta}{\frac{x_{ij}/y_j}{n_i}}. \tag{4}$$

That is, the trade cost elasticity is the preference parameter θ divided by the import share per good. Therefore, the larger a given import share, the smaller the trade cost elasticity in absolute magnitude. The ij subscript indicates that this elasticity varies by country pair.

In line with the literature, we assume that logarithmic trade costs $\ln(t_{ij})$ are a function of commonplace trade cost variables such as logarithmic bilateral distance, dummy variables for contiguity, common language as well as membership of trade agreements, currency unions, and so on. As an example, let us consider a dummy variable for currency union membership CU_{ij} which takes on the value of one if countries i and j are both members, with coefficient κ. We expect κ to be negative since a currency union is generally thought to lower bilateral trade costs (our empirical results will confirm this). Based on the expression in equation (4), the effect of currency union membership on trade follows as:

$$\frac{\Delta \ln(x_{ij})}{\Delta CU_{ij}} \approx -\frac{\theta\kappa}{\frac{x_{ij}/y_j}{n_i}}, \tag{5}$$

where ΔCU_{ij} indicates entry into a currency union. Given that κ is likely negative, we expect a positive currency union effect on bilateral trade.

We would like to highlight a key aspect of our framework. As the denominators of expressions (4) and (5) show, the heterogeneity of currency union effects is driven by variation across import shares. It would be conceivable that heterogeneity is instead driven by the currency union parameter in the trade cost function, perhaps because different currency unions have different trade cost effects.[13] However, as we show below in our empirical analysis, we find heterogeneous effects across different pairs *within* a given currency union, and even within a given bilateral country pair by direction of trade (due to bilaterally asymmetric import shares). This means that even if trade costs are bilaterally symmetric, trade cost effects can be bilaterally asymmetric in the translog gravity framework.[14]

In summary, the most important insight from this motivating framework is the variable trade cost effect in expression (4). Specifically, the trade cost effect should be larger in absolute magnitude for country pairs associated with smaller import shares. It also follows that a symmetric reduction in bilateral trade costs can lead to asymmetric increases in bilateral trade flows by direction of trade. These are testable predictions we will now examine. While we

[13]Instead of the constant κ we would then have to adopt currency union-specific trade cost parameters. We allow for such an approach in our analysis of the euro in Section 3.1.4.

[14]Trade flows can also be bilaterally asymmetric, but trade is balanced at the aggregate country level due to the general equilibrium nature of the model.

also estimate the translog specification in equation (1) directly, we will first turn towards an alternative approach.

3 Empirical Analysis

Our aim is to find out whether international trade data are characterised by variable trade cost elasticities. As a starting point, we first estimate gravity regressions with a standard constant trade cost elasticity. We then proceed by exploring variable trade cost elasticities. For that purpose, we adopt two approaches that are consistent with the theoretical framework in Section 2. The first approach is a modification of the standard gravity specification commonplace in the literature. Instead of estimating a single trade cost coefficient that is constant over the entire sample, we propose a flexible gravity framework that allows for heterogeneous trade cost effects across import shares. We explain this estimating strategy in more detail below (see Section 3.1). The second approach is to estimate the translog gravity equation (1) directly (see Section 3.2).

We introduce our approach with an application to the trade effect of currency unions. This is mainly for expositional purposes, and later in the paper we extend the analysis to other trade cost variables (see Section 4 in particular). We use a very large, comprehensive data set of aggregate annual bilateral trade flows that covers most of global trade in modern times. It consists of an unbalanced panel including 199 countries from 1949 to 2013. We provide details and descriptive statistics in Appendix A.

3.1 Gravity with Heterogeneity

This section describes our first approach. Focusing on currency unions, we start by estimating homogeneous trade cost effects with constant trade cost elasticities as in the standard gravity framework. We then modify the gravity specification and introduce a two-step procedure to allow for trade cost heterogeneity. We also explore the trade effect of the euro in more detail.

3.1.1 Homogeneous Trade Cost Effects in Standard Gravity

As pointed out by Santos Silva and Tenreyro (2006), the validity of estimating a log-linear gravity model by OLS depends crucially on the assumption that the variance of the error term is independent from the regressors. Otherwise, the log transformation prevents the error term from having a zero conditional expectation, leading to inconsistent estimates of the true elasticities. PPML instead delivers consistent coefficient estimates, even in the presence of heteroskedasticity (Head and Mayer, 2014). Another advantage of PPML is that by expressing the dependent variable in levels, zero trade observations can be incorporated in the estimation (the log-linear gravity equation may suffer from selection bias as the zero values drop out of the regression). In our sample, around 35% of import shares are equal to zero (see Appendix A). In what follows we therefore estimate our regressions by PPML.[15]

We initially estimate homogeneous trade cost effects with a constant elasticity as in the standard gravity framework, based on PPML regressions. But we use the bilateral import share per good as the dependent variable to make sure our results are comparable to subsequent estimates that allow for heterogeneous trade cost effects. We thus estimate:

$$\left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}}\right) = \exp\left(\alpha_1 CU_{ij,t} + \alpha_2 Z_{ij,t} + D_{i,t} + D_{j,t} + D_{ij}\right) + \varrho_{ij,t}, \tag{6}$$

where we add time subscripts such that $x_{ij,t}$ is the bilateral FOB export value from exporter i to importer j in year t, $y_{j,t}$ is country j's nominal GDP (both in US dollars), and $n_{i,t}$ denotes the number of goods in the exporting country which can be interpreted as an extensive margin measure. Trade costs depend on currency union membership $CU_{ij,t}$ which is a dummy variable taking on a value of one if countries i and j are both members in year t (and zero otherwise). Trade costs are also a function of other time-varying country pair variables $Z_{ij,t}$ which include dummy variables equal to one if both countries in the pair belong to an RTA or are members of the WTO, OECD, and IMF in each year, and zero otherwise (Rose, 2005). We return to those other trade cost variables in Section 4.

To measure the exporting countries' extensive margin $n_{i,t}$ we collect each country's total exports by product category from United Nations Comtrade which are available from 1962 onwards. As the HS classification was only introduced in 1988, we rely on data at the 4-digit HS level between 1988 and 2013, and at the 4-digit SITC level from 1962 to 1987. We define the extensive margin as the number of different product categories exported by each country in each year relative to the total number of categories exported by all countries in the same year. Given that the Comtrade data are only available from 1962, have poor country coverage in some years, and are reported according to two different classifications over time (i.e., SITC versus HS), we calculate the average extensive margin by exporter. This yields a time-invariant measure n_i but we believe that this measure should provide us with useful information regarding the variation in the extensive margin across exporting countries.[16]

We later check the robustness of our findings by using an alternative proxy for the extensive margin (see Table C5 in Appendix C). We rely on the cross-country measure constructed

[15] We employ the `ppmlhdfe` Stata command written by Correia *et al.* (2020). It estimates a Poisson Pseudo Maximum Likelihood regression allowing for multiple levels of fixed effects. In the previous version of our paper (Chen and Novy, 2018) results were based on OLS estimation. Those results are generally the same qualitatively, although individual magnitudes may be different between PPML and OLS.

[16] For each year from 1962 to 1987 we calculate the number of 4-digit SITC-level product categories exported by each country relative to the total number of 4-digit SITC-level categories exported by all countries. For the years 1988 to 2013 we do the same at the 4-digit HS level. For each country the time-invariant n_i measure (that we use for our full sample between 1949 and 2013) is given by the average of the two series between 1962 and 2013.

by Hummels and Klenow (2005) using data on exports from 126 exporting to 59 importing countries in more than 5,000 6-digit HS-level product categories in 1995. We also assume that the extensive margin is unity for all exporters, in which case the dependent variable is simply the bilateral import share.

We control for an extensive set of fixed effects. We include time-varying exporter and importer fixed effects $D_{i,t}$ and $D_{j,t}$ to control for multilateral trade resistance and other exporter and importer-specific terms such as income. We also include country pair fixed effects D_{ij} to absorb all time-invariant bilateral trade frictions in each cross-section. The country pair effects also help to control for the endogeneity of the currency union dummy if two countries deciding to join a currency union have traditionally traded a lot with each other (but the pair effects fail to do so if the two countries join following a surge in trade during the sample period, see Micco *et al.*, 2003, or Bun and Klaassen, 2007). Note that the pair effects are directional as non-directional pair effects would not capture the asymmetry in bilateral import shares within a pair. Identification is therefore achieved from the time series variation of each explanatory variable within a pair (e.g., from changes in bilateral currency union status over time).[17] To control for time-invariant idiosyncratic shocks correlated at the pair level (De Sousa, 2012), standard errors are clustered at the non-directional country pair level. The coefficients to be estimated are denoted by the α's. As sharing a common currency should be associated with more trade, we expect α_1 to be positive. The error term is $\varrho_{ij,t}$.

3.1.2 Heterogeneous Trade Cost Effects

We then focus on trade cost heterogeneity. Our aim is to investigate whether the trade effect of currency unions, as captured by α_1 in specification (6), is heterogeneous across bilateral import shares per good, as predicted by the theoretical framework in Section 2. If we simply allowed α_1 to vary with import shares, we would have a simultaneity bias problem as the currency union effect would vary with the values taken by the dependent variable (Novy, 2013).

To address this issue we modify the standard gravity specification by letting the currency union effect vary across *predicted* import shares. For that purpose, we propose a two-step methodology. In the first step we regress the import shares per good on geography-related variables (distance and contiguity) to generate the predicted shares. In the second step we investigate how the trade effect of currency unions varies across predicted shares. We now explain this approach in more detail.

In the first step we regress the import shares per good on time-invariant country pair

[17] Baier *et al.* (2019) use directional pair effects to estimate the within-pair asymmetric effects of FTAs. The recent literature concludes that time-varying exporter and importer dummies and time-invariant country pair fixed effects should be included (De Nardis and Vicarelli, 2003; Baldwin, 2006; Baldwin and Taglioni, 2007; Baldwin *et al.*, 2008; Eicher and Henn, 2011; Mika and Zymek, 2018; Campbell and Chentsov, 2020). The earlier literature failed to do so (e.g., Rose, 2000).

controls and exporter-year and importer-year fixed effects:

$$\left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}}\right) = \exp\left(\delta K_{ij} + D_{i,t} + D_{j,t}\right) + \nu_{ij,t}, \tag{7}$$

where K_{ij} includes geography-related variables, i.e., logarithmic bilateral distance and a contiguity dummy.[18] We do not include the time-varying pair variables for currency unions, RTAs, the WTO, OECD, or IMF as they are not geography-related and therefore more likely endogenous. We then generate the predicted shares which we denote by $\widehat{\left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}}\right)}$.

In the second step we include an interaction term between the currency union dummy variable and the logarithmic predicted import shares, with ξ_2 as the key coefficient of interest.[19] We estimate:

$$\left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}}\right) = \exp\left(\xi_1 CU_{ij,t} + \xi_2 CU_{ij,t} \times \ln\widehat{\left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}}\right)} + \xi_3 Z_{ij,t} + D_{i,t} + D_{j,t} + D_{ij}\right) + \varepsilon_{ij,t}. \tag{8}$$

Since this specification includes exporter-year, importer-year, and country pair fixed effects, the main effect of the logarithmic predicted import share drops out of the regression. The trade effect of currency unions is given by $\xi_1 + \xi_2 \ln\widehat{\left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}}\right)}$ and therefore depends on two components, i.e., the change in trade costs due to currency unions and the log predicted import share. If the trade effect of currency unions falls with bilateral import intensity as predicted by our theoretical framework, the interaction coefficient ξ_2 should be negative. As the log predicted import share is a generated regressor, we bootstrap standard errors with 100 replications.

The intuition of this two-step methodology is as follows. To avoid the simultaneity problem, the predicted import shares generated in the first step should not be correlated with the error term $\varepsilon_{ij,t}$ in the second step. The point of the first step is therefore to extract the exogenous component of import shares. We aim to achieve this by using geography-related regressors (distance and contiguity) as well as time-varying exporter and importer-specific fixed effects, and then predicting the import shares. In Appendix B we carry out Monte Carlo simulations to verify the validity of this two-step procedure. In Section 5 we explore the potential endogeneity of currency unions and reverse causality.

An alternative way of testing our prediction of heterogeneous currency union effects is to split the sample into intervals of predicted import shares per good ranked by value and to

[18] Our results remain robust if in the first-step regression (7) we allow for time-varying distance and contiguity coefficients, include further gravity variables or simply control for time-invariant (directional) country pair fixed effects (see Section 6). They also remain robust if we add the currency union, RTA, WTO, OECD, and IMF variables.

[19] We interact with the logarithmic share since the dependent variable and the interaction term are then expressed in the same units, i.e., they are expressed as level shares if we exponentiate the logarithmic share on the right-hand side of equation (8).

estimate:

$$\left(\frac{x_{ij,t}/y_{j,t}}{n_{i,t}}\right) = \exp\left(\beta_{1,h} CU_{ij,t} \times D_h + \beta_2 Z_{ij,t} + D_{i,t} + D_{j,t} + D_{ij} + D_h\right) + \epsilon_{ij,t}, \qquad (9)$$

where D_h is a dummy variable for h equally-sized intervals of predicted import shares per good. The currency union coefficient $\beta_{1,h}$ is estimated separately for each interval h. Consistent with our theoretical framework, we expect the currency union effect to be largest in the interval of lowest predicted shares, and to be weaker in intervals of higher shares.[20]

3.1.3 Baseline Results

We start by discussing homogeneous currency union estimates. Before turning to PPML estimation, in column (1) of Table 1 we first estimate the log-linear version of equation (6) by OLS, using the log bilateral import share per good as the dependent variable (the zero observations therefore drop out from the regression). The currency union coefficient is equal to 0.326, suggesting that a common currency is associated with an increase in bilateral trade of 39% on average ($\exp(0.326) - 1 = 0.385$). We note that this currency union estimate captures direct trade cost effects.[21] Joining an RTA, and becoming a member of the WTO, OECD, and IMF are associated with an increase in bilateral trade (Rose, 2005).

Next, we regress equation (6) by PPML but we omit the zero observations from the sample. This allows us to assess how PPML affects coefficient estimates. As explained by Mayer *et al.* (2019), OLS and PPML estimates may differ because the two estimators have different first-order conditions (Eaton *et al.*, 2013; Head and Mayer, 2014). While the OLS conditions involve logarithmic deviations of trade from its expected value, the PPML conditions involve level deviations and therefore tend to give more weight to country pairs with high levels of trade.[22] If country pairs with higher import intensity have smaller trade cost elasticities, as we argue, then the PPML currency union coefficient should be smaller than its OLS counterpart.

In column (2) the currency union estimate decreases to 0.202 such that sharing a common currency is associated with 22% more trade on average. This result is therefore consistent with

[20] Quantile regressions could also be used to test our predictions. Various fixed effect estimators have recently been developed but little is known about their performance. Using the `qreg2` Stata command of Parente and Santos Silva (2016), we instead estimated pooled quantile regressions with clustered standard errors. The currency union effect is overestimated due to the omission of the fixed effects but we find that it falls with bilateral import shares.

[21] We discuss indirect general equilibrium effects in Appendix B.4. Those are second-order effects that are quantitatively small. The intuition is that currency unions are relatively rare at the bilateral level (see Data Appendix A), and they are only one out of several trade cost components. We also show that the general equilibrium effects are not systematically related to the heterogeneity of currency union effects.

[22] To illustrate that PPML gives more weight to the country pairs with high levels of trade, Mayer *et al.* (2019) follow the approach of Eaton *et al.* (2013) who estimate a multinomial gravity model for aggregate bilateral trade shares. They regress the trade share (bilateral trade divided by total trade) by PPML, and as trade shares give less weight to the large trade flows in levels they find that the coefficient estimates lie between the OLS and PPML estimates of regressing bilateral trade flows.

our prediction of country pairs with higher import shares having a smaller trade cost elasticity.[23] It is also consistent with papers finding that PPML reduces the size and significance of currency union estimates (Santos Silva and Tenreyro, 2010; Mika and Zymek, 2018; Larch *et al.*, 2019; Mayer *et al.*, 2019). The WTO estimate becomes insignificant, while the RTA, OECD, and IMF coefficients remain positive (the RTA coefficient is smaller, while the OECD and IMF coefficients are larger than their OLS counterparts).[24]

In column (3) we include the zero observations in the sample. Compared to column (2), the currency union coefficient increases but only slightly to 0.252, suggesting that a common currency is associated with 29% more trade on average. The coefficients on the other time-varying pair controls do not change much either. Consistent with the literature, we therefore confirm that including the zero observations in the sample does not substantially affect coefficient estimates (see, for instance, Mika and Zymek, 2018, or Mayer *et al.*, 2019).

Table 1. *Baseline Results.*

	(1)	(2)	(3)	(4)	(5)
CU	0.326*** (0.057)	0.202*** (0.050)	0.252*** (0.055)	0.964*** (0.101)	−0.382** (0.149)
CU× ln import share	–	–	–	0.283*** (0.026)	–
CU× ln predicted share	–	–	–	–	−0.197*** (0.036)
RTA	0.415*** (0.028)	0.205*** (0.035)	0.127*** (0.037)	0.206*** (0.035)	0.123*** (0.041)
WTO	0.146*** (0.035)	0.029 (0.053)	−0.004 (0.053)	0.031 (0.053)	−0.010 (0.055)
OECD	0.366*** (0.051)	0.534*** (0.073)	0.590*** (0.081)	0.531*** (0.073)	0.582*** (0.091)
IMF	0.165** (0.065)	0.321*** (0.106)	0.203* (0.105)	0.334*** (0.106)	0.203* (0.105)
CU estimates					
Mean	–	–	–	−1.356*** (0.138)	0.980*** (0.129)
10^{th} percentile	–	–	–	−2.573*** (0.244)	1.505*** (0.218)
90^{th} percentile	–	–	–	−0.299*** (0.062)	0.478*** (0.065)
Observations	780,818	780,818	1,131,641	780,181	1,131,641
Zeros included	No	No	Yes	No	Yes
Estimator	OLS	PPML	PPML	PPML	PPML

Notes: 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 (4). Standard errors are bootstrapped in (5). ***, **, and * indicate significance at the 1%, 5%, and 10% levels, respectively. The dependent variable is the import share per good but the log import share per good in (1). 'predicted share' is the predicted import share per good.

Our next task is to demonstrate whether these results mask heterogeneity in the trade effect of currency unions across country pairs. Purely as an illustration, in column (4) we interact

[23] By finding that the PPML estimates for RTAs and sharing the euro are smaller than their OLS counterparts, Mayer *et al.* (2019) conclude that country pairs with high volumes of trade have a smaller trade cost elasticity.

[24] See Section 4 for a discussion of the magnitude of these coefficients.

the currency union dummy with *actual* logarithmic import shares per good. The coefficient on the interaction term is strongly positive. This is driven by the fact that for all currency union pairs, the interaction term contains the same values as the dependent variable. To be clear, this specification is misguided as it suffers from simultaneity bias. We do not recommend it, and we only include it here for comparative purposes.

To address the simultaneity bias we proceed with our two-step methodology. We estimate the first-step regression (7). Import intensity is stronger between less distant and contiguous countries (the estimated coefficients are significant at the 1% level). We then generate the log predicted import shares per good and estimate the second-step regression (8). Column (5) shows that the coefficient on the interaction term is negative and significant. The impact of currency unions is thus heterogeneous as it *falls* with predicted import shares.[25] It is clear that the two-step approach counteracts the simultaneity bias in column (4) as the sign of the interaction coefficient flips (also see Appendix B).[26]

In the lower part of Table 1 we report the implied currency union estimates at the mean and different percentiles of the log predicted import share distribution as well as the corresponding standard errors. When we interact the currency union dummy with actual log import shares in column (4), due to the simultaneity bias those estimates erroneously suggest that currency unions are associated with smaller import shares.[27] But once we interact with the log predicted import shares in column (5), the magnitude of the currency union estimate is positive and, most importantly, it goes down when we move from the 10^{th} to the 90^{th} percentile (i.e., from small to large shares). Specifically, while the currency union estimate is 0.980 at the mean value of log predicted shares, it is 1.505 for a country pair at the 10^{th} percentile and 0.478 at the 90^{th} percentile.[28] In other words, at the 10^{th} percentile currency unions are associated with 350% higher import shares ($\exp(1.505) - 1 = 3.504$), whereas at the 90^{th} percentile the corresponding effect is only 61%.

To shed further light on the heterogeneity, we choose a few examples of country pairs from across the world with either small or large import shares in the final year of our sample. Based on the estimates of column (5) in Table 1, we report the associated currency union estimates in Table 2 (evaluated at log predicted import shares for the year 2013). Currency union effects are large for country pairs with small import shares. Naturally, these include thin trading relationships such as Equatorial Guinea importing from Niger (290%), Mali from the Central

[25] Irarrazabal *et al.* (2015) introduce additive trade costs. Under a broad range of demand systems additive trade costs work to reduce the elasticity in magnitude. That is, ceteris paribus bilateral pairs with larger additive costs and thus a smaller trade share are associated with weaker (not stronger) elasticities.

[26] If we omit the zero import shares from the sample and estimate the log-linear versions of equations (7) and (8) by OLS, the trade effect of currency unions also falls with predicted import shares. See the previous version of our paper (Chen and Novy, 2018).

[27] See Appendix B.2 where we provide Monte Carlo simulation results on this point.

[28] The elasticities at the mean, the 10^{th}, and 90^{th} percentiles are calculated for non-zero import shares. The currency union estimate at the mean of log predicted shares underestimates the elasticity at the 10^{th} percentile by 53% (1.505/0.980), and overestimates the elasticity at the 90^{th} percentile by 51% (0.478/0.980).

African Republic (275%), the Bahamas from Liberia (213%), and Côte d'Ivoire from Chad (141%). Conversely, some country pairs with large import shares do not tend to be associated with increased trade shares through currency unions, the effect being insignificant for Bhutan importing from India, Guinea-Bissau from Senegal, Portugal from Spain, and the Netherlands from Germany.

Table 2. *Examples of Pair-Specific Currency Union Effects.*

Large Effects			**Small Effects**		
Exporter	Importer	CU estimates	Exporter	Importer	CU estimates
Niger	Equatorial Guinea	1.360*** (0.192)	India	Bhutan	0.080 (0.080)
Central African Republic	Mali	1.321*** (0.186)	Senegal	Guinea-Bissau	0.001 (0.090)
Liberia	The Bahamas	1.142*** (0.155)	Spain	Portugal	−0.012 (0.092)
Chad	Côte d'Ivoire	0.878*** (0.113)	Germany	Netherlands	−0.109 (0.106)

Notes: The currency union estimates for each country pair are calculated based on the estimates of column (5) in Table 1. They are evaluated at log predicted import shares for the year 2013. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. *** indicates significance at the 1% level.

We also find that the trade effect of currency unions is heterogeneous *within country pairs* and therefore asymmetric by direction of trade. In Table 3 we provide examples of country pairs with bilateral asymmetries in currency union effects (evaluated at log predicted import shares for the year 2013). For instance, the effect is large (62%) when Germany imports from Austria (a low share), but small (3%) and insignificant when Austria imports from Germany (a high share). The effect is also relatively large when France imports from Belgium-Luxembourg and when Côte d'Ivoire imports from Togo (low shares) but insignificant or small in the other direction (high shares). By contrast, as Spain and the Netherlands have similar bilateral import shares, using the same currency is associated with a similar effect in either direction.

Let us consider the example of Germany and Austria in more detail. The import share of Germany from Austria is low at 1.6% for the year 2013. But in the opposite direction the import share is large at 20.1%.[29] The corresponding trade flow values are \$57.1bn and \$82.9bn (i.e., Austria has a bilateral trade deficit with Germany). As a counterfactual exercise, suppose these two countries were no longer in a currency union, i.e., their bilateral currency union dummy would switch from 1 to 0, and bilateral trade costs would go up. According to expression (5) and the estimates in Table 3, the import share from Austria to Germany would decrease by 62% ($\exp(0.481) - 1 = 0.618$) all else being equal. In the data this would imply a reduction of trade from Austria to Germany by about \$35.3bn (to \$21.8bn). The import share in the other direction would only decrease by 3%, corresponding to a reduction of trade from

[29] While the currency union estimates in Table 3 are based on import shares per good, for simplicity we frame our example in terms of import shares. In our data the bilateral import shares for Germany and Austria (1.6% and 20.1%) are roughly the same as our measure of bilateral import shares per good (1.9% and 20.5%).

Table 3. *Examples of Pair-Specific Bilateral Asymmetries.*

Exporter	Importer	Import share	CU estimates	Actual Data CU=1 Bilateral trade	Actual Data CU=1 Bilateral balance	Counterfactual CU=0 Bilateral trade	Counterfactual CU=0 Bilateral balance
Austria	Germany	1.58%	0.481^{***} (0.066)	\$57.1bn	-\$25.8bn	\$21.8bn	-\$58.4bn
Germany	Austria	20.07%	0.032 (0.086)	\$82.9bn	\$25.8bn	\$80.2bn	\$58.4bn
Belgium/Lux.	France	2.96%	0.303^{***} (0.063)	\$79.6bn	\$30.4bn	\$51.4bn	\$2.4bn
France	Belgium/Lux.	8.79%	0.005 (0.090)	\$49.3bn	-\$30.4bn	\$49.0bn	-\$2.4bn
Togo	Côte d'Ivoire	0.05%	0.497^{***} (0.067)	\$15.2m	-\$97.9m	\$5.4m	-\$83.0m
Côte d'Ivoire	Togo	2.60%	0.197^{***} (0.069)	\$113.1m	\$97.9m	\$88.5m	\$83.0m
Spain	Netherlands	1.30%	0.460^{***} (0.064)	\$10.2bn	-\$9.4bn	\$4.2bn	-\$3.8bn
Netherlands	Spain	1.45%	0.465^{***} (0.065)	\$19.6bn	\$9.4bn	\$8.0bn	\$3.8bn

Notes: The currency union estimates for each country pair are calculated based on the estimates of column (5) in Table 1. They are evaluated at log predicted import shares for the year 2013. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. *** indicates significance at the 1% level. The bilateral trade data for CU=1 in 2013 are calculated by applying the growth rates of exports reported by the International Monetary Fund's Direction of Trade Statistics to the bilateral exports data provided by Head *et al.* (2010). See Data Appendix A for details.

Germany to Austria by roughly \$2.7bn (to \$80.2bn). Thus, the bilateral trade deficit would widen (from \$25.8bn to \$58.4bn). Vice versa, a reduction in bilateral trade costs would shrink the bilateral trade deficit in this particular case. We note that the translog gravity equation (1) is consistent with bilateral imbalances even if bilateral trade costs are symmetric as in our example, although in the theoretical model aggregate trade remains balanced through general equilibrium adjustments.[30] Table 3 also reports the results of the corresponding counterfactual exercise for the other country pairs in the table.

Given our reliance on the two-step procedure outlined above, we check in detail whether our methodology is valid and does not lead to spurious heterogeneity. In Appendix B we carry out Monte Carlo simulations to verify the validity of our procedure. When we assume that the data generating process is driven by variable trade cost elasticities as in our theoretical framework in Section 2, our regressions based on the two-step procedure indeed produce heterogeneous effects that match those implied by the model underlying the data generating process, both qualitatively and quantitatively.[31] Conversely, if standard gravity were the data generating process, we demonstrate that our two-step procedure would not spuriously produce heterogeneous trade cost effects.

[30] Apart from the direct trade cost effect mentioned in the text, indirect price index effects would also be in operation (see Appendix B.4).

[31] Also see Figure 1 in Section 5.

Table 4. *Heterogeneous Currency Union Effects: Intervals.*

	(1)	(2)	(3)
CU (first interval)	0.736^{***} (0.173)	0.802^{***} (0.214)	0.906^{***} (0.189)
CU (second interval)	0.238^{***} (0.054)	0.668^{***} (0.154)	0.628^{***} (0.106)
CU (third interval)	–	0.224^{***} (0.054)	0.201^{***} (0.054)
RTA	0.126^{***} (0.037)	0.125^{***} (0.037)	0.129^{***} (0.037)
WTO	-0.004 (0.053)	-0.004 (0.053)	-0.008 (0.053)
OECD	0.588^{***} (0.081)	0.585^{***} (0.081)	0.582^{***} (0.081)
IMF	0.205^{*} (0.105)	0.204^{*} (0.105)	0.204^{*} (0.105)
Intervals split by	# obs.	# obs.	# obs. CU=1
Observations	1,131,641	1,131,641	1,131,641

Notes: PPML estimation. Exporter-year, importer-year, (directional) country pair, and interval fixed effects are included. Robust standard errors adjusted for clustering at the (non-directional) country pair level are reported in parentheses. *** and * indicate significance at the 1% and 10% levels, respectively. The dependent variable is the import share per good.

We proceed by regressing equation (9). In Table 4 we report currency union effects estimated separately by intervals of log predicted import shares per good. Based on the median of log predicted shares, column (1) of Table 4 splits the data into two intervals where the first interval includes the lower shares. As expected, the currency union coefficient is larger (equal to 0.736) for the lower shares and smaller (equal to 0.238) for the larger shares. Column (2) splits the sample into three equally-sized intervals of log predicted import shares per good. The magnitude of the currency union coefficient declines from the first to the last interval. In column (3) we split the data into three intervals but in such a way that each includes the same number of observations for which the currency union dummy is equal to one. As before, the magnitude of the currency union estimate falls with predicted shares (in all columns, we can reject at the 1% level that the coefficients are equal across intervals).[32]

3.1.4 The Euro

Given the prominence of the European single currency, we investigate the trade effect of the euro in more detail. In column (1) of Table 5 we first estimate specification (6) but the currency union dummy is split between euro and non-euro currencies. Sharing a common currency is associated with 18% more trade for the euro ($\exp(0.163) - 1 = 0.177$), and 36% more trade for non-euro currencies ($\exp(0.309) - 1 = 0.362$). In column (2) we interact the currency union indicators with log predicted import shares, and we observe heterogeneity in the trade effects of both euro and non-euro currency unions.

[32] In column (2) the number of observations for which the currency union dummy is equal to one is 3,404 in the first interval, 6,227 in the second, and 8,225 in the third. In column (3) the number of observations for which the currency union dummy is equal to one is 5,952 in each of the three intervals.

Table 5. *The Euro.*

	(1)	(2)		(3)	
CU non-EURO	0.309^{***} (0.080)	-0.465^{**} (0.207)		-0.396^{**} (0.201)	
CU non-EURO× ln predicted share	–	-0.234^{***} (0.048)		-0.217^{***} (0.046)	
EURO	0.163^{**} (0.067)	-0.043 (0.167)		-0.564^{***} (0.151)	
EURO× ln predicted share	–	-0.068^{*} (0.040)		-0.119^{***} (0.036)	
RTA	0.129^{***} (0.037)	0.126^{***} (0.041)		0.112^{***} (0.041)	
WTO	-0.008 (0.053)	-0.013 (0.055)		0.009 (0.055)	
OECD	0.591^{***} (0.081)	0.581^{***} (0.091)		0.539^{***} (0.088)	
IMF	0.200^{*} (0.105)	0.202^{*} (0.105)		0.223^{**} (0.105)	
Trend EU countries	–	–		0.026^{***} (0.003)	
CU estimates		Non-EURO	EURO	Non-EURO	EURO
Mean	–	1.151^{***} (0.172)	0.425^{***} (0.147)	1.108^{***} (0.169)	0.259^{**} (0.130)
10^{th} percentile	–	1.774^{***} (0.286)	0.605^{**} (0.246)	1.687^{***} (0.281)	0.576^{***} (0.218)
90^{th} percentile	–	0.555^{***} (0.096)	0.253^{***} (0.078)	0.553^{***} (0.096)	-0.045 (0.069)
Observations	1,131,641	1,131,641		1,131,641	

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) and (3). ***, **, 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.

As argued by previous authors, one issue with the regressions in columns (1) and (2) is that they fail to control for the effect of European integration more broadly. As a result, the trade impact of the euro is likely to be overestimated because it confounds the effect of European integration with the effect of the single currency (see Baldwin, 2006, for a discussion). To address this issue, in column (3) we further include a time trend for EU countries (both in and out of the euro) to control for the ongoing European integration process (Micco *et al.*, 2003; Baldwin, 2006; Bun and Klaassen, 2007; Baldwin *et al.*, 2008; Berger and Nitsch, 2008; Mika and Zymek, 2018; Campbell and Chentsov, 2020). The positive coefficient on the trend indicates that on average, EU countries trade more intensively with each other over time.[33] Still, the inclusion of the trend does not affect our main insight as both euro and non-euro

[33] We include a trend for EU countries as EU integration has affected all EU countries whether or not they have adopted the euro (Baldwin, 2006). The trend controls for EU policies such as the Single Market, treaties on EU integration, the Exchange Rate Mechanism, etc. It is included for 27 EU countries (as Belgium and Luxembourg are merged together) and for the EU overseas territories. The trend varies across country pairs as it only starts in the year once the two countries in a pair are both members of the EU. Our results remain similar if we do not include a trend for the overseas territories. They also remain similar if we interact the trend with country pair dummy variables, but in that case we were unable to bootstrap the standard errors as the resampled samples encountered issues in fitting our model and the replications failed to converge.

currency unions are associated with heterogeneous trade effects.

As shown in the lower part of Table 5, at the mean, the 10^{th}, and 90^{th} percentiles of log predicted shares the euro estimates are smaller in magnitude once we include the trend (in column 3).[34] They are generally weaker than the estimates for non-euro currency unions. As the average import share per good in our sample is significantly larger for euro member pairs compared to non-euro currency union pairs (they are equal to 2% and 1.4%, respectively), the finding that the euro trade effect is weaker on average is thus consistent with the theoretical framework in Section 2. It is also consistent with evidence showing that PPML reduces the size and significance of the euro trade effect (Santos Silva and Tenreyro, 2010; Mika and Zymek, 2018; Larch *et al.*, 2019; Mayer *et al.*, 2019).

In column (3) the euro estimate is equal to 0.576 for a country pair at the 10^{th} percentile of log predicted shares. Examples of euro country pairs with small import shares associated with large trade effects are Ireland importing from Cyprus (70%), Finland from Malta (50%), and Finland from Greece (23%). In contrast, euro country pairs with large import shares that are not associated with increased trade shares include Cyprus importing from Greece and Germany importing from Italy (the effects are insignificant). We also find evidence of heterogeneity by direction of trade. For instance, the trade effect of sharing the euro is large when Austria imports from Malta (low predicted shares). But it is insignificant when Malta imports from Austria (high predicted shares).

Although our primary objective is not to determine whether the effect of the euro is stronger or weaker on average compared to other currency unions, our results suggest that its effect on trade is more modest compared to other common currencies. Yet our main interest is in the heterogeneity of trade cost effects. Consistent with the predictions of our model we find that the euro effect is heterogeneous across and within country pairs.[35]

3.2 Translog Approach

We now report the results of implementing our second approach where we estimate the translog gravity equation (1) directly using OLS estimation. We can then compute the pair-specific currency union effects with the help of expression (5). We report two sets of results, i.e., excluding and including the zero import share observations in the sample. We note that in contrast to the two-step regressions reported earlier, the translog approach does not require us to predict the bilateral import shares per good in a first step.

[34] Bun and Klaassen (2007), Berger and Nitsch (2008), and Mika and Zymek (2018) also find that the inclusion of a time trend reduces the magnitude of the euro trade effect.

[35] In Table C2 of Appendix C we show that our main results are robust to controlling for wars and political conflicts which have been argued to drive the trade effect of currency unions (Campbell, 2013; Campbell and Chentsov, 2020). As the EU has essentially experienced a period of uninterrupted peace since the end of World War II, our results for the euro provide further evidence that our findings are not driven by geopolitical events.

Table 6. *Translog Estimation.*

	(1)	(2)
CU	0.006^{***}	0.003^{***}
	(0.001)	(0.001)
RTA	0.005^{***}	0.004^{***}
	(0.000)	(0.000)
WTO	-0.001	0.000
	(0.000)	(0.000)
OECD	0.003^{***}	0.002^{***}
	(0.001)	(0.001)
IMF	0.001^{**}	0.000
	(0.001)	(0.000)
CU estimates		
Mean	0.912^{***}	0.470^{***}
	(0.235)	(0.137)
10^{th} percentile	$1,514.591^{***}$	780.223^{***}
	(391.203)	(227.256)
90^{th} percentile	0.484^{***}	0.250^{***}
	(0.125)	(0.073)
Observations	780,818	1,203,322
Zeros included	No	Yes
R-squared	0.644	0.588

Notes: OLS 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. *** and ** indicate significance at the 1% and 5% levels, respectively. The dependent variable is the import share per good.

Column (1) of Table 6 reports the results excluding the zero observations from the sample and the currency union coefficient is equal to 0.006. As shown in the lower part of the table, this corresponds to an estimate of 0.912 at the mean value of import shares. As predicted by the translog framework, the effect is heterogeneous across country pairs, and the currency union estimate decreases from the 10^{th} to the 90^{th} percentile of import shares per good. However, we note that the currency union estimate at the 10^{th} percentile is extremely large compared to previous tables. The reason is that translog imposes a hyperbolic functional form for the calculation of trade cost elasticities. This can be seen in expression (5) in that the estimated coefficient, $-\theta\kappa$, is divided by import shares. Since import shares at low percentiles are very close to zero (see the descriptive statistics in Data Appendix A), the implied elasticities mechanically become very large. We therefore treat the currency union estimates at low percentiles with a particular degree of caution. Besides, all other regressors are significant with the expected signs, with the exception of the WTO dummy variable.

In column (2) when we include the zero observations in the sample, the heterogeneity across percentiles of import shares continues to hold. That is, sharing a common currency is associated with more bilateral trade, and this effect is stronger for country pairs with smaller import shares. The magnitude of the currency union estimate at the mean value of (non-zero) import shares is smaller at 0.470. This magnitude corresponds to the mean estimate of 0.980 in column (5) of Table 1. The mean effect is thus larger in Table 1 but due to the specific translog functional form the heterogeneity in Table 6 is more pronounced.

4 Other Trade Cost Variables

In the previous section we focused on currency union effects but this was mainly for exposition. Our approach is equally applicable to other trade cost components, and we discuss them now in turn. We discuss trade cost components represented by dummy variables (such as membership of trade agreements) that already appeared in earlier regression tables, and we also discuss continuous trade cost variables such as bilateral distance and tariffs.

We present the regression results in Table 7. In column (1) we estimate equation (8) where we interact the currency union dummy with log predicted import shares, but in the same way we now also interact the other time-varying trade cost components represented by dummy variables. The coefficients on the RTA and WTO interaction terms are negative. The trade effects of RTAs and the WTO are thus heterogeneous and smaller for country pairs with larger import shares. Specifically, the coefficient on the RTA dummy variable is equal to 0.489 at the mean value of log predicted shares, 0.773 for a country pair at the 10^{th} percentile, and 0.218 at the 90^{th} percentile. Joining an RTA is thus associated with 117% more bilateral trade ($\exp(0.773) - 1 = 1.166$) at the 10^{th} percentile, and 24% more trade only at the 90^{th} percentile. The coefficient on the WTO dummy variable is equal to 0.137 at the mean value of log predicted shares, 0.295 at the 10^{th} percentile, and -0.014 at the 90^{th} percentile (the latter is insignificant). Becoming a member of the WTO is thus associated with 34% more bilateral trade at the 10^{th} percentile, and with no change in trade at the 90^{th} percentile. These findings are broadly consistent with the literature showing that the trade effects of trade agreements and WTO membership are heterogeneous.[36]

The coefficients on the IMF and OECD interaction terms are positive, however. The trade effects of joining these organisations therefore increase with bilateral import shares. This finding is consistent with columns (1) and (2) of Table 1 which show that the PPML coefficients for the IMF and OECD dummy variables are larger than their OLS counterparts. As PPML gives more weight to country pairs with high levels of trade, the larger coefficients indicate that the effects of IMF and OECD membership are stronger for country pairs that trade intensively.[37] But we believe that these findings should be interpreted with caution because it is not clear to what extent the purpose of the two organisations is focused on the reduction of trade costs. As explained by Rose (2005), although the IMF and the OECD are interested in trade creation, they also have various objectives other than trade promotion. This contrasts with the WTO which is primarily concerned with trade liberalisation and arguably can more easily be viewed as having a trade cost reducing effect.

[36] Key references that stress heterogeneity include Glick (2017) and Baier *et al.* (2019) for RTAs, and Subramanian and Wei (2007) and Felbermayr *et al.* (2020) for WTO membership.

[37] By contrast, columns (1) and (2) of Table 1 show that the PPML estimates for currency unions, RTAs, and the WTO are smaller than their OLS counterparts. This is consistent with column (1) of Table 7 which shows that these variables are associated with smaller increases in bilateral trade for country pairs with large import shares.

Table 7. *Heterogeneous Trade Cost Effects.*

	(1)	(2)	(3)	(4)	(5)	(6)
CU	-0.367^{**} (0.158)	-0.839^{***} (0.240)	-0.616^{***} (0.235)	-0.061 (0.042)	-0.434^{***} (0.122)	-0.750^{***} (0.229)
CU× ln predicted share	-0.190^{***} (0.037)	-0.355^{***} (0.049)	-0.298^{***} (0.047)	–	-0.131^{***} (0.031)	-0.209^{***} (0.050)
RTA	-0.246^{**} (0.113)	0.188 (0.165)	0.505^{***} (0.181)	-0.058 (0.041)	-0.545^{***} (0.122)	0.421^{**} (0.213)
RTA× ln predicted share	-0.106^{***} (0.025)	-0.044 (0.033)	0.042 (0.036)	–	-0.168^{***} (0.028)	0.029 (0.043)
WTO	-0.273^{***} (0.096)	-0.133 (0.131)	-0.105 (0.135)	0.172^{***} (0.039)	0.107 (0.140)	-0.204 (0.214)
WTO× ln predicted share	-0.059^{***} (0.017)	-0.043^{**} (0.020)	-0.039^{*} (0.021)	–	-0.044 (0.029)	-0.141^{***} (0.038)
OECD	1.047^{***} (0.202)	-1.145^{***} (0.205)	-1.055^{***} (0.213)	0.138^{**} (0.062)	0.386 (0.255)	-0.225 (0.203)
OECD× ln predicted share	0.111^{***} (0.034)	-0.144^{***} (0.040)	-0.125^{***} (0.042)	–	0.018 (0.046)	-0.021 (0.039)
IMF	0.537^{***} (0.151)	0.549^{***} (0.174)	0.613^{***} (0.166)	0.324^{***} (0.115)	0.465 (0.524)	0.409 (0.551)
IMF× ln predicted share	0.077^{***} (0.023)	0.078^{***} (0.026)	0.074^{***} (0.025)	–	-0.041 (0.069)	0.007 (0.055)
ln Distance	–	-0.997^{***} (0.037)	-0.367 (0.226)	–	–	-0.595^{**} (0.294)
ln Distance× ln predicted share	–	–	0.049^{***} (0.016)	–	–	0.039^{*} (0.021)
Contiguity	–	0.505^{***} (0.067)	0.010 (0.161)	–	–	-0.001 (0.202)
Contiguity× ln predicted share	–	–	-0.095^{**} (0.042)	–	–	-0.169^{***} (0.050)
Shared language	–	0.516^{***} (0.051)	0.345^{***} (0.124)	–	–	0.263 (0.161)
Shared language× ln predicted share	–	–	-0.043^{*} (0.024)	–	–	-0.039 (0.031)
ln (1+tariff)	–	–	–	-0.380^{**} (0.176)	–	–
ln (1+tariff)× ln predicted share	–	–	–	–	0.190^{**} (0.086)	0.471^{***} (0.161)
ln (exporter GDP×importer GDP)	–	–	–	0.266^{***} (0.031)	–	–
Observations	1,131,641	1,161,329	1,161,329	356,491	368,733	388,798
Exporter-year fixed effects	Yes	Yes	Yes	No	Yes	Yes
Importer-year fixed effects	Yes	Yes	Yes	No	Yes	Yes
Pair fixed effects (directional)	Yes	No	No	Yes	Yes	No
Exporter fixed effects	No	No	No	Yes	No	No
Importer fixed effects	No	No	No	Yes	No	No
Year fixed effects	No	No	No	Yes	No	No

Notes: PPML estimation. 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. The weighted mean applied tariff rate (in percentage terms) only varies by importer and year.

In column (2) of Table 7 we add bilateral distance and dummy variables for sharing a common border and a common language and therefore drop the country pair fixed effects.[38] In

[38] As there are no country pair fixed effects, the sample size is slightly larger as fewer singletons perfectly

column (3) we further interact these three controls with log predicted import shares. The trade effects of all three variables are strongly heterogeneous across bilateral import shares (Novy, 2013). At the mean value of log predicted shares, distance reduces trade with a coefficient of -0.707, while sharing a common border and a common language promotes trade with coefficients of 0.667 and 0.646. These effects are larger in magnitude at the 10^{th} percentile of log predicted shares (the coefficients on distance, contiguity, and common language are -0.839, 0.921, and 0.763). They are smaller at the 90^{th} percentile (the coefficients are -0.581, 0.424, and 0.535). All the while, the results for currency unions and WTO membership remain. But the omission of country pair fixed effects in columns (2) and (3) turns the RTA interaction term insignificant. This suggests that the trade effects of RTAs are heterogeneous when countries join an RTA but not necessarily in the cross-section.

Next, we investigate whether tariffs have a heterogeneous effect on import shares. From the World Bank's World Development Indicators we extract the weighted mean effectively applied tariff rate (in percentage terms) imposed by each importing country on all products from all trading partners.[39] As the data are only available from 1988, our sample size is significantly reduced. Also, as the weighted mean tariff is specific to each importing country and is not defined on a bilateral basis, it simply captures each country's overall degree of protectionism.

To get a sense of the homogeneous effect of tariffs on bilateral import shares, in column (4) of Table 7 we regress the import shares per good on dummy variables for currency unions, RTA, WTO, OECD, and IMF membership, the logarithm of one plus the tariff rate, the logarithmic product of exporter and importer GDP, as well as year fixed effects and time-invariant exporter, importer, and country pair fixed effects. On average, the currency union and RTA effects are insignificant, while WTO, OECD, and IMF membership are associated with more trade. As expected, tariffs are associated with reduced bilateral import shares. But we stress that this specification does not include time-varying exporter and importer fixed effects and should be interpreted with caution.

In column (5), we estimate the same specification as in column (1) but include an interaction term between tariffs and log predicted import shares. As we now include time-varying importer fixed effects, the main effect of tariffs drops out but the coefficient on the tariff interaction term is positive and significant. The (negative) effect of tariffs is therefore heterogeneous and smaller in magnitude for the country pairs with larger import shares. The effects of currency unions and RTAs also fall with bilateral import shares. The WTO, IMF, and OECD variables and their interaction terms with log predicted shares are insignificant.

In column (6) we omit country pair fixed effects and add distance, dummy variables for

predicted by the fixed effects are dropped.

[39]The effectively applied bilateral tariffs are preferential rates if applicable, and Most Favoured Nation ones otherwise. For each importer they are averaged across bilateral partners using product import shares as weights. In results available upon request we show that our results remain similar if we instead use the weighted Most Favoured Nation tariff rates of each country on all imports from the rest of the world.

sharing a common border and a common language, and their interactions with log predicted import shares. Our results of heterogeneous trade cost effects continue to hold (although the interaction terms for RTAs and a common language become insignificant in this particular specification).

Table 8. *Heterogeneous Trade Cost Effects (One by One).*

	(1)	(2)	(3)	(4)	(5)
CU	-0.387^{**} (0.151)	–	–	–	–
CU$\times$ ln predicted share	-0.202^{***} (0.036)	–	–	–	–
RTA	–	-0.191^{*} (0.112)	–	–	–
RTA$\times$ ln predicted share	–	-0.099^{***} (0.026)	–	–	–
WTO	–	–	-0.152 (0.093)	–	–
WTO$\times$ ln predicted share	–	–	-0.033^{**} (0.016)	–	–
OECD	–	–	–	0.945^{***} (0.181)	–
OECD$\times$ ln predicted share	–	–	–	0.074^{**} (0.032)	–
IMF	–	–	–	–	0.511^{***} (0.148)
IMF$\times$ ln predicted share	–	–	–	–	0.070^{***} (0.021)
Trade cost estimates					
Mean	1.008^{***} (0.129)	0.497^{***} (0.081)	0.074 (0.065)	0.435^{***} (0.105)	0.027 (0.115)
10^{th} percentile	1.545^{***} (0.218)	0.761^{***} (0.145)	0.162^{*} (0.095)	0.239 (0.170)	-0.160 (0.145)
90^{th} percentile	0.493^{***} (0.067)	0.243^{***} (0.038)	-0.009 (0.055)	0.623^{***} (0.088)	0.205^{*} (0.108)
Observations	1,131,641	1,131,641	1,131,641	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.

Finally, in Table 8 we run simple specifications where we only include the individual time-varying trade cost dummy variables and their interaction terms, one at a time. As before, we report the implied trade cost estimates at the bottom of the table. The coefficient patterns as well as the trade cost estimates are similar to the previous table.

Overall, we conclude that the predictions of our model are not limited to the effects of currency unions. They apply more generally to a large set of popular trade cost variables including RTAs, WTO membership, bilateral distance, sharing a common border, a common language, and tariffs.

5 Simulation and Endogeneity

Many popular trade cost variables in the literature are potentially endogenous. For example, it would be implausible to assume that the formation of trade agreements or currency unions is exogenous to countries' trading patterns. Our aim is to explore the effect of trade cost endogeneity on our preferred two-step estimation procedure. For that purpose we run simulations and demonstrate the validity of the procedure. We again lean on currency unions as the main illustration.

Currency unions are not randomly assigned. Santos Silva and Tenreyro (2010) argue that joining a currency union becomes more likely when countries are geographically close, speak the same language, and have a former colonial link. Persson (2001) addresses selection on observables. By applying a propensity-score matching estimator, he accounts for the fact that characteristics such as distance and trade agreement status are different between pairs inside and outside a currency union (we perform the same estimator in Section 6).

Here, we address selection on an unobservable factor. Consistent with the idea that currency unions are more likely formed between countries that trade intensively, we assume that both high bilateral import shares and selection into a currency union are driven by an underlying positive shock. Vice versa, a negative shock can drive both a low bilateral import share and selection out of a currency union.

Specifically, to generate our endogenous currency union variable $\widetilde{CU}_{ij}$, we randomly choose observations of the CU_{ij} variable as observed in the data and then flip the status of non-currency unions pairs to positive in response to a positive shock, and vice versa for a negative shock. We keep the mean value of the endogenous $\widetilde{CU}_{ij}$ variable the same as for CU_{ij}, and about 95% of the pairs in a currency union preserve their status.[40]

We then run a simulation to trace out the impact of currency union endogeneity. We refer to Appendix B where we outline our simulation procedure in more detail. In brief, we construct bilateral trade costs on the basis of trade cost function (B.1) specified in that appendix where we replace CU_{ij} with the endogenous $\widetilde{CU}_{ij}$. We then generate the simulated import shares. But crucially, we use the *same* error term for the import shares as for $\widetilde{CU}_{ij}$ to generate endogeneity between the import shares and the currency union dummy. We assume that the translog gravity model is the data generating process so that we have heterogeneous currency union effects. We run the first and second-step regressions (7) and (8) with PPML as described in Section 3.1.2, iterating the procedure 100 times with fresh error terms for a sample over the period from 1990 to 2013.

Econometrically, this approach generates a positive endogeneity bias for the currency union coefficients since the bilateral trade shock is by construction correlated with the $\widetilde{CU}_{ij}$ variable.

[40] $\widetilde{CU}_{ij}$ and CU_{ij} have a correlation of around 97%.

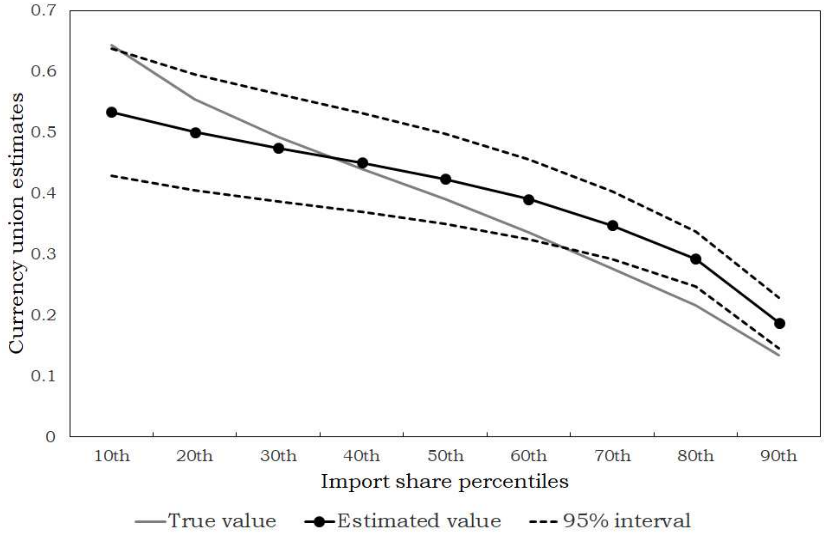

Figure 1. *Simulated Currency Union Estimates.*

Notes: A comparison of true values (in grey) and estimated values (in black, with 95% confidence intervals as dashed lines) of currency union estimates, based on a Monte Carlo simulation for a sample over the period from 1990 to 2013. The values are reported by deciles of import shares, with the first decile denoting the lowest import shares. For example, the estimated value at the last decile (i.e., the 90^{th} percentile) is equal to 0.187. This would imply that a currency union in the last decile is associated with an increase in bilateral trade of 21% (exp(0.187)–1 = 0.206). See Appendix B for details.

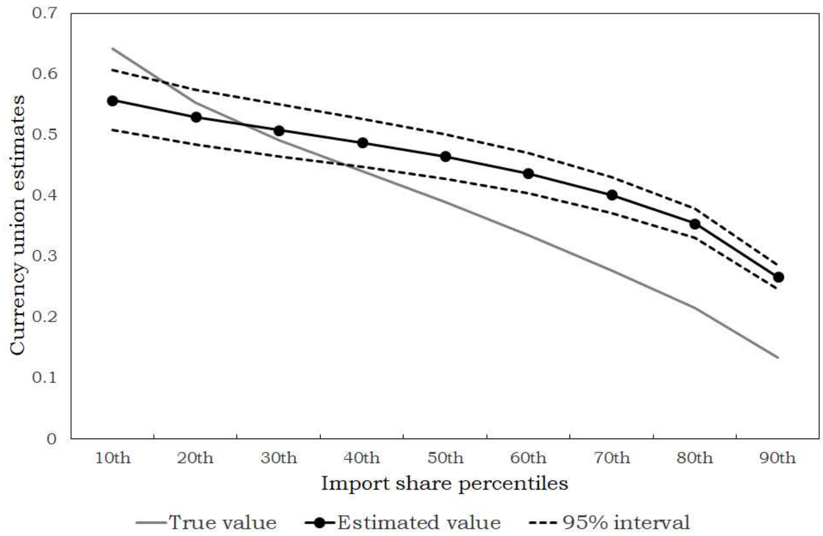

Figure 2. *Simulated Currency Union Estimates with Endogeneity Bias.*

Notes: A comparison of true values (in grey) and estimated values (in black, with 95% confidence intervals as dashed lines) of currency union estimates subject to positive endogeneity bias, based on a Monte Carlo simulation for a sample over the period from 1990 to 2013. The values are reported by deciles of import shares, with the first decile denoting the lowest import shares. For example, the estimated value at the last decile (i.e., the 90^{th} percentile) is equal to 0.266. This would imply that a currency union at the last decile is associated with an increase in bilateral trade of 30% (exp(0.266)–1 = 0.305). See Appendix B for details.

It follows that the ξ_1 main coefficient and the ξ_2 interaction coefficient in regression (8) are biased. For the ξ_1 main coefficient we obtain a highly significant point estimate of -0.309, and for the ξ_2 interaction coefficient we obtain a highly significant coefficient of -0.185. Both coefficients are pushed upwards.[41] The resulting currency union estimates at the mean, the 10^{th}, and the 90^{th} percentiles follow as 0.431, 0.557, and 0.266 (all significant at the 1% level).

Figures 1 and 2 illustrate the effect of the positive endogeneity bias (we again refer to Appendix B for details). Both figures show the true currency union estimates in grey (those are the same across the two figures). The black lines show the estimated values (with 95% confidence intervals as dashed lines). Figure 1 plots the *unbiased* currency union estimates in the absence of endogeneity. Figure 2 plots the corresponding *biased* estimates when endogeneity is present. The estimates have roughly the same profile in both figures, indicating relatively strong currency union effects at low import share percentiles and relatively weak effects at high percentiles. This is consistent with the empirical results in Section 3. Our estimation procedure thus correctly identifies the downward sloping profile of currency union effects, validating our approach. However, the estimates in Figure 2 are pushed upwards especially for high import shares, flattening the profile. This means that the gap between the actual and the true estimates grows for high import shares. Endogeneity thus leads to an overestimation of currency union effects for country pairs that trade intensively.

Overall, we of course do not observe the precise extent of currency union endogeneity in the actual data. But our simulation implies that if we were to correct for it, this would strengthen, rather than weaken, the heterogeneity patterns in our results. Currency union endogeneity would therefore work against us in the sense that it would make it harder to find evidence of heterogeneity patterns as in Section 3.

Finally, we also run a placebo simulation with endogenous currency unions, assuming that standard log-linear gravity is the data generating process (as opposed to translog gravity) so that by construction there is no currency union heterogeneity. We obtain currency union estimates at the mean, the 10^{th}, and the 90^{th} percentiles of 0.298, 0.324, and 0.273 (all significant at the 1% level).[42] These estimates are biased upwards, but they do not exhibit any quantitatively meaningful pattern of currency union heterogeneity.

6 Robustness

To ensure the robustness of our findings, in Appendix C we report a battery of sensitivity checks based on alternative specifications and data samples. As in Section 3, we focus on currency

[41] The simulated results with endogeneity are directly comparable to those without endogeneity in Table B1 where we verify our two-step procedure. In particular, the ξ_1 main coefficient of -0.309 can be compared to the -0.498 coefficient in column (3) of Table B1. The ξ_2 interaction coefficient of -0.185 can be compared to the -0.221 coefficient in column (3) of Table B1.

[42] This is in analogy to Appendix B.3. The currency union estimates are directly comparable to those without endogeneity in column (3) of Table B2.

unions as the main illustration. While the magnitude of the trade effect of currency unions may vary across specifications, we continue to find that it falls with bilateral import shares.

In Table C1 we apply the nearest matching estimator of Persson (2001). Our results are robust to non-random selection on observables. In Table C2 we show that currency unions continue to be associated with a heterogeneous trade effect once we control for wars, decolonisation episodes, and missing data (Campbell, 2013; Campbell and Chentsov, 2020). In Table C3 we distinguish *multilateral* currency unions (i.e., between countries of similar size and wealth) from *bilateral* currency unions (i.e., when a small or poor country adopts the currency of a larger and richer country, De Sousa, 2012). Our results hold for both types of currency unions.

In Table C4 we classify our currency union observations into three groups: *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). The currency union interaction terms with log predicted shares are negative for the continuous and exit unions only. But among the entry currency unions, the common currency interaction term is negative for the euro.

Table C5 addresses the measurement of import shares per good. First, we use alternative proxies for the extensive margin n_i. We use the Hummels and Klenow (2005) measure, and we assume that the extensive margin is unity for all exporters. Second, instead of using the importing country's GDP to compute the import shares per good, we experiment with total or manufacturing gross output from the OECD STAN database (in which case our sample is reduced to 19 OECD importing countries).

In Table C6 we consider three alternative specifications for the first-step regression (7). First, 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, part of the same country. Second, we replace bilateral distance and contiguity with (directional) country pair fixed effects. Third, we let the distance and contiguity elasticities vary over time (by interacting the two variables with year dummy variables). For the second-step regression (8), we show that our results remain robust to including time-varying distance and contiguity variables, a lagged dependent variable, and a trend for EU countries or for all countries in a currency union in our sample.

In Table C7 we use alternative data samples. We use the 1949–2006 exports and GDP data from Head *et al.* (2010), and exports from the International Monetary Fund's Direction of Trade Statistics combined with GDP data from the World Bank's World Development Indicators between 1960 and 2013. We use a balanced sample between 1994 and 2013. We drop the countries (mostly island nations) omitted from the analysis of Glick and Rose (2016), the smaller nations with GDP below 500 million US dollars in 2013, the poorer countries with GDP per capita below 500 US dollars in 2013, and the post-Soviet states.

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) of the currency union dummy variable and its interaction with log predicted shares, and their coefficients are insignificant. Similar to Baier and Bergstrand (2007) we therefore do not find evidence of feedback effects.

7 Concluding Remarks

This paper offers a new approach to estimating a flexible gravity equation. Our framework has variable trade cost elasticities at its core, implying that trade costs do not always have the same trade effect across all country pairs. To introduce this form of heterogeneity we develop a gravity framework motivated by a translog gravity equation. This approach generates variable trade cost elasticities across and within country pairs. The key prediction is that the impact of trade costs should be larger for country pairs associated with smaller import shares.

We test this prediction by employing an extensive data set of aggregate bilateral import shares for 199 countries between 1949 and 2013. We apply it to the effect of currency unions on international trade as well as a host of other trade cost variables that are popular in the literature such as the formation of regional trade agreements and membership of the WTO. Our results lend strong support to our theoretical prediction.

For example, we present evidence that the euro has promoted bilateral trade among Eurozone members but this effect is heterogeneous across country pairs. Pairs which do not trade intensively with each other tend to increase their bilateral trade by more in response to joining the euro currency union. Pairs that already have a strong trading relationship do not increase bilateral trade at all.

Regarding the trade effect of currency unions in particular, our results shed light on some of the disparities between estimates reported in the literature. By emphasising that country pairs with higher import intensity have smaller trade cost elasticities, our framework helps to explain why PPML currency union estimates are typically smaller than their OLS counterparts. In addition, as the average import share is significantly larger among euro member pairs compared to non-euro currency union pairs, our framework also helps to explain why the euro trade effect typically proves weaker on average. Our results suggest that relying on a single currency union estimate can be misleading if the objective is to assess, or to predict, the impact of a common currency on bilateral trade.

Although in our empirical application we study the trade effect of currency unions in most detail, we also demonstrate that the predictions of our theoretical framework apply more generally to a broader set of trade cost-related variables including RTAs, WTO membership, distance, sharing a common border, a common language, and tariffs. These results provide strong evidence that the aggregate trade cost elasticity is variable and heterogeneous across country pairs. One potential implication is that the gains from trade liberalisation could be mismeasured if researchers erroneously assume a constant trade cost elasticity (Arkolakis *et al.*, 2012; Melitz and Redding, 2015; Bas *et al.*, 2017). Although exploring this aspect remains outside the scope of this paper, understanding the welfare implications of our results would be an important next step.

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References

Alesina, A. and Barro, R.J. (2002). 'Currency unions', *Quarterly Journal of Economics*, vol. 117(2), pp. 409–36.

Alesina, A., Barro, R.J. and Tenreyro, S. (2002). 'Optimal currency areas', *NBER Macroeconomics Annual*, vol. 17, pp. 301–45.

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.

Arkolakis, C., Costinot, A. and Rodríguez-Clare, A. (2012). 'New trade models, same old gains?', *American Economic Review*, vol. 102(1), pp. 94–130.

Atkeson, A. and Burstein, A. (2008). 'Trade costs, pricing-to-market, and international relative prices', *American Economic Review*, vol. 98(5), pp. 1998–2031.

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.

Baier, S.L., Yotov, Y.V. and Zylkin, T. (2019). 'On the widely differing effects of free trade agreements: lessons from twenty years of trade integration', *Journal of International Economics*, vol. 116, pp. 206–26.

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.

Baldwin, R. and Taglioni, D. (2007). 'Trade effects of the euro: a comparison of estimators', *Journal of Economic Integration*, vol. 22(4), pp. 780–818.

Barro, R. and Tenreyro, S. (2007). 'Economic effects of currency unions', *Economic Inquiry*, vol. 45(1), pp. 1–23.

Bas, M., Mayer, M. and Thoenig, M. (2017). 'From micro to macro: demand, supply, and heterogeneity in the trade elasticity', *Journal of International Economics*, vol. 108, pp. 1–19.

Berger, H. and Nitsch, V. (2008). 'Zooming out: the trade effect of the euro in historical perspective', *Journal of International Money and Finance*, vol. 27(8), pp. 1244–60.

Bergin, P.R. and Lin, C.-Y. (2012). 'The dynamic effects of a currency union on trade', *Journal of International Economics*, vol. 87(2), pp. 191–204.

Berthou, A. and Fontagné, L. (2008). 'The euro effects on the firm and product-level trade margins: evidence from France', CEPII Working Paper 2008–21.

Broda, C. and Romalis, J. (2010). 'Identifying the relationship between trade and exchange rate volatility', in (I. Takatoshi and A.K. Rose, eds.), *Commodity Prices and Markets, East Asia Seminar on Economics*, Volume 20, University of Chicago Press, Chicago, pp. 79–110.

Bun, M.J.G. and Klaassen, F.J.M. (2007). 'The euro effect on trade is not as large as commonly thought', *Oxford Bulletin of Economics and Statistics*, vol. 69(4), pp. 473–96.

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.

Carrère, C., Mrázová, M. and Neary, J.P. (2020). 'Gravity without apology: the science of elasticities, distance, and trade', *Economic Journal*, vol. 130(628), pp. 880–910.

Chaney, T. (2008). 'Distorted gravity: the intensive and extensive margins of international trade', *American Economic Review*, vol. 98(4), pp. 1707–21.

Chen, N. and Novy, D. (2018). 'Currency unions, trade, and heterogeneity', CEPR Discussion Paper 12954.

Correia, S., Guimarães, P. and Zylkin, T. (2020). 'Fast poisson estimation with high-dimensional fixed effects', *Stata Journal*, vol. 20(1), pp. 95–115.

De Nardis, S. and Vicarelli, C. (2003). 'Currency unions and trade: the special case of EMU', *Review of World Economics*, vol. 139(4), pp. 625–49.

De Sousa, J. (2012). 'The currency union effect on trade is decreasing over time', *Economics Letters*, vol. 117(3), pp. 917–20.

Devereux, M.B. and Lane, P.R. (2003). 'Understanding bilateral exchange rate volatility', *Journal of International Economics*, vol. 60(1), pp. 109–32.

Eaton, J. and Kortum, S. (2002). 'Technology, geography, and trade', *Econometrica*, vol. 70(5), pp. 1741–79.

Eaton, J., Kortum, S. and Sotelo, S. (2013). 'International trade: linking micro to macro', in (D. Acemoglu, M. Arellano and E. Dekel, eds.), *Advances in Economics and Econometrics Tenth World Congress*, Volume 2: Applied Economics, Cambridge University Press, Cambridge, pp. 329–70.

Eicher, T.S. and Henn, C. (2011). 'One money, one market: a revised benchmark', *Review of International Economics*, vol. 19(3), pp. 419–35.

Feenstra, R.C. (2003). ‘A homothetic utility function for monopolistic competition models, without constant price elasticity’, *Economics Letters*, vol. 78(1), pp. 79–86.

Felbermayr, G., Larch, M., Yalcin, E. and Yotov, Y.V. (2020). ‘On the heterogeneous trade and welfare effects of GATT/WTO membership’, CESifo Working Paper 8555.

Flam, H. and Nordström, H. (2007). ‘Explaining large euro effects on trade: the extensive margin and vertical specialization’, Institute for International Economic Studies, Stockholm University, mimeo.

Frankel, J. (2010). ‘The estimated trade effects of the euro: why are they below those from historical monetary unions among smaller countries?’, in (A. Alesina and F. Giavazzi, eds.), *Europe and the Euro*, University of Chicago Press, Chicago, pp. 169–212.

Frankel, J. and Rose, A. (2002). ‘An estimate of the effect of common currencies on trade and income’, *Quarterly Journal of Economics*, vol. 117(2), pp. 437–66.

Glick, R. (2017). ‘Currency unions and regional trade agreements: EMU and EU effects on trade’, *Comparative Economic Studies*, vol. 59(2), pp. 194–209.

Glick, R. and Rose, A.K. (2002). ‘Does a currency union affect trade? The time-series evidence’, *European Economic Review*, vol. 46(6), pp. 1125–51.

Glick, R. and Rose, A.K. (2016). ‘Currency unions and trade: a post-EMU reassessment’, *European Economic Review*, vol. 87, pp. 78–91.

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., Mayer, T. and Ries, J. (2010). ‘The erosion of colonial linkages after independence’, *Journal of International Economics*, vol. 81(1), pp. 1–14.

Helpman, E., Melitz, M. and Rubinstein, Y. (2008). ‘Estimating trade flows: trading partners and trading volumes’, *Quarterly Journal of Economics*, vol. 123(2), pp. 441–87.

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.

Irarrazabal, A., Moxnes, A. and Opromolla, L.D. (2015). ‘The tip of the iceberg: a quantitative framework for estimating trade costs’, *Review of Economics and Statistics*, vol. 97(4), pp. 777–92.

Klein, M.W. (2005). ‘Dollarization and trade’, *Journal of International Money and Finance*, vol. 24(6), pp. 935–43.

Klein, M.W. and Shambaugh, J.C. (2006). 'Fixed exchange rates and trade', *Journal of International Economics*, vol. 70(2), pp. 359–83.

Larch, M., Wanner, J., Yotov, Y. and Zylkin, T. (2019). 'Currency unions and trade: a PPML re-assessment with high-dimensional fixed effects', *Oxford Bulletin of Economics and Statistics*, vol. 81(3), pp. 487–510.

López-Córdova, J.E. and Meissner, C.M. (2003). 'Exchange-rate regimes and international trade: evidence from the classical gold standard era', *American Economic Review*, vol. 93(1), pp. 344–53.

Mayer, T., Vicard, V. and Zignago, S. (2019). 'The cost of non-Europe, revisited', *Economic Policy*, vol. 34(98), pp. 147–99.

Melitz, M.J. and Ottaviano, G.I.P. (2008). 'Market size, trade, and productivity', *Review of Economic Studies*, vol. 75(1), pp. 295–316.

Melitz, M.J. and Redding, S.J. (2015). 'New trade models, new welfare implications', *American Economic Review*, vol. 105(3), pp. 1105–46.

Micco, A., Stein, E. and Ordoñez, G. (2003). 'The currency union effect on trade: early evidence from EMU', *Economic Policy*, vol. 37(18), pp. 315–56.

Mika, A. and Zymek, R. (2018). 'Friends without benefits? New EMU members and the "euro effect" on trade', *Journal of International Money and Finance*, vol. 83, pp. 75–92.

Mundell, R.A. (1961). 'A theory of optimum currency areas', *American Economic Review*, vol. 51(4), pp. 657–65.

Nitsch, V. (2002). 'Honey, I shrunk the currency union effect on trade', *The World Economy*, vol. 25(4), pp. 457–74.

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

Parente, P.M.D.C. and Santos Silva, J.M.C. (2016). 'Quantile regression with clustered data', *Journal of Econometric Methods*, vol. 5(1), pp. 1–5.

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

Rose, A.K. (2000). 'One money, one market: estimating the effect of common currencies on trade', *Economic Policy*, vol. 30(15), pp. 8–45.

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

Rose, A.K. (2005). 'Which international institutions promote international trade?', *Review of International Economics*, vol. 13(4), pp. 682–98.

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.

Rose, A. and van Wincoop, E. (2001). 'National money as a barrier to international trade: the real case for currency union', *American Economic Review*, vol. 91(2), pp. 386–90.

Saia, A. (2017). 'Choosing the open sea: the cost to the UK of staying out of the euro', *Journal of International Economics*, vol. 108, pp. 82–98.

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

Santos Silva, J.M.C. and Tenreyro, S. (2010). 'Currency unions in prospect and retrospect', *Annual Review of Economics*, vol. 2, pp. 51–74.

Spearot, A.C. (2013). 'Variable demand elasticities and tariff liberalization', *Journal of International Economics*, vol. 89(1), pp. 26–41.

Subramanian, A. and Wei, S.-J. (2007). 'The WTO promotes trade, strongly but unevenly', *Journal of International Economics*, vol. 72(1), pp. 151–75.

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).[43] 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.,

[43] Togo 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.

35% of the sample).[44] 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.

[44] Note 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:

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

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.[45] We then compute trade costs on the basis of equation (B.1) using the actual observations for our trade cost variables.

[45] Assuming 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 $\theta = 0.095$.[46] 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.[47]

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).[48] 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 10^{th}, and the 90^{th} 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 10^{th}, and the 90^{th} 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 10^{th} percentile (i.e., for relatively small import shares), implying 70.4% more bilateral trade ceteris paribus. At the 90^{th} 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.

[46] In 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 $\theta = -0.006/\kappa = 0.095$.

[47] To reduce computing time we use a subset of data starting in 1990.

[48] Similar 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 10^{th} percentile and slightly overshooting at the 90^{th} 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.[49]

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 10^{th}, and the 90^{th} 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.[50] 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:

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

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:

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

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)

[49] Also see the discussion in Section 3.2.

[50] See 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.

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 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:

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

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 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.[51] 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

[51] That is, $\Delta \ln \left(y_{i,t}/y_t^W\right) = 0$. 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 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.

is that currency unions are relatively rare at the bilateral level (see Data 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.

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.[52]

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:

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

[52]In 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.

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 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.[53] 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 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

[53] That is, $\Delta \left(y_{i,t}/y_t^W \right) = 0$ and $\Delta n_{i,t} = 0$.

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 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.[54]

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

[54] As 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.

is heterogeneous across predicted import shares. Our findings thus remain robust to non-random selection on observables.

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.[55] 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$\times$ 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.[56] 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).[57] The negative

[55] Examples 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.

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

[57] Due 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.

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 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.[58] We

[58]The 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

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.

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.[59] 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

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.

[59] Belgium 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.

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 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	Comtrade	Comtrade
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.$\times D_t$, contig.$\times D_t$	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).[60]

[60] The 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	-0.360^{***}	-0.472^{***}	-0.394^{**}	-0.419^{***}	-0.485^{***}	-0.359^{**}
	(0.163)	(0.135)	(0.139)	(0.157)	(0.138)	(0.135)	(0.163)
CU$\times$ ln predicted share	-0.130^{***}	-0.180^{***}	-0.156^{***}	-0.208^{***}	-0.195^{***}	-0.215^{***}	-0.195^{***}
	(0.038)	(0.033)	(0.039)	(0.038)	(0.035)	(0.034)	(0.040)
CU estimates							
Mean	0.768^{***}	0.942^{***}	0.547^{***}	1.046^{***}	0.933^{***}	0.998^{***}	0.990^{***}
	(0.133)	(0.137)	(0.133)	(0.140)	(0.127)	(0.124)	(0.138)
10^{th} percentile	1.117^{***}	1.453^{***}	0.934^{***}	1.606^{***}	1.445^{***}	1.558^{***}	1.511^{***}
	(0.229)	(0.225)	(0.224)	(0.236)	(0.212)	(0.206)	(0.239)
90^{th} percentile	0.432^{***}	0.457^{***}	0.180^{***}	0.510^{***}	0.439^{***}	0.453^{***}	0.490^{***}
	(0.065)	(0.071)	(0.061)	(0.071)	(0.061)	(0.061)	(0.062)
Observations	986,961	970,993	310,080	992,368	1,102,783	1,012,463	1,053,636
Sample	Head *et al.* (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.