Currency Unions, Trade, and Heterogeneity[*][†]

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Abstract

What is the effect of currency unions on international trade? This paper offers a new approach. We rely on a translog gravity equation that predicts variable trade cost elasticities, both across and within country pairs. While we estimate that currency unions are associated with a trade increase of around 38 percent on average, we find substantial underlying heterogeneity. Consistent with the predictions of our model, we find effects around three times as strong for country pairs associated with small import shares, and a zero effect for large import shares. Our results imply that conventional homogeneous currency union estimates do not provide helpful guidance for countries considering to join a currency union such as the euro.

JEL Classification: F10, F15
Keywords: Currency Unions, Euro, Gravity, Heterogeneity, Trade Costs, Trade Elasticity, Translog

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1   Introduction

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.[1] Countries may have several reasons to join a currency union. One of them is that currency unions are said to be associated with deeper economic integration. But does that also mean they are associated with more international trade?

To evaluate the trade effect of currency unions, researchers typically rely on a standard gravity equation framework, and insert a simple currency union dummy variable as a right-hand side regressor (e.g., Rose, 2000). This yields a single coefficient to assess the trade effect of currency unions, and by construction this effect is homogeneous across all currency union country pairs in the sample.[2] In this paper, we challenge the view that currency unions have a homogeneous "one-size-fits-all" effect on bilateral trade flows. Our contribution is to argue theoretically, and to demonstrate empirically, that the trade effect of currency unions is heterogeneous across country pairs.

As our theoretical tool, we introduce heterogeneous currency union effects by using a translog gravity equation that predicts variable trade cost elasticities (Novy, 2013). In this framework, 'thin' bilateral trade relationships (characterized by small import shares) are more sensitive to trade cost changes compared to more established 'thick' trade relationships (characterized by large 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 reduction in trade costs induced by a currency union generates heterogeneous effects on trade flows, and we should therefore expect larger trade effects for country pairs associated with smaller import shares.[3]

From a methodological point of view, the approach we propose in this paper can be applied more widely in the international trade literature, and should therefore be of interest to other researchers in the field. Although our paper focuses specifically on the trade effect of currency unions, the translog gravity framework can be applied more broadly to investigate the hetero-

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[1]Currency unions, or monetary unions, "are groups of countries that share a single money" (Rose, 2006). See our 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, the talks have stalled).

[2]General equilibrium effects might differ across countries but these are typically second-order.

[3]We emphasize that our framework is consistent with the fact that countries in a currency union tend to trade more intensively with each other. The point is to show that a symmetric reduction in bilateral trade costs induced by a currency union is associated with asymmetric increases in bilateral trade flows, both across as well as within country pairs.

geneous trade effects of any type of trade costs including transportation costs, tariffs, non-tariff barriers, or of regional trade agreements, among others.

We start by laying out the translog gravity framework and relating it to currency union effects in international trade.[4] This provides 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 model to the data. We adopt two main approaches to test whether the currency union effect on trade is heterogeneous across import shares. The first approach is based on the standard log-linear gravity specification that is commonplace in the literature. But instead of estimating a single currency union coefficient that is constant over the entire sample, we allow for heterogeneous currency union estimates. The second approach is to estimate the translog gravity equation directly.

In the first approach, we run a standard gravity regression with the logarithmic import share as the dependent variable, and examine whether the trade effect of currency unions is heterogeneous across bilateral import shares. However, this form of coefficient heterogeneity creates a simultaneity bias problem as the currency union effect varies with the values taken by the dependent variable. We address this issue by letting the currency union effect vary across *predicted* import shares instead. This can be achieved through a two-step methodology. In the first step we generate the predicted shares by regressing the import shares on geography-related variables such as distance and contiguity, while in the second step we assess how the trade effect of currency unions varies across predicted import shares.

When we estimate a standard gravity regression without heterogeneous effects, we find that sharing a common currency is associated with 38 percent more trade, on average. Our contribution through the translog framework is to demonstrate that this average hides a significant amount of heterogeneity *across country pairs*. For instance, at the 90th percentile of the distribution of predicted import shares where shares are large, we find that the trade effect of sharing the same currency is 30 percent. In contrast, at the 10th percentile of the distribution where shares are small, we find a substantially stronger effect of 94 percent.[5] Examples of country pairs with small import shares which are associated with large currency union effects are Denmark importing from Greenland (115 percent), Equatorial Guinea from Niger (105 percent), Mali from the Central African Republic (98 percent), and Gabon from Niger (96 percent). In contrast, country pairs with large import shares that benefit much less from joining a currency union (i.e., the currency union effects are insignificant) include Belgium-Luxembourg importing from the Netherlands or from Germany, or the Netherlands importing

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[4]It is well known that the gravity model fits the data very well. By adopting the translog gravity equation, our aim is not to improve fit, but to introduce variable trade cost elasticities.

[5]In our framework, a reduction in bilateral trade costs induced by a currency union implies that multilateral trade resistance falls as well. As a result, the stronger the pre-union trade among the members of a currency union, the smaller the percentage increase in trade among currency union members (De Nardis and Vicarelli, 2003; Eicher and Henn, 2011; Rose and van Wincoop, 2001). But such general equilibrium effects do not dominate our results on heterogeneity. See Novy (2013) for a discussion.

from Belgium-Luxembourg or from Germany.

We also find that the trade effect of currency unions is heterogeneous *within country pairs* and therefore asymmetric by direction of trade. For instance, the effect is large (at around 58 percent) when Germany or France import from Malta (i.e., low predicted shares), but is insignificant when Malta imports from Germany or from France (i.e., large predicted shares). Another example of asymmetric bilateral currency union effect is observed between the US and Panama (i.e., the effect is large at 48 percent when the US imports from Panama, but is insignificant when Panama imports from the US). Overall, heterogeneity in the trade effect of currency unions remains robust to using different samples or specifications, to controlling for non-random selection, and to including the zero trade observations in the sample.

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 modest.[6] Still, we find that the effect is heterogeneous across country pairs. It is insignificant at the 90th percentile of the import shares distribution, but it becomes significant and equal to 36 percent at the 10th percentile. Examples of country pairs with small import shares which are associated with large trade effects of the euro are Ireland importing from Cyprus (31 percent), Finland from Malta (30 percent), and Austria from Estonia (25 percent). In contrast, country pairs with large import shares which do not benefit much from the euro include Belgium-Luxembourg importing from the Netherlands or from Germany (the effects are insignificant).

In an appendix we carry out Monte Carlo simulations to verify the validity of our two-step procedure to estimate heterogeneous currency union effects. When we assume that the true data generating process is given by the translog model, our simulations based on the two-step procedure yield results that are similar both qualitatively and quantitatively to the underlying true model. In contrast, we demonstrate that if standard gravity were the underlying true model, we would not be able to explain the heterogeneity of currency union effects that we find in the data.[7]

We also explore the predictions of our model by estimating the translog gravity equation directly. In this case, since the dependent variable is the bilateral import share in levels (rather than in logarithmic form), the zero trade observations can be included in the sample. We therefore report two sets of results, excluding and including the zeros. Our regressions show that on average, sharing a common currency is associated with between 13 and 25 percent more trade. And consistent with our model, the magnitude of the effect falls with bilateral import shares.

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[6]See Baldwin (2006), Baldwin et al. (2008), Baldwin and Taglioni (2007), Berger and Nitsch (2008), Eicher and Henn (2011), Glick and Rose (2016), Mika and Zymek (2016), and Santos Silva and Tenreyro (2010a).

[7]We also investigate the consequences of ignoring the first step altogether by erroneously letting the currency union dummy vary with the actual import shares (as opposed to the predicted import shares). In that case, we find that the simulated coefficients exhibit the opposite pattern of the true estimates.

One potential concern with our estimations relates to the possibly endogenous nature of currency unions. 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.[8] Attempts in the literature to instrument the currency union dummy prove disappointing, however, as the instrumentation tends to increase, rather than decrease, the magnitude of currency union estimates (e.g., Alesina, Barro, and Tenreyro, 2002; Barro and Tenreyro, 2007; Rose, 2000). 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 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 high import intensity (i.e., large import shares) and pushing down the large effects associated with low import intensity (i.e., small import shares). Thus, removing this potential bias would lead to even stronger heterogeneity patterns.

As they improve our understanding of how currency unions shape trade flows between trading partners, our results have important policy implications. First, by confirming that currency unions are associated with more trade between their members, our results lend support to the view that, by creating a permanent commitment to fixed exchange rates, currency unions go beyond the simple elimination of exchange rate volatility and are likely to change the perceptions and expectations of economic agents. Second and most importantly, our results help to evaluate the potential trade benefits that countries can expect to reap when joining a currency union in the future. For instance, suppose Bulgaria, Croatia, the Czech Republic, Hungary, Poland, Romania, and Sweden were to join the euro in the next few years. As these countries are relatively small compared to some existing members of the Eurozone such as France and Germany, they have relatively large import shares. Our results suggest that these import shares will grow modestly (consistent with Baldwin, 2006; Glick, 2016; Mika and Zymek, 2016). However, trade shares in the opposite direction are small and can therefore be expected to grow faster.

Our paper is related to two strands of the literature. The first, and earlier one, is concerned with the trade impact of exchange rate fluctuations (for a review, see Auboin and Ruta, 2013). By creating uncertainty, the received view is that exchange rate volatility discourages trade

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[8]For instance, exporting and importing 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 for instance Broda and Romalis (2010) and Devereux and Lane (2003). From a theoretical point of view, see Mundell (1961) who suggests that by reducing real exchange rate fluctuations, trade reduces the costs of forming a currency union. Alesina and Barro (2002) show that countries that trade more with each other are more likely to form currency unions.

flows. The empirical evidence is mixed, however, as the effect of volatility on trade tends to be small and not robust (e.g., Frankel and Wei, 1993).[9]

The second strand explores more specifically whether by eliminating exchange rate uncertainty, currency unions promote trade flows. In his seminal work, Rose (2000) shows that sharing a common currency more than triples bilateral trade flows. The magnitude of the effect is surprising, especially given the modest impact of exchange rate volatility estimated in the earlier literature. Subsequent work by Rose and co-authors shows that the currency union effect is smaller than initially found, but remains large and robust to using different samples, specifications, and to controlling for reverse causality (Frankel and Rose, 2002; Glick and Rose, 2002; Rose and van Wincoop, 2001).[10]

These findings have inspired a large and growing literature on the topic. The common view is that the original "Rose" effect is plagued by omitted variables, econometric errors, self selection, and the presence of currency unions formed by very small or poor countries, and that the trade effect of currency unions is likely to be small or even insignificant (e.g., Baldwin, 2006; Baldwin, Di Nino, Fontagné, De Santis, and Taglioni, 2008).[11] Applying newer econometric techniques, Glick and Rose (2016) conclude that the empirical literature based on the standard gravity approach fails to deliver "reliable and robust" estimates of currency unions effects since the results turn out to be highly sensitive to the econometric methodology, specification, and data sample used.[12]

Nevertheless, there is empirical evidence to suggest that heterogeneity in the trade impact of currency unions may exist along several dimensions. For instance, the effect is found to be larger for developing economies (Santos Silva and Tenreyro, 2010a), smaller countries (e.g., Baldwin, 2006; Micco, Stein, and Ordoñez, 2003), and to fall over time (De Sousa, 2012). The effect is also shown to vary across currency unions (Eicher and Henn, 2011; Nitsch, 2002), and consensus estimates for the euro are for instance substantially more modest than those for broader samples, falling between five and 15 percent (Baldwin, 2006; Baldwin et al., 2008). The trade effect appears stronger for the industries producing highly differentiated goods (e.g., Flam and Nordström, 2003, 2007), and for larger, and more productive firms that adjust both

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[9]The weak response of trade to exchange rate volatility could be due, among other factors, to firms hedging against exchange rate risk or to the offsetting impact arising from imported inputs.

[10]Rose and Stanley (2005) carry out a meta-analysis based on the point estimates of 34 different studies and conclude that currency unions have a positive and robust effect on trade.

[11]Also see Berger and Nitsch (2008), Broda and Romalis (2010), Bun and Klaassen (2007), Campbell (2013), De Nardis and Vicarelli (2003), De Sousa (2002), Eicher and Henn (2011), Flam and Nordström (2003, 2007), Frankel (2010), Glick (2016), Klein and Shambaugh (2006), Larch, Wanner, Yotov and Zylkin (2017), López-Córdova and Meissner (2003), Micco, Stein, and Ordoñez (2003), Mika and Zymek (2016), Nitsch (2002), Persson (2001), Saia (2017), and Santos Silva and Tenreyro (2010a), among others.

[12]Baldwin, Di Nino, Fontagné, De Santis, and Taglioni (2008) go as far as claiming that the empirical literature on the trade effect of currency unions "is a disaster" as the estimates reported by prominent researchers range from zero percent (e.g., Berger and Nitsch, 2008) to 1,387 percent (Alesina, Barro, and Tenreyro, 2002), most of them being "fatally flawed by misspecification and/or econometric errors."

at the intensive and at the extensive margins (Berthou and Fontagné, 2008).[13] In contrast to these papers where the different sources of heterogeneity are explored without theoretical motivation, we guide our empirical specifications by deriving predictions from a model based on translog gravity.[14,15]

Our paper is organized as follows. In Section 2 we introduce the translog gravity equation which predicts that the trade effect of currency unions is heterogeneous. In Section 3 we present the empirical methodology based on the standard gravity equation framework. We describe our main results, the trade effect of the euro, and address the inclusion of the zero observations in the sample. We also present the translog specifications. In Section 4 we carry out Monte Carlo simulations that explore the endogeneity of currency unions. We provide an extensive battery of robustness checks in Section 5. We conclude in Section 6 and offer possible directions for future research. Appendix A summarizes our data and sources. In Appendix B we carry out Monte Carlo simulations that scrutinize our estimation strategy in more detail.

2 Theoretical Background

We follow Novy (2013) in using translog gravity as the theoretical framework of our analysis. This model features multiple countries that are endowed with an arbitrary number of differentiated goods. Following Feenstra (2003), demand is derived from a symmetric translog expenditure function. 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 $t_{ij} \neq t_{ji}$.

We impose market clearing and solve for general equilibrium. Ignoring time indices for now, this results in the translog gravity equation

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

where x_{ij} is the bilateral trade flow between the exporting country i and the importing country j, y_j is the importer's income, and n_i denotes the number of goods of country i. The dependent variable is thus the import share x_{ij}/y_j per good n_i of the exporting country. On the right-hand side, $\theta > 0$ is the translog preference parameter. D_i and D_j denote exporter and importer-

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[13]For more evidence on the intensive and extensive margins, see Baldwin and Di Nino (2006), Baldwin et al. (2008), Bergin and Lin (2012), Flam and Nordström (2007), and Machado, Santos Silva, and Wei (2016).

[14]For evidence on the heterogeneous trade effects of Free Trade Agreements, see Baier, Yotov, and Zylkin (2016) and Glick (2016). Spearot (2013) and Subramanian and Wei (2007) investigate the heterogeneous trade effects of tariff liberalization and of WTO membership, respectively.

[15]The numerous robustness checks carried out by many papers also implicitly search for heterogeneity in the trade effect of currency unions. But again such exercises are, in general, not motivated by theory.

specific terms given by

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

$$D_j = \theta \ln(T_j) \tag{3}$$

where y^W denotes world income and S is the number of countries in the world. T_j is akin to a multilateral resistance term since it represents a weighted average of bilateral trade costs. It is given by

$$\ln\left(T_j\right) = \sum_{s=1}^{S} \frac{n_s}{N} \ln(t_{sj}) \tag{4}$$

where N is the number of products in the world with $N \geq S$.

The translog gravity equation (1) differs in one key respect from standard gravity equations as in Anderson and van Wincoop (2003) and Eaton and Kortum (2002).[16] That is, the dependent variable is the import share per good in levels, not the logarithmic bilateral trade flow. The gravity relationship is therefore not log-linear in trade costs. This implies a variable trade cost elasticity, and it is this crucial feature that we examine in the context of currency unions. More specifically, define the trade cost elasticity as $\eta \equiv \partial \ln\left(x_{ij}\right)/\partial \ln(t_{ij})$. In standard gravity equations this elasticity would be constant.[17] In the translog gravity model, however, this elasticity is variable. It follows from equation (1) as

$$\eta_{ij} = -\frac{\theta}{\frac{x_{ij}/y_j}{n_i}}. \tag{5}$$

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 the elasticity varies by country pair.

In line with the literature, we assume that log trade costs $\ln(t_{ij})$ are a function of a dummy variable for currency union membership, CU_{ij}, which takes on a value of one if countries i and j are both members, with coefficient κ. We expect κ to be negative in general since a currency union is generally thought to lower bilateral trade costs (our empirical results will confirm this). Furthermore, we add common explanatory variables such as distance and a dummy for membership of a regional trade agreement. Trade costs are thus bilaterally symmetric. We provide more details in Section 3.

Given the expression in equation (5), the elasticity of trade with respect to the currency

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[16] See Head and Mayer (2014) for an overview of gravity equations. See Novy (2013) for a more detailed discussion of the translog gravity model.

[17] 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.

union dummy follows as

$$\frac{\partial \ln(x_{ij})}{\partial CU_{ij}} = -\frac{\theta\kappa}{\frac{x_{ij}/y_j}{n_i}}. \tag{6}$$

Given that κ is generally negative, we expect a positive currency union effect on bilateral trade. Most importantly, the currency union effect should be larger for country pairs associated with smaller import shares. It also follows that a symmetric reduction in bilateral trade costs induced by a currency union can lead to asymmetric increases in bilateral trade flows by direction of trade. These are testable predictions that we will in turn examine.

3 Empirical Analysis

We first estimate standard gravity regressions so we can compare the currency union coefficients in our sample to those in the literature. Then, we adopt two main approaches to test whether the currency union effect on trade is heterogeneous across import shares. The first approach is based on the standard log-linear gravity specification that is commonplace in the literature. But instead of estimating a single currency union coefficient that is constant over the entire sample, we allow for heterogeneous currency union estimates. We explain this estimating strategy in more detail below. The second approach is to estimate the translog gravity equation (1) directly. We can then compute the pair-specific effects with the help of equation (6). We use a comprehensive data set of aggregate bilateral trade flows, covering most of global trade in modern times. It consists of an unbalanced panel including 199 countries between 1949 and 2013. We provide details and descriptive statistics in Appendix A.

3.1 Standard Gravity Approach

This section describes our approach to estimate homogeneous and heterogeneous currency union effects on bilateral trade flows using a standard gravity equation framework. It also presents our baseline results, the trade effect of the euro, and addresses the inclusion of the zero observations in the sample.

3.1.1 Homogeneous Currency Union Effects

The dependent variable in the translog gravity equation (1) is the import share per good in levels, which is regressed on bilateral trade costs and on exporter and importer-specific terms. However, we first run regressions based on the standard log-linear gravity framework where the dependent variable is in logarithms. Specifically, we estimate

$$\ln ms_{ij,t} = \alpha_1 CU_{ij,t} + \alpha_2 Z_{ij,t} + D_{i,t} + D_{j,t} + D_{ij} + \varrho_{ij,t} \tag{7}$$

where the import share per good is $ms_{ij,t} = \frac{x_{ij,t}/y_{j,t}}{n_{i,t}}$ and we add time subscripts such that $x_{ij,t}$ is the FOB bilateral export value from exporter i to importer j in year t, $y_{j,t}$ is country

j's nominal GDP (both in current US dollars), and $n_{i,t}$ denotes the number of goods in the exporting country, which can be seen as an extensive margin measure (see details below). 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 time-varying country pair variables $Z_{ij,t}$ which include dummy variables equal to one if both countries in the pair belong to a RTA or are members of the IMF, OECD, and WTO in each year, and to zero otherwise (Rose, 2005). We include time-varying exporter and importer fixed effects, $D_{i,t}$ and $D_{j,t}$, which control for multilateral trade resistance and for the exporter and importer-specific terms included in (1).

We further include country pair fixed effects D_{ij} to absorb all unobserved bilateral trade frictions in each cross section. The pair effects also control for the endogeneity of the currency union dummy if two countries that decide to join a currency union have traditionally traded a lot with each other (but fail to do so if the two countries decide to join following a surge in trade during the sample period, see Bun and Klaassen, 2007; Micco et al., 2003). Note that the pair effects are directional as non-directional pair effects would otherwise eliminate the asymmetry in bilateral import shares within a pair.[18] The inclusion of pair fixed effects implies that identification is achieved from the time series variation of each explanatory variable within each country pair.[19] For our main variable of interest, this means that identification stems from changes in bilateral currency union status over time. To control for time-invariant idiosyncratic shocks correlated at the pair-level which may affect both directions of trade in a similar way (De Sousa, 2012), standard errors are clustered by non-directional country pair. The coefficients to be estimated are denoted by the α's, and $\varrho_{ij,t}$ is an error term. As sharing a common currency is expected to promote trade, we expect α_1 to be positive.

As the dependent variable in (7) is in logarithmic form, the zero import shares per good are excluded from the regression, and our analysis focuses on the intensive bilateral margin of adjustment only. Also due to the log-linear nature of specification (7), the $n_{i,t}$ and $y_{j,t}$ terms are absorbed by the exporter and importer fixed effects $D_{i,t}$ and $D_{j,t}$ so that in effect, we yield the same coefficients of interest as in the standard gravity specification that simply has the logarithmic bilateral trade flow on the left-hand side. However, as will become clearer later, for comparability we retain the dependent variable as specified in equation (7).

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

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[18]Baier et al. (2016) use non-directional pair effects to estimate the within-pair asymmetric effects of FTAs.

[19]The recent literature concludes that time-varying exporter and importer dummies and time-invariant country pair fixed effects should be included (e.g., Baldwin, 2006; Baldwin and Taglioni, 2007; Baldwin et al., 2008; De Nardis and Vicarelli, 2003; Eicher and Henn, 2011; Mika and Zymek, 2016). The earlier literature failed to do so (e.g., Rose, 2000).

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 it provides us with some useful information regarding the variation in the extensive margin across exporting countries.

We check the robustness of our findings by using alternative proxies for the extensive margin. First, we rely on the cross-country measure constructed by Hummels and Klenow (2005), using exports data from 126 exporting to 59 importing countries in more than 5,000 6-digit HS-level product categories for 1995. Second, as these authors observe that the extensive margin tends to be stronger for larger economies, we rely on the GDP of the origin country as an alternative proxy.[20] Finally, we report results where we assume that the extensive margin is unity for all exporters, in which case the dependent variable is simply the bilateral import share.

3.1.2 Heterogeneous Currency Union Effects

Our aim is to investigate whether the trade effect of currency unions, as captured by α_1 in equation (7), is heterogeneous across bilateral import shares per good. This approach, however, suffers from a simultaneity bias problem as it requires the currency union effect to vary with the values taken by the dependent variable (Novy, 2013). To address this issue, we let the currency union effect vary across *predicted* import shares instead. We adopt a two-step methodology, whereby in the first step we regress the import shares per good on geography-related variables (distance and contiguity) to generate the predicted shares, and in the second step we investigate how the trade effect of currency unions varies across predicted shares.

In the first step, we regress the import shares per good on exporter-year and importer-year fixed effects, and on time-invariant country pair controls

$$\ln ms_{ij,t} = D_{i,t} + D_{j,t} + \delta K_{ij} + \nu_{ij,t} \tag{8}$$

where K_{ij} includes geography-related variables, i.e., logarithmic bilateral distance and a contiguity dummy. We then generate the predicted shares which we denote by $\ln \widehat{ms}_{ij,t}$. As we show later, our results are robust to including further gravity controls in specification (8), or to simply controlling for time-invariant country pair fixed effects.[21]

In the second step, we include an interaction term between the currency union dummy and

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[20]In that case, the proxy for the exporter's extensive margin is time-varying.

[21]We do not include the time-varying pair variables for RTAs, currency unions, the OECD, IMF, or WTO in the first step as they are not geography-related and therefore more likely endogenous. Our results, however, are robust to including these variables in the first step (available upon request), which is akin to running an Instrumental Variables regression.

predicted import shares. We estimate

$$\ln ms_{ij,t} = \xi_1 CU_{ij,t} + \xi_2 CU_{ij,t} \times \ln \widehat{ms}_{ij,t} + \xi_3 Z_{ij,t} + D_{i,t} + D_{j,t} + D_{ij} + \varepsilon_{ij,t}. \tag{9}$$

Since this specification includes exporter-year, importer-year and country pair fixed effects, the main effect of the predicted import shares drops out from the regression. If the trade effect of currency unions falls with bilateral import intensity as predicted by our theoretical framework, the coefficient ξ_2 on the interaction term should be negative. As the predicted import share is a generated regressor, standard errors are bootstrapped with 100 replications.[22]

An alternative way of testing our prediction is to split the sample into equally-sized intervals of predicted import shares per good ranked by value, and to estimate

$$\ln ms_{ij,t} = \beta_{1,h} CU_{ij,t} \times D_h + \beta_2 Z_{ij,t} + D_{i,t} + D_{j,t} + D_{ij} + D_h + \epsilon_{ij,t} \tag{10}$$

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. The regression also includes interval fixed effects, D_h. Consistent with our theoretical framework, we expect the currency union effect to be the largest in the interval of the lowest predicted shares, and to be weaker in intervals of higher shares.[23]

For a given distribution of predicted import shares per good recall that due to their logarithmic form, the estimation of equations (9) or (10) yields exactly the same coefficients regardless of whether we use the logarithmic import share, import share per good, or bilateral trade flow as the dependent variable. The reason is that the exporter-year and importer-year fixed effects absorb all country-specific variables such as $n_{i,t}$ and $y_{j,t}$. In contrast, note that for the first-step regression (8), we must use the import share per good as the regressand since this is the variable we need to predict.

3.1.3   Baseline Results

We start by discussing average currency union estimates. In column (1) of Table 1, we estimate equation (7) but only include the currency union dummy as a regressor.[24] Its estimated coefficient is equal to 0.363, suggesting that a common currency is associated with an increase

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[22]Non-bootstrapped standard errors are very similar.

[23]According to theory, the effects of the RTA, IMF, OECD, and WTO variables should also be heterogeneous across import shares. We show that our results remain robust to also interacting these variables with the predicted shares in equation (9), or to estimating their effects separately by intervals of predicted shares in equation (10). 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 magnitude of the currency union effect is overestimated due to the omission of the fixed effects, but we still find evidence that the effect falls with bilateral import shares.

[24]In all tables, the number of observations differs from the total number of observations included in the sample because the observations that are perfectly predicted by the fixed effects (i.e., singletons) are dropped.

in bilateral trade of 44 percent on average ($\exp(0.363) - 1 = 0.438$). When we add the time-varying country pair controls in column (2), the magnitude of the effect slightly decreases to 38 percent. Belonging to a RTA, and membership of the OECD, IMF and WTO all have a positive association with bilateral trade (Rose, 2005).

Table 1: Baseline Results

	(1)	(2)	(3)	(4)	(5)
CU	0.363^a (0.058)	0.326^a (0.057)	-0.075 (0.109)	-0.040 (0.107)	0.066 (0.110)
CU×predicted share	–	–	-0.073^a (0.018)	-0.061^a (0.017)	-0.047^a (0.018)
RTA	–	0.415^a (0.028)	–	0.413^a (0.026)	–
IMF	–	0.165^b (0.065)	–	0.164^a (0.053)	–
OECD	–	0.366^a (0.051)	–	0.365^a (0.037)	–
WTO	–	0.146^a (0.035)	–	0.144^a (0.030)	–
CU estimates					
Mean	–	–	0.525^a (0.072)	0.462^a (0.071)	0.453^a (0.071)
10th percentile	–	–	0.765^a (0.120)	0.663^a (0.117)	0.608^a (0.118)
90th percentile	–	–	0.288^a (0.054)	0.263^a (0.053)	0.300^a (0.053)
R-squared	0.807	0.808	0.807	0.808	0.808
Observations	780,818	780,818	780,818	780,818	780,818

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) and (2). Standard errors are bootstrapped in (3) to (5). In (5), the time-varying country pair controls are interacted with predicted import shares per good (not reported). ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good. "predicted share" is the predicted log import share per good.

Our next task is to demonstrate that these results hide some heterogeneity in the trade effect of currency unions across country pairs. To do so, we first run regression (8). As expected, import intensity is stronger between closer and contiguous countries (the estimated coefficients are significant at the one percent level). We then generate the predicted import shares per good and run regression (9).

Columns (3) and (4) report the same specifications as columns (1) and (2) but include an interaction between the currency union dummy and the predicted shares. In column (5) we further interact the time-varying pair controls with the predicted shares (not reported).[25] In all cases, the interaction terms with the currency union dummy are negative and significant. Therefore, the impact of currency unions is heterogeneous, and falls with bilateral import shares.

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[25] Also consistent with our model's predictions, the interactions between the time-varying pair controls and the predicted import shares are negative and significant (with the exception of the IMF and WTO variables).

As shown in the lower part of Table 1 in columns (3) to (5), the magnitude of the implied currency union estimate falls when we move from the 10th to the 90th percentile of the predicted shares distribution. For instance in column (4), the currency union estimate is equal to 0.462 at the mean value of predicted shares, 0.663 for a country pair at the 10th percentile of the predicted shares distribution, and 0.263 at the 90th percentile. In other words, at the 10th percentile, currency unions are associated with 94 percent more trade ($\exp(0.663) - 1 = 0.941$), whereas at the 90th percentile, the corresponding effect is only 30 percent.

Table 2: Pair Specific Currency Union Effects and Bilateral Asymmetries

Largest CU Effects			**Lowest CU Effects**		
Exporter	Importer	CU estimates	Exporter	Importer	CU estimates
Greenland	Denmark	0.768^a (0.145)	Netherlands	Belg.-Lux.	-0.148 (0.134)
Niger	Eq. Guinea	0.719^a (0.132)	Belg.-Lux.	Netherlands	-0.146 (0.134)
Central Afr. Rep.	Mali	0.683^a (0.123)	Germany	Netherlands	-0.124 (0.128)
Niger	Gabon	0.675^a (0.121)	Germany	Belg.-Lux.	-0.098 (0.121)
Central Afr. Rep.	Senegal	0.668^a (0.119)	Singapore	Malaysia	-0.093 (0.120)
Liberia	United States	0.666^a (0.118)	Malaysia	Singapore	-0.085 (0.118)
Mali	Central Afr. Rep.	0.663^a (0.118)	France	Belg.-Lux.	-0.055 (0.110)
Chad	Côte d'Ivoire	0.661^a (0.117)	Netherlands	Germany	-0.024 (0.103)
Liberia	Bahamas	0.657^a (0.116)	France	Netherlands	-0.010 (0.099)
Guinea-Bissau	Benin	0.656^a (0.116)	Belg.-Lux.	Germany	0.004 (0.096)
Bilateral Asymmetries					
Exporter	Importer	CU estimates	Exporter	Importer	CU estimates
Malta	Germany	0.458^a (0.071)	Germany	Malta	0.111 (0.073)
Malta	France	0.451^a (0.069)	France	Malta	0.121^c (0.071)
France	Germany	0.027 (0.091)	Germany	France	0.010 (0.095)
Panama	United States	0.394^a (0.060)	United States	Panama	0.074 (0.080)

Notes: Currency union estimates evaluated at 2013 predicted import shares using the estimated coefficients reported in column (4) of Table 1. Bootstrapped standard errors adjusted for clustering at the (non-directional) country pair-level are reported in parentheses. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively.

As an illustration, the upper part of Table 2 reports the ten country pairs with the largest and the lowest currency union estimates (evaluated at 2013 predicted import shares). Currency union effects are large for country pairs with small import shares such as Denmark importing from Greenland (115 percent), Equatorial Guinea from Niger (105 percent), Mali from the Central African Republic (98 percent), and Gabon from Niger (96 percent). In contrast, country pairs with large import shares benefit much less from joining a currency union, the effect being

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insignificant for Belgium-Luxembourg importing from the Netherlands or from Germany, and for the Netherlands importing from Belgium-Luxembourg or from Germany.

The lower part of Table 2 shows that the trade effect of currency unions is also heterogeneous *within country pairs* and therefore asymmetric by direction of trade. For instance, the effect is large (at 58 and 57 percent) when Germany or France import from Malta (i.e., low predicted shares), but is insignificant or small (and significant at the 10 percent level only) when Malta imports from Germany or from France (i.e., large predicted shares). In contrast, as France and Germany both import intensively from each other, sharing the same currency has no effect on their bilateral trade in either direction. Another example of asymmetric bilateral currency union effect can be observed between the US and Panama (i.e., the effect is large at 48 percent when the US imports from Panama, but is insignificant when Panama imports from the US).

Table 3: Heterogeneous Currency Union Effects: Intervals

	(1)	(2)	(3)	(4)	(5)
CU (first interval)	0.481^a (0.093)	0.630^a (0.137)	0.696^a (0.161)	0.718^a (0.160)	0.496^a (0.117)
CU (second interval)	0.285^a (0.059)	0.415^a (0.079)	0.445^a (0.098)	0.413^a (0.097)	0.428^a (0.087)
CU (third interval)	–	0.249^a (0.064)	0.347^a (0.076)	0.341^a (0.076)	0.213^a (0.080)
CU (fourth interval)	–	–	0.253^a (0.067)	0.281^a (0.067)	0.308^a (0.073)
RTA	0.415^a (0.028)	0.409^a (0.028)	0.403^a (0.028)	–	0.406^a (0.028)
IMF	0.164^b (0.065)	0.168^a (0.064)	0.169^a (0.064)	–	0.168^a (0.064)
OECD	0.366^a (0.051)	0.358^a (0.051)	0.349^a (0.051)	–	0.351^a (0.051)
WTO	0.146^a (0.035)	0.146^a (0.035)	0.146^a (0.035)	–	0.146^a (0.035)
Intervals split by	# obs.	# obs.	# obs.	# obs.	# obs. CU=1
R-squared	0.808	0.808	0.808	0.808	0.808
Observations	780,818	780,818	780,818	780,818	780,818

Notes: 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. In (4), the time-varying country pair controls are interacted with the interval fixed effects (not reported). ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good.

We proceed by regressing equation (10). In Table 3 we report currency union effects estimated separately by intervals of predicted import shares per good. Based on the median of the predicted shares distribution, column (1) of Table 3 splits the data into two distinct intervals, where the first and the second interval refer to the intervals with the lowest and highest shares, respectively. As expected, the currency union coefficient is largest (equal to 0.481) for the lowest shares and smallest (equal to 0.285) for the largest shares. Columns (2) and (3) split the sample into three and four equally-sized intervals of predicted import shares per good. In both cases the magnitude of the currency union coefficient gradually declines from the first to the

fourth interval.[26] In column (4) we let the effects of the time-varying pair controls vary across the four intervals as well (not reported). The results remain qualitatively similar. Finally, in column (5) we split the data into four intervals but in such a way that each includes roughly the same number of observations for which the currency union dummy is equal to one.[27] Compared to column (3), the currency union estimates are slightly smaller but their magnitudes continue to fall with predicted shares (with the exception of the interval with the lowest shares).[28]

3.1.4 The Euro

Table 4: Homogeneous Euro Effects

	(1)	(2)	(3)	(4)
CU non EURO	0.266^a (0.087)	0.270^a (0.087)	0.270^a (0.087)	0.269^a (0.087)
EURO	–	0.403^a (0.063)	0.023 (0.069)	0.035 (0.069)
RTA	0.417^a (0.028)	0.414^a (0.028)	0.400^a (0.028)	0.400^a (0.028)
IMF	0.166^b (0.064)	0.165^b (0.064)	0.172^a (0.065)	0.172^a (0.065)
OECD	0.369^a (0.052)	0.365^a (0.051)	0.343^a (0.051)	0.343^a (0.051)
WTO	0.147^a (0.035)	0.147^a (0.035)	0.157^a (0.035)	0.157^a (0.035)
Trend EU countries	–	–	0.027^a (0.003)	0.027^a (0.003)
Sample	Excl. EZ	Full	Full	Full
Overseas territories	No	Yes	Yes	No
R-squared	0.807	0.808	0.808	0.808
Observations	778,467	780,818	780,818	780,640

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. [a], [b], and [c] indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good.

We investigate the trade effect of the European single currency. We start by providing average estimates. In column (1) of Table 4, we first run specification (7) on the full sample excluding the Eurozone. Compared to a magnitude of 38 percent in the full sample (column 2 of Table 1), the trade effect of sharing a common currency is now 30 percent on average $(\exp(0.266) - 1 = 0.304)$. At first glance this suggests that compared to other common currencies, the positive trade impact of the euro may be larger. This finding is corroborated by the regression in column (2) which is estimated on the full sample, but the currency union dummy

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[26] In column (3), the number of observations for which the currency union dummy is equal to one is 1,379 in the first, 3,171 in the second, 3,816 in the third, and 4,719 in the fourth interval.

[27] There are 3,271 observations for which the currency union dummy is equal to one in the first three intervals and 3,272 in the fourth.

[28] We can reject that the currency union coefficients are equal across intervals at the five percent level in columns (1) and (2), and at the ten percent level in columns (3) to (5).

is split between euro and non-euro currencies. Sharing a common currency is associated with 50 percent more trade for the euro ($\exp(0.403) - 1 = 0.496$), and with 31 percent more trade for non-euro currencies ($\exp(0.270) - 1 = 0.310$).

However, as argued by previous authors, one issue with the regression in column (2) is that it fails to control for the effect of European Union integration more broadly. As a result, the trade impact of the euro is likely to be overestimated because it confounds the effect of the Single Market with the effect of the single currency (see Baldwin, 2006, for a discussion). To address this issue, in column (3) we further include a pair-specific time trend for EU countries (both in and out of the euro) to control for the ongoing integration process through the Single Market (e.g., Baldwin, 2006; Baldwin et al., 2008; Berger and Nitsch, 2008; Bun and Klaassen, 2007; Micco et al., 2003; Mika and Zymek, 2016). The positive coefficient on the trend indicates that on average, EU countries trade more intensively with each other over time.[29] Interestingly, the inclusion of the trend turns the euro effect insignificant.[30] Berger and Nitsch (2008), Bun and Klaassen (2007), and Mika and Zymek (2016) also find that the inclusion of a time trend dramatically reduces the magnitude and significance of the euro trade effect.

To make sure that our results are not affected by small overseas territories that use the euro and are associated with EU countries (in our sample these are Saint Pierre et Miquelon, French Guiana, Guadeloupe, Martinique, and Réunion), in column (4) we exclude them from the sample, with little effect on our results.[31] The estimated coefficient on the euro dummy remains insignificant. As the average import share per good in our sample is significantly larger for euro member pairs compared to non-euro currency union pairs, finding that the euro trade effect is weaker on average is thus consistent with the theoretical framework in Section 2.[32]

Table 5 reports the same specifications as in Table 4, but we interact the currency union indicators with the predicted import shares. In all cases we observe heterogeneity in the trade effect of non-euro currency unions. For the euro, the interaction term is negative and significant in columns (3) and (4) only once the pair-specific EU trend is included. In other words, although the euro effect is on average insignificant, it is heterogeneous across country pairs, and it is larger for the pairs associated with smaller import shares.[33]

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[29]The trend is included for 27 EU countries (as Belgium and Luxembourg are merged) and for the overseas territories of the EU including French Guiana, Greenland (between 1973 and 1985 only), Guadeloupe, Martinique, and Réunion (Gibraltar belongs to the EU but is excluded from our data set). Another way to control for the effect of EU integration is to run regressions for the EU15 or the EU28 only (Baldwin, 2006). Also see Saia (2017) who employs a synthetic control method to assess the trade effect of the euro.

[30]If we include a pair-specific trend for Eurozone countries only, the euro coefficient becomes smaller but remains significant. Including a trend for EU countries is, however, more appropriate as EU integration has affected all EU countries equally, whether or not they adopted the euro (Baldwin, 2006).

[31]Note that Andorra, Kosovo, Montenegro, and San Marino, neither of which belong to the EU, also use the euro. Only Andorra is included in our sample.

[32]The import shares per good are two percent and 1.4 percent, respectively.

[33]We get similar results if we assume that the euro was introduced in 2002 (as a paper currency) as opposed to 1999 (as an electronic currency).

Table 5: Heterogeneous Euro Effects

	(1)	(2)	(3)	(4)
CU non EURO	-0.717^a (0.222)	-0.718^a (0.226)	-0.653^a (0.227)	-0.655^a (0.219)
CU non EURO×predicted share	-0.143^a (0.030)	-0.144^a (0.030)	-0.135^a (0.030)	-0.135^a (0.031)
EURO	$-$	0.471^a (0.094)	-0.194^c (0.110)	-0.213^c (0.119)
EURO×predicted share	$-$	0.015 (0.020)	-0.044^b (0.021)	-0.051^b (0.021)
RTA	0.411^a (0.026)	0.409^a (0.026)	0.394^a (0.026)	0.394^a (0.024)
IMF	0.167^a (0.052)	0.167^a (0.052)	0.173^a (0.052)	0.173^a (0.056)
OECD	0.364^a (0.038)	0.361^a (0.037)	0.338^a (0.037)	0.338^a (0.041)
WTO	0.148^a (0.030)	0.149^a (0.030)	0.158^a (0.030)	0.158^a (0.031)
Trend EU countries	$-$	$-$	0.028^a (0.003)	0.028^a (0.003)
CU estimates				
Mean (CU non EURO)	0.462^a (0.086)	0.466^a (0.084)	0.453^a (0.083)	0.452^a (0.092)
10th percentile (CU non EURO)	0.933^a (0.155)	0.939^a (0.154)	0.896^a (0.151)	0.895^a (0.173)
90th percentile (CU non EURO)	-0.004 (0.099)	-0.003 (0.099)	0.015 (0.101)	0.014 (0.090)
Mean (EURO)	$-$	0.349^a (0.109)	0.167 (0.112)	0.203^b (0.091)
10th percentile (EURO)	$-$	0.301^c (0.166)	0.311^c (0.169)	0.369^b (0.151)
90th percentile (EURO)	$-$	0.397^a (0.067)	0.024 (0.074)	0.039 (0.059)
Sample	Excl. EZ	Full	Full	Full
Overseas territories	No	Yes	Yes	No
R-squared	0.807	0.808	0.808	0.808
Observations	778,467	780,818	780,818	780,640

Notes: 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. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good. "predicted share" is the predicted log import share per good.

As shown in the lower part of Table 5, while in column (3) the euro estimate is insignificant at the mean value of predicted shares, it is equal to 0.311 for a country pair at the 10th percentile of the predicted shares distribution, and it becomes insignificant at the 90th percentile. Examples of country pairs with small import shares which are associated with large trade effects of the euro are Ireland importing from Cyprus (31 percent), Finland from Malta (30 percent), and Austria from Estonia (25 percent). In contrast, country pairs with large import shares which do not benefit much from the euro include Belgium-Luxembourg importing from the Netherlands or from Germany (the effects are insignificant). We also find evidence of heterogeneity by direction of trade. As was shown in Table 2, the trade effect of sharing the euro is large when Germany or France import from Malta (i.e., lower predicted shares), but is insignificant when Malta imports from Germany or from France (i.e., higher predicted shares). The results remain

similar in column (4) once the overseas territories are excluded from the sample.

3.1.5 Zero Observations

Table 6: Zero Observations

	(1)	(2)	(3)	(4)	(5)
CU	0.202^a (0.050)	-0.340^a (0.100)	0.252^a (0.055)	-0.378^a (0.116)	—
CU×predicted share	—	-0.175^a (0.028)	—	-0.196^a (0.031)	—
CU non EURO	—	—	—	—	-0.392^a (0.148)
CU non EURO×predicted share	—	—	—	—	-0.216^a (0.038)
EURO	—	—	—	—	-0.562^a (0.123)
EURO×predicted share	—	—	—	—	-0.118^a (0.028)
RTA	0.205^a (0.035)	0.202^a (0.035)	0.127^a (0.037)	0.123^a (0.037)	0.112^a (0.036)
IMF	0.321^a (0.106)	0.320^a (0.106)	0.203^c (0.105)	0.203^c (0.105)	0.223^b (0.105)
OECD	0.534^a (0.073)	0.529^a (0.073)	0.590^a (0.081)	0.582^a (0.080)	0.539^a (0.079)
WTO	0.029 (0.053)	0.025 (0.052)	-0.004 (0.053)	-0.010 (0.053)	0.009 (0.053)
Trend EU countries	—	—	—	—	0.026^a (0.003)
CU estimates					
Mean	—	0.826^a (0.106)	—	0.979^a (0.121)	—
10th percentile	—	1.251^a (0.168)	—	1.504^a (0.200)	—
90th percentile	—	0.412^a (0.055)	—	0.477^a (0.058)	—
Mean (CU non EURO)	—	—	—	—	1.106^a (0.148)
10th percentile (CU non EURO)	—	—	—	—	1.685^a (0.244)
90th percentile (CU non EURO)	—	—	—	—	0.552^a (0.075)
Mean (EURO)	—	—	—	—	0.259^b (0.112)
10th percentile (EURO)	—	—	—	—	0.577^a (0.179)
90th percentile (EURO)	—	—	—	—	-0.044 (0.067)
Zeros included	No	No	Yes	Yes	Yes
Observations	782,469	782,469	1,131,876	1,131,876	1,131,876

Notes: PPML estimations where 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. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the import share per good in levels. "predicted share" is the predicted import share per good.

We have so far excluded the zero import share observations from our sample. One way to deal with the zero observations is to estimate our regressions by Poisson Pseudo Maximum

Likelihood (PPML), using the import shares per good in levels as a dependent variable (Santos Silva and Tenreyro, 2006).[34]

In column (1) of Table 6, we regress the import shares per good in levels on the controls of equation (7), but first exclude the zero observations. The currency union dummy variable indicates that sharing a common currency is associated with 22 percent more trade, on average $(\exp(0.202) - 1 = 0.224)$. Column (2) shows that the effect is heterogeneous across country pairs since we find a negative interaction between the currency union dummy and the predicted shares.[35] This shows that, when excluding the zero observations from the sample, the OLS and PPML estimations yield very similar results.

We proceed by including the zero observations in the sample. Columns (3) and (4) report the same specifications as in the two previous columns. According to column (3), sharing a common currency is associated with 29 percent more trade. Evidence of heterogeneity again arises in column (4) where we interact the currency union dummy with the predicted shares.[36] Finally, in column (5) we distinguish between the trade effects of euro and non-euro currencies. Again, our results remain largely similar, and the trade effects of both euro and non-euro currencies are heterogeneous across country pairs. Overall, these results suggest that incorporating the zero observations in the sample does not qualitatively affect our conclusions, which support the notion that the trade effect of currency unions falls with bilateral import shares. This contrasts with the results of De Sousa (2012), Glick and Rose (2016), and Mika and Zymek (2016) who find that OLS and PPML currency union estimates significantly diverge from each other.[37,38]

3.2 Translog Approach

We now report the results of implementing our second approach where we estimate the translog gravity equation (1) directly. We can then compute the pair-specific currency union effects with the help of equation (6). As the dependent variable in (1) is in levels (rather than in logarithmic form), the zero observations can be included in the sample. We therefore report two sets of results, i.e., excluding and including the zeros. Also notice that in contrast to the two-step OLS and PPML regressions reported earlier, the translog approach does not require us to predict the bilateral import shares per good in a first step.

Columns (1) and (2) of Table 7 report the results excluding and including the zero observations. In column (1) the currency union coefficient is equal to 0.006. As shown in the

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[34]We employ the `ppml_panel_sg` Stata command written by Larch et al. (2017) which implements an iterative PPML algorithm that eases the computational burden of a large number of fixed effects.

[35]The predicted shares are constructed based on a PPML specification analogous to (8).

[36]The elasticities at the mean, 10th, and 90th percentiles are calculated for positive import shares only.

[37]Only Mika and Zymek (2016) report PPML estimates with country pair and time-varying exporter and importer fixed effects. De Sousa (2012) and Glick and Rose (2016) only provide cross-sectional estimates.

[38]Due to the specific structure of the PPML estimation and to the inclusion of several sets of fixed effects, we are unable to bootstrap the standard errors in columns (2), (4) and (6). TBC.

lower part of the table, this corresponds to an estimate of 0.912 at the mean value of import shares. Therefore, sharing a common currency is associated with 91 percent more bilateral trade, a magnitude which is larger than the average of 38 percent estimated in the standard gravity framework (column 2 of Table 1). As predicted by the translog framework, the effect is heterogeneous across country pairs, and the currency union estimates decrease from the 10th to the 90th percentile of import shares per good. However, we note that the currency union estimates at the 10th percentile are extremely large compared to previous tables. The reason is that translog imposes a hyperbolic functional form on the way the currency union elasticities are computed. This can be seen in equation (6) in that the estimated coefficients, $\theta\kappa$, are divided by import shares. Since import shares at low percentiles are very close to zero, the implied elasticities tend to become very large.

Table 7: Translog Estimation

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

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. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the import share per good in levels.

Besides, all other regressors are significant and with expected signs, with the exception of the WTO dummy variable. In column (2), when we include the zero observations in the sample, the magnitude of the currency union effect at the mean value of (positive) import shares is smaller at 47 percent, but qualitatively our results continue to hold. Sharing a common currency is associated with more bilateral trade, and this effect is stronger for the country pairs with smaller import shares.

4   Endogeneity

Currency unions are not randomly assigned. Santos Silva and Tenreyro (2010a) 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. He accounts for the fact that characteristics such as distance and trade agreement status are different between pairs inside and outside a currency union, applying a propensity-score matching estimator (we perform the same estimator in Section 5).

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 take the CU_{ij} variable as observed in the data and combine it with a randomly drawn error term in an additive way. We round the resulting values to 0 and 1 to preserve the dummy nature of this variable. Overall, 95 percent of the pairs in a currency union preserve their status, and we keep the mean value of the endogenous $\widetilde{CU}_{ij}$ variable roughly the same as for CU_{ij}.[39]

We then construct bilateral trade costs on the basis of trade cost function (11) where we replace CU_{ij} with the endogenous $\widetilde{CU}_{ij}$. We generate the simulated import shares in the same way as in Section B.1 using the same data sample. 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. As in Section B.1, we assume that the translog gravity model is the true data generating process. We run the usual first and second-step regressions, iterating the procedure 100 times with fresh error terms.

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. It follows that the ξ_1 main coefficient and the ξ_2 interaction coefficient in regression (9) are pushed upwards. The simulated results with endogeneity are directly comparable to those without endogeneity in Table B1. For the ξ_1 main coefficient we obtain a highly significant point estimate of 0.235 (as opposed to -1.103 in column (3) of Table B1), and for the ξ_2 interaction coefficient we obtain a coefficient of -0.063 (as opposed to -0.363), significant at the five percent level. Thus, both coefficients are subject to upward bias. The resulting currency union estimates at the mean, 10th and the 90th percentiles follow as 0.478, 0.573 and 0.399 (all significant at the one percent level but not significantly different from each other). Compared to Table B1, the heterogeneity profile is therefore dramatically flattened, with small import shares no longer having currency union estimates that are statistically different from

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

large import shares. Figure 2 illustrates these estimates subject to positive endogeneity bias. Figure 2 can be directly compared to Figure 1 in that both figures plot the same true values.

In analogy to Section B.2, we also run placebo checks based on endogenous currency unions, assuming that standard gravity is the true data generating process. The results are directly comparable to those without endogeneity in column (3) of Table B2. We obtain currency union estimates at the mean, 10th and the 90th percentiles of 0.909, 0.471 and 1.351 (all significant at the one percent level and significantly different from each other). These estimates are clearly far from the true values in column (1) of Table B2. Not only are they biased upwards, they also exhibit a heterogeneity pattern that goes in the *opposite* direction of what our theory predicts. That is, larger import shares are associated with larger currency union effects.

Overall, we conclude that endogeneity either dampens or in some cases even overturns the heterogeneity patterns predicted by theory. The endogeneity of currency unions – to the extent that it exists – would therefore work against us and make it harder to find evidence of heterogeneity patterns as we do in Section 3.

5 Robustness

To ensure the robustness of our findings, this section discusses our results based on alternative specifications and data samples. Despite some variation in the magnitude of the trade effect of currency unions across specifications, we still find heterogeneous effects across country pairs, thus supporting our paper's main conclusions. The results are reported in Appendix C.

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 (see, also, Baldwin, 2006; Baldwin et al., 2008). To address this issue Persson (2001) applies a matching technique to identify the non-currency union country pairs that are most similar to the currency union pairs. He then compares bilateral trade flows between currency union members and their matched non-currency union counterparts, and finds that the trade effect of currency unions is insignificant. In contrast, Rose (2001) provides evidence that the magnitude of his currency union estimates remains robust to matching. To check whether non-random selection matters for our results, we apply the nearest matching estimator of Persson (2001) and Rose (2001). We run a probit regression to generate the propensity score, and match the currency union observations with the non-currency union observations that deviate by no more than a small distance from the propensity score.[40]

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[40] As in Persson (2001) and Rose (2001), the probit regresses the currency union indicator on the product of the GDPs and the 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 (available upon request). Due to the inclusion of GDP and GDP per capita, the probit is run on a smaller sample that includes 753,183 observations, of which 12,032 correspond to currency union pairs. Similar to Rose (2001), our results are unaffected by the value chosen for the maximum distance between the non-currency union observations and the propensity score.

We estimate regressions (7), (9), and (10) on the matched sample.[41] Column (1) of Table C1 reports the results for equation (7). On average, currency unions are associated with 42 percent more trade. The trade effect of currency unions is heterogeneous across country pairs, as shown in column (2) which interacts the currency union indicator with predicted import shares per good. Column (3) regresses equation (10) by splitting the sample of predicted shares by quartiles, and the currency union estimates fall with predicted import intensity. We therefore conclude that our findings remain robust to non-random selection on observables.

Currency Union Types De Sousa (2012) provides information on currency union membership which we use to construct the indicator variable for common currencies (see the Data Appendix A). He 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. In Table C2 we broadly split currency unions into two groups, i.e., multilateral versus bilateral, and separately include a dummy variable for each group.[42] We then allow for heterogeneity in the trade impact of multilateral unions in column (1), bilateral unions in column (2), and for both types simultaneously in column (3). As the interactions between the currency union dummy variables and predicted import shares are negative and significant in all cases, we conclude that both types of unions are associated with heterogeneous trade effects.

Currency Union Entry and Exit Our sample includes 342 and 459 (directional) switches into and out of currency unions. Among the 342 entries, 249 correspond to the euro.[43] To check whether the different types of switches matter for heterogeneity, 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 both as entry and exit when they first entered and subsequently left a currency union.

Distinguishing between the three types of unions, we regress equation (9) and report the results in column (1) of Table C3 (for the continuous unions, the currency union dummy is

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In Table C1, this distance is equal to 0.000001.

[41] The 12,032 currency union observations are matched with 57,781 non-currency union observations. The sample therefore includes a total of 69,813 observations, which represents one-ninth of our full sample size.

[42] Interchangeable money observations are categorized according to the currency involved. The currencies used in multilateral unions include the British West Indies currency, the Central America and the Caribbean currency, the CFA and CFP francs, the East African currency, and the euro. The currencies circulating in bilateral unions are the Australian, Malaysian, and US dollars, the Indian, Mauritian, and Pakistani rupees, the Belgian and French francs, the South African rand, the Danish krone, the Portuguese escudo, the Saudi riyal, the Spanish peseta, and the British pound sterling.

[43] Belgium and Luxembourg are merged into a single entity, while Latvia and Lithuania only adopted the euro in 2014 and 2015, respectively. Our sample therefore includes 16 countries that switched to the euro, and they account for $16 \times 15 = 240$ directional switches. The nine other switches occurred between Saint Pierre et Miquelon and Eurozone countries.

omitted due to collinearity with the pair fixed effects). Interestingly, the interactions with the predicted shares are negative and significant for the continuous and exit unions only. In column (2), we further split the entry currency unions between euro and non-euro, and the interaction is negative and significant for the euro only.[44] We therefore conclude that with the exception of the non-euro entry currency unions, all the others are associated with heterogeneous trade effects, as predicted by theory.

Import Shares per Good Our findings remain robust to using alternative proxies for the extensive margin $n_{i,t}$ in measuring the bilateral import shares per good. In columns (1), (2), and (3) of Table C4, respectively, the import shares per good are computed using the Hummels and Klenow (2005) measure, the GDP of the exporting country, or assuming that the extensive margin is unity for all exporters.

Instead of using the importing country's GDP to compute the import shares per good, we experiment using total (column 4) or manufacturing (column 5) gross output from the OECD STAN database (available in domestic currency, and converted to US dollars using the bilateral exchange rates from the IMF's International Financial Statistics). As the data are only available for OECD nations, our sample is reduced to 19 importing countries, but our results continue to hold.

Specifications We consider two alternative specifications for the first-step regression (8) that generates the predicted import shares per good. First, in addition to bilateral distance and contiguity we include indicator variables for sharing a common language, a common colonizer post-1945, pairs in a colonial relationship post-1945, and for territories that were, or are, the same country.[45] Second, we replace the K_{ij} controls with a full set of (directional) country pair fixed effects. In both cases we derive the predicted import shares per good, which we then interact with the currency union dummy variable to estimate equation (9). The results based on the first step with the full set of gravity controls, and with the pair fixed effects, are reported in columns (1) and (2) of Table C5, respectively. Consistent with our baseline results, the interaction terms between the currency union dummy and the predicted shares are negative and highly significant. The trade impact of currency unions therefore falls with bilateral import intensity.

We also show that our results remain robust to including a lagged dependent variable (column 3), to explaining the log-difference of bilateral import shares between subsequent years (column 4), to controlling for a country pair-specific trend for EU countries (column 5),

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[44]The regression includes a pair-specific trend for EU countries. The results remain similar without the trend.

[45]The estimated coefficients are significant and with expected signs, import intensity being larger between closer and contiguous countries that share a common language, colonial ties, and are the same country. Our results are similar if we also control for the number of landlocked and island nations in each pair (but those are insignificant).

and to including more generally a country-pair specific trend for all countries in a currency union in our sample (column 6).

Samples Our main analysis uses the bilateral exports and GDP data from Head, Mayer, and Ries (2010), which we extended from 2007 to 2013 using the export flows and GDPs from the IMF's DOTS and the World Bank's WDI, respectively (see the Data Appendix A for more details). As a robustness check, we run our regressions using the original exports and GDP data from Head et al. (2010) over the 1949 to 2006 period, and the exports data from the DOTS combined with the GDPs from the WDI between 1960 and 2013 (columns 1 and 2 of Table C6, respectively). These alternative samples leave our results qualitatively unchanged.

We also run regressions using a balanced sample over the period 1994 to 2013 (column 3), and at five-year intervals (column 4). We drop (in column 5) the countries (mostly island nations) omitted from Glick and Rose (2016), the smaller nations with a nominal GDP less than 500 million US dollars in 2013 (column 6), and the poorer countries with an annual GDP per capita below 500 US dollars in 2013 (column 7). Finally, we restrict the sample to similarly sized country pairs, i.e., those with GDPs that differ less than threefold (column 8), and exclude the post-Soviet states (column 9).[46] Our results on heterogeneity hold up.

6   Concluding Remarks

This paper analyzes the heterogeneous effects of currency unions on bilateral trade flows. To introduce heterogeneity, we derive predictions on the trade effect of common currencies by applying a translog gravity equation. This approach generates variable trade cost elasticities across and within country pairs. In this framework, the dependent variable is the bilateral import share per good in levels, and the prediction is that the impact of currency unions should be larger for country pairs associated with smaller import shares.

We test this prediction by employing an extensive data set of bilateral import shares for 199 countries between 1949 and 2013. The results lend strong support to our theoretical prediction. Our findings are robust to including zero import shares in the sample and allowing for non-random selection into currency unions. In line with the literature, we find weak evidence that the euro has promoted bilateral trade among Eurozone members on average. However, we find that even within the Eurozone, the currency union effect is heterogeneous across and within country pairs.

By highlighting heterogeneity, our results have implications for understanding some of the disparity in the currency union estimates reported in the literature. While we agree with other researchers that the methodology (e.g., OLS versus PPML), the specification (e.g., types of

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

fixed effects and right-hand side regressors), and the data used (e.g., Eurozone versus worldwide trade) matter for the magnitude and significance of currency union estimates, our contribution is to show that relying on a single currency union coefficient can be misleading if the objective is to assess, or to predict, the impact of sharing a common currency on bilateral trade flows. As we show, the trade effect of currency unions varies systematically across and within country pairs, and it is larger for pairs associated with lower import intensity.

As with any empirical work, our analysis suffers from a number of limitations. First, due to the lack of appropriate instruments for currency union membership, we are unable to fully control for potential reverse causality (although the inclusion of pair fixed effects should partially address this problem). However, as we show in our simulation, correcting for endogeneity bias would result in even stronger heterogeneity patterns than those we already find. Second, our analysis relies on aggregate country-level trade flows. One promising avenue for future research would be to extend our analysis to the level of industries, or even the level of firms. Thanks to the increasing availability of highly disaggregated firm- and product-level trade data, we believe that further disaggregating our analysis would be an important step forward.

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A   Data Appendix

Bilateral Exports   The IMF's Direction of Trade Statistics (DOTS) is the most widely used data set for studying the effect of currency unions on international trade (e.g., Alesina, Barro, and Tenreyro, 2002; Baldwin and Taglioni, 2007; Berger and Nitsch, 2008; Bun and Klaassen, 2007; De Nardis and Vicarelli, 2003; De Sousa, 2012; Glick, 2016; Glick and Rose, 2002, 2016; Micco, Stein, and Ordoñez, 2003; Mika and Zymek, 2016; Santos Silva and Tenreyro, 2010a). For more than 200 countries between 1948 and 2014, it reports their bilateral FOB merchandise exports (in current US dollars), of which 46 percent are recorded as being equal to zero. However, Head, Mayer, and Ries (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 and on regression analysis, these authors identify a number of problematic zeros, and replace them by positive values or set them to missing entries. They also fix a number of typos that, they argue, are due to incorrect reporting between FOB versus CIF values. Our main analysis therefore relies on the data set cleaned by Head et al. (2010). But as their sample 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. As a robustness check, we also run regressions using the original export flows provided by the DOTS, and the data set compiled by Head et al. (2010) up to 2006.

GDP and Population   Nominal GDP (in current US dollars) and population data are from Head et al. (2010) who complement, using national data sources and historical databases, the series from the World Bank's World Development Indicators (WDI) which start in 1960. As the series provided by Head et al. (2010) are available between 1949 and 2006 only, we update them up to 2013 using the growth rates of GDP and population from the WDI. GDP per capita is calculated as GDP divided by population.

Gravity   Gravity controls are from the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII). These include bilateral (population weighted) distances (in kilometers), and dummies for sharing a common land border (contiguity), a common (official) language, a common colonizer post-1945, pairs in a colonial relationship post-1945, and countries that were, or are, the same country. Dummy variables for membership with the OECD, IMF, and WTO are constructed using online sources (in each case, the dummy is equal to one if both countries in a pair are members in each year, and zero otherwise). De Sousa (2012) provides information on Regional Trade Agreements (RTAs) between 1958 and 2015. Using data from the CEPII we update his series from 1949 to 1957.

Currency Unions   De Sousa (2012) provides information on currency union membership between 1948 and 2014 (based on Glick and Rose, 2002, and extended to include the euro). 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."

De Sousa's (2012) data set includes 230 countries between 1948 and 2014 and reports 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. As we describe in more detail below, our samples with and without the zero import share observations only include 19,514 and 13,085 currency union observations, respectively. There are several reasons for these differences. First, a number of currency union countries are omitted from the Head et al. (2010) data set on exports and GDPs. 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 aggregate them over the entire period). Second, for other countries the import shares per good cannot be calculated if either bilateral exports, the importer's GDP, or the extensive margin are not observed. These include currency union countries such as Montserrat, San Marino, and Wallis and Futuna which do not have any export and import data; the Falkland Islands, Gibraltar, Nauru, and Saint Helena which have no extensive margin and GDP data; Guadeloupe, French Guiana, Martinique, Réunion, and Saint Pierre et Miquelon which are omitted as importers as they have no GDP data; Andorra which is excluded as an importer because in the sample it only imports from Taiwan which does not have any extensive margin data; and finally, Equatorial Guinea which is omitted as an exporter because it lacks extensive margin data.

Notice that other countries, which according to De Sousa (2012) never belonged to a currency union, are also excluded from our data set: Anguilla, the 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 export and import 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 whose extensive margin is not available.

Descriptive Statistics As the pre-1997 trade flows for Belgium and Luxembourg are reported jointly, we aggregate the two countries into a single entity over the entire period (and count the two countries as one). Our main 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 percent of the sample size. Bilateral import shares *per good* are then obtained by dividing the import shares by the number of 4-digit HS- or SITC-level product categories exported by each country as a share of the total number of categories exported in each year, averaged over time (from United Nations Comtrade).

As shown in Table A1, our full sample includes 1,203,583 observations, of which 782,469 import shares (and therefore import shares per good) are positive, and 421,114 are equal to zero (i.e., 35 percent of the sample). In the sample of positive import shares, the lowest import share is close to zero percent (from Angola to Colombia), the largest is equal to 41.3 percent (from Singapore to the Maldives), and the mean and standard deviation are equal to 0.4 and 1.9 percent, respectively.[47] Overall, 924 country pairs (directional) share a common currency at least at some point (amounting to 13,085 observations, or about 1.7 percent of the positive import shares sample). There are 342 and 459 country pairs (directional) that switched into or out of currency unions, respectively.

Table A1: Descriptive Statistics

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

Source: Authors' calculations.

Table A2 provides descriptive statistics for currency unions and non-unions in the sample of positive import shares. For most variables, the sample means are similar for both groups of countries, with some exceptions: countries in a currency union have higher import shares, are closer, are more likely to be in a colonial relationship and more likely to both belong to the OECD and WTO.

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[47]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 Table A1.

Table A2: Currency Unions and Non-Unions

	Non-Unions	Currency Unions
Import share (%)	0.427 (1.777)	1.583 (4.672)
RTA	0.071 (0.256)	0.399 (0.490)
IMF	0.801 (0.398)	0.802 (0.398)
OECD	0.039 (0.193)	0.147 (0.355)
WTO	0.519 (0.500)	0.685 (0.464)
ln Distance	8.617 (0.820)	7.411 (0.929)
Contiguity	0.027 (0.163)	0.184 (0.387)
Shared language	0.168 (0.374)	0.719 (0.449)
Common colonizer	0.083 (0.275)	0.563 (0.496)
Colonial relationship	0.013 (0.115)	0.069 (0.253)
Same country	0.010 (0.101)	0.210 (0.407)
Observations	769,384	13,085

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

B   Monte Carlo Analysis

B.1   Analysis of the Two-Step Procedure

When running log-linear gravity regressions in Section 3, we adopted a two-step procedure to estimate heterogeneous currency union effects. In the first step, we predicted the import shares per good. In the second step, we interacted the currency union dummy with the 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

$$\ln(t_{ij,t}) = \kappa CU_{ij,t} + \zeta W_{ij,t} \tag{11}$$

where $W_{ij,t}$ contains all bilateral trade cost variables used in our analysis, 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 IMF, OECD and WTO). We choose values for the trade cost parameters that are derived from our baseline regression in column (2) of Table 1.[48] We then compute trade costs on the basis of equation (11) using the actual observations of our trade cost variables.

We assume that the true data generating process is given by the translog gravity model in Section 2. We choose the translog parameter value as $\theta = 0.073$.[49] Based on equations (1)–(4), 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 $(y_{i,t}, y_{j,t})$ and the trade cost variables underlying equation (11) for 120 origin and destination countries over the period from 1990 to 2013.[50]

Then we include an additive error term in the translog gravity equation (1). We choose its standard deviation to match the R-squared of around 60 percent in our translog regressions as in Table 7.[51] We take the natural logarithm of the simulated import shares, thus dropping non-positive values. We run first-step and second-step regressions as in Section 3, where the import shares predicted in the first step are interacted with the currency union dummy in the

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[48]Assuming an elasticity of substitution of $\sigma = 5$ for the standard log-linear gravity framework as in Anderson and van Wincoop (2003), the κ parameter for the currency union dummy in (11) follows as the estimated coefficient of 0.326 in column (2) of Table 1 divided by $(1-\sigma)$, i.e., $\kappa = 0.326/(1-5) = -0.082$. The parameters for RTA, IMF, OECD and WTO follow analogously as -0.104, -0.041, -0.092 and -0.037, respectively. For distance and contiguity, we run a regression as in (8) based on the observed import shares, with estimated coefficients of -1.411 and 0.805 (both significant at the one percent level). Their parameters in (11) thus follow as 0.353 and -0.201.

[49]In the translog regression in column (1) of Table 7, we obtain a currency union coefficient of 0.006. Assuming the same currency union coefficient as above, it therefore follows $\theta = -0.006/\kappa = 0.073$.

[50]Simulations would in principle also be feasible over a longer period. But to reduce computing time we use a subset of data starting in 1990.

[51]A value of 0.028 for the standard deviation leads to an R-squared of 62 percent.

second step. Standard errors are clustered around country pairs. For simplicity we assume $n_{i,t} = 1$ for all i.[52] We run 100 iterations of this procedure, drawing a new set of error terms for every iteration.

Table B1: Monte Carlo Simulation

	(1)	(2)	(3)
		First step	Second step
CU		–	-1.103^a (0.168)
CU×predicted share		–	-0.363^a (0.049)
RTA		–	0.145^a (0.017)
IMF		–	0.085 (0.162)
OECD		–	0.141^a (0.042)
WTO		–	0.049^c (0.030)
ln Distance		-0.546^a (0.005)	–
Contiguity		0.226^a (0.014)	–
CU estimates	**True**		**Estimated**
Mean	0.278		0.290^a (0.049)
10th percentile	1.262		0.839^a (0.107)
90th percentile	0.080		-0.162^a (0.056)
R-squared		0.307	0.373
Observations		187,468	187,468
Corresponding table, (column)		–	Table 1, (4)

Notes: Exporter-year and importer-year fixed effects are included. Directional country pair fixed effects are further included in (3). The regressions are estimated between 1990 and 2013 based on OLS estimation of a standard log-linear gravity model with the log import share as the dependent variable. But translog gravity is the true underlying data generating process (with the true currency union elasticities reported in the first column). The reported coefficients are averages over the (100) iterations. Robust standard errors clustered at the country pair level. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. "predicted share" is the predicted log import share.

We report the results in Table B1, averaged over all iterations. Analogous to specification (8), the first-step regression in column (2) simply includes distance and a contiguity dummy, and it yields the expected signs. The second-step regression in column (3) includes the currency union dummy and an interaction term with the log predicted import shares, as well as the additional time-varying policy variables. Consistent with column (4) of Table 1, we obtain negative coefficients on both the CU dummy and the interaction term. The middle panel of column (3) reports the implied currency union estimates, evaluated at the mean, the 10th, and the 90th percentiles. We find a mean estimate of 0.290, implying that evaluated at the average

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[52]We also ran specifications with the extensive margin measure as observed in the data based on Comtrade (see Section 3.1.1). The overall results are very similar.

import share, two countries trade 33.6 percent more bilaterally if they are in a currency union. Consistent with translog gravity, we find a larger estimate of 0.839 at the 10th percentile (i.e., for relatively small import shares), implying 131 percent more bilateral trade ceteris paribus. At the 90th percentile (i.e., for relatively large import shares) we find an estimate of -0.162, implying reduced bilateral trade by 15 percent. These estimates can be compared to the true values underlying the simulation indicated in column (1).

Overall, the simulation in Table B1 based on the translog model confirms the validity of our two-step procedure in the sense that qualitatively, it yields the same results as in the underlying true model. Quantitatively, our results are similar for the mean, but they somewhat undershoot the true effect at the 10th and 90th percentiles. Figure 1 visually compares the true values against the estimates across the deciles of (predicted) import shares. 95 percent confidence intervals are indicated in dashed lines. The true values lie within the confidence intervals – except for very small and very large percentiles. The reason for the relatively large deviation between the true and the estimated values at the lowest percentile is the functional form of the translog specification. As equation (5) shows, the translog elasticity is given by the translog preference parameter divided by the import share. This generates a hyperbolic shape such that elasticity values decline rapidly with growing import shares.[53] Our simple interaction term between the currency union dummy and the log predicted import shares struggles to capture the very large effects at small import shares, but it matches the remaining percentiles rather well.

As an additional check, we also investigate the consequences of ignoring the first step altogether by erroneously interacting the currency union dummy with *actual* log import shares (as opposed to predicted log 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. It even turns positive with high significance.[54] The resulting estimates at the mean, 10th and the 90th percentiles follow as -0.436, -1.860 and 0.735 (all significant at the one percent level). Thus, they exhibit the opposite pattern of the true values in Table 8 in that they *rise* with the import share, which is incorrect. This check therefore underlines the importance of predicting shares in the first step.

B.2   Placebo Checks

We also carry out placebo checks that are based on the assumption that the standard log-linear gravity model represents the true underlying data generating process. We construct the import

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[53] Also see the discussion in Section 3.2.

[54] This pattern is also confirmed by our regressions based on observed data. If in equation (9) we interact the currency union dummy with actual import shares per good, the interaction term is positive and significant at the one percent level.

Table B2: Monte Carlo Simulation (Placebo Checks)

	(1)	(2)	(3)
		First step	Second step
CU		–	0.329^a (0.114)
CU×predicted share		–	0.001 (0.019)
RTA		–	0.418^a (0.013)
IMF		–	0.180 (0.150)
OECD		–	0.368^a (0.035)
WTO		–	0.143^a (0.024)
ln Distance		-1.533^a (0.005)	
Contiguity		0.964^a (0.023)	
CU estimates	**True**		**Estimated**
Mean	0.326		0.323^a (0.058)
10th percentile	0.326		0.320^a (0.111)
90th percentile	0.326		0.326^a (0.048)
R-squared		0.811	0.822
Observations		345,600	345,600
Corresponding table (column)		–	Table 1, (4)

Notes: Exporter-year and importer-year fixed effects are included. Directional country pair fixed effects are further included in (3). The regressions are estimated between 1990 and 2013 based on OLS estimation of a standard log-linear gravity model with the log import share as the dependent variable. Standard gravity is the true underlying data generating process (with the true currency union elasticities reported in the first column). The reported coefficients are averages over the (100) iterations. Robust standard errors clustered at the country pair level. ^{a} indicates significance at the one percent level. "predicted share" is the predicted log import share.

shares for the standard gravity model using the relationship

$$\frac{x_{ij,t}}{y_{j,t}} = \frac{y_{i,t}}{y_t^W} \left(\frac{t_{ij,t}}{P_{i,t} P_{j,t}} \right)^{1-\sigma} \tag{12}$$

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

$$P_{i,t}^{1-\sigma} = \sum_{j=1}^{J} P_{j,t}^{\sigma-1} \frac{y_{j,t}}{y_t^W} t_{ji,t}^{1-\sigma} \tag{13}$$

where J is the number of countries in the world. We assume $\sigma = 5$. We use equations (12)–(13) as well as trade cost function (11) 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. We choose the standard deviation of a lognormal

multiplicative error term in order to match the R-squared of 81 percent in our standard gravity regressions (see Table 1). As above, we run first-step and second-step regressions, iterating the procedure 100 times with fresh error terms.

We report the results of the placebo checks in Table B2. The first-step regression in column (2) includes coefficients on distance and contiguity with the expected signs and magnitudes. Most importantly, the second-step regression in column (3) does not exhibit a significant interaction term for the currency union dummy and the log predicted import shares. Therefore, the estimated currency union effects reported in the middle panel do not vary between the mean and 10th and 90th percentiles. Neither are they significantly different from the true effects in column (1).

Overall, the placebo results confirm that if standard gravity were the true underlying model, our two-step framework would not give rise to currency union effects that systematically differ across percentiles. We therefore conclude that it is important to use a gravity model that accommodates variable elasticities to capture the heterogeneous patterns we find in our main regression results.
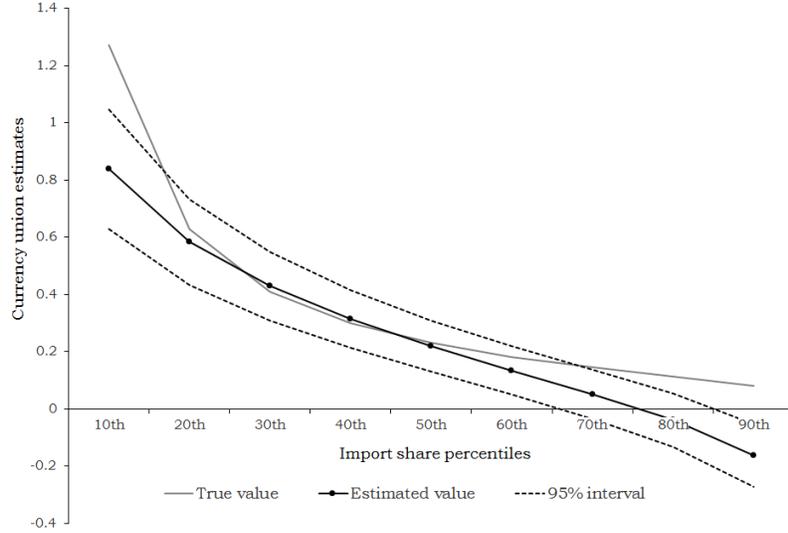
Figure 1: A comparison of true values (in grey) and estimated values (in black, with 95 percent confidence intervals as dashed lines) of currency union estimates, based on Monte Carlo simulation. The values are reported by deciles of import shares, with the first decile denoting the lowest import shares. For example, the estimated value at the first decile (i.e., 10th percentile) is equal to 0.839. This would imply that a currency union at the first decile is associated with an increase in bilateral trade of 131 percent (exp(0.839)-1 = 1.31). See Section B.1 for details.
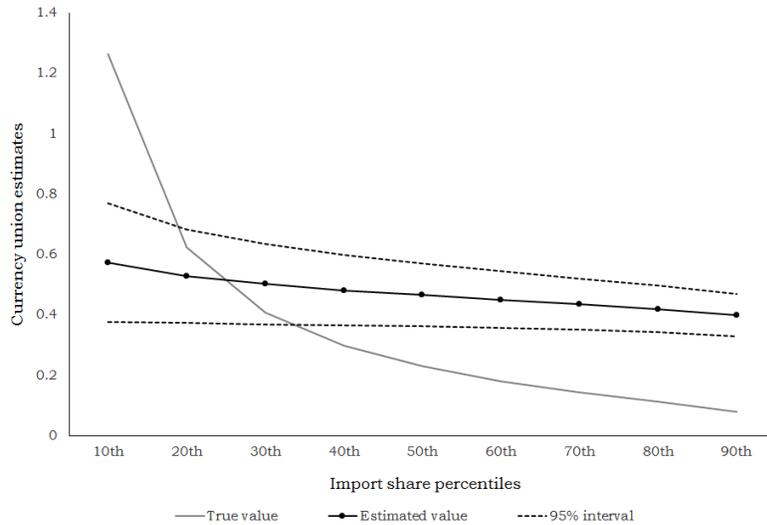
Figure 2: A comparison of true values (in grey) and estimated values (in black, with 95 percent confidence intervals as dashed lines) of currency union estimates subject to positive endogeneity bias, based on Monte Carlo simulation. Endogeneity bias flattens the heterogeneity profile. The values are reported by deciles of import shares, with the first decile denoting the lowest import shares. For example, the estimated value at the first decile (i.e., 10th percentile) is equal to 0.573. This would imply that a currency union at the first decile is associated with an increase in bilateral trade of 77 percent (exp(0.573)-1 = 0.77). See Section 4 for details.

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C   Robustness Appendix

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

	(1)	(2)	(3)
CU	0.352^a (0.081)	-0.161 (0.258)	—
CU×predicted share	—	-0.086^b (0.043)	—
CU (first interval)	—	—	0.602^a (0.161)
CU (second interval)	—	—	0.444^a (0.113)
CU (third interval)	—	—	0.273^a (0.099)
CU (fourth interval)	—	—	0.293^a (0.088)
RTA	0.245^a (0.076)	0.235^a (0.083)	0.232^a (0.076)
IMF	0.305 (0.191)	0.300 (0.227)	0.310 (0.190)
OECD	0.279^b (0.109)	0.271^b (0.117)	0.268^b (0.110)
WTO	0.202^b (0.086)	0.198^b (0.098)	0.198^b (0.086)
CU estimates			
Mean	—	0.509^a (0.124)	—
10th percentile	—	0.815^a (0.257)	—
90th percentile	—	0.214^b (0.102)	—
R-squared	0.904	0.904	0.904
Observations	64,779	64,779	64,779

Notes: Exporter-year, importer-year, and (directional) country pair fixed effects are included. Interval fixed effects are further included in (3). Robust standard errors adjusted for clustering at the (non-directional) country pair-level are reported in parentheses in (1) and (3). Standard errors are bootstrapped in (2). ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good. The sample includes the currency union observations and the non-currency union observations that deviate by no more than a small distance (equal to 0.000001) from the propensity score estimated from a probit regression of the currency union dummy on a number of gravity regressors. "predicted share" is the predicted log import share per good.

Table C2: Robustness: Currency Union Types

	(1)	(2)	(3)
CU multilateral	0.033 (0.117)	0.326^a (0.063)	0.040 (0.117)
CU multilateral×predicted share	−0.053^b (0.021)	−	−0.052^b (0.021)
CU bilateral	0.292^a (0.075)	−0.323 (0.240)	−0.317 (0.241)
CU bilateral×predicted share	−	−0.092^a (0.034)	−0.091^a (0.034)
RTA	0.414^a (0.027)	0.414^a (0.026)	0.413^a (0.026)
IMF	0.165^a (0.052)	0.163^a (0.053)	0.163^a (0.053)
OECD	0.366^a (0.037)	0.364^a (0.037)	0.364^a (0.037)
WTO	0.145^a (0.030)	0.146^a (0.030)	0.145^a (0.030)
CU estimates			
Mean (CU multilateral)	0.469^a (0.095)	−	0.469^a (0.095)
10th percentile (CU multilateral)	0.643^a (0.156)	−	0.641^a (0.156)
90th percentile (CU multilateral)	0.296^a (0.060)	−	0.299^a (0.060)
Mean (CU bilateral)	−	0.437^a (0.094)	0.435^a (0.094)
10th percentile (CU bilateral)	−	0.741^a (0.182)	0.735^a (0.183)
90th percentile (CU bilateral)	−	0.136 (0.097)	0.137 (0.097)
R-squared	0.808	0.808	0.808
Observations	780,818	780,818	780,818

Notes: 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. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good. "predicted share" is the predicted log import share per good.

Table C3: Robustness: Currency Union Entry and Exit

	(1)	(2)
CU entry	0.442^a (0.103)	–
CU entry×predicted share	0.023 (0.020)	–
CU non EURO entry	–	−0.435 (0.590)
CU non EURO entry×predicted share	–	−0.054 (0.074)
EURO entry	–	$−0.198^b$ (0.099)
EURO entry×predicted share	–	$−0.044^b$ (0.020)
CU exit	−0.405 (0.249)	−0.311 (0.265)
CU exit×predicted share	$−0.098^a$ (0.033)	$−0.087^b$ (0.038)
CU continuous×predicted share	$−0.317^a$ (0.075)	$−0.307^a$ (0.072)
Trend EU countries	–	0.028^a (0.003)
CU estimates		
Mean (CU entry)	0.254^a (0.096)	–
10th percentile (CU entry)	0.178 (0.155)	–
90th percentile (CU entry)	0.328^a (0.057)	–
Mean (CU non EURO entry)	–	0.009 (0.216)
10th percentile (CU non EURO entry)	–	0.187 (0.361)
90th percentile (CU non EURO entry)	–	−0.167 (0.280)
Mean (EURO entry)	–	0.163 (0.110)
10th percentile (EURO entry)	–	0.308^c (0.168)
90th percentile (EURO entry)	–	0.021 (0.069)
Mean (CU exit)	0.399^a (0.088)	0.405^a (0.095)
10th percentile (CU exit)	0.721^a (0.168)	0.691^a (0.200)
90th percentile (CU exit)	0.081 (0.106)	0.122 (0.098)
R-squared	0.808	0.808
Observations	780,818	780,818

Notes: 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. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good. "predicted share" is the predicted log import share per good. Dummy variables for RTAs, IMF, OECD, and WTO memberships are included but not reported.

Table C4: Robustness: Import Shares

	(1)	(2)	(3)	(4)	(5)
CU	0.053 (0.109)	0.080 (0.086)	0.029 (0.102)	-0.671^c (0.346)	-0.344 (0.266)
CU×predicted share	-0.069^a (0.021)	-0.097^a (0.022)	-0.045^a (0.015)	-0.149^b (0.064)	-0.135^b (0.057)
RTA	0.396^a (0.024)	0.388^a (0.023)	0.412^a (0.021)	0.199^a (0.068)	0.153^a (0.056)
IMF	0.170^b (0.066)	0.262^a (0.059)	0.158^a (0.061)	-0.108 (0.536)	-0.118 (0.468)
OECD	0.311^a (0.049)	0.395^a (0.043)	0.370^a (0.047)	0.290^b (0.142)	0.395^a (0.139)
WTO	0.107^a (0.032)	0.141^a (0.028)	0.142^a (0.031)	0.419 (0.268)	0.439^c (0.265)
CU estimates					
Mean	0.524^a (0.076)	0.574^a (0.069)	0.428^a (0.065)	0.612^a (0.235)	0.625^a (0.173)
10th percentile	0.699^a (0.119)	0.817^a (0.112)	0.601^a (0.113)	1.253^b (0.504)	1.211^a (0.409)
90th percentile	0.345^a (0.056)	0.302^a (0.056)	0.263^a (0.049)	-0.119 (0.128)	-0.034 (0.147)
Exporter extensive margin	HK (2005)	GDP	Unity	Comtrade	Comtrade
Importer output	GDP	GDP	GDP	Total output	Manuf. output
R-squared	0.771	0.769	0.840	0.921	0.917
Observations	623,141	760,883	795,189	73,480	89,040

Notes: 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. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good. "predicted share" is the predicted log import share per good. In (1), HK (2005) stands for Hummels and Klenow (2005).

Table C5: Robustness: Specifications

	(1)	(2)	(3)	(4)	(5)	(6)
Lagged dep. var.	–	–	0.555^a (0.003)	–	–	–
CU	-0.010 (0.119)	-0.231^c (0.134)	-0.013 (0.056)	-0.058^b (0.026)	-0.453^a (0.113)	-0.044 (0.109)
CU×predicted share	-0.059^a (0.019)	-0.093^a (0.022)	-0.030^a (0.009)	-0.010^b (0.005)	-0.103^a (0.017)	-0.052^a (0.017)
RTA	0.413^a (0.027)	0.413^a (0.025)	0.189^a (0.011)	0.021^a (0.005)	0.393^a (0.026)	0.412^a (0.026)
IMF	0.164^a (0.059)	0.164^a (0.057)	0.077^b (0.032)	0.007 (0.011)	0.173^a (0.052)	0.165^a (0.053)
OECD	0.365^a (0.045)	0.366^a (0.052)	0.217^a (0.021)	0.017^b (0.007)	0.337^a (0.037)	0.366^a (0.037)
WTO	0.144^a (0.032)	0.144^a (0.031)	0.045^b (0.018)	-0.010 (0.009)	0.158^a (0.030)	0.145^a (0.030)
Trend EU countries	–	–	–	–	0.028^a (0.003)	–
Trend CU pairs	–	–	–	–	–	0.005 (0.004)
CU estimates						
Mean	0.473^a (0.076)	0.532^a (0.075)	0.224^a (0.033)	0.022 (0.017)	0.391^a (0.070)	0.384^a (0.091)
10th percentile	0.668^a (0.128)	0.892^a (0.152)	0.319^a (0.056)	0.054^c (0.030)	0.729^a (0.112)	0.555^a (0.132)
90th percentile	0.281^a (0.058)	0.202^a (0.052)	0.131^a (0.025)	-0.009 (0.010)	0.057 (0.058)	0.214^a (0.071)
Dependent variable	Log	Log	Log	Log-diff.	Log	Log
First-step pair controls	Gravity	Pair FE	Dist/Contig	Dist/Contig	Dist/Contig	Dist/Contig
R-squared	0.808	0.808	0.879	0.083	0.808	0.808
Observations	780,818	780,818	702,693	702,693	780,818	780,818

Notes: 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. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten percent levels, respectively. The dependent variable is the log import share per good in all columns but the log-difference of the import share per good in (4). "predicted share" is the predicted log import share per good.

Table C6: Robustness: Samples

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8
CU	−0.165 (0.144)	−0.075 (0.117)	0.102 (0.119)	−0.043 (0.125)	0.014 (0.129)	0.129 (0.118)	0.062 (0.117)	− (
CU×predicted share	−0.069^a (0.021)	−0.065^a (0.018)	−0.038^c (0.023)	−0.072^a (0.022)	−0.057^a (0.021)	−0.042^b (0.019)	−0.047^a (0.018)	− (
RTA	0.505^a (0.027)	0.361^a (0.027)	0.033 (0.024)	0.403^a (0.026)	0.419^a (0.025)	0.353^a (0.026)	0.339^a (0.026)	0. (
IMF	0.165^a (0.051)	0.171 (0.128)	0.319 (0.804)	0.095 (0.075)	0.216^a (0.059)	0.226^a (0.063)	0.216^a (0.067)	0. (
OECD	0.193^a (0.045)	0.250^a (0.050)	0.445^a (0.045)	0.421^a (0.045)	0.347^a (0.040)	0.412^a (0.045)	0.410^a (0.043)	0. (
WTO	0.133^a (0.031)	0.100^b (0.043)	0.343^a (0.066)	0.186^a (0.048)	0.143^a (0.034)	0.151^a (0.034)	0.151^a (0.034)	0. (
CU estimates								
Mean	0.402^a (0.071)	0.480^a (0.073)	0.383^a (0.080)	0.548^a (0.094)	0.482^a (0.076)	0.462^a (0.067)	0.433^a (0.068)	0. (
10th percentile	0.624^a (0.123)	0.707^a (0.122)	0.500^a (0.140)	0.785^a (0.157)	0.670^a (0.131)	0.591^a (0.113)	0.577^a (0.110)	0. (
90th percentile	0.182^a (0.063)	0.254^a (0.057)	0.271^a (0.053)	0.313^a (0.060)	0.296^a (0.058)	0.332^a (0.053)	0.288^a (0.058)	0. (
Sample	Head et al. (2010)	IMF DOTS	Balanced 1994–2013	5-year intervals	Excl. islands	Excl. small countries	Excl. poor countries	Si co
R-squared	0.815	0.832	0.887	0.824	0.808	0.806	0.811	0.
Observations	644,439	607,218	237,340	158,281	695,467	651,305	609,695	17

Notes: Exporter-year, importer-year, and (directional) country pair fixed effects are included. Bootstrapped standard errors ad
the (non-directional) country pair-level are reported in parentheses. ^{a}, ^{b}, and ^{c} indicate significance at the one, five, and ten per
The dependent variable is the log import share per good. "predicted share" is the predicted log import share per good.

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