The Effect of the Euro on the Bilateral Trade Distribution

Erik Figueiredo[a] Luiz Renato Lima[a,b*], Georg Schaur[b]
[a] Federal University of Paraiba, Brazil
[b] Department of Economics, University of Tennessee at Knoxville, TN, USA

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Abstract

This paper investigates whether the introduction of the Euro has affected trade. Contrary to the existing literature and motivated by recent development in trade theory, we apply quantile regressions for panel data to examine the effect of the Euro at moments other than the conditional mean of the trade flow distribution. Our results show that even with this more general approach the Euro's effect on trade remains bleak.

Keywords: Euro Zone, Identification of Gravity Equations, Quantile Estimation, Bilateral Trade
JEL Codes: F1, C1

*Correspondence to: Luiz Renato Lima, Department of Economics, University of Tennessee at Knoxville, 527A Stokely Management Center, TN, 37996-0550, USA. Phone: (865) 974-1698. Fax: (865) 974-4601. E-mail: llima@utk.edu. We thank two anonymous reviewers and the editor for helpful comments and suggestions.

1 Introduction

Currency unions eliminate exchange rate risk, reduce trade costs and deliver clear advantages for firms operating on international markets. Therefore, it is no surprise that a series of papers by Andrew Rose (Rose, 2000; Rose, 2001; Rose and van Wincoop 2001) on the effects of common currencies on international trade sparked extensive research on the effects of common currencies and the introduction of the Euro on internal trade. Initial estimates showed positive trade effects (e.g. Micco et al, 2003; Bun and Klaasen, 2002, 2007), but the conclusion is currently bleak. Santos Silva and Tenreyro (2010a, 2010b) ask if the Euro increases trade? Their answer is firm: No. This result is disappointing given the potential costs of currency unions. Currency unions sacrifice monetary policy independence and flexible exchange rates as adjustment mechanisms to asymmetric shocks that result in price and unit labor cost heterogeneity (Krugman, 2012; Mundell 1961).

In this paper we examine the Euro's trade effect and asymmetry in trade shocks in one combined empirical framework. We apply a panel data quantile regression estimation technique which has several identification advantages. First, quantile regression estimation of log-linear models is robust with respect to heteroskedasticity bias (Santos Silva and Tenreyro, 2006; Figueiredo et al., 2014). Second, quantile estimation identifies the effect of the Euro across the entire trade flow distribution. Consider a set of countries that are similar in characteristics that predict bilateral trade. Within that group of countries, the quantile estimator identifies if the least integrated trade relationships gain relative to the most integrated trade relationships.

Given recent evidence that fails to identify an effect of the Euro on the mean of trade (e.g. Havránek, 2010; Anderton et al., 2002; Berger and Nitsch, 2008; Campbell 2013; Santos Silva and Tenreyro, 2010a), the proposed methodology allows us to examine if the benefits of the Euro appear mostly in the lower or upper tails of the trade flow distribution and if it affects equality among trade relationships between member countries. There are several reasons why we may expect that the Euro does not have a symmetric effect across the entire trade flow distribution. Spearot (2007) uses a model with linear demands based on Melitz and Ottaviano (2008) to show that the elasticity of trade with respect to a tariff liberalization depends on the level of trade itself. Based on this intuition, a decrease in exchange rate uncertainty and policy barriers will translate into lower trade costs, but the elasticity that translates the cost reduction into a trade response varies across the trade flow distribution. Similarly, Santos Silva and Tenreyro (2010b) anticipate heterogeneity with larger trade effects for economies that "were not so deeply integrated before joining the Euro." Finally, Handley and Limao (2015) provide firm level evidence that the currency union reduced uncertainty in trade policy and led to entry in the previously less integrated economies of the Euro area.

Investigating the asymmetric effect of the Euro may also be important to the literature of optimal size of currency unions. Indeed, the optimal size of a currency union depends on the pattern of shocks across its members (Mundell, 1961) and empirical researchers examine correlation patterns across countries to detect asymmetry in economic shocks (e.g. Bayoumi and Eichengreen, 1993, 1997) and the effect of currency unions on the asymmetry of shocks (e.g. Alesina et al., 2002; Barro and Tenreyro, 2007; Frankel and Rose, 1998; Rose 2008). If asymmetric shocks affect trade flows then we expect that automatic adjustment mechanisms such as flexible exchange rates mitigate relative shocks. If currency unions eliminate this adjustment, then we expect that currency unions increases the dispersion in the bilateral trade flow distribution. On the other hand, if currency unions lead to more equality in the fundamental shocks, then currency unions may lead to less dispersion in the trade flow distribution. We provide an empirical framework that is able to identify such relationships based on a theoretically consistent gravity model.

We find that the Euro has no significant effect on the central tendency nor the quantiles of the bilateral trade flow distribution at conventional significance levels. A substantial amount of research shows that the impact of common currencies on trade was much smaller than initially reported by Rose's estimates. Subsequent studies, i.e., Micco et al. (2003), Flam and Nordström (2003, 2006), Barr et al. (2003), Bun and Klaasen (2002, 2007), Baldwin et al. (2005), Baldwin (2006) and Baldwin and Taglioni (2006) found evidence of a Rose effect for the Eurozone. Anderton et al. (2002) and Berger and Nitsch (2008) find no direct evidence of a Rose effect on the Eurozone. The literature's reliance on gravity estimation and the differences in existing conclusions led Santos Silva and Tenreyro (2010a) to report that the Euro effect on the conditional mean of trade is negligible. By taking a deeper look at the Euro effect, our results extend the conclusion of Santos Silva and Tenreyro (2010a) to the entire trade flow distribution.

This is paper is organized as follows. Section 2 discusses the econometric modeling and data. Section 3 discusses the estimation results. Section 4 concludes.

2 Econometric Modeling and Data

2.1 Specification and Identification

We consider the following double-indexed exponential model studied by Santos Silva and Tenreyro (2006)

$$f_{ij} = \exp(x_{ij}\beta)\eta_{ij}, \tag{1}$$

where, in this paper, f_{ij} are the exports from country i to country j, x_{ij} represents the explanatory variables, β is a vector of parameters and, η_{ij} is a non-negative random variable. In the presence of positive observations of f_{ij}, we can linearize the model by taking logarithms of both sides of the equation to obtain

$$\ln f_{ij} = x_{ij}\beta + \ln \eta_{ij}, \tag{2}$$

where $\ln f_{ij}$ is now defined on the real line $\mathbb{R}$.

Heteroskedasticity can be included in this model by assuming that $\eta_{ij} = \exp\left[\left(x_{ij}\gamma\right)\varepsilon_{ij}\right]$, where ε_{ij} is i.i.d.. In this case, the above model becomes

$$\ln f_{ij} = x_{ij}\beta + \left(x_{ij}\gamma\right)\varepsilon_{ij}. \tag{3}$$

This is a location-scale or linear heteroskedasticity model, in which the covariates x_{ij} affect not only the location (mean) of the conditional distribution of $\ln f_{ij}$, but also its scale and quantiles through $\left(x_{ij}\gamma\right)$. Model (3) has a long-time tradition in statistics and has been studied by Gutenbrunner and Jurečková (1992) and Koenker and Zhao (1994) among others.

Santos Silva and Tenreyro (2006) [hereafter SST (2006)] show that if $E\left(\eta_{ij}|x\right) = 1$ and $\gamma \neq 0$ (meaning that there exists heteroskedasticity), then estimating model (3) by OLS yields an inconsistent estimator of β. To address this problem, we can estimate the log-linear model by using quantile regression. This idea relies on the fact that, unlike the mean function, the quantile function is invariant to monotone transformations. In other words, if $h(\cdot)$ is a nondecreasing function on $\mathbb{R}$, then for any random variable Y, $Q_\tau(h(Y)) = h\left(Q_\tau(Y)\right)$,where $Q_\tau(\cdot)$ is the $\tau - th$ quantile function. Based on this property, a quantile regression estimation of the log-linear model is not subject to the Jensen's inequality issue that affects OLS estimation of log-linear models in the presence of heteroskedasticity.

In particular, we consider the following extension of the exponential model

$$\begin{aligned} f_{ij} &= \exp\left(x_{ij}\beta\right)\eta_{ij} \\ \eta_{ij} &= \exp\left[\left(x_{ij}\gamma\right)\varepsilon_{ij}\right] \\ \varepsilon_{ij} &\sim i.i.d.F_{\varepsilon}(0,1) \end{aligned} \tag{4}$$

where $F_{\varepsilon}(\cdot)$ is an unknown distribution function of ε_{ij} and $F_{\varepsilon}^{-1}(\tau) = Q_{\tau}(\varepsilon)$, the $\tau - th$ quantile of ε_{ij}, $\tau \in (0,1)$. From the equivariance property of quantiles, the conditional quantile of f_{ij} (and of $\ln\left(f_{ij}\right)$) can now be defined as

$$\begin{aligned} Q_{\tau}\left(f_{ij}|x_{ij}\right) &= \exp\left[x_{ij}\beta(\tau)\right] \\ Q_{\tau}\left(\ln(f_{ij})|x_{ij}\right) &= x_{ij}\beta(\tau) \\ \beta(\tau) &= \beta + \gamma \cdot Q_{\tau}(\varepsilon) \end{aligned} \tag{5}$$

Notice that $Q_{\tau}\left(f_{ij}|x_{ij}\right)$ can be obtained from the estimates of the log-linear quantile regression. In other words, $Q_{\tau}\left(f_{ij}|x_{ij}\right) = \exp\left[Q_{\tau}\left(\ln(f_{ij})|x_{ij}\right)\right] = \exp\left[x_{ij}\beta(\tau)\right]$.[1]

In model (5), $\beta = \left(\beta_0, \beta_1, ...\beta_k\right)'$ and $\gamma = \left(\gamma_0, \gamma_1, ...\gamma_k\right)'$ are $k \times 1$ parameter vectors, x_i is a $1 \times k$ vector of covariates that includes "1" as its first element. Notice that both models are indexed by the same parameter vector $\theta = \left(\beta', \gamma'\right)'$ and that homoskedasticity occurs when $\gamma_1 = ... = \gamma_k = 0$. Under homoskedasticity, the OLS estimator consistently estimates β. The quantile regression parameters are given by $\beta(\tau) = \left(\beta_0(\tau), \beta_1(\tau), ...\beta_k(\tau)\right)'$ where $\beta_j(\tau) = \beta_j + \gamma_j \times Q_{\tau}(\varepsilon)$, $j = 0, ..., k$. Under *homoskedasticity* the quantile regression estimator developed by Koenker and Basset (1978) $\widehat{\beta}(\tau)$ converges to $\beta(\tau) = \left(\beta_0(\tau), \beta_1, ...\beta_k\right)$ and therefore the quantile estimator and the OLS estimator identify the same *slope* coefficients,

[1] This is not true for the conditional mean.

but different intercepts, under homoskedasticity.

Now consider the most general case in which we have heteroskedasticity $\gamma_s \neq 0$, $s = 1, ..., k$. As shown by Santos Silva and Tenreyro (2006), the OLS estimator is inconsistent and does not identify the vector β, but the PPML estimator, $\widehat{\beta}_{PPML}$, is consistent for β if $E[\eta_{ij}|x] = 1$. Without further assumptions on the conditional quantiles of ε_{ij}, $Q_\tau(\varepsilon)$, the quantile regression estimator $\widehat{\beta}(\tau)$ will not identify the slope coefficients $\beta_1, ...\beta_k$ since $\beta_s(\tau) = \beta_s + \gamma_s \times Q_\tau(\varepsilon) \neq \beta_s$, $s = 1, ..., k$. This is intuitive because quantile regression is designed to capture the effect of heteroskedasticity on the slope coefficients. Thus, under hetoreskedasticity, $\widehat{\beta}_{OLS}$, $\widehat{\beta}_{PPML}$ and $\widehat{\beta}(\tau)$ are, in general, not identifying the same parameter vector.[2]

Under the additional assumption that the median of ε_{ij} is equal to zero, i.e. $Q_{0.5}(\varepsilon) = Median(\varepsilon) = 0$, the median estimator, $\widehat{\beta}(0.5)$, can identify the parameter vector β. Recall that the median and mean are both measures of central tendency of a random variable, but the mean is much more sensitive to outliers than the median. In this sense, one might prefer estimating $Median\left(f_{ij}|x_{ij}\right) = Q_{0.5}\left(f_{ij}|x_{ij}\right)$ rather than $E\left(f_{ij}|x_{ij}\right)$. The idea of using the median estimator to identify the parameter vector β is not new in the literature. Indeed, it was suggested by Santos Silva and Tenreyro (2006) in their footnote 6:

> "Notice that if $\exp(x\beta)$ is interpreted as describing the conditional median of y_i (or some other conditional quantile) rather than the conditional expectation, estimates of the elasticities of interest can be obtained estimating the log linear model using the appropriate quantile regression estimator (Koenker and Basset, 1978). However, interpreting $\exp(x\beta)$ as a conditional median is problematic when y_i has a large mass of zero observations, as in trade data. Indeed, in this case the conditional median of y_i will be a discontinuous function of the regressors, which is generally not compatible with standard economic theory."

[2] We thank an anonymous referee for this useful comment.

Since the trade data of European Union countries used in this paper do not have a large mass of zero observations, the second part of the above footnote does not apply to the empirical problem considered here. Thus, we can use quantile regression for panel data developed by Koenker (2004) and Kato et al. (2012) to study the Euro's effect on the entire distribution of trade by estimating $\beta(\tau)$ for $\tau \in (0,1)$.

Notice that Model (2) is a panel data model through its use of double-indexed data (see Baltagi, Egger, and Pfaffermayr, 2015). Clearly, with the repeated observation of country-pairs' trade flows over time, the model involves triple-indexed data. Using t to denote a time index,we obtain the following conditional quantiles of $\ln\left(f_{ijt}\right)$

$$Q_{\tau}\left[\ln\left(f_{ijt}\right)|x_{ijt},\alpha_{ij},\alpha_{it,}\alpha_{jt}\right]=\alpha_{ij}(\tau)+\alpha_{it}(\tau)+\alpha_{jt}(\tau)+x_{ijt}\beta(\tau) \tag{6}$$

where $\beta(\tau)$ is a vector of structural parameters that measures the effect of x_{ijt} on the $\tau - th$ conditional quantile of $\ln\left(f_{ijt}\right)$, $\alpha_{it}(\tau)$ and $\alpha_{jt}(\tau)$ are the quantile coefficients on exporter by year and importer by year dummies used to capture the multilateral resistance terms (MRT) and $\alpha_{ij}(\tau)$ are the quantile coefficients on dummies representing the country pair fixed effects used to capture potential endogeneity in some elements of x_{ijt}.

Based on standard trade theory (Anderson and van Wincoop, 2003), we follow the same model specification as in Santos Silva and Tenreyro (2010a). Specifically, they suggest comparing trade flows among countries in the treatment group, the so-called Euro-12 (Austria, Belgium-Luxembourg, Finland, France, Germany, Greece, Ireland, Italy, The Netherlands, Portugal and Spain) with other groups of trading partners (the control groups). They considered three control groups. The first one, called EU15, included Denmark, Sweden, and the United Kingdom. The second one expands the set of countries by adding three other members of the European Economic area, that is, Iceland, Norway, and Switzerland. This control group is called EEA and, according to Santos Silva and Tenreyro (2010a), it represents the best compromise between comparability with the treatment group and sample size. The third group (labeled OECD93) includes five additional countries that were members of the Organization for Economic Co-operation and Development (OECD) in 1993: Australia, Canada, Japan, New Zealand, and the United States. Hence, our quantile regression takes on the following form

$$
\begin{aligned}
Q_\tau\left[ln(f_{ijt})|x_{ijt},\alpha_{it,}\alpha_{jt}\right] &= \beta_0(\tau)+\beta_1(\tau)ln(\text{dist}_{ij})+\beta_2(\tau)\text{CU}_{ijt} \\
&\quad +\beta_3(\tau)\text{Euro12}_{ijt}+\beta_4(\tau)\text{Contiguity}_{ij}+\beta_5(\tau)\text{Language}_{ij} \\
&\quad +\beta_6(\tau)\text{Colonial}_{ij}+\alpha_{it}(\tau)+\alpha_{jt}(\tau),
\end{aligned}
\tag{7}
$$

The variables of interest is an indicator on currency union membership (CU). In addition we account for whether the trade partners are contiguous, share a common language, have colonial ties and importer-by-year as well as exporter-by-year indicators to absorb multilateral resistance terms. When applicable, we also include an indicator that equals one if the trade partners are in a regional trade agreement (RTA).[3] This makes interpretation of the specifications and the effect of currency unions straight forward. For any quantile of interest, the empirical model (7) is a quantile generalization of the mean model studied by SST (2010). The $Euro12$ indicator captures differences between a control group (which we select according to Santos Silva and Tenreyro 2010a) and the Euro12 countries. The currency union indicator then identifies systematic differences in the dependent variables before and after the introduction of the Euro. Consistent with most of the existing literature, we assume that Euro membership is exogenous since Baier and Bergstrand's (2007) paper indicates that the endogeneity bias is not too large when conditioning on multilateral trade costs (multilateral resistance terms). Therefore, suppose we are interested in the effect of

[3] A RTA dummy is not included in the regressions with EEA and EU15 because all the countries in these groups already share a RTA. The regression with OECD countries includes a RTA dummy because not all OECD countries share a RTA and therefore there will be enough variation in the dummy variable representing a RTA.

the Euro on the 25th percentile of the trade flow distribution, then, the quantile regression estimate $\widehat{\beta}_2(0.25)$ identifies such an effect.

An identification concern related to the multilateral resistance terms is worth discussing. Our specification accounts for multilateral resistance using a large set of fixed effects. Quantiles are non-linear operators which raises incidental parameter concerns. Kato et al. (2012) addresses the issue of incidental parameters in quantile regression with panel data by allowing for large N, large T asymptotics. Nevertheless, their Monte-Carlo simulations show that a good approximation of the asymptotic distribution is already obtained when T=10, which is easily satisfied in our database since we have T=14.[4]

2.2 Data

The data on exports used in this paper are from the International Monetary Fund's Direction of Trade Statistics.[5] This is the same data as in Santos Silva and Tenreyro (2010a). Given the break in the methodology used to compute trade statistics in Europe, we consider a sample that runs from 1993 to 2007.

Our specification compares trade flows among countries in the treatment group, the so-called Euro-12 (Austria, Belgium-Luxembourg, Finland, France, Germany, Greece, Ireland, Italy, The Netherlands, Portugal and Spain) with other groups of trading partners (the control groups). Santos Silva and Tenreyro consider three control groups described in the previous section. The advantage of the control group EU15 is that it includes countries that are most similar to the Euro 12. The second group EEA represents the best compromise between comparability with the treatment group and sample size, and the third control group called OECD93 maximizes the sample size, but adds noise in terms of comparability to the Euro-12. In this sample we observe exports except for two pairs of countries (2 missing observations)

[4]For cross-sectional data, the asymptotic theory for quantile regression under an increasing number of regressors has been studied by He and Shao (2000) and Belloni et al. (2011).

[5]We thank Silvana Tenreyro for sharing this data with us.

and therefore we drop them. Table 1 reports the summary statistics.

3 Results

Tables 2, 3 and 4 report the Euro effect on trade across quantiles $\tau \in (0.10; 0.25; 0.50; 0.75; 0.90)$ taking OECD93, EEA and EU15 as control groups, respectively.[6] Since the median is also a measure of central tendency, we can interpret the effect at the conditional median as a robust version of the Euro's effect at the conditional mean obtained elsewhere in the literature.

Our estimates for the currency union effect is significant only on the EEA sample, albeit negative. This suggests that at the median, if anything, the common currency reduced trade. This finding is similar to the one obtained by Santos Silva and Tenreyro (2010) that used the PPML estimator to compute the Euro's effect at the conditional mean of trade. This reinforces the suggestion of Santos Silva and Tenreyro (2006) that, in the absence of zeros, the median (quantile) estimator could be used to obtain robust estimates of the gravity model. The other coefficient estimates are as expected. Members of the Euro-12 group trade more at the median. Contiguity and common language have a positive and significant effect on trade across all samples. Colonial ties have a positive and significant effect only in the larger OECD sample. This is likely due to the lack of variation in this indicator in the smaller samples. Similarly, regional trade agreements have a positive and significant effect. Consistent with Santos Silva and Tenreyro (2010a), Table 5 breaks distance into categories and examine the effect of these discrete distance measure on trade. As is standard in the literature, the coefficients indicate that countries separated by longer distances trade less with each other.

The decision of analyzing the Euro's effect at quantiles other than the median is supported by recent research in the trade literature where larger trade effects of the Euro could

[6] All tables we discuss in this section report estimates obtained using the quantile regression estimator. The standard errors are clustered and robust with respect to heteroskedasticity and serial correlation (Santos Silva and Parente, forthcoming).

be found for economies that were not so deeply integrated before joining the Euro (Santos Silva and Tenreyro, 2010b) or by the evidence that a currency union reduces uncertainty in trade policy and leads to entry in the previously less integrated economies of the Euro area (Handley and Limao, 2015). If this is true, then the Euro's effect would have been stronger at the low quantiles of the trade distribution, contributing to reduce trade inequality. This conjecture can be tested by estimating the coefficient on CU across different quantile levels τ and, for this reason, quantile regression may represent an important methodological innovation to the empirical trade literature.

To save space, we only report on Tables 2, 3 and 4 the results for the specification with the log of distance instead of breaking distance into several categories. The results are qualitatively the same. Across all three samples, our quantile regression estimates suggest that the Euro's effect on the trade flow distribution is essentially zero. There are a few exceptions. In the EEA sample reported in Table 3, the currency union has a negative and significant effect at the 25th and 50th percentiles. The coefficients are not statistically different from zero at the other percentiles. In the EU15 sample reported in Table 4, the currency union has a positive and significant effect at the highest quantiles.

With these results in mind, the question is whether the inconsistent non-effects of the currency union are driven by sampling issues, specification issues, or, potentially our estimator. To answer this question it is useful to examine the coefficients on the other variables. Table 2, 3 and 4 show that the Euro-12 indicator is positive and significant for the three samples, similar as in Santos Silva and Tenreyro (2010a). We identify positive and significant effects for common language and contiguity in all samples. Consistent with the literature (Head et al, 2010), but contrary to Santos Silva and Tenreyro (2010a), we identify significant effects of colonial ties in the sample that allows for a sufficient amount of variation. These results are consistent across samples and at most of the quantiles.

Table 2 shows that regional trade agreements have a positive effect with the highest elasticity at the low end of the trade flow distribution. This result is in the spirit of Spearot (2013) who provides evidence that low volume varieties have the greatest elasticity with respect to tariff liberalization, sometimes at the cost of high value varieties. Tables 2, 3 and 4 show that the effect of distance is negative and significant, with the strongest effect at the high end of the distribution. This implies that trade costs approximated by geographic proximity especially affect the high end of the trade flow distribution. This could be the case because at the high end of the distribution countries trade products that are especially sensitive to trade delays due to long distances, or, uncertainty in the supply chain correlated with geographic proximity such as with trade in intermediate inputs (Hummels and Schaur, 2013).

We conclude that our regressions and samples perform well with respect to identifying gravity models. Therefore, the result that the Euro does not effect bilateral trade in a conclusive way is not likely driven by our estimation approach or samples of interest. The Euro may have had an effect on small countries and for particular products such as reported in Handley and Limao (2015), or research papers that examine the extensive margin of trade (Baldwin and Di Nino, 2006; Flam and Nordström, 2006, Berthou and Fontagnè, 2008). Our results indicate that these effects are not strong enough to drive significant changes in the aggregate trade flow distribution. Therefore, we extend Santos Silva and Tenreyro's (2010a, 2010b) pessimism of the Euro effect to the entire trade flow distribution.

4 Concluding Remarks

The existing literature gives conflicting evidence on the effect of the Euro on bilateral trade. Various estimation procedures may disagree about the Euro effect for several reasons. The most common concern is that necessary identification assumptions may be too restrictive. In addition, the effect of the Euro may be heterogeneous across the bilateral trade flow distribution and affect small trade relationships differently than high volume trade relationships.

Contrary to the existing literature that attempts to identify the Euro's effect on the conditional mean of trade, this paper takes into account recent trade theory that suggests that the Euro's effect might reside at other moments (quantiles) of the trade distribution. Indeed, Santos Silva and Tenreyro (2010b) suggested that larger trade effects of the Euro could be found for economies that were not so deeply integrated before joining the Euro, whereas Handley and Limao (2015) argued that as the currency union reduces uncertainty in trade policy it leads to entry in the previously less integrated economies of the Euro area, contributing to reduce trade inequality by affecting more strongly the low quantiles of the trade distribution. This paper took this result as a motivation to introduce quantile regression analysis to the empirical trade literature.

Consistent with some of the existing evidence we do not find a statistically significant effect of the Euro on the central tendency (median) of the bilateral trade flow distribution (e.g. Havránek, 2010; Anderton et al., 2002; Berger and Nitsch, 2008; Campbell 2013; Santos Silva and Tenreyro, 2010a). Furthermore, based on our estimates, there is no clear evidence that suggests that the Euro increases trade at any other point on the trade flow distribution. Consequently, applying a more general estimation approach and allowing for heterogeneity of the Euro effect across the trade flow distribution, the effect of the Euro on trade remains bleak.

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Table 1: Descriptive Statistics

	Mean	SD	Min	Max
Exports	6.63e+09	1.80e+10	121,562	3.32e+11
Currency Union	0.142	0.349	0	1
Log of Distance	8.010	1.136	5.398	9.894
Contiguity	0.086	0.281	0	1
Common-language	0.116	0.321	0	1
Colonial-tie	0.064	0.246	0	1
RTA	0.480	0.463	0	1

Table 2: Gravity Equation: Euro's Effect Across Quantiles – OECD93

	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
Currency Union	-0.024	-0.081	-0.051	-0.098	0.009
	(0.079)	(0.081)	(0.065)	(0.081)	(0.073)
Euro-12	0.266^a	0.361^a	0.364^a	0.484^a	0.554^a
	(0.056)	(0.067)	(0.049)	(0.065)	(0.052)
Log of Distance	-0.849^a	-0.903^a	-0.881^a	-1.048^a	-1.068^a
	(0.035)	(0.029)	(0.025)	(0.031)	(0.029)
Contiguity	0.078	0.026	0.120^b	0.145^a	0.180^a
	(0.050)	(0.048)	(0.057)	(0.042)	(0.040)
Common-language	0.161^b	0.314^a	0.272^a	0.192^a	0.129^a
	(0.079)	(0.055)	(0.055)	(0.047)	(0.052)
Colonial-tie	0.719	0.388^a	0.310^a	0.339^a	0.379^a
	(0.086)	(0.073)	(0.064)	(0.074)	(0.074)
RTA	0.193^a	0.175^a	0.177^a	0.166^a	0.109^a
	(0.032)	(0.026)	(0.022)	(0.023)	(0.026)
MRT	yes	yes	yes	yes	yes
R^2	0.912	0.928	0.933	0.927	0.917
Sample	6,928	6,928	6,928	6,928	6,928

Notes: (^{a}), (^{b}) and (^{c}) denote statistical significance at 1%, 5% and 10%, respectively. Standard errors in parentheses.

Table 3: Gravity Equation: Euro's Effect Across Quantiles – EEA

	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
Currency Union	-0.138	-0.200[b]	-0.168[c]	-0.102	-0.137
	(0.120)	(0.099)	(0.095)	(0.187)	(0.186)
Euro-12	0.397[a]	0.470[a]	0.611[a]	0.682[a]	0.554[a]
	(0.086)	(0.088)	(0.067)	(0.163)	(0.161)
Log of Distance	-0.790[a]	-0.807[a]	-0.952[a]	-0.984[a]	-0.974[a]
	(0.069)	(0.050)	(0.035)	(0.035)	(0.030)
Contiguity	0.191[a]	0.159[a]	0.044	0.124[a]	0.113[a]
	(0.047)	(0.059)	(0.042)	(0.041)	(0.031)
Common-language	0.189[a]	0.341[a]	0.485[a]	0.423[a]	0.555[a]
	(0.068)	(0.052)	(0.050)	(0.060)	(0.072)
Colonial-tie	0.241	0.131	-0.043	0.635[a]	0.483[a]
	(0.156)	(0.114)	(0.324)	(0.108)	(0.085)
MRT	yes	yes	yes	yes	yes
R^2	0.931	0.945	0.947	0.946	0.930
Sample	4,078	4,078	4,078	4,078	4,078

Notes: ([a]), ([b]) and ([c]) denote statistical significance at 1%, 5% and 10%, respectively. Standard errors in parentheses.

Table 4: Gravity Equation: Euro's Effect Across Quantiles – EU15

	$\tau = 0.10$	$\tau = 0.25$	$\tau = 0.50$	$\tau = 0.75$	$\tau = 0.90$
Currency Union	0.027	0.015	-0.042	0.295	0.441^b
	(0.086)	(0.105)	(0.085)	(0.322)	(0.216)
Euro-12	0.245^a	0.177^b	0.124^c	0.760^a	0.370^a
	(0.063)	(0.083)	(0.071)	(0.194)	(0.099)
Log of Distance	-0.640^a	-0.693^a	-0.908^a	-0.975^a	-0.993^a
	(0.048)	(0.048)	(0.034)	(0.035)	(0.025)
Contiguity	0.099^b	0.149^b	0.040	0.101^a	0.090^a
	(0.044)	(0.062)	(0.036)	(0.033)	(0.025)
Common-language	0.719^a	0.616^a	0.539^a	0.464^a	0.656^a
	(0.054)	(0.056)	(0.061)	(0.103)	(0.088)
Colonial-tie	0.052	-0.038	0.515^a	0.608^a	0.475^a
	(0.210)	(0.093)	(0.488)	(0.139)	(0.098)
MRT	yes	yes	yes	yes	yes
R^2	0.954	0.958	0.960	0.959	0.950
Sample	2,728	2,728	2,728	2,728	2,728

Notes: (^{a}), (^{b}) and (^{c}) denote statistical significance at 1%, 5% and 10%, respectively. Standard errors in parentheses.

Table 5: Gravity Equation: Euro's Effect with Distance Heterogeneity – QR Model*

	OECD93	EEA	EU15
Currency Union	-0.055	-0.195[b]	0.018
	(0.073)	(0.096)	(0.085)
Euro-12	0.397[a]	0.493[a]	0.062
	(0.062)	(0.065)	(0.051)
Contiguity	0.613[a]	0.205[a]	0.219[a]
	(0.036)	(0.039)	(0.030)
Common-language	0.356[a]	0.465[a]	0.544[a]
	(0.041)	(0.046)	(0.040)
Colonial-tie	0.348[a]	-0.035	0.095
	(0.070)	(0.181)	(0.608)
RTA	0.137[a]	–	–
	(0.021)		
Distance Heterogeneity			
ln(Distance) (first quartile)	0.005	-0.719[a]	-0.737[a]
	(0.006)	(0.056)	(0.054)
ln(Distance) (second quartile)	-0.056[a]	-0.710[a]	-0.712[a]
	(0.005)	(0.053)	(0.051)
ln(Distance) (third quartile)	-0.137[a]	-0.731[a]	-0.724[a]
	(0.008)	(0.051)	(0.048)
ln(Distance) (fourth quartile)	-0.194[a]	-0.775[a]	-0.757[a]
	(0.009)	(0.050)	(0.047)
MRT	yes	yes	yes
R^2	0.923	0.953	0.963
Sample	6,928	4,078	2,728

Notes: ([a]), ([b]) and ([c]) denote statistical significance at 1%, 5% and 10%, respectively. * model with $\tau = 0.50$. Standard errors in parentheses.