Why Do Estimates of the EMU Effect On Trade Vary so Much?

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Abstract

Larger data sets, with more countries and a longer span of time, exhibit systematically larger effects of European monetary union on trade. I establish this stylized fact with meta-analysis and confirm it by estimating a plain-vanilla gravity model. I explain this finding by systematic biases in "multilateral resistance to trade" in time-varying country fixed effects; bias grows as the sample is truncated by dropping small poor countries. I conclude by pointing out a number of unresolved questions in the literature.

Keywords: gravity, exports, span, country, meta, common, monetary, union, panel.

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1. Motivation

The downside of European Economic and Monetary Union is clear; it prevents its members from pursuing nationalistic monetary policies to offset idiosyncratic business cycle shocks. This loss is potentially offset, in part, by any stimulus that monetary union gives to trade. So the latter effect – that of monetary union on trade – is of concern to policy-makers. As I show below, there are dozens of estimates of the effect of EMU on trade. They vary enormously; in this paper, I ask why. My answer is that estimates of the EMU trade effect vary because researchers choose different samples of countries and years to estimate this effect. Including observations for all available countries and periods of time delivers both the most theoretically sensible and empirically largest effects.

2. Meta-Analysis

I begin with a meta-analysis of the literature. There are 45 papers circulating that estimate the effect of EMU on trade. Each estimates a version of:

$$\ln(Y_{ijt}) = \gamma EMU_{ijt} + \beta_Z Z_{ijt} + \{\lambda_{it}\} + \{\psi_{jt}\} + \{\xi_i\} + \{\phi_j\} + \{\tau_t\} + \{\delta_{ij}\} + \varepsilon_{ijt} \qquad (1)$$

where:

- Y_{ijt} denotes either bilateral exports from country i to country j at time t, or trade between i and j (the average of i's exports to j and i's imports from j),
- EMU is unity if i and j use the euro at time t and 0 otherwise,
- β is a vector of nuisance coefficients,
- Z is a vector of controls,
- $\{\lambda_{it}\}$ is a complete set of time-varying exporter/country dummy variables,
- $\{\psi_{jt}\}$ is the analogue for importers,
- $\{\xi_i\}$ is a set of time-invariant exporter/country dummy variables,
- $\{\phi_{jt}\}$ is a the analogue for importers,

- $\{\tau_t\}$ is a set of time dummy variables,
- $\{\delta_{ij}\}$ is a set of time-invariant country-pair dyadic dummy variables, and
- ε_{ij} represents other influences.

From each of these 45 studies I collect the authors' preferred estimate of γ, the partial effect of EMU on trade/exports, along with its standard error and other study features.

Figure 1 is a Forest plot that summarizes the literature. The (45) papers are listed at the left; separate columns list when the data used in the study begin and end, and how many countries are included. Three other features are also tabulated on the left: a) whether the study examines bilateral exports or trade; b) whether it includes dyadic {δ} fixed effects; and c) whether it includes time-varying country {λ} and {ψ} fixed effects. The study effect – γ, the trade effect of EMU – is tabulated at the right, along with a 95% confidence interval and a weight for random effects analysis (more on this below). Six of the study effects are negative, and many are positive and small (31 are positive but below .2).

How does the literature collectively quantify the EMU trade effect? A fixed effect estimator tabulated in the top row of Table 1 assumes there is a single underlying effect of EMU. The estimate is small but economically substantive; it implies that EMU stimulates trade/exports by (exp(.085)-1≈) 8.9%, an effect statistically different from zero. This estimator is based on the assumption of no heterogeneity between studies, a hypothesis that is easily rejected, as shown in the extreme right. Accordingly, I trust a random effects estimator (the vertical line in Figure 1), which allows each study to have a different treatment effect around a common mean. This estimate, tabulated in the second row of Table 1 indicates a statistically and economically significant EMU trade effect of (exp(.116)-1≈) 12.3%. Different sub-sets of the data deliver comparable results.

Do the (45) estimates give an accurate picture of the literature? Twenty studies are unpublished but more might never have made it to the internet. To get a handle on publication bias, I use funnel plots. The top-left graph of Figure 2 plots 45 estimates of γ on the x-axis against precision (the inverse of within-study standard error) on the y-axis. There are two striking features of this funnel plot. First, the estimates are skewed to the right of the random-effects estimate (the solid vertical line). However, this finding is weak; the Egger et al test for bias is significant only at the .12 significance level. Second, many estimates fall outside the 95% confidence interval, the area below the dashed lines. Both findings characterize other data sub-sets, as shown by the remaining funnel-plots in Figure 2. While there is little evidence of publication bias, the dispersion of the 45 estimates of γ is worrying.

Why do the estimates of γ vary so much? Figure 3 provides some clues; it contains four graphs which compare estimated γ (the effect of EMU on trade/exports, always portrayed on the y-axis, and labelled on the right) to the sample size, measured (on the x-axis) in four different ways. At the top-left of Figure 3, γ is compared to the (natural) logarithm of the total number of observations used to estimate γ. For convenience, a histogram of log observations is provided (labelled on the left), as is a least-squares line. The majority of studies have few observations; the median study has only 5300 observations and even the 90th percentile has fewer than 30,000. This might seem reasonable; EMU currently has only admitted nineteen countries over its eighteen year history, making for a maximum of (19*18*18=) 6156 annual observations. However, the larger the number of observations used to estimate γ, the higher it is. Interestingly, the critical thing about the time-dimension is *not* the number of EMU years in the sample, as shown in the flat distribution at the top-right of Figure 3. Rather, the span of years included in the study is important, as shown in the bottom-left. The median study includes only seventeen years of recent data, but including older data is systematically associated with higher estimates. Finally, and most strikingly, there is a correlation between γ and the number of countries included in the study, as shown in the lower-right. Most studies include few countries; the median number is 22, while even the 90th percentile is less than 50. This seems natural; most studies focus on rich large countries comparable to those in EMU. Still, the few studies that include large numbers of countries are associated with higher estimates of the EMU trade effect.

To summarize, longer wider spans of data are associated with higher estimates of the EMU trade effect. Expressed alternately, the point estimate of the EMU effect rises with the number of observations/years/countries, *even if these extra observations are not directly relevant to EMU*. Curious.

Figure 3 is striking but not completely persuasive. The simple correlations are bivariate, unweighted, and implicit. Accordingly, I turn to meta-regression analysis to investigate the linkages rigorously. I ask why the estimated effect of EMU on trade/exports, γ, varies across the (45) studies.

Table 2 provides six meta-regressions. The first, at the extreme left, includes regressors for six different features of the studies, along with an intercept. Consistent with the ocular evidence of Figure 3, both the (log) number of countries and span of years are positively related to the estimated EMU effect; both coefficients – and only those – are significantly different from zero at conventional levels. The remaining columns of Table 2 show that this result is insensitive to weighting, and the inclusion/exclusion of other study features.

The meta-regression analysis points to the conclusion that the estimated effect of EMU on trade/exports rise systematically as the number of countries and/or years rises, consistent with Figure 3. I am reluctant to over-interpret these results. The meta-regressions do not fit well, with adjusted-R^2s less than .3. More importantly for me, many of the results rely on equations with serious theoretical problems (Baldwin and Taglioni, 2007); only seven employ my preferred specification which models exports, and includes both time-varying exporter/importer and dyadic fixed effects. Most of the latter cover a small span of countries (the median is 22) and years (median 20). The few relevant estimates cannot provide much evidence of the relationship between γ estimates and the span of countries/time.

3. Empirical Confirmation

I now confirm the observations made in my meta-analysis, using the technique and data set of Glick and Rose (2016). I do this in part because of the paucity of methodologicallyreasonable studies; I also use my estimates to confirm my interpretation of the variation in study effects. I present my methodology briefly; Glick and Rose (2016) provide details.

Methodology

I use "theory-consistent estimation" of the gravity equation, following Head and Mayer (2014). I use least squares on:

$$\ln(X_{ijt}) = \gamma EMU_{ijt} + \beta_{CU}CU_{ijt} + \beta_Z Z_{ijt} + \{\lambda_{it}\} + \{\psi_{jt}\} + \{\delta_{ij}\} + \varepsilon_{ijt} \quad (2)$$

where:

- X_{ijt} denotes the nominal value of bilateral exports from i to j at time t, and
- CU is unity if i and j use the same non-euro money at time t and 0 otherwise.

I use *Direction of Trade* data, including annual trade between over 200 country codes, spanning 1948 through 2013 (with gaps). Bilateral trade on FOB exports and CIF imports is in U.S. dollars; I average i's exports to j and j's imports from i. The CIA's *World Factbook* provides colonial history; the WTO, regional trade agreements. This straightforward methodology focuses on the key aspect of the empirics, namely the relationship between the sample size and the coefficient of interest, γ, the EMU export effect.

Estimates of the Effect of EMU on Exports

Estimates of (1) using data for all countries, are tabulated in Table 3. The seven columns correspond to samples that begin in 1948 but end in the year listed in the top row. The coefficient of interest γ is presented in the second row. When the sample ends in 2001 (two years after EMU begins and before the physical introduction of the Euro), the coefficient is small in both economic and statistical senses. As I add years, the effect grows in economic size and statistical precision. My data ends in 2013; by that point, the point estimate of .43

corresponds to a substantive economic impact of (exp(.43)-1≈) 54%, with a robust t-statistic of over 20, despite over 50,000 fixed effects.

In the third row of Table 3, I tabulate estimates of γ when the same empirical model is estimated, but only for rich countries, using the World Bank definition of annual GDP per capita of at least $12,736. Below that, I also tabulate the analogues when the sample includes all actual or eventual EU countries. More data, either across countries or time, typically delivers a larger estimate of γ; the number of observations is tabulated. It is striking how the estimate of γ varies with the number of countries; it also rises, though less consistently, with the span of years.

This point is easy to convey graphically in Figure 4, which summarizes the empirics of Table 3. This presents the EMU export estimates, with a +/- two standard error confidence interval. There are two sources of variation: span of countries and time. The top line connects estimates of the EMU export effect that use data for all (>200) countries. The middle line is similar, but includes only data for rich countries. I have data on >34,000 country-pairs, but there are only ≈4,000 pairs of rich countries, an order of magnitude lower. The bottom line is an analogue for the approximately 800 country-pairs ever inside the EU (European Union, now some 28 countries, 19 in EMU).

There are two interesting findings in Figure 4. First, the estimates tend to rise with the sample's span of time. Second, EMU estimates that employ data from the entire world are positive and economically significant, the upper-income analogues are usually insignificantly different from zero, and the EU data delivers significantly *negative* point estimates of the EMU export effect, *despite the latter's understandable focus on the data most obviously relevant to EMU*.

All this is reassuringly consistent with the meta-analysis above, and essentially fills in gaps missing in the literature. It points to three conclusions. First, throwing away data easily allows one to estimate a small and/or negative export effect of EMU. Second, increasing the span of time by adding observations relevant to EMU tends to increases the estimated EMU export effect. Finally, increasing the span of countries – adding observations for countries that seem irrelevant to EMU – also increases the EMU export effect. While the first two observations are intuitive and appealing, the last seems odd.

Exploring and Interpreting the Fixed Effects

The evidence of both the meta-analysis and empirical work is clear. The estimated EMU export effect rises as the cross-section of countries expands, even if the extra countries appear unconnected to EMU. I now explore this curious result.

Consider the time-varying exporter and importer fixed effects. These represent multilateral indices of "trade resistance," Anderson and van Wincoop (2003). Omitting these fixed effects altogether would be a mistake; Baldwin and Taglioni (2007) refer to this omission as a "gold medal" mistake. But simply dropping small and poor countries may lead to significant selection bias if those countries have systematically different trade resistance, or if the trade resistance of large countries is reflected in trade with smaller countries.

Selection bias seems to be a serious problem in this context. Consider the estimates tabulated at the extreme top-right of Table 3, which use data for *all* (211) countries over the *entire* (1948-2013) period of time. It turns out that the countries with high fixed (country-time) effects and multilateral trade resistance are large, relatively closed countries like the United States and China; those with big negative fixed effects are small, open countries like Lesotho and Palau. Moreover, the estimated country-time fixed effects differ systematically for different types of monetary unions. For EMU observations, the average estimated fixed effect (multilateral trade resistance) is large and *positive*; for monetary unions other than EMU, the estimated fixed effects are, on average, large and *negative*. Finally, estimated fixed effects fall on average for both exporters and importers, *including those inside EMU*, as one throws away data from poorer countries.

Dropping small and poor countries induces bias in the estimates of multilateral resistance. This bias helps explain why γ estimates change systematically with the breadth of the data sample; the estimated trade effect is biased downward when small/poor countries are omitted from the sample and the fixed effects change accordingly. Anderson and van Wincoop (2003, p 176) explain why; multilateral trade resistance depends positively on trade barriers with *all* trading partners. Dropping small and/or poor countries, likely to have systematically different trade resistance, leads to biased estimates of multilateral trade resistance. As Anderson and van Wincoop note, higher multilateral resistance leads to trade; so downward-biased resistance estimates biases γ down. As multilateral trade resistance is a function of all bilateral trade barriers, all trade partners should be included for the most accurate estimates.

4. Conclusion

Why do estimates of the EMU trade effect vary so much? Including more observations – over time, or especially by country – increases the estimated effect of EMU on trade. In this short paper, I have established this stylized fact with meta-analysis and empirics, and then interpreted it. The dependency of the EMU export effect on the number of countries is more striking and less intuitive than the time-dependency. My explanation is that truncating the sample by omitting small/poor countries biases downward the estimates of the country-time fixed effects. This leads to downward bias in the estimated partial effect of EMU on exports. Succinctly, one can shrink the estimated EMU export effect by inappropriately dropping observations. In general, there is little reason to drop data without necessity; in this case, it is important to include as much data as possible when estimating the EMU trade effect.

Before I have real confidence in my explanation, this works need to be verified independently and broadly. Placebo tests would build confidence; it would also be interesting to examine other study effects, particularly the export effects of other (non-EMU) monetary unions and regional trade agreements (especially the EU). A Monte Carlo study on the effects of truncation bias would be helpful, as would an explicit model of the selection bias implicit in the data truncation, so long as both are done with a reasonable model. It would also be good to verify this result with Poisson pseudo-maximum likelihood to account for zeros and missing observations; this is currently infeasible for computational reasons. Much remains to be done.

References

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Table 1: Meta-Estimates of the EMU Effect on Trade/Exports

Estimator	Sample	Point Estimate	95% Confidence Interval		P-value, no Heterogeneity
			Lower	Upper	
Fixed	All (45)	.085	.078	.091	.000
Random	All (45)	.116	.084	.147	.000
Random	Export (27)	.140	.092	.189	.000
Random	Dyadic (35)	.126	.088	.164	.000
Random	Monadic (9)	.132	-.027	.291	.000
Random	Preferred (7)	.151	-.033	.336	.000

Notes: "Dyadic" denotes country-pair time-invariant fixed effects; "Monadic" denotes time-varying country fixed effects; "Preferred" denotes export regressand, with both dyadic and time-varying country fixed effects.

Table 2: Meta Regression Analysis of the EMU Effect on Trade/Exports

Weight	Std. Err.	Obs^{-1}	$GSCites^{-1}$	Std. Err.	Std. Err.	Std. Err.
Log Countries	.16 (.06)	.15 (.05)	.20 (.05)	.15 (.06)	.11 (.04)	
Log Years	.14 (.05)	.13 (.05)	.09 (.05)	.11 (.05)	.09 (.04)	
Log Observations	-.05 (.04)	-.03 (.03)	.01 (.04)	-.03 (.03)		
Time-Varying Country FE	-.03 (.06)	-.04 (.07)	-.07 (.07)			-.00 (.07)
Export Regressand	.07 (.06)	.04 (.06)	.05 (.06)			.05 (.06)
Dyadic FE	.03 (.06)	.02 (.06)	-.01 (.07)			.05 (.07)
Intercept	-.45 (.18)	-.51 (.20)	-.87 (.29)	-.44 (.17)	-.51 (.15)	.05 (.07)
P(value)	.63	.81	.78			
Adjusted R^2	.26	.27	.47	.27	.29	-.04

Meta-regression coefficients (weighted by precision unless otherwise noted); standard errors in parentheses. 45 observations. "Obs" denotes number of observations; "GSCites" denotes number of Google Scholar citations. P(value) denotes p-value for joint null hypothesis that effects of log observations, export regressand, and both time-varying and dyadic fixed effects are all zero.

Table 3: Gravity Estimates for Bilateral Exports, different country samples

Sample ends:	2001	2003	2005	2007	2009	2011	2013
EMU Coefficient, Full Sample (γ)	.08 (.05)	.12 (.04)	.17 (.03)	.19 (.03)	.25 (.02)	.36 (.02)	.43 (.02)
EMU Coefficient, Rich Countries (γ)	.00 (.05)	-.01 (.04)	-.02 (.04)	-.04 (.03)	.00 (.03)	.07 (.03)	.11 (.03)
EMU Coefficient, EU Countries (γ)	-.33 (.06)	-.36 (.05)	-.32 (.04)	-.28 (.04)	-.26 (.07)	-.25 (.03)	-.24 (.03)
Observations							
Full Sample	597,565	642,571	688,519	735,025	782,047	829,708	877,736
Rich Countries	42,673	46,851	51,824	57,317	62,764	68,428	75,096
EU Countries	22,887	24,341	25,788	27,350	28,891	30,434	31,982

Regressand: log of bilateral exports. Controls included but not recorded: non-EMU monetary union; regional trade agreement, colonial relationship, exporter-year, importer-year, and dyadic fixed effects included not reported. Robust standard errors recorded in parentheses. Annual observations, 1948-year tabulated. Full sample includes >200; rich countries have real GDP per capita ≥$12,736; EU countries are all (28) eventual members of the European Union.

Figure 1: Forest plot of 45 literature estimates of the EMU effect on trade/exports

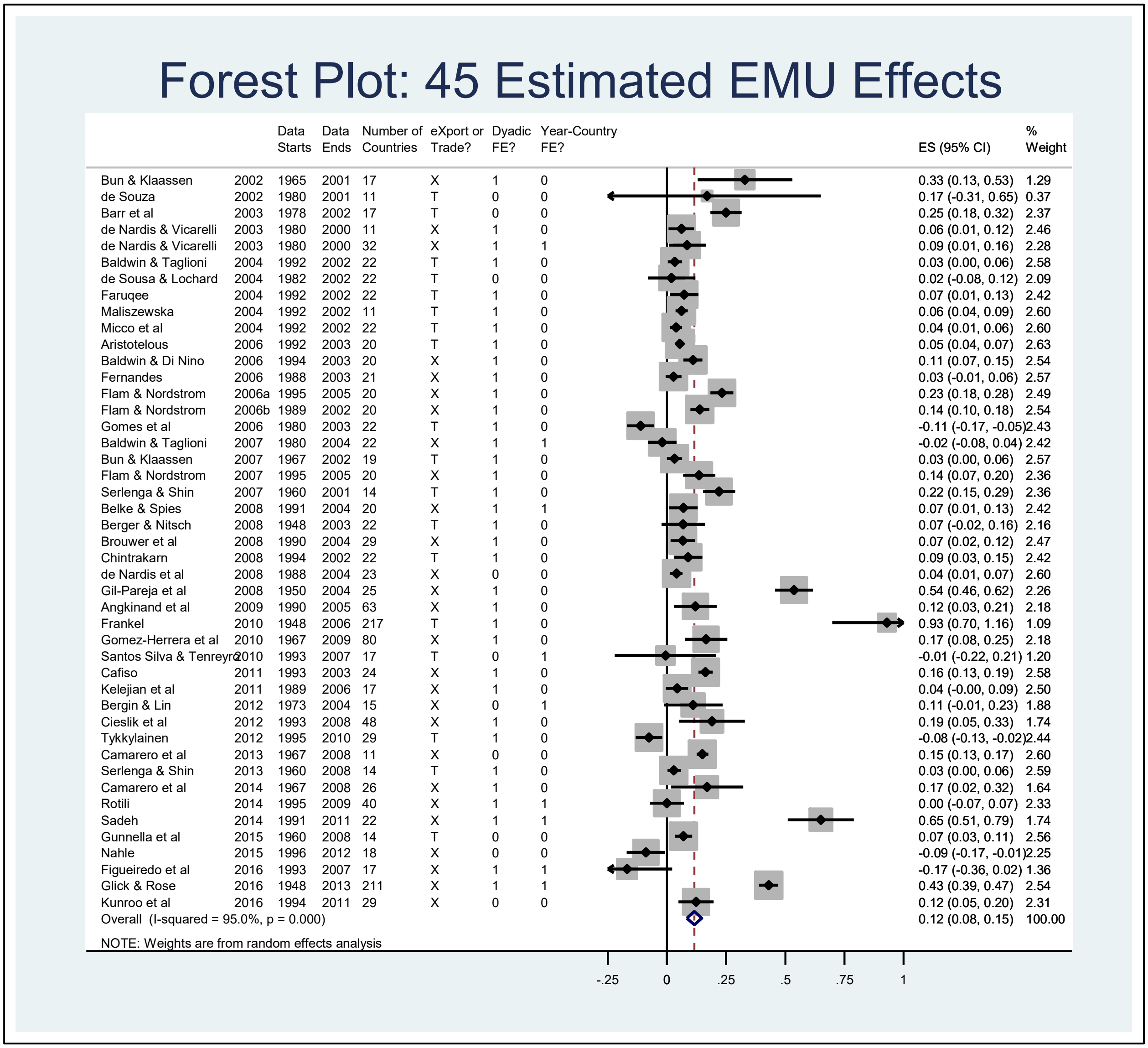

Figure 2: Funnel plots of literature estimates of EMU effect on trade/exports

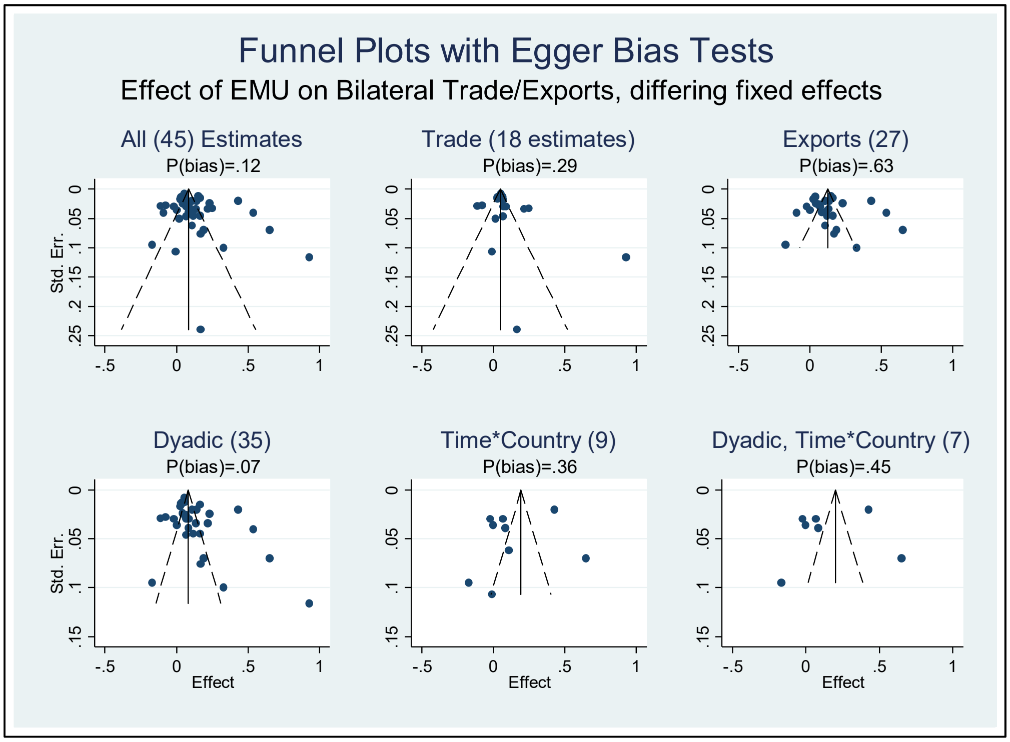

Figure 3: Relationship between estimates of EMU effect and sample size

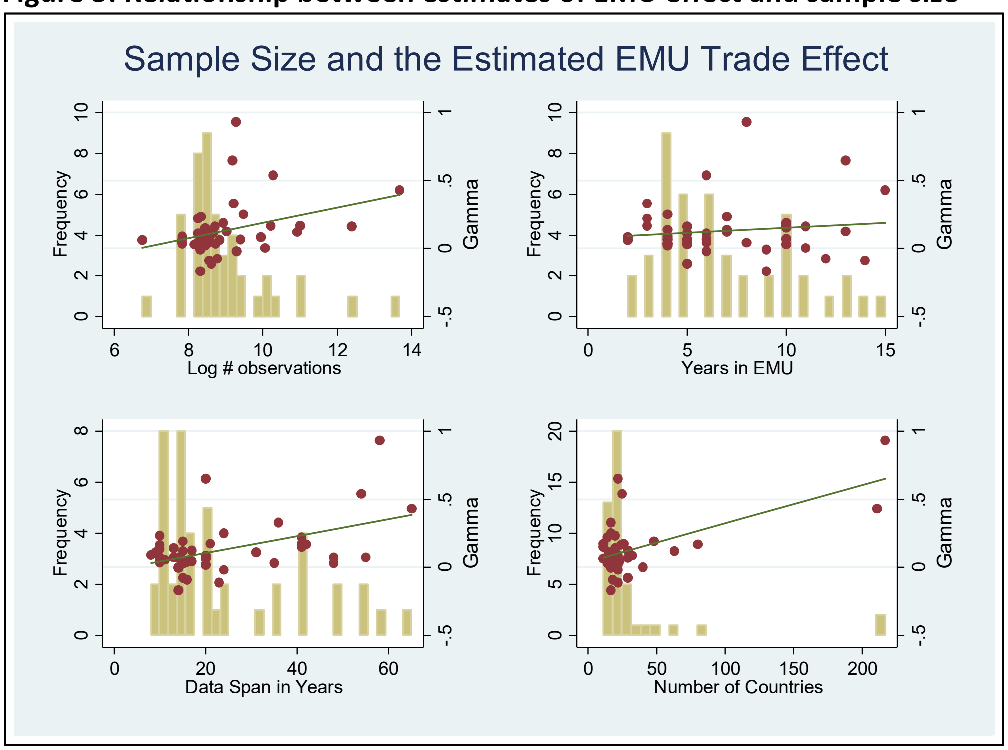

Figure 4: Estimates of the EMU effect on trade with varying samples