How Much Does International Trade Affect Business Cycle Synchronization

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Abstract

In a recent article, Jeffrey Frankel and Andrew Rose (1998) examine the hypothesis that greater trade flows between two countries cause greater synchronicity between their business cycles. The increase in business cycle synchronicity may be seen as rationalizing a common monetary policy and, so, a shared currency. Arguing that product specialization would lower the synchronicity of business cycles, Frankel and Rose posit that a regression of output correlation on overall trade will indicate whether (positive) common demand shocks and productivity spillovers dominate or (negative) specialization effects do. The authors apply instrumental variables to confirm a causal relationship. In this paper, we refine the estimation in two ways. First, we test for instrument validity and find that the confirming null hypothesis is rejected in most cases. We find evidence to suggest that the instrumental variables method applied is inappropriate and results in inflated coefficients. We develop and apply an alternative OLS-based estimation procedure. Second, we add structure-of-trade variables to the model to separate the effects of intra- and inter-industry trade flows. Although our results suggest that the Frankel and Rose model overestimates the effect of trade on business cycle correlation, the overall results of our model are consistent with theirs. With our own model estimation, we find that specialization generally does not significantly asynchronize business cycles between two countries.

Key Words: Business Cycles Synchronization, Optimum Currency Area Criteria, Trade, Trade Specialization.

JEL Codes: F15, F14, E32

How Much Does International Trade Affect Business Cycle Synchronization?

In one of the most significant papers in the optimal currency area (OCA) literature, Frankel and Rose (1998, hereafter F&R) offer evidence that currency area optimality is endogenous. They find that greater overall trade – and by assumption trade liberalization – leads to an increase in business cycle harmonization between two countries. According to the insight common throughout the OCA literature, the more fully harmonized two countries' business cycles are, the more appropriate it is for them to share a monetary policy and therefore a currency. Following F&R, Glick and Rose (2002), Frankel and Rose (2001) and Rose (2000) argue that currency union significantly increases trade among member countries.[1] Pooling the two phases of research leads to the conclusion that a common currency area could be self-fulfillingly optimal.[2]

However, F&R's empirical approach elides some of the fundamental issues embedded in the supporting theory. F&R themselves raise one of these issues – that the greater intra-industry trade (IIT) is as a share of total trade, the more important trade will be to business cycle harmonization. Insofar as trade flows reflect the overall structure of the economy, less export specialization means that the economies are more subject to common shocks. Yet even specialized trade has certain correlation-enhancing effects linked to its contribution to common aggregate demand and to productivity spillovers.

While F&R conclude that their estimate of the effect of overall trade on business cycle correlation demonstrates the dominance of positive factors over specialization, they

[1] Before F&R, empirical OCA models traditionally used structural models to analyze business cycles and shocks affecting potential OCA countries – quantifying the potential importance of national monetary policies. See Bayoumi and Eichengreen (1994) and Eichengreen and Bayoumi (1999) among others. It

consider the composition of trade to be an important part of the trade-cycle correlation linkage, as we do. Indeed, F&R note that "it would also be valuable to have more dis-aggregated evidence on the decomposition of trade into intra-industry and inter-industry parts." It is clearly plausible that trade's overall effect will be fairly represented by a regression of business cycle correlation measures on aggregate trade measures, consistent with F&R's modeling approach. However, that approach to the problem, as we will show, imposes a restriction on the empirical model that substantively affects estimation and that, with sufficient data, can be tested.

We address the results of F&R empirically, using the same 21-country sample in order to test and refine their specifications. Our results confirm F&R's general conclusion, that increased trade leads to increased business cycle correlation. However, adjusting F&R's model as suggested by certain common diagnostic tests, we find that trade's effect on business cycle correlation is much smaller, about half of F&R's point estimate. Moreover, F&R maintain that "reduced trade barriers can result in increased industrial specialization by country and therefore more asynchronous business cycles…." We find that increases in inter-industry trade – which may indicate the same rising specialization that F&R mention – turn out not to have a significantly negative effect on business cycle synchronicity for the countries that F&R study. Our tests also reject F&R's implicit hypothesis that the coefficients for intra-industry trade and inter-industry trade are the same.

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was F&R's innovation to see trade openness and business cycle harmonization as simultaneously determined.

[2] Some criticism on the second phase of this research can be found in Rogoff (2001) and Rodrik (2000).

1. The Frankel and Rose Model

Since our study of intra-industry trade and business cycle synchronicity is an attempt to refine F&R's econometric approach, it is useful to first introduce their method and results. F&R use quarterly data on real GDP, an index of industrial production, total employment, and the unemployment rate for each of 21 countries as measures of overall output. Natural logarithms (logs) of the data are used for all series except the unemployment rate. (From now on, when we refer to the "original" data, we mean these transformed series.) For each variable, F&R use four alternative approaches to approximate the cyclical part of output: (1) Fourth differences (because most variables are in logs, this corresponds to the four-quarter growth rate). (2) The residual from a regression of the original series on a linear time trend, a quadratic time trend, and three quarterly dummies. (3) The original series minus the Hodrick-Prescott (HP) trend. (4) The residuals from a regression of the original series on a constant and three quarterly dummies, minus the HP trend of the residuals. F&R therefore compute 16 bilateral (country-by-country) correlations (four variables and four measures of the "business cycle" per variable) of real activity for each pair of countries, for four periods each (1959Q1 to 1967Q3; 1967Q4 to 1976Q2; 1976Q3 to 1985Q1; and 1985Q2 to 1993Q4).

The regressions F&R use take the form

(1) $$\text{Corr}\,(\text{v,s})_{\text{i,j,}\tau} = \alpha + \beta \cdot \text{Trade}\,(\omega)_{\text{i,j,}\tau} + \varepsilon_{\text{i,j,}\tau}$$

where $\mathrm{Corr}\,(v,s)_{i,j,\tau}$ signifies the correlation between country i and country j over time period τ for variable type v (GDP, industrial production, employment, unemployment) detrended by method s (growth rate, quadratic trend, HP filter, HP filter of the seasonally adjusted residual). $\mathrm{Trade}\,(\omega)_{i,j,\tau}$ signifies the log of the average bilateral trade intensity between countries i and j over time period τ using trade intensity concept ω (which is total bilateral trade normalized either by total trade or GDP). Note that these two approaches to normalization – normalization by trade and normalization by GDP – receive considerable attention in subsequent narratives.

In this simple model the key coefficient is β, which expresses the relationship between trade intensity and business cycle correlation. In each variant of their basic model, F&R find the coefficient to be positive and significant. F&R use both OLS and Instrumental Variables (IV) techniques, but advocate the IV approach, on the premises that (i) monetary coordination with large trade partners (e.g., pegs) may cause a spurious correlation between trade and business cycle correlation, and (ii) trade regressors are measured with error[3]. F&R use the log of distance and adjacency and language dummies as instruments, based on the success of these variables in explaining trade (in "gravity equation" models) and the presumption that they are otherwise unrelated to the business cycle.

F&R's estimate of the impact of trade on business cycle correlation is large, particularly the IV estimates. For the GDP growth rates version of the model (which F&R use as representative), increasing total trade-normalized trade intensity by one

[3] OLS results are reported only in the working paper version.

standard deviation increases bilateral business cycle correlation to 0.35 from the pre-trade-increase level of 0.22. This is a large increase, indeed.

2. Some Complications of the F&R Model

Although applying diagnostics to F&R's results confirm their general narrative, close statistical attention does raise questions about the details of their arguments – particularly about the large increases in business cycle correlations that derive from more trade. A problematic detail is that IV coefficient estimates are as much as three times the size of the corresponding OLS estimates. We know from basic econometrics that

$$(2) \qquad b_{OLS} \xrightarrow[p]{} \beta + \frac{\sigma_{Trade,\varepsilon}}{\sigma^2_{Trade}}$$

where $\sigma_{Trade,\varepsilon}$ is the covariance of trade and ε, σ^2_{Trade} is the variance of trade, and $\xrightarrow[p]{}$ denotes the probability limit. Recall that F&R instrument trade because similar monetary policies may also cause business cycle correlations. Persistent correlations between two countries' monetary policies imply that $\sigma_{Trade,\varepsilon} \geq 0$; thus, if IV simply corrects for the effects of similar monetary policies, we would expect IV to produce an estimate no larger than OLS, and probably much smaller.

A likely cause of the large difference between b_{OLS} and b_{IV} is a statistical association between the instrumental and omitted variables (which would be part of the error term), which can result in a bias much greater than that from OLS (see, for example, Anderson and van Wincoop, 2001). As Rodrik (2000) points out, "for an instrument to be valid, it is not enough that it be exogenous. It must also affect the outcome variable only through the variable that is instrumented."

As Figure 2 suggests, in the present case not only trade intensity and a common approach to monetary policy but factor mobility can influence the business cycle synchronization of two countries. To complicate the issue all three factors – trade intensity, factor mobility and a common approach to monetary policy – can be seen as instrumentable with the same variables derived from the gravity model that F&R use just to instrument trade intensity. We may reasonably conjecture that two countries that are geographically closer, share a border and use the same language may have greater labor mobility than two countries that are distant from one another, that have distinct languages, and that have no common border. Ceteris paribus, neighboring countries with similar cultures (language) may be more disposed towards similar monetary policies. In sum, the instruments that F&R use to capture the influences of trade may ultimately be seen as capturing the effects of all three influences, upwardly biasing the estimated impact of trade alone. A statistical test confirming this hypothesis (technically, a test for overidentifying restrictions) is presented in the context of our own estimation, in the next section[4].

F&R also claim that IV is needed because measurement error in the trade intensity series will attenuate (bias towards zero) the OLS estimate, which is consistent with the observed estimates. However, the bias would then be proportionate to measurement error variance divided by the variance in actual trade intensity. Even a measurement error variance that is 50% the variance of actual trade intensity is probably

[4] It should be noted that we are not arguing that F&R's instruments are not sufficient, but that their instruments simply reflect more factors than trade.

implausibly high (and many estimates would require even greater ratios). We therefore abandon IV estimation in favor of OLS and incorporate F&R's three instruments into the system as independent variables, hoping that these serve as adequate proxies for the other, difficult-to-measure factors in Figure 2.

A second issue is that F&R estimate the relationship between synchronicity and trade using total trade, rather than intra-industry trade, a theoretically stronger foundation for business cycle synchronicity. Total trade consists of intra-industry trade and inter-industry trade. Economic theory suggests that industry-specific shocks would lead to similar aggregate shocks only if the distribution of industries is also similar. Using a total trade independent variable – as F&R do – instead of separate intra- and inter-industry trade variables implicitly assumes that the coefficients of the latter two variables are the same. That assumption is inconsistent with much international economic theory and may also result in estimation bias due to misspecification.

More generally, the mechanisms by which international trade affects business cycle synchronicity may be more clearly understood when intra- and inter-industry trade effects are accounted for separately. With our more fully specified model, we hope to put the effect of industry specific shocks on international business cycle synchronization in a more detailed perspective.

3. Empirical Methodology

3.1. *Measuring Intra-Industry Trade Flows*

We use an index of intra-industry trade developed by Grubel and Lloyd (1975) to measure the proportion of IIT in total trade,

$$\text{(3)} \qquad \mathrm{IIT}_{\mathrm{i,j}} = \frac{\sum_k (\mathrm{X}_{\mathrm{i,j}} + \mathrm{M}_{\mathrm{i,j}}) - \sum_k \left|\mathrm{X}_{\mathrm{i,j}} - \mathrm{M}_{\mathrm{i,j}}\right|}{\sum_k (\mathrm{X}_{\mathrm{i,j}} + \mathrm{M}_{\mathrm{i,j}})} = 1 - \frac{\sum_k \left|\mathrm{X}_{\mathrm{i,j}} - \mathrm{M}_{\mathrm{i,j}}\right|}{\sum_k (\mathrm{X}_{\mathrm{i,j}} + \mathrm{M}_{\mathrm{i,j}})}$$

where $X_{i,j}$ and $M_{i,j}$ are exports from country *i* to country *j* and imports of country *i* from country *j*, respectively, and *k* is a index over industry classes. In practice, we use only reported imports to calculate the index (that is, we use $M_{j,i}$ instead of $X_{i,j}$), following Feenstra's (2000) argument that reported data are more reliable for imports than exports.

By multiplying $IIT_{i,j}$ and trade intensity, Trade $(\omega)_{i,j}$, as defined by FR, we have intra-industry trade intensity (IntraTrade):

$$\text{(4)} \qquad \mathrm{IntraTrade}\ (\omega)_{\mathrm{i,j}} = \mathrm{IIT}_{\mathrm{i,j}} \cdot \mathrm{Trade}\ (\omega)_{\mathrm{i,j}}$$

Following the same intuition, inter-industry trade intensity (InterTrade) is defined as

$$\text{(5)} \qquad \mathrm{InterTrade}\ (\omega)_{\mathrm{i,j}} = (1 - \mathrm{IIT}_{\mathrm{i,j}}) \cdot \mathrm{Trade}\ (\omega)_{\mathrm{i,j}}$$

It is obvious that by adding IntraTrade and InterTrade we can recover F&R's overall trade intensity measure. We use this identity below in formally testing the restrictions that F&R impose to our more general model.

3.2. *Empirical Model*

Our econometric model, which incorporates intra-industry trade, inter-industry trade, and common components (log of distance, adjacency dummy, and language dummy), is (where i and j represent individual countries and τ represents time):

$$\text{(6)} \quad \begin{aligned} \text{Corr (v,s)}_{\text{i,j},\tau} &= \alpha + \beta_1 \cdot \text{IntraTrade}\,(\omega)_{\text{i,j},\tau} + \beta_2 \cdot \text{InterTrade}\,(\omega)_{\text{i,j},\tau} \\ &\quad + \gamma_1 \cdot \text{Dist}_{\text{i,j}} + \gamma_2 \cdot \text{Adjacent}_{\text{i,j}} + \gamma_3 \cdot \text{Language}_{\text{i,j}} + \varepsilon_{\text{i,j},\tau} \end{aligned}$$

where IntraTrade (ω) $_{\text{i,j},\tau}$ and InterTrade (ω) $_{\text{i,j},\tau}$ are defined as above, as proportions of Trade (ω) $_{\text{i,j},\tau}$ (again recall that the intensity of trade between two countries is normalized separately with respect to total trade and GDP, so a separate estimation may be performed for each of the two measures of trade intensity). Dist $_{\text{i,j}}$, Adjacent $_{\text{i,j}}$, and Language $_{\text{i,j}}$ are the log of distance between country i and country j, a dummy for sharing a border, and a dummy for sharing a language, respectively. Since IntraTrade (ω) $_{\text{i,j},\tau}$ + InterTrade (ω) $_{\text{i,j},\tau}$ = Trade (ω) $_{\text{i,j},\tau}$, the equation can be written as

$$\text{(7)} \quad \begin{aligned} \text{Corr (v,s)}_{\text{i,j},\tau} &= \alpha + \beta_1 \cdot \text{IntraTrade}\,(\omega)_{\text{i,j},\tau} \\ &\quad + \beta_2 \cdot (\text{Trade}\,(\omega)_{\text{i,j},\tau} - \text{IntraTrade}\,(\omega)_{\text{i,j},\tau}) + \text{Z}'_{\text{i,j}} \cdot \gamma + \varepsilon_{\text{i,j},\tau} \\ &= \alpha + (\beta_1 - \beta_2) \cdot \text{IntraTrade}\,(\omega)_{\text{i,j},\tau} + \beta_2 \cdot \text{Trade}\,(\omega)_{\text{i,j},\tau} \\ &\quad + \text{Z}'_{\text{i,j}} \cdot \gamma + \varepsilon_{\text{i,j},\tau} \end{aligned}$$

where (for notational convenience) $Z_{i,j}$ is the vector of fixed factors and γ is a vector containing the corresponding coefficients. Industry specific shocks would increase business cycle correlation to the extent that IntraTrade exceeds InterTrade. Common demand shocks and productivity spillovers will have positive effects on business cycle correlation as overall trade intensity increases, regardless of its composition. Since high IntraTrade would result in high business cycle correlation regardless of the nature of shock, we expect $\beta_1 > 0$. However, the sign of β_2 is uncertain. If industry specific shocks dominate, β_2 will be negative. If common demand shocks or productivity spillovers dominate, β_2 will be positive.

F&R's estimation of equation (1) can be interpreted within the structure of (7). When $\beta_1 = \beta_2$ and γ is a vector of zeros, (7) reduces to equation (1) exactly. If tests do not support these assumptions, there would be a strong suggestion that F&R's results are affected by omitted variable bias. As we discuss below, we find both restrictions to be incorrect and important sources of the coefficient inflation.

3.3. *Data*

We calculate IIT indices from three-digit (Standard International Industrial Code) trade flows for the same 21 countries studied by FR[5]. However, we employ a slightly

[5] The countries are: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Greece, Ireland, Italy, Japan, Norway, Netherlands, New Zealand, Portugal, Spain, Sweden, Switzerland, the UK and the United States.

different observation period than F&R (1965-1998, while F&R use 1959-1993) because industry-level trade data are not available for F&R's entire sample period.[6]

We use the same real activity measures as F&R: real GDP, an index of industrial production, total employment, and the unemployment rate. All the real activity data are quarterly covering 1965-1998, and each measure except the unemployment rate is transformed to logs. We detrend each variable to focus on cyclical behavior, using four different detrending methods. Like F&R, we use fourth-differencing (growth rates), quadratic time detrending, and the Hodrick-Prescott (HP) filter. We also use the Band Pass (BP) filter. Although F&R do not use the BP filter, we felt that its advantages and wide currency warrant its addition (Baxter and King 1999).

We compute bilateral correlations for the cyclical components of real activity. These correlations are estimated over a given span of time. We split our sample into four parts: 1965Q1:1972Q4, 1973Q1:1981Q4, 1982Q1:1990Q4, 1991Q1:1999Q4. We thus have a sample with 840 total observations, 210 pairs of countries and 4 observations for each pair, the same size as F&R's sample.

4. Empirical Results

4.1. *Baseline estimates*

[6] Our data source for industry-level trade flows is the National Asia Pacific Economic and Scientific Database (NAPES), maintained by the Australian National University at http://iedb.anu.edu.au/iedb/napes/napes.htm. Nominal GDP data are mostly from the International Monetary Fund's (IMF) *World Economic Outlook*, but these have been spliced to data from the World Bank's *World Development Indicators* and the IMF's *International Financial Statistics*. Total international trade data are from the IMF's *International Financial Statistics*. All data used to construct trade intensity and structure-of-trade series are annual.

Before we estimate our model (6), we ought to examine whether a slightly different sample period would yield significantly different results. We thus use our data set to estimate equation (1) with OLS and IV techniques and compare the results with F&R's. Qualitatively, the results are very similar. The simple average of F&R's twenty OLS estimates (the working paper also uses oil-price adjusted real GDP as a measure of output) of β is 5.9, the average of the IV estimates, 9.9. Our averages for β are 7.5 for OLS and 11.5 for IV. The t-statistics are also comparable.

After performing the IV estimation on our own dataset, we are in a position to test the appropriateness of F&R's instruments, using a standard overidentifying restrictions test, the results of which are reported in Table 1. (While a single instrument would be orthogonal to the residual by construction, a set of more than one instrument can be tested with the null hypothesis: Presuming one instrument in the set is orthogonal to the error term, the other terms are also orthogonal.) In all but a few cases this test soundly rejects the null that the chosen instruments affect business cycle correlation only through trade intensity.

As mentioned earlier, we use OLS instead of IV to estimate our equation (6), as we are including F&R's instruments as independent variables, according to our notion of the true model (Figure 2). We follow F&R in using logs of the independent trade variables, but the levels regressions are reported as well. The resulting estimates are given in Tables 2 and 3. Consider first the regressions that include variables for distance, adjacency, and common languages ("fixed factors"), the second and fourth columns in each table (we prefer the fourth column, with logs of trade intensity, as did F&R). The estimated effect of IIT on economic correlation (β_1) is almost always positive. The only exception when trade intensity is used in logs is the correlation of BP detrended unemployment rates when trade intensity is normalized by overall international trade (rather than the alternative normalizer, GDP). Eight (out of 32) coefficients are negative when trade intensity is used in levels instead of logs. None of these are significantly different from zero, and most estimates are significant and positive. However, our t-statistics are less consistently significant than F&R's. Indeed, 7 out of 16 estimates are not significant at 95% when fixed factors are included in the regression.

The presence of geographical and language variables usually causes a marked reduction in the measured importance of trade. If we omit these, as shown in the first and third columns, then the significance level for trade increases, meaning that β_1 becomes more significant than in the full equation, (6), and it is never negative. Nevertheless, for one case using trade normalization and for ten cases using GDP normalization measurement, β_1 is still not significant at the 95% level (unemployment rate correlations lead to especially weak estimates). Insofar as our significance levels in this case are exaggerated by deliberate misspecifications through the omission of variables – yet still remain below F&R's significance levels – our results do offer weaker substantiation than F&R that "a close trade linkage between two countries is strongly and consistently associated with more tightly correlated economic activity between two countries (p. 1010)."

The results for the coefficient β_2 – which represent the effect of inter-industry trade intensity on business cycle correlation – are mixed. We will focus on the estimates that use the logs of trade intensities, but the levels estimates are quite similar. When inter-industry trade is normalized by total international trade, 11 out of 16 estimates are negative, but only 3 are significant at the 95 percent level (Table 4, column 4). When the variable is normalized by GDP, 8 out of 16 estimates are negative and not one of them is significant at the 95 percent level (Table 5, column 4). The results do not change much when we estimate equation (6) without fixed factors (Tables 4 and 5, column 3). The estimates indicate that specialization does not de-harmonize the business cycles between two countries. These results contradict Backus, Kehoe, and Kydland's (1992) well-known result that the elimination of trading frictions lowers the cross-country correlation of business cycles. Our results do, however, fall in line with empirical studies by Gregory, Head, and Raynauld (1997) and Norrbin and Schlagenhauf (1996) that world common shocks play important roles in business cycles.

The estimation of equation (6) gives a chance to test the implicit hypothesis of F&R that $\beta_1 - \beta_2 = 0$. In practice, we just run the regression in its alternate form, (7), and test the coefficient on IntraTrade. As might be guessed from the size and precision of the estimates of β_1 and β_2, this hypothesis is often rejected (see Tables 6 and 7). The results are stronger when we drop the dummies from the model. We can also test the hypothesis that the fixed factors are insignificant (that is, that γ_1, γ_2, and γ_3 are each equal to zero), which is done in Table 8. This hypothesis is rejected soundly for most equations. These results indicate that F&R's estimation of (1) has significant misspecification bias.

F&R provide an intuitive summary of their results by calculating the increase in synchronicity that attends a one-standard deviation shock in trade intensity. To summarize our results, we repeat this exercise in Table 9.[7] Each refinement of F&R's original model (1) diminishes the gain in cyclical correlation. Setting most values to their means, the pre-shock correlation of F&R's IV model is 0.346. The post shock correlation is 0.116 greater, rising to 0.462. However, our preferred estimations of equation (6) show an increase in correlation from a pre-shock level of 0.308, to a post shock level of only 0.366, signifying a much smaller increase of 0.058. Controlling for the composition of trade makes the synchronization gains from trade even smaller than in the F&R OLS estimation, with or without fixed factor controls.

4.2. *Panel estimation*

Our discussions of distance, contiguity and language variables have implicitly treated them as fixed effects (FE) in a panel data sense. That is, we believe that these three factors affect business cycle correlation but not strictly through trade flows. For example, proximity and a common language obviously make labor movement (immigration) easier. However, it is possible in a panel data set to control for all FE by using simple data transformations. We use the most common FE transformations, deviation-from-means (the "within" transformation) and the first-difference operator.

F&R report that FE estimation of their model does not substantively change their results: "adding either period-specific or country-specific 'fixed effect' controls (or both) also does not affect the sign or statistical significance of β" (1022). We find that the sign of the FE beta is indeed the same as in F&R's baseline model. However, we also find

[7] Instead of choosing a single set of parameter estimates, as F&R do, we average the parameter estimates for all sixteen variants of the model that use GDP-normalization, using the Kalman filter. Our results for the model of F&R are extremely similar to theirs, however.

that the size and significance of the beta coefficient is noticeably affected, as shown in Figures 3 and 4.[8]

Using FE methods on our own model produces similar noisy estimates, as reported in Tables 10-13. Some patterns can be seen. For example, unemployment data usually produce negative coefficients and estimates of β_2 are fairly strong when trade is normalized with GDP. However, the most obvious aspect of our FE estimates is the failure of any robust relationship to emerge.

There are two potential explanations of the FE results. First, as pointed out in Griliches and Hausman (1986), when independent variables are measured with error, FE transformations strip much of the signal from the data. The result is that measurement noise accounts for a greater proportion of the variance. This problem causes an attenuation bias in the estimated coefficients. Moreover, although stripping much of the signal from the dependent variable does not bias the estimate, it does reduce its precision. We expect that measured correlation from our data is a noisy estimate of "synchronicity," so it is possible that our data set does not allow us to capture the true relationship using the "within" aspect of the data, only.

The second possibility, which is open for more research, is that correlation between business cycles and trade comes mostly from common fixed factors of trade. The common factors must not be included in our set of geography and language variables. In this case, FE estimation would filter out the entire signal.

[8] Recall that our estimates are for country pairs. Our fixed effects are accordingly specific to country pair estimate.

5. Conclusion

In this paper, we have considered how much international trade affects business cycle synchronization between countries. By using 3-digit intra-industry trade data, we disaggregated the trade intensity measures used by F&R and enriched the model specification to include omitted variables. Despite the large number of amendments we have made, our results still suggest that F&R's general conclusions hold, but that estimation biases and the omission of some variables caused their model to overstate the effects of international trade upon business cycle synchronization by a factor of about two.

The split of trade data into intra- and inter-industry trade provides us with a unique environment to test whether specialization reduces business cycle correlation, as some theoretical and calibration results, especially in the real business cycle literature, show. Our estimates do not support in general the notion that specialization has a negative effect on business cycle correlation. The high share of intra-industry trade in total trade means that industry-specific shocks will not, through specialization, dominate common demand shocks and productivity spillovers, and may even contribute to greater correspondence.

Reference:

Angrist, Joshua D. and Alan B. Krueger (2001), “Instrumental Variables and the Search for Indentification: From Supply and Demand to Natural Experiments,” *Journal of Economic Perspectives*, vol. 15, pp. 69-85.

Anderson, James E. and Eric van Wincoop (2001), “Gravity with Gravitas: A Solution to the Border Puzzle,” NBER Working paper #8079.

Backus, David K., Patrick J. Kehoe and Finn E. Kydland (1992), “International Real Business Cycles,” *Journal of Political Economy*, vol. 100(4), pp. 745-75.

Baxter, Marianne and Robert G. King (1999), “Measuring Business Cycles: Approximate Band-Pass Filters for Economic Time Series,” *Review of Economics and Statistics*, vol. 81, pp. 575-93.

Bayoumi, Tamim and Barry Eichengreen (1994), “Monetary and Exchange Rate Arrangements for NAFTA,” *Journal of Development Economics*, 43 pp. 125-165.

Bound, John, David A. Jaeger, and Regina M. Baker (1995), “Problems With Instrumental Variables Estimation When the Correlation Between the Instruments and the Endogenous Explanatory Variable is Weak,” *Journal of American Statistical Association*, vol. 90, pp. 443-450.

Eichengreen, Barry and Tamim Bayoumi (1999), “Is Asia an Optimal Currency Area? Can It Be One? Regional, Global and Historical Perspective on Asian Monetary Relations,” in Collignon, S. and J. Pisani-Ferry (eds), *Exchange Rate Policies in Emerging Asian Countries: Domestic and International Aspects*, London: Routledge

Feenstra, Robert C. (2000), “World Trade Flows, 1980-1997,” The Center for International Data at UC Davis (mimeo).

Frankel, Jeffery A. and David Romer (1999), “Does Trade Cause Growth?” *American Economic Review*, 89, pp. 379-99.

Frankel, Jeffrey A. and Andrew K. Rose (1998), "The Endogeneity of the Optimum Currency Area Criteria," *Economic Journal*, pp. 1009-1025.

________________________________ (2001), “An Estimate of the Effect of Common Currencies on Trade and Income,” JFK School of Government Working Paper # RWP01-013.

Glick, Reuven and Andrew K. Rose (2002), “Does A Currency Union Affect Trade? The Time Series Evidence,” forthcoming *European Economic Review.*

Gregory, Allan W., Allen C. Head, and Jacques Raynauld (1997), "Measuring World Business Cycles," *International Economic Review*, vol. 38 (3), pp. 677-701.

Griliches, Z. and J. Hausman, (1986), "Errors in Variables in Panel Data," *Journal of Econometrics*, vol. 31, pp. 93-118.

Grubel, Herbert. G. and Peter. J. Lloyd (1975), Intra-Industry Trade: the theory and measurement of international trade in differentiated products, London, John Wiley & Sons.

Kenen, Peter B. (2000), "Currency Areas, Policy Domains and the Institutionalization of Fixed Exchange Rates," London School of Economics, Centre for Economic Performance Discussion Paper # 467.

Maddala, G. S. (1977), *Econometrics,* McGraw-Hill, New York.

Mundell, Robert (1961), "A Theory of Optimum Currency Areas," *American Economic Review*, 51 November, pp. 509-17.

_______________ (2000), "Currency Areas, Volatility and Intervention," *Journal of Economic Modeling,* 22(3): pp. 281-99.

Norrbin, Stefan C. and Don E. Schlagenhauf (1996), "The Role of International Factors in the Business Cycle: A Multi-Country Study," *Journal of International Economics*, vol. 40, pp. 85-104.

Rodrik, Dani (2000), "Comments on Frankel and Rose: Estimating the Effects of Currency Unions on Trade and Output," (mimeo).

Rogoff, Kenneth (2001), "Why Not a Global Currency?" *American Economic Review,* 91 pp. 243-47.

Rose, Andrew K. (2000), "One Money, One Markets: Estimating the Effect of Common Currencies on Trade," Economic Policy: A European Forum, April, pp. 7-33.

__________ and Eric van Wincoop (2001), "National Money as a Barrier to International Trade: The Real Case of Currency Union," *American Economic Review*, vol. 92, pp. 386-390.

Ruffin, Roy J. (1999), "The Nature and Significance of Intra-industry Trade," *Economic and Financial Review*, Fourth Quarter, pp. 2-9. Federal Reserve Bank of Dallas.

Figure 1:
Effect of Instrumenting

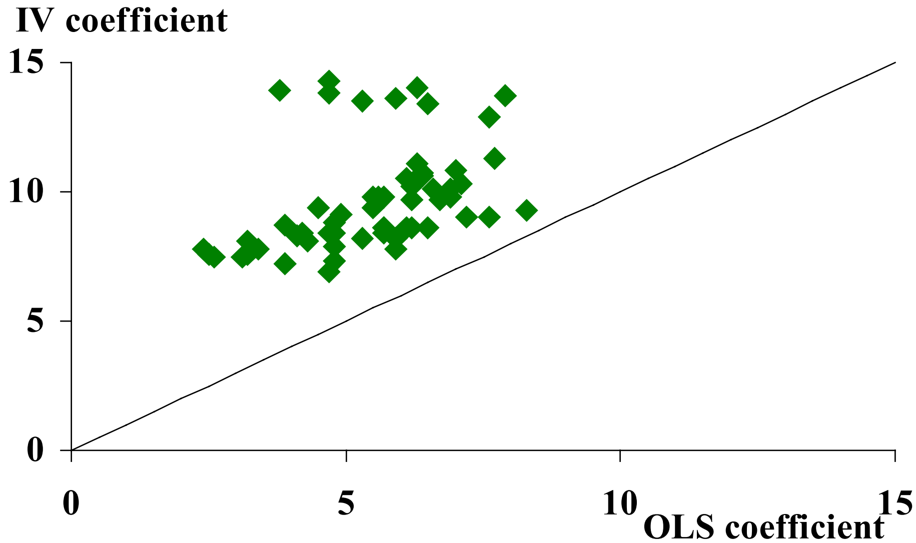

Figure 2:
Structure of the Underlying Model
(F&R model in bold, other plausible links dashed)

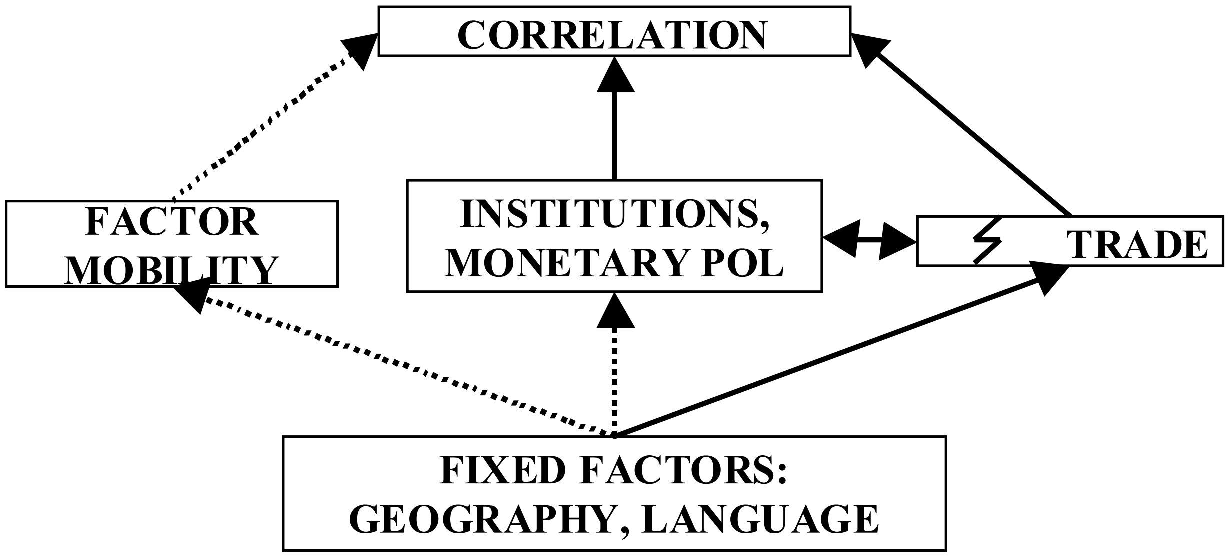

Figure 3:
Do fixed effects change the estimates?

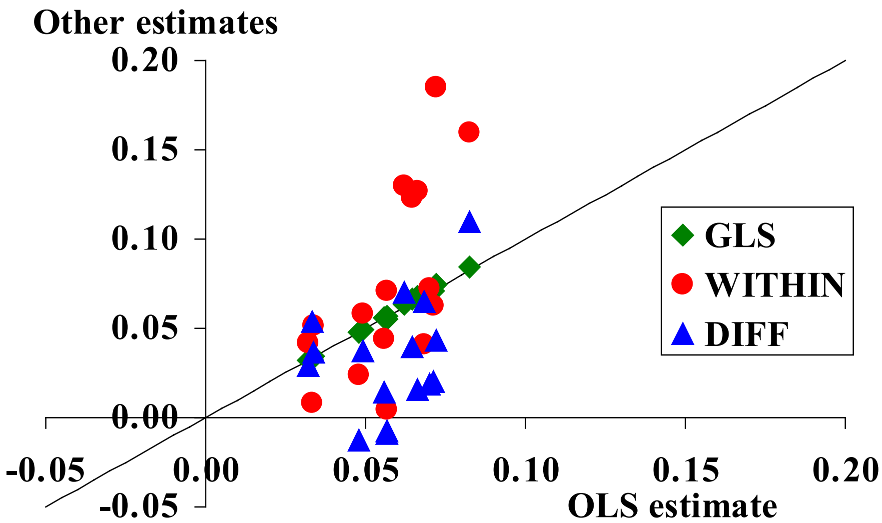

Figure 4:
Do fixed effects change the significance?

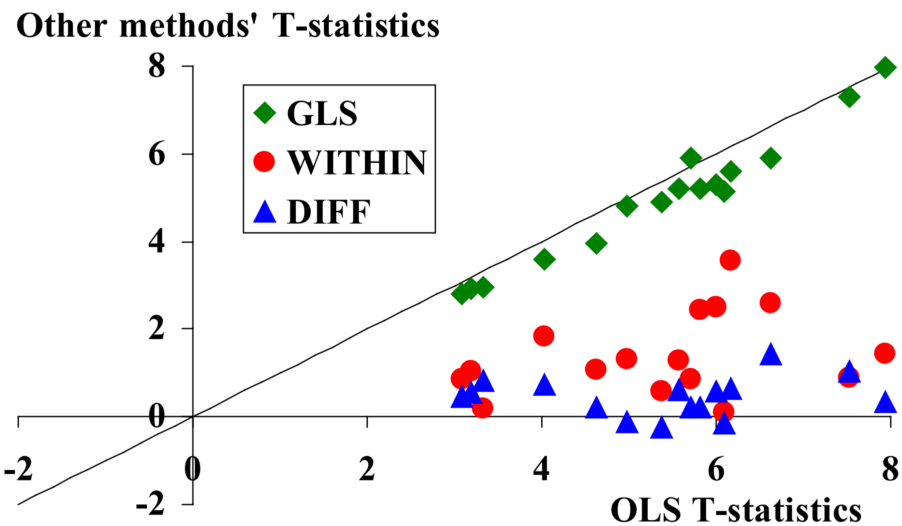

Table 1: Test of overidentifying restrictions in Frankel & Rose model (p-values)

	IV (trade norm)	IV (GDP norm)
GDP yoy	0.26%	0.03%
GDP trend	0.39%	0.10%
GDP hp	0.14%	0.04%
GDP bp	0.49%	0.07%
IP yoy	0.36%	0.01%
IP trend	3.75%	1.47%
IP hp	6.68%	0.84%
IP bp	2.55%	0.51%
EMP yoy	0.33%	0.44%
EMP trend	17.22%	40.65%
EMP hp	0.01%	0.01%
EMP bp	1.69%	8.34%
UR yoy	0.09%	0.03%
UR trend	8.92%	8.37%
UR hp	0.42%	0.16%
UR bp	1.05%	0.45%

Notes: Null hypothesis is that instruments are uncorrelated with the residual

Cell is shaded if null is not rejected at 5%

Table 2: OLS estimate of intra-industry trade coefficient (total trade normalization)

	Levels	Levels + dummies	Logs	Logs + dummies
GDP yoy	10.456 (7.049)	5.168 (3.124)	0.079 (5.785)	0.057 (3.282)
GDP trend	9.416 (5.223)	5.065 (2.146)	0.070 (3.819)	0.075 (3.212)
GDP hp	10.374 (6.213)	6.107 (3.471)	0.076 (5.588)	0.059 (3.429)
GDP bp	10.269 (5.017)	2.527 (1.137)	0.065 (3.722)	0.028 (1.270)
IP yoy	5.838 (3.724)	2.864 (1.694)	0.050 (4.582)	0.055 (4.606)
IP trend	5.255 (3.535)	2.334 (1.157)	0.060 (4.156)	0.070 (4.168)
IP hp	4.483 (3.105)	1.208 (0.745)	0.043 (4.331)	0.047 (4.026)
IP bp	5.757 (3.572)	-0.060 (-0.032)	0.048 (3.746)	0.035 (2.214)
EMP yoy	11.067 (5.610)	8.125 (3.710)	0.055 (3.479)	0.019 (0.998)
EMP trend	11.510 (4.644)	11.976 (4.220)	0.108 (4.830)	0.116 (4.337)
EMP hp	8.525 (5.151)	8.379 (4.477)	0.046 (2.959)	0.040 (2.094)
EMP bp	12.922 (5.537)	9.706 (3.863)	0.064 (3.483)	0.014 (0.637)
UR yoy	8.172 (4.381)	1.249 (0.493)	0.057 (2.440)	0.000 (0.009)
UR trend	7.897 (3.281)	1.759 (0.547)	0.073 (2.576)	0.030 (0.747)
UR hp	7.788 (3.902)	0.399 (0.145)	0.054 (2.380)	0.001 (0.041)
UR bp	6.445 (2.884)	0.334 (0.115)	0.034 (1.274)	-0.003 (-0.076)

Notes: White heteroscedasticity consistent t-statistics in parentheses

Table 3: OLS estimate of intra-industry trade coefficient (GDP normalization)

	Levels	Levels + dummies	Logs	Logs + dummies
GDP yoy	16.454 (2.328)	4.960 (0.767)	0.063 (4.571)	0.052 (3.047)
GDP trend	17.758 (2.326)	10.717 (1.285)	0.066 (3.443)	0.079 (3.498)
GDP hp	17.131 (2.885)	8.900 (1.602)	0.061 (4.423)	0.059 (3.495)
GDP bp	13.588 (1.631)	-0.339 (-0.044)	0.044 (2.532)	0.027 (1.232)
IP yoy	7.757 (1.311)	0.547 (0.095)	0.051 (4.563)	0.056 (4.798)
IP trend	12.325 (1.795)	6.743 (0.923)	0.066 (4.280)	0.073 (4.458)
IP hp	2.832 (0.517)	-3.379 (-0.632)	0.044 (4.247)	0.050 (4.382)
IP bp	5.792 (0.960)	-2.984 (-0.502)	0.048 (3.586)	0.040 (2.594)
EMP yoy	19.906 (2.522)	17.578 (2.131)	0.035 (2.239)	0.014 (0.772)
EMP trend	18.568 (1.955)	28.269 (2.516)	0.099 (4.324)	0.115 (4.400)
EMP hp	21.953 (2.748)	26.560 (2.631)	0.037 (2.321)	0.046 (2.412)
EMP bp	27.897 (3.259)	27.325 (3.040)	0.042 (2.224)	0.010 (0.461)
UR yoy	8.120 (1.117)	-4.074 (-0.505)	0.027 (1.149)	0.006 (0.187)
UR trend	6.682 (0.677)	-0.354 (-0.031)	0.053 (1.823)	0.041 (1.065)
UR hp	9.049 (1.064)	-4.299 (-0.462)	0.036 (1.506)	0.010 (0.325)
UR bp	6.080 (0.623)	-5.660 (-0.518)	0.021 (0.790)	0.011 (0.299)

Notes: White heteroscedasticity consistent t-statistics in parentheses

Table 4: OLS estimate of Non-IIT coefficient (total trade normalization)

	Levels	Levels + dummies	Logs	Logs + dummies
GDP yoy	-5.958 (-3.247)	-4.403 (-2.474)	-0.066 (-2.497)	-0.071 (-2.687)
GDP trend	-3.333 (-1.460)	-2.239 (-1.017)	-0.017 (-0.480)	-0.034 (-0.935)
GDP hp	-5.869 (-2.790)	-4.553 (-2.158)	-0.049 (-1.913)	-0.052 (-1.990)
GDP bp	-4.444 (-1.766)	-2.257 (-0.956)	-0.013 (-0.369)	-0.011 (-0.331)
IP yoy	-0.661 (-0.325)	-0.038 (-0.019)	-0.022 (-1.077)	-0.036 (-1.734)
IP trend	0.113 (0.057)	0.735 (0.363)	-0.033 (-1.195)	-0.044 (-1.577)
IP hp	0.676 (0.365)	1.393 (0.752)	-0.003 (-0.174)	-0.012 (-0.612)
IP bp	0.462 (0.211)	1.789 (0.834)	0.010 (0.412)	0.008 (0.297)
EMP yoy	-6.864 (-2.663)	-5.618 (-2.211)	-0.037 (-1.217)	-0.018 (-0.575)
EMP trend	-3.774 (-1.316)	-3.688 (-1.264)	-0.087 (-2.060)	-0.086 (-2.006)
EMP hp	-3.360 (-1.669)	-3.275 (-1.591)	-0.005 (-0.196)	-0.003 (-0.097)
EMP bp	-8.684 (-2.843)	-7.359 (-2.386)	-0.043 (-1.243)	-0.015 (-0.430)
UR yoy	-2.893 (-1.158)	0.416 (0.170)	-0.001 (-0.014)	0.032 (0.723)
UR trend	-0.967 (-0.306)	1.980 (0.633)	0.002 (0.029)	0.031 (0.548)
UR hp	-2.274 (-0.909)	1.067 (0.425)	0.013 (0.306)	0.045 (1.001)
UR bp	-0.282 (-0.092)	2.459 (0.829)	0.049 (1.018)	0.070 (1.349)

Notes: White heteroscedasticity consistent t-statistics in parentheses

Table 5: OLS estimate of Non-IIT coefficient (GDP normalization)

	Levels	Levels + dummies	Logs	Logs + dummies
GDP yoy	0.309 (0.038)	-7.762 (-0.997)	-0.020 (-0.743)	-0.031 (-1.179)
GDP trend	4.928 (0.449)	1.694 (0.160)	-0.008 (-0.224)	-0.015 (-0.405)
GDP hp	0.429 (0.057)	-6.385 (-0.896)	-0.009 (-0.341)	-0.017 (-0.647)
GDP bp	12.172 (1.137)	2.613 (0.252)	0.044 (1.309)	0.031 (0.911)
IP yoy	5.383 (0.737)	2.839 (0.381)	-0.027 (-1.320)	-0.029 (-1.427)
IP trend	0.019 (0.002)	-3.982 (-0.386)	-0.051 (-1.751)	-0.051 (-1.761)
IP hp	12.523 (1.845)	7.832 (1.137)	-0.009 (-0.445)	-0.011 (-0.530)
IP bp	14.533 (1.722)	5.085 (0.591)	0.006 (0.245)	0.000 (-0.016)
EMP yoy	4.039 (0.339)	-2.317 (-0.198)	0.021 (0.696)	0.023 (0.750)
EMP trend	19.568 (1.366)	12.769 (0.865)	-0.060 (-1.398)	-0.055 (-1.284)
EMP hp	-1.465 (-0.136)	-3.566 (-0.331)	0.018 (0.610)	0.021 (0.719)
EMP bp	-3.104 (-0.245)	-17.029 (-1.366)	0.024 (0.682)	0.021 (0.608)
UR yoy	20.026 (1.709)	20.813 (1.783)	0.078 (1.801)	0.085 (1.954)
UR trend	28.227 (1.808)	22.091 (1.385)	0.055 (1.030)	0.058 (1.078)
UR hp	16.804 (1.283)	13.308 (1.006)	0.062 (1.418)	0.067 (1.529)
UR bp	19.918 (1.320)	19.866 (1.283)	0.079 (1.598)	0.083 (1.680)

Notes: White heteroscedasticity consistent t-statistics in parentheses

Table 6: P-value for test of $\beta_1=\beta_2$ (total trade normalization)

	Levels	Levels + dummies	Logs	Logs + dummies
GDP yoy	0.000%	0.332%	0.002%	0.260%
GDP trend	0.087%	8.402%	1.952%	1.872%
GDP hp	0.001%	0.445%	0.009%	0.510%
GDP bp	0.079%	26.858%	3.223%	45.035%
IP yoy	6.431%	41.843%	0.059%	0.008%
IP trend	12.084%	67.753%	0.177%	0.050%
IP hp	23.403%	95.568%	0.090%	0.045%
IP bp	14.820%	63.030%	0.822%	6.055%
EMP yoy	0.005%	0.254%	1.124%	52.048%
EMP trend	0.275%	0.399%	0.003%	0.010%
EMP hp	0.079%	0.186%	4.763%	18.641%
EMP bp	0.004%	0.145%	0.775%	66.554%
UR yoy	0.873%	85.977%	14.260%	81.636%
UR trend	9.482%	97.035%	8.563%	63.642%
UR hp	1.964%	89.379%	15.350%	84.269%
UR bp	18.420%	69.913%	65.341%	69.130%

Notes: From estimation of equation (7) by OLS

Table 7: P-value for test of β_1=β_2 (GDP normalization)

	Levels	Levels + dummies	Logs	Logs + dummies
GDP yoy	25.727%	32.106%	0.189%	0.987%
GDP trend	47.622%	60.803%	4.023%	1.164%
GDP hp	19.451%	19.226%	0.516%	0.838%
GDP bp	93.802%	86.044%	36.683%	63.207%
IP yoy	85.289%	85.383%	0.054%	0.005%
IP trend	46.598%	52.588%	0.081%	0.017%
IP hp	41.407%	33.052%	0.084%	0.016%
IP bp	53.367%	56.101%	0.940%	2.457%
EMP yoy	40.955%	28.579%	22.233%	83.257%
EMP trend	96.532%	51.743%	0.023%	0.014%
EMP hp	19.504%	11.307%	17.769%	14.108%
EMP bp	13.053%	2.537%	17.431%	91.641%
UR yoy	52.162%	18.429%	92.246%	69.559%
UR trend	38.563%	38.291%	32.891%	54.224%
UR hp	71.167%	41.252%	57.834%	92.143%
UR bp	56.611%	30.538%	98.134%	85.364%

Notes: From estimation of equation (7) by OLS

Table 8: P-value for test of γ_1=0 and γ_2=0 and γ_3=0

	Trade norm, Levels	Trade norm, Logs	GDP norm, Levels	GDP norm, Logs
GDP yoy	0.000%	0.001%	0.000%	0.016%
GDP trend	0.132%	0.511%	0.325%	0.187%
GDP hp	0.000%	0.034%	0.000%	0.225%
GDP bp	0.000%	0.002%	0.000%	0.053%
IP yoy	0.641%	0.035%	0.020%	0.008%
IP trend	2.959%	2.669%	1.759%	1.616%
IP hp	0.193%	2.636%	0.043%	0.555%
IP bp	0.000%	0.293%	0.000%	0.290%
EMP yoy	0.004%	0.029%	0.022%	0.360%
EMP trend	1.178%	57.649%	6.069%	39.230%
EMP hp	0.003%	0.100%	0.003%	0.056%
EMP bp	0.001%	0.032%	0.005%	0.979%
UR yoy	0.006%	0.016%	0.041%	0.176%
UR trend	0.250%	17.146%	4.638%	47.695%
UR hp	0.006%	0.139%	0.030%	0.806%
UR bp	0.334%	1.395%	0.729%	2.291%

Notes: γ_1, γ_2, and γ_3 are coefficients of the fixed factors in equation (6)

Table 9: Effect of a 25% (one standard deviation) shock to volume of trade

	F&R (IV)	F&R (OLS)	F&R (OLS + dummies)	Composition of Trade
Pre-Shock	0.346	0.334	0.318	0.308
Post-Shock	0.462	0.435	0.390	0.366
Effect	+ 0.116	+ 0.101	+ 0.072	+ 0.058

Notes: The average correlation in the sample is 0.316.

The Pre-Shock value assumes mean values for the logs of intra-industry trade (IIT), trade intensity (TI), and distance, and common language/common border dummies are set to zero. The shock only affects TI.

Table 10: FE estimate of intra-industry trade coefficient (total trade normalization)

	Levels, Within	Levels, Differenced	Logs, Within	Logs, Differenced
GDP yoy	-6.593 (-1.180)	-5.669 (-0.695)	0.011 (0.272)	0.007 (0.119)
GDP trend	-12.139 (-1.424)	-13.369 (-1.435)	0.041 (0.686)	0.072 (0.844)
GDP hp	19.614 (3.970)	10.953 (1.793)	0.221 (6.298)	0.113 (2.275)
GDP bp	-2.208 (-0.248)	-2.008 (-0.184)	-0.039 (-0.667)	-0.092 (-1.110)
IP yoy	1.450 (0.320)	0.964 (0.122)	0.032 (1.460)	0.043 (1.072)
IP trend	-12.505 (-2.692)	-12.607 (-1.638)	-0.077 (-3.017)	-0.073 (-1.650)
IP hp	1.777 (0.414)	-4.286 (-0.666)	0.022 (1.049)	0.018 (0.489)
IP bp	-6.514 (-1.188)	-9.729 (-1.214)	-0.025 (-0.888)	-0.014 (-0.305)
EMP yoy	-0.230 (-0.031)	-0.236 (-0.026)	0.094 (2.707)	0.060 (1.006)
EMP trend	18.056 (1.811)	6.182 (0.433)	0.159 (2.992)	0.053 (0.654)
EMP hp	11.635 (1.536)	15.770 (1.405)	0.054 (1.372)	-0.004 (-0.055)
EMP bp	9.403 (0.782)	16.769 (1.464)	0.101 (2.320)	0.079 (1.078)
UR yoy	-18.932 (-2.204)	-12.917 (-1.225)	-0.202 (-2.188)	-0.147 (-1.133)
UR trend	-21.280 (-1.864)	-22.471 (-1.502)	-0.426 (-4.268)	-0.489 (-4.068)
UR hp	-8.591 (-0.903)	-3.489 (-0.289)	-0.237 (-2.881)	-0.232 (-2.206)
UR bp	-16.650 (-1.191)	-8.884 (-0.613)	-0.221 (-2.088)	-0.238 (-1.892)

Notes: White heteroscedasticity consistent t-statistics in parentheses

Table 11: FE estimate of intra-industry trade coefficient (GDP normalization)

	Levels, Within	Levels, Differenced	Logs, Within	Logs, Differenced
GDP yoy	5.531 (0.490)	5.348 (0.313)	0.090 (2.296)	0.092 (1.827)
GDP trend	-17.667 (-0.954)	-23.583 (-1.223)	0.067 (1.256)	0.069 (0.898)
GDP hp	40.065 (4.142)	17.170 (1.320)	0.232 (7.360)	0.143 (3.196)
GDP bp	11.188 (0.748)	-10.654 (-0.465)	-0.007 (-0.133)	-0.072 (-0.968)
IP yoy	-3.498 (-0.437)	10.450 (0.693)	0.027 (1.336)	0.086 (2.439)
IP trend	-35.079 (-4.491)	-37.025 (-2.679)	-0.051 (-2.088)	-0.038 (-0.902)
IP hp	-3.028 (-0.373)	-5.075 (-0.341)	0.015 (0.758)	0.048 (1.425)
IP bp	-11.290 (-1.305)	-20.588 (-1.392)	-0.034 (-1.264)	-0.001 (-0.032)
EMP yoy	36.076 (2.359)	33.595 (1.415)	0.104 (3.129)	0.094 (1.687)
EMP trend	49.259 (2.362)	22.377 (0.542)	0.163 (3.310)	0.057 (0.778)
EMP hp	59.566 (4.472)	55.939 (2.407)	0.075 (2.231)	0.027 (0.487)
EMP bp	51.647 (2.773)	54.404 (2.316)	0.101 (2.460)	0.082 (1.204)
UR yoy	-35.116 (-1.995)	-34.789 (-1.581)	-0.050 (-0.593)	-0.032 (-0.290)
UR trend	-64.396 (-2.695)	-84.500 (-2.587)	-0.291 (-3.116)	-0.383 (-3.557)
UR hp	-27.097 (-1.400)	-33.515 (-1.186)	-0.155 (-2.002)	-0.179 (-1.916)
UR bp	-53.823 (-2.001)	-60.137 (-1.713)	-0.195 (-1.985)	-0.227 (-2.006)

Notes: White heteroscedasticity consistent t-statistics in parentheses

Table 12: FE estimate of Non-IIT coefficient (total trade normalization)

	Levels, Within	Levels, Differenced	Logs, Within	Logs, Differenced
GDP yoy	-9.652 (-2.158)	-6.762 (-1.036)	-0.175 (-2.792)	-0.098 (-1.142)
GDP trend	-3.276 (-0.645)	7.347 (1.228)	-0.064 (-0.796)	0.140 (1.189)
GDP hp	-10.998 (-3.180)	-8.017 (-2.054)	-0.161 (-3.091)	-0.070 (-0.985)
GDP bp	-4.584 (-0.866)	1.123 (0.149)	0.012 (0.150)	0.204 (1.884)
IP yoy	-4.811 (-1.516)	-12.031 (-1.967)	-0.033 (-0.860)	-0.138 (-2.072)
IP trend	4.400 (1.366)	8.923 (1.954)	-0.043 (-0.971)	-0.061 (-0.774)
IP hp	-3.095 (-1.089)	-6.553 (-1.330)	-0.001 (-0.014)	-0.048 (-0.798)
IP bp	2.294 (0.658)	3.778 (0.621)	0.055 (1.201)	0.048 (0.632)
EMP yoy	-11.148 (-2.030)	-13.295 (-1.639)	-0.141 (-2.078)	-0.139 (-1.264)
EMP trend	0.976 (0.153)	15.971 (1.798)	-0.190 (-2.010)	0.064 (0.457)
EMP hp	-15.115 (-3.406)	-17.309 (-2.648)	-0.100 (-1.647)	-0.056 (-0.563)
EMP bp	-7.237 (-1.107)	-8.495 (-0.732)	-0.092 (-1.219)	-0.019 (-0.170)
UR yoy	4.386 (0.780)	6.643 (0.879)	0.070 (0.506)	0.147 (0.861)
UR trend	13.950 (1.754)	22.868 (2.228)	0.421 (2.830)	0.569 (3.359)
UR hp	2.416 (0.442)	2.815 (0.331)	0.240 (1.910)	0.335 (2.262)
UR bp	11.330 (1.554)	14.403 (1.356)	0.506 (3.334)	0.606 (3.218)

Notes: White heteroscedasticity consistent t-statistics in parentheses

Table 13: FE estimate of Non-IIT coefficient (GDP normalization)

	Levels, Within	Levels, Differenced	Logs, Within	Logs, Differenced
GDP yoy	-9.430 (-0.541)	4.788 (0.211)	0.037 (0.532)	0.150 (1.648)
GDP trend	30.804 (1.452)	62.974 (2.377)	0.100 (1.099)	0.262 (2.124)
GDP hp	-12.124 (-0.945)	0.253 (0.016)	0.008 (0.144)	0.098 (1.349)
GDP bp	-6.512 (-0.321)	18.936 (0.733)	0.215 (2.459)	0.376 (3.361)
IP yoy	25.743 (1.859)	24.979 (1.305)	0.116 (2.655)	0.168 (2.352)
IP trend	37.266 (2.875)	57.952 (2.924)	0.013 (0.265)	0.050 (0.590)
IP hp	34.730 (2.920)	48.923 (2.856)	0.144 (3.598)	0.245 (3.910)
IP bp	37.500 (2.692)	65.710 (3.173)	0.178 (3.392)	0.290 (3.503)
EMP yoy	4.955 (0.185)	-10.220 (-0.321)	0.015 (0.212)	0.069 (0.627)
EMP trend	65.825 (2.284)	96.322 (2.619)	-0.043 (-0.420)	0.248 (1.824)
EMP hp	-43.147 (-2.060)	-44.283 (-1.722)	0.028 (0.440)	0.061 (0.610)
EMP bp	-13.389 (-0.493)	-28.451 (-0.909)	-0.003 (-0.043)	0.066 (0.596)
UR yoy	63.006 (2.634)	56.815 (1.910)	0.463 (3.847)	0.465 (2.942)
UR trend	106.430 (3.196)	108.194 (2.606)	0.818 (6.136)	0.867 (5.290)
UR hp	40.901 (1.711)	36.680 (1.220)	0.481 (4.682)	0.499 (3.758)
UR bp	53.070 (1.661)	47.240 (1.196)	0.700 (5.238)	0.716 (4.097)

Notes: White heteroscedasticity consistent t-statistics in parentheses