ARE INSTRUMENTS GENERATED FROM GEOGRAPHIC CHARACTERISTICS IN BILATERAL RELATIONSHIPS VALID?[1]

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Abstract. In their highly influential paper, 'Does Trade Cause Growth?,' Frankel and Romer (FR) estimate a trade equation to predict bilateral trade shares, which are in turn aggregated to construct an instrument for trade openness in income regressions. The FR approach has gained widespread popularity as a method to generate instruments for trade, foreign aid, FDI, immigration, knowledge diffusion, immigration diversity etc. from bilateral relationships. This research shows analytically and empirically that the FR instrument is endogenous when fitted shares for zero and missing bilateral trade are omitted from the instrument set. Furthermore, we show that the power of the FR instrument can be enhanced by using weights exogenous to income in the aggregation of fitted bilateral trade shares over all possible observations.

JEL: F14, F43; O40
Key words: Instruments generated from bilateral flows; trade-growth nexus; randomly generated instruments; instrument efficiency

1. Introduction

Following the seminal paper on trade and growth by Frankel and Romer (1999, FR henceforth), it has become common practice to use regressors or instrumental variables (IV) in structural estimates generated by aggregating fitted values from auxiliary regressions based on the gravity equation and other bilateral flow models. Specifically, FR regress bilateral trade shares between country *i* and *j* on geographic characteristics and sum over the *j*'s to form an instrument for trade openness in cross-country growth regressions. Though originally developed for trade, the FR IV approach has gained popularity in

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non-trade applications, such as immigration, knowledge diffusion, cross-border banking, fertility, currency unions, immigration diversity and foreign aid, to test their effects on per capita income, TFP, institutions, child labor, the environment, nation building, and labor market regulation, among other outcome variables.[2]

Even though the FR approach seems clear-cut their approach is not straightforward because the conclusion reached from the structural regression is sensitive to whether predicted zero or missing bilateral trade shares are included or excluded from the instrument used for trade openness; an important issue since a large fraction of bilateral flows, particularly for low-income countries, are missing or zero. For comparative purposes this is problematic because some studies exclude zero or missing bilateral flow predictions from the auxiliary regressions, others do not and most studies are not clear about their identification method.[3] This raises the following question: Should predicted zero or missing bilateral trade shares be included in the instrument for trade openness or any other variable that is instrumented by aggregating bilateral flows?

In this paper we seek to answer the question of whether zero and missing bilateral trade shares should be included in the instrument for trade openness. We show analytically and empirically that the FR IV approach may potentially aggravate the endogeneity bias that is present in the OLS regressions because the number of non-zero bilateral relationships is endogenous to the outcome variable. In the case of trade, we find that the number of non-zero bilateral relationships is significantly positively related to

[2] Prominent studies using the FR identification strategy to estimate the income effects of trade and non-trading flows include the following. Trade: Bosworth and Collins (2003), Dollar and Kraay (2003), Yanikkaya (2003), Redding and Venables (2004), Noguer and Siscart (2005), Freund and Bolaky (2008), Feyrer (2009), Kim and Lin (2009), Felbermayr and Gröschl (2013), Ortega and Peri (2014), Gervais (2015), Brambilla and Porto (2016), Blanchard and Olney (2017), Pascali (2017), Feyrer (forthcoming). Foreign aid: Rajan and Subramanian (2008, 2011). Immigration diversity: Alesina et al. (2016). Migration: Felbermayr et al. (2010), Ortega and Peri (2014), Bahar and Rapoport (2018). Birthplace diversity: Bove and Elia (2017). Currency unions: Frankel and Rose (2002). Globalization. Potrafke (2013). Prominent studies using the FR identification strategy in which the effects of trade openness on non-income outcome variables are examined include the following. Productivity: Andersen and Dalgaard (2011). Fertility: Do et al. (2016). Child labor: Edmonds and Pavcnik (2006). Education: Blanchard and Olney (2017), Environment: Frankel and Rose (2005). Employment: Volpe Martincus et al. (2017). Financial development: Rajan and Zingales (2003), Do and Levchenko (2007). Resource dependence: Brunnschweiler and Bulte (2008). Output volatility: di Giovanni and Levchenko (2009) and Ardelean *et al*. (2017). Nation building. Alesina et al. (2000), Credit market deregulation: Eppinger and Potrafke (2016). Democracy: Acemoglu et al. (2008), Docquier et al. (2016). Institutions: Levchenko (2013). Labor market regulation: Potrafke (2013).

[3] Studies that clearly state that their identification strategy is based on observed bilateral flows and, therefore, that only include predictions for observations of actual positive bilateral flows to form the instrument, include, among others: Noguer and Siscart (2005), Do and Levchenko (2007), Rajan and Subramanian (2008, 2011), di Giovanni and Levchenko (2009), Felbermayr et al. (2010), Levchenko (2013), Gervais (2015), and Blanchard and Olney (2017). Studies explicitly stating that they include all potential bilateral relationships include: Cavallo and Frankel (2008), Feyrer (2009), Felbermayr and Gröschl (2013), Brambilla and Porto (2016), Do et al. (2016), Docquier et al. (2016), Eppinger and Potrafke (2016), Ardelean et al. (2017), Pascali (2018), and Feyrer (forthcoming). Finally, studies that do not state clearly whether non-observed positive bilateral flows are included in the instrument set include, among other papers, Alesina et al. (2000), Frankel and Rose (2002), Bosworth and Collins (2003), Dollar and Kraay (2003), Levy-Yeyati and Sturzenegger (2003), Ranjan and Zingales (2003), Yanikkaya (2003), Frankel and Rose (2005), Edmonds and Pavcnik (2006), Acemoglu et al. (2008), Brunnschweiler and Bulte (2008), Freund and Bolaky (2008), Kim and Lin (2009), Felbermayr et al. (2010), Andersen and Dalgaard (2011), Potrafke (2013), Ortega and Peri (2014), Alesina et al. (2016), Bove and Elia (2017), and Volpe Martincus et al. (2017).

income, thus creating a positive relationship between income and trade when only non-zero bilateral relationships are used to form the instrument for trade - even when there is no causal effect from trade to income. Stated differently, we show that the IV regression results are biased when predicted zero or missing bilateral trade flows are excluded from the instrument set.

To this end, we generate bilateral trade shares predicted from randomly generated geographical characteristics to construct instruments for trade openness. The predicted trade shares are then used to test whether trade causes growth in the structural regressions. Excepting type I errors, randomly generated instruments should be weak and result in insignificant relationships between trade and income, regardless of whether any relationship exists. However, this is not what we find. The coefficients of trade openness are, on average, significantly positive in 97-100% of the counterfactual structural regressions when predictions for observed shares only are used to create the instrument for trade openness; thus casting serious doubt on this approach. Conversely, the coefficients of trade openness are, on average, insignificant in 99% of the simulations when predictions for all bilateral shares are included in the IV set, as we would expect from a randomized experiment. From these experiments we conclude that the parameter estimates are biased against the null hypothesis of no relationship when predictions for only observed non-zero bilateral shares are used to create the instrument for trade openness and that this bias is eliminated if predictions for all bilateral shares are included in the IV set.

Why does the exclusion of the predicted bilateral shares for zero or missing observations in the IV set create a spurious positive relationship between income and trade? We show analytically that this result arises because the instruments capture the distinct number of trade partners of each country. This outcome is problematic as the number of partners a country actively trades with is not exogenous to income. Low-income countries trade with fewer partners than high-income countries; often because they face higher trading costs induced by poor institutions, infrastructure and business environment (Djankov *et al*., 2002). Furthermore, high fixed costs of exporting might preclude firms in low-income countries from penetrating some foreign markets (Helpman et al., 2008). Thus, instruments that include only predicted values for observed trade shares are endogenous – a result that generalizes to instruments created from bilateral relationships such as immigration, foreign aid, knowledge diffusion, immigration diversity, currency unions, globalization and other applications involving bilateral flows. In a nutshell, one should always include predictions for all bilateral trade shares and other bilateral values regardless of whether they are observed, exactly as originally done by FR.

As an additional contribution to the literature, we provide a method to enhance the power of the instruments generated by aggregating fitted values from auxiliary regressions by using weights when the probability of observing the dependent variable in the auxiliary regression is endogenous to the outcome of interest. Indeed, just summing over fitted values from the auxiliary regression for all possible data points implicitly assumes that each observation is equally likely to occur with probability of 1. The method is to extract the exogenous variation in the probability of observing the dependent variable in the auxiliary regression and use it as a weight in the aggregation of predicted values from the auxiliary regression over all possible observations. We develop and apply this approach in the context of our trade-growth application and find that the proposed weighted instrument for trade openness relative to the original FR instrument generates higher *t*-statistics for the coefficient of trade openness by, on average, 17%.

The reminder of the paper is organized as follows. Section 2 briefly shows the empirical strategy. Section 3 demonstrates that the estimated effects of trade on income are highly sensitive to the way in which predicted values from auxiliary regressions are aggregated into the instrument, and it further shows that the statistical significance of trade is amplified due to an endogeneity bias through an experiment in which the instruments are randomly generated. In Section 4, we show that an instrument that excludes predicted bilateral shares for zero or missing observations is invalid because it captures the number of a country's trading partners, which is endogenous to income. Furthermore, we generalize the FR IV approach to applications in which the instrument is created by summing predicted values from auxiliary regressions. In Section 5 we propose an approach to increase the power of the FR instrument by allowing the probability of engaging in a bilateral trade relationship to differ from one by using exogenous information on the probability of engaging in trade. Section 6 concludes.

2. Empirical strategy

Following FR, our empirical strategy is as follows. First, consider the following structural income equation:

$$lnY_i = \alpha_0 + \alpha_1 T_i + \alpha_2 lnN_i + \alpha_3 lnA_i + \boldsymbol{X'\alpha} + e_i, \qquad (1)$$

where Y_i is country i's income per capita; T_i is country i's ratio of total trade (exports + imports) to GDP, i.e. trade openness; N_i is country i's population; A_i is country i's land area; and $\boldsymbol{X}$ is a vector of control variables. Population and country area are included to capture within-country trade. Identifying the effect of trade on income is complicated because of the two-way causal relationship between these two variables. We address this issue following the FR two-step IV procedure.

In the first-step we generate instruments for trade openness using an auxiliary equation where bilateral trade openness is determined by the following set of geographic characteristics:

$$\begin{aligned}\ln\,(\tau_{ij}/GDP_i) = {} & \beta_0 + \beta_1 \ln\, D_{ij} + \beta_2 lnN_i + \beta_3 lnA_i + \beta_4 lnN_j + \beta_5 lnA_j + \beta_6 (L_i + L_j) \\ & + \beta_7 B_{ij} + \beta_8 B_{ij} D_{ij} + \beta_9 B_{ij} N_j + \beta_{10} B_{ij} A_i + \beta_{11} B_{ij} N_i + \beta_{12} B_{ij} A_j + \beta_{13} B_{ij} (L_i + L_j) + \varepsilon_{1,ij}, \qquad (2)\end{aligned}$$

where τ_{ij} is the total bilateral trade between country *i* and *j*; GDP_i is *i*'s total income; D_{ij} is the geographic distance between country *i* and *j*; *L* is a dummy variable that takes the value of 1 for landlocked countries and zero otherwise; B_{ij} is an indicator variable taking the value of 1 if countries *i* and *j* share a border and zero otherwise; and ε is a stochastic error term.

We use estimates of Eq. (2) to form two instruments for country *i*'s trade openness, T_i:

$$\hat{T}_i^{Pos*} = \sum_{j\in\Omega_{ij}} e^{\ln\left(\widehat{\frac{\tau_{ij}}{GDP_i}}\right)}, \tag{3}$$

$$\hat{T}_i^{All*} = \sum_{j\in\Psi_{ij}} e^{ln\left(\widehat{\frac{\tau_{ij}}{GDP_i}}\right)}, \tag{4}$$

where Ω_{ij} is the set of countries with which *i* actively trades; Ψ_{ij} is the set of all countries with which *i* can potentially trade (i.e., those with which country *i* does and does not trade), including unobservables. In words, $\hat{T}_i^{Pos*}$ only includes predictions for observations of actual positive bilateral trade using the coefficients from Eq. (2), while $\hat{T}_i^{All*}$ includes predictions over all possible trade flows within the data set and is the instrument originally proposed by FR.

In the second-step we employ the generated instruments to investigate the relationship between trade and income using Two-Stage Least Squares (2SLS). Specifically, we estimate the following first-stage regressions:

$$T_i = \gamma_0 + \gamma_1\hat{T}_i^{Pos*} + \gamma_2 \ln N_i + \gamma_3 \ln A_i + \boldsymbol{X'\gamma} + e_{1,i}, \tag{5}$$

$$T_i = \mu_0 + \mu_1\hat{T}_i^{All*} + \mu_2 \ln N_i + \mu_3 \ln A_i + \boldsymbol{X'\mu} + e_{2,i}, \tag{6}$$

where *e* is a stochastic error term. These regressions yield the instruments $\hat{T}_i^{Pos}$ (Eq. (5)) and $\hat{T}_i^{All}$ (Eq. (6)). We estimate the following second-stage regressions:

$$lnY_i = a_0 + a_1\hat{T}_i^{Pos} + a_2 \ln N_i + a_3 \ln A_i + \boldsymbol{X'\xi} + e_{3i}, \tag{7}$$

$$lnY_i = b_0 + b_1\hat{T}_i^{All} + b_2 \ln N_i + b_3 \ln A_i + \boldsymbol{X'\varsigma} + e_{4i}. \tag{8}$$

Using Eq. (8) without the ***X*** control variables as their baseline regression, FR find per capita income to be a weakly significant increasing function of trade openness. Following Rodriguez and Rodrik's (2001, RR henceforth) finding that geography not only affects income through trade, but also through human capital and the quality of institutions, we include geographic and institutional variables as controls in some of the estimates below.

The key question asked in this paper is whether one should include or exclude predictions for zero or missing bilateral trade observations when generating an instrument for trade; i.e., should one use

$\hat{T}_i^{Pos*}$ or $\hat{T}_i^{All*}$ as an instrument for trade? This is not a trivial issue because the maximum number of bilateral trading partners is significantly higher than the number of recorded trade flows, and the results in most samples are influenced by this choice, as we show below. We would have a maximum number of bilateral trade flows of 15,778 in our 98-country sample *if* all countries traded with each other and every other possible partner, noting that there are 161 potential trading partners for each country when the rest of the world is included. Instead, however, there are only 9,757 recorded positive trade flows, which are used to estimate Eq. (2). The rationale in favor of using $\hat{T}_i^{Pos*}$ over $\hat{T}_i^{All*}$ is that the inclusion of predictions for zero or missing bilateral trade shares to form the instrument introduces noise in the instrument, weakens it, and renders it inefficient (see, e.g., Noguer and Siscart, 2005).[4] However, a much greater concern than efficiency is whether the parameter estimates are biased in the income models given by Eqs. (7) and (8); an issue we address in the next section.

3. Empirical analysis

In the empirical analysis we proceed as follows. First, we show that the estimated income effects of trade are highly sensitive to whether $\hat{T}_i^{Pos}$ or $\hat{T}_i^{All}$ is used as an instrument. More specifically, we generate instruments for trade openness, $\hat{T}_i^{Pos}$ and $\hat{T}_i^{All}$, and estimate the first- and second-stage regressions for different specifications of the structural income equation (Eq. (1)). Throughout the rest of the paper we report the results for four different specifications of Eq. (1): 1) Baseline regression without controls in $\boldsymbol{X}$; 2) baseline regression plus a country's distance to the equator; 3) baseline regression plus the percentage of a country's land in the tropics; and 4) baseline regression plus continental dummies. The last three specifications follow RR and have been widely used in the literature. In the Appendix and online Appendix we also consider 10 additional structural models that contain variables that are often considered important for income in the growth literature (see, e.g., Noguer and Siscart, 2005). Second, to identify whether the models provide unbiased estimates, we estimate the auxiliary equation (2) using randomly generated geographic data in place of actual data (1000 iterations). Then, for each draw we use predicted bilateral trade shares to generate two instruments, $\tilde{T}_i^{Pos}$ and $\tilde{T}_i^{All}$, following Eqs. (3) and (4), and estimate the first- and second-stage regressions for all the specifications of the structural equation.

[4] This paper's key question is quite distinct from the issue of accounting for zero and/or missing trade when estimating the bilateral trade equation, Eq. (2). In the online Appendix A we show that the improved performance of $\hat{T}_i^{Pos}$ over $\hat{T}_i^{All}$ is not sensitive to whether the bilateral trade equation is estimated using the Poisson pseudo-maximum likelihood (PPML) method, which allows us to obtain consistent predicted bilateral shares in the presence of errors whose variance depends on the regressors while accounting for the missing values/zeros.

3.1 Data

Following FR we use bilateral trade flows in 1985 from the IMF Direction of Trade Statistics between the 98 countries in Mankiw *et al.*'s (1992) sample and 161 possible trading partners (98 - 1 = 97 partners within the sample and 64 countries in the rest of the world). These 98 countries tend to have the most reliable data in the world, and have per capita income levels that are less likely to be determined by idiosyncratic factors. Population, income (real GDP per capita) and trade openness are from PWT Mark 5.6. The CEPII GeoDist database is used as the source for the geographic variables: area, the landlocked dummy, latitudinal coordinates, bilateral distance (population-weighted) and dummy variables for common border. Data on the percentage of land or population in the tropics, and regional dummies (per continent) is from the Centre for International Development (CID). More details on the data are provided in Appendix A.

3.2 FR and RR Replications

Table 1 shows the estimates for the gravity equation, Eq. (2). The coefficients of the geographic characteristics are almost all statistically significant (left panel of Table 1), while the coefficients of the interaction terms are mostly insignificant (right panel of Table 1). These results are in line with those of FR.

Table 1. Estimation of the Bilateral Trade Equation using OLS

	Variable	Border interaction
Constant	-7.189***	4.728**
	(0.487)	(2.035)
Ln distance$_{ij}$	-1.110***	0.286
	(0.034)	(0.338)
Ln population$_i$	-0.134***	-0.284**
	(0.024)	(0.140)
Ln population$_j$	0.933***	-0.091
	(0.021)	(0.130)
Ln area$_i$	-0.141***	0.052
	(0.017)	(0.144)
Ln area$_j$	-0.234***	-0.056
	(0.017)	(0.157)
Landlocked$_{ij}$	-0.671***	0.159
	(0.053)	(0.181)
Observations	9,757	
R^2	0.318	

Note. The dependent variable is ln(τ_{ji}/GDP_i). Column (1) reports the coefficient of the variable listed, and column (2) shows the coefficient of the interaction between the variable in the first column and 'border' (i.e. countries *ij* sharing a border). Heteroscedasticity consistent standard errors are in parentheses. **, *** Significant at 5 and 1 percent, respectively.

Table 2 reports estimates for the structural income regressions for our main four models; each estimated by OLS, and 2SLS/IV using $\hat{T}_i^{Pos}$ and $\hat{T}_i^{All}$ as instruments for trade openness. The standard errors in the IV regressions are adjusted to account for the fact that the standard errors of the coefficients of the instrumented trade openness depend on the standard errors of the bilateral trade equation following the approach proposed by FR.[5] The table further reports the Kleibergen-Paap (KP) *rk* Wald *F*-statistic for weak identification.

The following conclusions emerge from the regressions in Table 2: First, the null hypothesis of weak instruments is rejected in all cases - the KP *rk* Wald *F*-statistic is always greater than 10, suggesting that $\hat{T}_i^{Pos}$ and $\hat{T}_i^{All}$ are both potentially good instruments.[6] Second, the coefficients of trade openness in the second-stage regression are positive and statistically significant, regardless of whether $\hat{T}_i^{Pos}$ or $\hat{T}_i^{All}$ are used as instruments or whether continental fixed effects are added to the baseline model (Model (4)). Consistent with the findings of RR, the coefficients of trade openness become smaller and insignificant in the IV-$\hat{T}_i^{All}$-regressions when the share of the fraction of land within the tropics or the distance to the equator are included in the regressions as controls (Models (2) and (3)). However, when predictions for observations of zero or missing bilateral trade are excluded from the IV-set (IV-$\hat{T}_i^{Pos}$-regressions), the coefficient of trade-openness becomes significant at least at the 5% level in all specifications; a key result of Noguer and Siscart (2005), for example. Third, the coefficients of trade openness in the OLS estimates are statistically quite significant and their magnitudes are smaller than those of the IV-regressions when controls are excluded from the regressions but comparable between the OLS and IV regressions when controls are included; a result that resonates with the RR results and their discussion.

Fourth, and most importantly, comparing the significance of the coefficients of $\hat{T}_i^{Pos}$ with that of $\hat{T}_i^{All}$ in Tables 2 and A.2 yields some stark results, where Appendix Table A.2 contains the results from ten additional specifications of the income model that include as controls various institutional and geographical variables often considered important for cross-country per capita income regressions, as noted above. The coefficients of trade openness are significant at least at the 10% level in 6 of the 14 cases (42.9%) when $\hat{T}_i^{All}$ is used as instrument; not far from what we would expect from a coin toss. By contrast, if $\hat{T}_i^{Pos}$ is used as the instrument for trade, then the coefficient of trade openness is significant at least at the 10% level in 12 of the 14 cases (86%). Furthermore, not in any single model is the coefficient of $\hat{T}_i^{All}$ statistically significant when that of $\hat{T}_i^{Pos}$ is not. The results do not change if we

[5] We discuss the details of FR approach to standard errors correction in Footnote # 14.

[6] We use Staiger and Stock's (1997) "rule of thumb" that the *F*-statistic should be at least 10 for identification because the critical values (maximal IV size) calibrated by Stock and Yogo (2005) are only valid when errors are i.i.d. (Baum et al., 2007).

estimate the bilateral trade equation using the Poisson pseudo-maximum-likelihood technique, as shown and discussed in the online Appendix A.

Table 2. Estimates of the Income Equation using Actual Data and the "OLS instrument"

Income regressions:	**Model (1)**			**Model (2)**		
	OLS	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	OLS	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$
Trade share$_i$	0.911***	2.454***	2.743***	0.578***	0.463	0.702**
	(0.306)	(0.686)	(0.736)	(0.204)	(0.377)	(0.339)
Ln population$_i$	0.271***	0.381***	0.402***	0.106	0.097	0.116
	(0.102)	(0.131)	(0.140)	(0.072)	(0.074)	(0.073)
Ln area$_i$	-0.087	0.084	0.116	-0.087	-0.100	-0.074
	(0.088)	(0.129)	(0.131)	(0.065)	(0.074)	(0.073)
Distance to equator$_i$				-0.087***	4.190***	4.124
				(0.065)	(0.332)	(0.325)
Obs.	98	98	98	98	98	98
R^2	0.145	-	-	0.600	-	-
First-stage regressions:						
$\hat{T}_i^*$	-	6.818***	7.166***	-	7.606***	8.484***
		(1.356)	(1.427)		(1.931)	(2.095)
Partial R^2	-	0.284	0.321	-	0.282	0.336
KP *rk* Wald *F*-stat	-	25.27	25.20	-	15.51	16.40
Income regressions:	**Model (3)**			**Model (4)**		
	OLS	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	OLS	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$
Trade share$_i$	0.636***	0.643	1.083***	0.704***	1.073**	1.217***
	(0.205)	(0.416)	(0.382)	(0.254)	(0.507)	(0.442)
Ln population$_i$	0.072	0.073	0.109	-0.037	0.018	0.040
	(0.076)	(0.077)	(0.078)	(0.104)	(0.109)	(0.103)
Ln area$_i$	-0.082	-0.081	-0.033	0.040	0.065	0.074
	(0.070)	(0.082)	(0.082)	(0.065)	(0.076)	(0.073)
% Land in tropics$_i$	-1.580***	-1.579***	-1.536***			
	(0.167)	(0.169)	(0.167)			
Sub-Saharan Africa$_i$				-1.889***	-1.830***	-1.806***
				(0.206)	(0.210)	(0.206)
East Asia$_i$				-0.626*	-0.776**	-0.834**
				(0.340)	(0.367)	(0.348)
Latin America$_i$				-0.581**	-0.472*	-0.430*
				(0.221)	(0.250)	(0.233)
Obs.	98	98	98	98	98	98
R^2	0.547	-	-	0.594	-	-
First-stage regressions:						
$\hat{T}_i^*$	-	7.673***	8.128***	-	6.745***	7.843***
		(1.729)	(1.861)		(1.435)	(1.588)
Partial R^2	-	0.289	0.331	-	0.230	0.305
KP *rk* Wald *F*-stat	-	19.70	19.09	-	22.08	24.39

Note. The dependent variable is the log of real GDP per capita reported by PWT Mark 5.6 for the year 1985. Heteroscedastic consistent standard errors are in parentheses. Standard errors in the IV-regressions are corrected for the fact that the instruments depend on the standard errors of the bilateral trade equation. $\hat{T}_i^{Pos}$is the predicted trade openness based only on predictions for positive observed bilateral trade shares. $\hat{T}_i^{All}$ is the predicted trade openness based on all possible observations, i.e., including predictions for observations of zero or missing bilateral trade shares. The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic for weak instruments. The exogenous variables are included in the first-stage regressions but not shown. *,**, *** indicate significant at 10, 5 and 1 percent, respectively.

From these conflicting results it can be inferred that the coefficients of trade openness in the income equations must be biased in either the IV-$\hat{T}_i^{Pos}$-regressions or the IV-$\hat{T}_i^{All}$-regressions. Thus it can be concluded that the growth-trade nexus cannot be resolved before we know 1) which of the sampling procedures yields biased parameter estimates; and 2) the source of the bias. To identify which sampling procedure produces biased estimates we first generate instruments for trade by aggregating bilateral trade shares predicted from randomly generated geographical characteristics. We then analyze the randomized instruments to identify the source of the bias, which we show is systematically related to per capita income.

3.3 Random Generated Instruments

In this sub-section we undertake a random experiment to see whether the coefficients of $\tilde{T}_i^{Pos}$ and $\tilde{T}_i^{All}$ are biased. For this purpose we generate two *random* instruments for trade, $\tilde{T}_i^{Pos}$ and $\tilde{T}_i^{All}$, following Eqs. (3) and (4) in which the predictions are aggregated from bilateral trade equations that are estimated using randomly drawn geographic characteristics as independent variables. Specifically, for each Monte-Carlo replication $b = 1,\ldots,1000$, we randomly draw bilateral distances, areas and populations from normal distributions with means and standard deviations that are equal to those observed in the data. For each replication we ensure that geographic distances are symmetric across bilateral trading partners, $D_{ij}(b) = D_{ji}(b)$, and that country i's area and population do not change regardless of whether i is the origin or the destination country, i.e., $A_i(b) = A_{j=i}(b)$ and $N_i(b) = N_{j=i}(b)$. The landlocked status is drawn from a random variable where the probability of drawing 1 (e.g. landlocked) equals the observed frequency of landlocked countries in the data. For each replication we ensure that country i's landlocked status does not change, regardless of whether i is the origin or the destination country, i.e., $L_i(b) = L_{j=i}(b)$. Finally, we draw symmetric borders from a random variable where the probability of drawing 1 equals the observed incidence of a border in the data.

First- and second-stage regressions are estimated for each replication. Table 3 summarizes the 2SLS/IV results when the instruments are randomly generated (1000 replications for each Model (1)-(4)). The table reports 1) the average coefficients and the corresponding standard deviation (in parentheses); 2) the number of replications for which the coefficients of trade openness in the income regressions are statistically significant at the 10% [in square brackets] and 5% {in curly brackets} levels; 3) the number of Kleibergen-Paap *rk* Wald weak identification tests for which the *F*-statistic in the first-stage regression is greater than 10 <in angle brackets>.

The results are remarkably sensitive to whether predictions for all possible partners are included in the IV set.[7] Considering the results from the first-stage regressions, when only predictions for positive bilateral trade observations are included in the regressions, IV-$\tilde{T}_i^{Pos}$, the instruments turn out to be potentially strong in most cases. The KP *rk* Wald *F*-stats are larger than 10 in 43-96.5% of the cases and range, on average, between 9.5 and 19.0. Furthermore, the simulated coefficients of trade are statistically significant at the 5% level in at least 98% of the replications in the income regressions.

The results are quite different when $\tilde{T}_i^{All}$ is used as the instrument. In only 1% of the cases, at the most, is the coefficient of trade openness significant at conventional significance levels. This suggests that the coefficients of trade openness are unbiased when $\tilde{T}_i^{All}$ is used as an instrument for trade openness and, therefore, that causality is not found where it does not exist. Similarly, the *F*-tests for excluded restrictions are, on average, extremely low and the KP *rk* Wald *F*-statistics are, on average, very low and greater than 10 in only 0.3% of the simulations in Model (4); results we would expect from a randomized

Table 3. Estimates of the Income Equation using Randomized Instruments (1000 replications)

Second-stage results:	Model (1)		Model (2)		Model (3)		Model (4)	
	IV- $\tilde{T}_i^{All}$	IV-$\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV-$\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV-$\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV-$\tilde{T}_i^{Pos}$
Trade share$_i$	3.319	6.609	0.396	3.523	2.395	4.203	0.814	6.109
	(255.203)	(0.848)	(45.571)	(0.652)	(48.156)	(0.688)	(59.637)	(1.716)
	[10]	[1000]	[4]	[995]	[5]	[1000]	[8]	[987]
	{3}	{999}	{2}	{989}	{2}	{996}	{2}	{969}
Obs.	98	98	98	98	98	98	98	98
First-stage regressions:								
$\tilde{T}_i^*$	5.766	26.501	5.172	31.678	5.288	29.651	5.424	21.354
	(27.767)	(4.153)	(27.903)	(6.488)	(27.934)	(5.555)	(24.991)	(4.749)
	[124]	[1000]	[119]	[995]	[116]	[999]	[141]	[984]
	{54}	{1000}	{51}	{978}	{48}	{997}	{67}	{958}
Partial R^2	0.012	0.129	0.012	0.118	0.012	0.119	0.013	0.075
	(0.016)	(0.028)	(0.016)	(0.033)	(0.016)	(0.031)	(.017)	(0.027)
KP *rk* Wald *F*-stat	1.177	18.966	1.156	9.471	1.156	13.292	1.244	11.564
	<2>	<965>	<1>	<430>	<1>	<831>	<3>	<632>

Notes. The table reports average values from 1000 replications. The standard deviation of this average is reported in parentheses. For the estimated coefficients, the number of replications that produce an estimate significant at least at the 10% level is in [square brackets] and the number of replications in which the estimate is significant at least at the 5% level is in {curly brackets}. Standard errors underlying our calculations are corrected for the fact that each instrument depends on the parameters of a bilateral trade equation following FR. The number of times the KP *rk* Wald *F*-stat is greater than 10 is in <angle brackets>. Model (1) controls for area and population (in logs). Models (2), (3) and (4) add distance to the equator, percentage of land in the tropics and continental dummies, respectively, as control variables. Exogenous variables are included in the first-stage regressions but not shown. Full results for the second-stage regressions are reported in online Appendix Table OB.1.

[7] We obtain similar results when the remaining ten specifications of the income regressions are estimated (see online Appendix Table OB.2).

experiment. Again, this suggests that trade openness is independent of geographic characteristics when these are randomly generated, as expected.

Overall, the simulations show that researchers relying on predictions for observed positive bilateral trade only will almost surely find a positive relationship between trade and income even if such a relationship does not exist; a relationship that disappears when predictions for all partners are included in the instrument set. This implies that the estimated effect of trade is biased when the subset of predictions for actual observed positive bilateral trade are used in the instrument set. We identify the cause of this bias as feedback effects from income to trade openness – a result we prove analytically in the next section.

4. The nexus between per capita income and the number of trade partners:

So what is giving these seemingly paradoxical results in the previous section? To answer this question we need to focus on the first-step, in which the instruments are generated. When geographic characteristics are randomly generated, the bilateral trade equation (Eq. (2)) approximately predicts the average of the log bilateral trade openness. More formally,

$$\widehat{ln\frac{\tau_{ij}}{GDP_i}}(b) \cong \overline{ln\frac{\tau_{ij}}{GDP_i}} = k,$$

where *k* is a constant equal to the average log bilateral trade openness and a bar over a variable signifies the average. Substituting this expression into Eqs. (3) and (4), yields the following two distinctive instruments:

$$\tilde{T}_i^{Pos}(b) = \sum_{j\in\Omega_{ij}} e^{ln\left(\widehat{\frac{\tau_{ij}}{GDP_i}}(b)\right)} \cong \sum_{j\in\Omega_{ij}} e^k = N_i e^k,$$

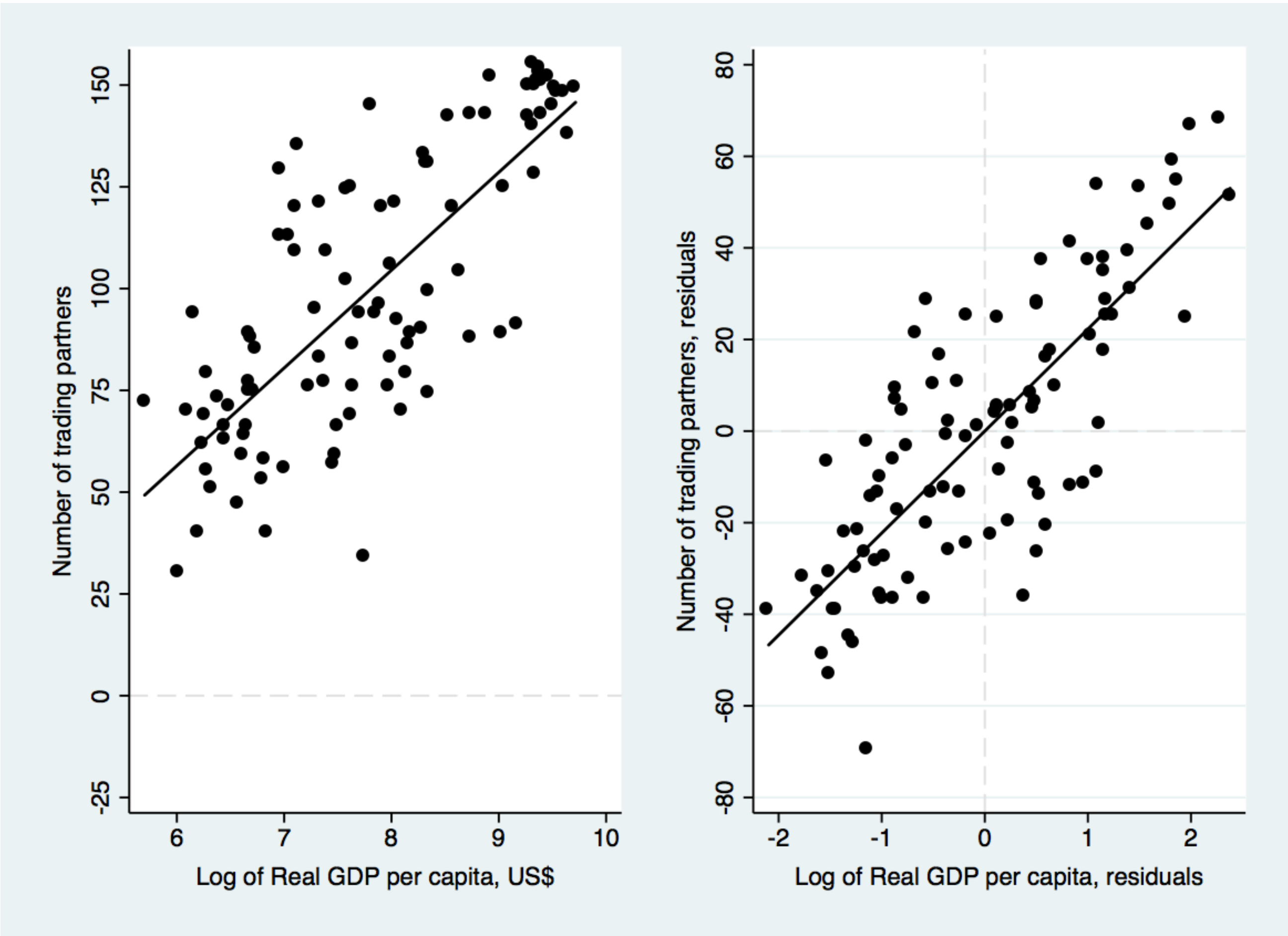
$$\tilde{T}_i^{All}(b) = \sum_{j\in\Psi_{ij}} e^{ln\left(\widehat{\frac{\tau_{ij}}{GDP_i}}(b)\right)} \cong \sum_{j\in\Psi_{ij}} e^k = 161e^k,$$

where N_i is the number of countries with which country *i* trades actively, and the number "161" is the maximum number of potential trade partners country *i* can trade with in our data. Thus, in each replication, $\tilde{T}_i^{Pos}$ captures the number of effective trade partners, which varies from country to country. By contrast, when predictions for all possible trade partners are included in the data, $\tilde{T}_i^{All}(b)$ captures stochastic values that are scattered around the value $161e^k$ for all countries; where 161 is close to the values recovered from the estimates in this paper.[8]

[8] In our data, the average log of the bilateral trade share is -8.922, which implies a value for e^k of 0.0013. With an average of 99.56 partners, the approximated average values for $\tilde{T}_i^{Pos}$ and $\tilde{T}_i^{All}$ are 0.0133 and 0.0215, respectively. These numbers are close to the average values for $\tilde{T}_i^{Pos}$ and $\tilde{T}_i^{All}$ of 0.0147 and 0.0227 across all countries and replications in this paper.

The variation captured by $\tilde{T}_i^{Pos}$ implies that the coefficient of $\tilde{T}_i^{Pos}$ is deemed to be significantly positive in the structural income regression, even if there is no relationship between income and trade. There are two reasons for this. First, the estimated coefficient of $\tilde{T}_i^{Pos}$ in the first-stage regression, γ_1, in Eq. (5), tends to be significantly positive because a country's trade openness and number of trading partners are positively correlated. Second, as shown in Figure 1, there is a close positive relationship between per capita income and the number of trading partners as signified by a significantly positive correlation between income and the number of trading partners. In the left-hand side panel of Figure 1 the correlation coefficient is 0.76, and it increases when population and area are controlled for (right-hand side panel of Figure 1). Based on the 1987 World Bank income group classification, the low-, middle- and high-income countries have, on average, 76, 97 and 143 trading partners, suggesting significant differences.

Figure 1. The relationship between the number of trading partners and per capita income.



Notes. The left-hand-side panel plots the actual observations, while the right-hand-side panel plots the residuals for each variable after accounting for the logs of population and area.

More formally, since the estimated trade coefficient in the income equation can be derived as the ratio of the coefficients of the instruments from the reduced form model and the first-stage regressions, the positive correlations of income per capita and trade with the number of trading partners imply that the estimated coefficient of trade openness, $\hat{\alpha}_1$, in the second-stage Eq. (7), tends to be positive and significant, even when the instruments are randomly generated. If, by contrast, the predictions for all potential bilateral relationships are included in the instrument, the generated instrument $\tilde{T}_i^{All}$ does not have any identifying variation. The significance of the estimates in the first-stage regressions Eq. (6), $\hat{\mu}_1$, and that of the estimated trade effects in the second-stage Eq. (8), $\hat{\alpha}_2$, tends towards zero. This is exactly what the results in Table 3 show.

The direct implication of these results is that when geography characteristics are *non*-random, then the exclusion of zero or missing bilateral trade from the instrument yields an instrument, $\hat{T}_i^{Pos}$, that varies positively with the number of a country's trading partners. To show this more explicitly, we decompose the variation in $\hat{T}_i^{Pos*}$ into average bilateral trade openness (intensive margin) and the number of countries that country *i* trades with, N_i (extensive margin):

$$\hat{T}_i^{Pos*} = \sum_{j\in\Omega_{ij}} e^{ln\left(\frac{\widehat{\tau_{ij}}}{GDP_i}\right)} = N_i * \sum_{j\in\Omega_{ij}} e^{ln\left(\frac{\widehat{\tau_{ij}}}{GDP_i}\right)} / N_i = N_i * \frac{\hat{T}_i^{Pos*}}{NP_i} = N_i * \overline{\hat{T}_i^{Pos}},$$

where $\overline{\hat{T}_i^{Pos}}$ is each country's average predicted bilateral trade openness.

To determine how much each margin contributes to the variation of $\hat{T}_i^{Pos*}$ we regress the logarithm of each component of $\hat{T}_i^{Pos*}$ on the logarithm of $\hat{T}_i^{Pos*}$. The coefficients from these regressions summarize the share of the overall variation due to each component and add up to one. Our results suggest that the extensive margin, N_i, accounts for 22-44 percent of the variation in $\hat{T}_i^{Pos*}$, depending on the inclusion of covariates in the income regressions (the results are reported in the online Appendix Table OC.1).

Table 4 shows the effects of $\overline{\hat{T}_i^{Pos}}$ and N_i on per capita income in Models (1)-(4) when $\hat{T}_i^{Pos*}$is used as the instrument for trade, noting that the results remain unaltered for the estimates of Models (5)-(14), as reported in the online Appendix Table OD.1. Under each model heading the first column reports the 2SLS estimates from Table 2, while the second and third columns show how these estimates change once the extensive and the intensive margin of $\hat{T}_i^{Pos*}$ are separately controlled for in the income regression. A distinct pattern appears from Table 4: the coefficients of $\hat{T}_i^{Pos}$ become insignificant once N_i is included as a control (second column for each model).[9] Put differently, filtering out the variation

[9] Estimated trade effects are also insignificant when N_i and $\overline{\hat{T}_i^{Pos}}$ are introduced simultaneously as control variables.

in $\hat{T}_i^{Pos}$ that is driven by the variation in N_i is sufficient to make the estimated trade effect on income insignificant. However, the coefficients of $\hat{T}_i^{Pos}$ remains significant when $\overline{\hat{T}_i^{Pos}}$ is controlled for instead of N_i (third column for each model). These findings suggest that it is the cross-country variation in N_i that makes the coefficient of $\hat{T}_i^{Pos}$ more significant than the coefficient of $\hat{T}_i^{All}$ in the income regressions (see the results in Tables 2, and Appendix Table A.2). However, it is the same variation that makes $\hat{T}_i^{Pos}$ an invalid instrument for trade because the number of trading partners is endogenous to income, i.e., the Cov $(\hat{T}^{Pos}, e_3) \neq 0$; a violation of the exclusion restriction.

Table 4. 2SLS Estimates of the Income Equation: Disentangling the role of $\hat{T}_i^{Pos*}$'s margins

Second-stage regressions:						
	Model (1)			Model (2)		
Trade share$_i$	2.743***	0.006	3.712***	0.702**	-0.380	1.408***
	(0.736)	(0.408)	(0.923)	(0.339)	(0.422)	(0.329)
N_i		0.028***			0.022***	
		(0.096)			(0.003)	
$\overline{\hat{T}_i^{Pos}}$			-1437.94**			-971.99***
			(627.23)			(323.12)
Obs.	98	98	98	98	98	98
First-stage regressions:						
$\hat{T}_i^{Pos*}$	7.166***	6.869***	8.879***	8.484***	7.554**	11.79***
	(1.427)	(1.869)	(1.686)	(2.095)	(2.006)	(2.574)
Partial R^2	0.321	0.212	0.324	0.336	0.324	0.377
KP *rk* Wald *F*-stat	25.20	13.51	27.73	16.40	14.18	21.00
Second-stage regressions:						
	Model (3)			Model (4)		
Trade share$_i$	1.083***	-0.364	1.975***	1.217***	-0.022	2.236***
	(0.382)	(0.406)	(0.443)	(0.442)	(0.334)	(0.495)
N_i		0.023***			0.022***	
		(0.003)			(0.003)	
$\overline{\hat{T}_i^{Pos}}$			-1320.70**			-1492.21**
			(365.04)			(409.09)
Obs.	98	98	98	98	98	98
First-stage regressions:						
$\hat{T}_i^{Pos*}$	8.128***	7.366***	10.50***	7.843***	7.432***	9.546***
	(1.861)	(1.981)	(2.148)	(1.588)	(1.772)	(1.758)
Partial R^2	0.331	0.239	0.353	0.305	0.252	0.320
KP *rk* Wald *F*-stat	19.09	13.82	23.89	24.39	17.60	29.48

Note. Heteroscedastic consistent standard errors are in parentheses. The standard errors in the second-stage are corrected for the errors created from the generated regressors using the approach devised by FR. $\hat{T}_i^{Pos*}$ is the predicted trade openness based only on predictions for observations of actual positive bilateral trade. N_i and $\overline{\hat{T}_i^{Pos}}$are *i*'s number of trading partners and average bilateral predicted trade openness, respectively. Model (1) controls for area and population (in logs). Models (2), (3) and (4) add distance to the equator, percentage of land in the tropics and continental dummies, respectively, as control variables. The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic. Exogenous variables are included in the first-stage regressions but not shown. *, **, *** indicate significant at 10, 5 and 1 percent, respectively.

4.1. Trade costs, trade and income

As high-income countries have better institutions, infrastructure and business environments than low-income countries (Djankov *et al*., 2002), it follows that the costs of engaging in trade are lower for high-income than low-income countries; thus establishing a positive relationship between income and number of trade partners. To check for the possibility that the number of trade partners and trade costs are negatively related, we examine how various measures of trade costs affect the number of a country's trade partners.

To achieve this, we collect data on countries' regulation costs of firm entry from Djankov et al. (2002) and the quality of infrastructure from Limao and Venables (2001).[10] Following Helpman et al. (2008) we use firm entry regulation costs as measures of the fixed costs faced by firms exporting to or from other countries. The data underlying our variables are based on firm entry regulation costs as a percentage of GDP per capita as well as the number of days and legal procedures that are required for an entrepreneur to legally start operating a business. Specifically, we consider two indicators of high fixed-cost of trade: 1) I(*High Regulation Cost*)$_i$, which takes the value of 1 if country i's relative costs are above the cross-country median; and 2) I(*High # of days and procedures*)$_i$, which equals 1 if country i's required number of days and legal procedures are above the median. Limao and Venables's (2001) infrastructure index is based on road and rail density as well as telephone lines per capita, where higher values are associated with lower infrastructure quality. Following Limao and Venables (2001), we also consider the (average) infrastructure index for landlocked countries' transit routes.

Table 5. Number of partners, trading costs and income per capita

	N_i	N_i	N_i
I(High Regulation Cost)$_i$	-37.359***	-22.017***	-6.987
	(6.879)	(6.800)	(7.383)
I(*High # of Days and Procedures*)$_i$	-14.806**	-9.272*	-5.780
	(7.054)	(5.554)	(6.006)
Own Infrastructure$_i$		-19.295***	-10.985***
		(4.414)	(3.592)
Transit Infrastructure$_i$		-8.916*	-4.495
		(4.847)	(4.446)
Log *Income per Capita*$_i$			15.673***
			(3.527)
Obs.	92	88	88

The estimation results are shown in Table 5. The results in column (1) show that high trading costs are associated with a small number of trading partners, as implied by the significantly negative

[10] Dictated by data availability, we use regulation costs for 1999 and infrastructure data for 1990.

coefficient of the number of days and legal procedures. The model by Helpman *et al*. (2008) offers a framework to rationalize this pattern. Extending the model of Melitz (2003) to include fixed costs of exporting and bounded productivity distributions, Helpman et al. (2008) show that some countries do not trade with each other because the firms are not sufficiently productive to penetrate each other's markets. In this framework destinations with lower fixed costs of exporting are, *ceteris paribus*, more likely to trade with other countries.

Turning to Column (2) in Table 5, it is evident that the number of trading partners is a decreasing function of underprovided infrastructure. These coefficient estimates become smaller and less significant when we include a country's income per capita as a control due to the high negative correlation between income per capita and trading costs. Income per capita correlates positively with N_i, as already shown in Figure 1.[11] Overall, these results indicate that that the lower trade costs of the advanced countries is a contributing factor to the positive relationship between the number of trade partners and per capita income.

4.2. Lessons for the validity of generated (instrumental) variables in other applications

In this section, we consider a generalization of the FR method and show the conditions under which a valid instrument can be created by aggregating predicted values from auxiliary regressions. We then discuss three examples from other strands of the literature where invalid instruments are mechanically generated from aggregated predictions.

Consider the following structural model:

$$Y_i = \gamma + \delta T_i + \varepsilon_{2,i}, \quad (9)$$

where T_i is endogenous. Then, suppose an instrument for T_i is generated from the following auxiliary regression:

$$\tau_{ij} = \alpha + \beta X_{ij} + v_{ij}, \quad (10)$$

where v_{ij} is an error term. Since τ_{ij} and X_{ij} are both ij-specific, the predicted values, $\hat{\tau}_{ij}$, can be aggregated in two ways. One approach is to generate an instrument for T_i, $\hat{Z}_i$, which sums over the predicted values from equation (10) over $j = 0, \ldots, N$ for which τ_{ij} is observed as follows:

$$\hat{Z}_i = \sum_{i \neq j \ni \tau_{ij} != .} \hat{\tau}_{ij}, \quad (11)$$

where $\tau_{ij} != .$ stands for τ_{ij} with non-missing values. In the case of a log specification for τ_{ij}, this method sums only over positive values for τ_{ij}.

[11]In line with our results Baldwin and Harrigan (2011) show that richer countries are more likely to import from the US than poor countries.

The second approach sums predicted values from equation (10) over all js to create the instrument, $\hat{P}_i$, including observations for missing values of τ_{ij} (or zero values in the case of a log specification for τ_{ij}):

$$\hat{P}_i = \sum_{i \neq j=0}^{N} \hat{\tau}_{ij}. \tag{12}$$

Now, consider two cases, one in which X_{ij} is random noise and the other in which it is not. In the first case, neither $\hat{P}_i$ nor $\hat{Z}_i$ should contain any identifying variation. However, this is not the case. Indeed, $\hat{Z}_i$ has an i-specific variation, as can be seen from the following approximation: $\hat{Z}_i = \sum_{i \neq j \ni \tau_{ij} != .} \hat{\tau}_{ij} \simeq N_i \bar{\tau}$, where $\bar{\tau}$ is the average τ_{ij}; and N_i is the number of js for which τ_{ij} is non missing. At the same time, $\hat{P}_i = \sum_{i \neq j=0}^{N} \hat{\tau}_{ij} \simeq N\bar{\tau}$, thus it yields random values around a constant and, therefore, does not contain any identifying variation. Most importantly, for $\hat{Z}_i$ to satisfy the exclusion restriction, N_i must be exogenous to Y_i; if not, then $\hat{Z}_i$ is invalid.

In the second case, when X_{ij} in the auxiliary regression is not noise, $\hat{Z}_i$ is endogenous and invalid if N_i is endogenous to Y_i because some of the variation in $\hat{Z}_i$ is due to N_i. Notice that in this context endogeneity arises mechanically because of the aggregation. In contrast, if X_{ij} is exogenous to Y_i and not random, $\hat{P}_i$ is a valid instrument.

Generalizing further, one can obtain $\hat{Z}_i$ and $\hat{P}_i$ from the following expression: $\sum_{j \neq i}^{N} d_{ij} \hat{\tau}_{ij}$. If one defines

$$d_{ij} = \begin{cases} 1 & \text{if } \tau_{ij} \text{ is not missing} \\ 0 & \text{Otherwise} \end{cases},$$

then the expression delivers $\hat{Z}_i$. If instead one sets $d_{ij} = 1$ for all ij, then the expression delivers $\hat{P}_i$. Restating the problem in this way clarifies the source of endogeneity in $\hat{Z}_i$, i.e., that observations for τ_{ij} might be missing due to or for unobserved reasons related to Y_i: a problem that exists independently of how consistently $\hat{\tau}_{ij}$ is estimated. It also highlights an implicit assumption in $\hat{P}_i$ that all fitted values from the auxiliary regressions are equally likely with probability one.

This generalization is helpful because it shows that endogeneity might mechanically arise inadvertently when a limited set of all possible predicted values from auxiliary regressions are aggregated to generate an instrument. Three examples of mechanical endogeneity in applications other than the trade-income nexus are worth mentioning.

The first example is from the growth literature. Examining the effects of foreign aid on economic growth, Rajan and Subramanian (2008) generate an instrument for foreign aid in cross-sectional income growth regressions in two steps. In the first step they estimate the following bilateral aid equation: $Aid_{drt}/GDP_{rt} = \boldsymbol{\beta}'\boldsymbol{Y}_{drt} + v_{drt}$, where Y_{drt} measures the historic relationship between the donor country d and the recipient country r; and Aid_{dr} is bilateral aid from country d to country r. In the second step they sum predicted bilateral aid shares from the first step over *observed* donors only. Thus, the variation in the generated instrument for aid captures the number of a country's donors, which is likely to be endogenous to the recipient's income per capita because the net benefit of aid tends to be higher in destinations with better institutions and infrastructure - not all of which are observable. Based on our framework, instruments that sum across all potential donors should be used to overcome a potential endogeneity bias.

The second example comes from Amiti et al. (2017) whose main objective is to study the effects of China's entry to the WTO on the aggregate price index for the US. In an effort to determine how expanded input imports affected Chinese firms' TFP, Amiti et al. (2017) estimate the following import demand equation: $lnM_{fnt} = \xi_1 lnTar_{nt} + \xi_2 lnTar_{nt} \cdot Process_f + \xi_f + \xi_t + \varepsilon_{fnt}$, where M_{fnt} is the value of firm f's imports of product n at time t; Tar_{nt} is the MFN tariff on product n; $Process_f$ is a dummy taking the value of one if f is a processing firm, otherwise it takes the value of zero; and ξ_f and ξ_t are firm and year fixed effects. From the regression above, after controlling for selection, they generate a time-varying instrument for the firm f's imports, $ln\ \widehat{M}_{tot,ft}$, by aggregating the exponent of the predicted imports summing only across traded inputs before taking the logarithm. This variable is included among the explanatory variables of Chinese firms' TFP. However, this approach is problematic: Since the change in the number of firm f's inputs is positively correlated with its TFP, as in standard product-variety endogenous growth models, the generated variable is likely to be endogenous. Based on our results, the endogeneity bias can be rectified by summing over all possible inputs.

The final example relates to the growing migration literature in which instruments are often created using the FR approach. Examples include Felbermayr et al. (2010), Ortega and Peri (2014), Alesina et al. (2016), and Bove and Elia (2017). These studies typically substitute bilateral migration for bilateral trade in the gravity model (Eq. (2)) and use predicted bilateral migration to construct an instrument for immigration or, as in the case of Alesina et al. (2016) and Bove and Elia (2017), a diversity index. In regressions where per capita income is the outcome variable in the structural regression, the *t*-values of the coefficients of immigration are upward biased since immigrants from low- and middle-income countries tend to be drawn to the high-income countries. For example, the number of non-zero coded immigrant countries for the US is 150, while the number is less than 34 for the sub-Saharan countries in 2015.[12]

5. Does trade really matter for growth? Evidence using a weighted instrument

In the construction of $\hat{T}_i^{All*}$ it has so far been assumed that the probability of trading is 1 for all country pairs *ij*. While this assumption does not affect the validity of $\hat{T}_i^{All*}$ as an instrument for T_i, it affects its power because the probability of trading d_{ij} is positively related to a country's income per capita. In this instance, a valid and a more powerful instrument can be generated by extracting the exogenous variation in d_{ij} to construct a weighted instrument, $\hat{T}_i^{DMP*}$, as follows:

$$\hat{T}_i^{DMP*} = \sum_{j\neq i}^{N} \hat{d}_{ij} e^{ln\left(\widehat{\frac{\tau_{ji}}{GDP_i}}\right)}, \tag{13}$$

where $\hat{d}_{ij}$ absorbs the variation in d_{ij} that is exogenous to country *i*'s income per capita. Intuitively, in addition to bilateral trade, this instrument accounts for the probability of engaging in trade.

More explicitly, two auxiliary regressions are required to generate the instrument. First, the gravity equation proposed by FR is estimated:

$$\ln\left(\frac{\tau_{ji}}{GDP_i}\right) = \boldsymbol{\beta} * G_{ij} + \varepsilon_{3,ij}, \tag{14}$$

where G_{ij} is geographic characteristics including all the covariates in Eq. (2).

Second, the probability of *i* and *j* engaging in trade is estimated from the following probit model:

$$d_{ij} = \boldsymbol{\Phi}\left(\boldsymbol{\gamma} \cdot G_{ij} + \alpha_1 Religion_{ij} + \alpha_2 N\_islands_{ij} + \alpha_3 Religion_{ij} \cdot B_{ij} + v_{2,ij}\right), \tag{15}$$

where *Religion* is a variable taking the values between 0 and 1 reflecting the degree to which the *ij* country pair share the same religion (see Appendix A for details); its interaction with the border dummy, *B*; and the number of islands in the pair, $N\_islands_{ij}$.[13] Common religion and the number of islands are both exogenous to income and have been shown to affect the probability of country pairs *ij* to engage in trade without affecting their trade volume (see Helpman et al., 2008; and Manova, 2008). The gain from expanding the instrument set beyond geographic characteristics, G_{ij}, is that it reduces the correlation between $\hat{d}_{ij}$ and $e^{ln\left(\widehat{\frac{\tau_{ji}}{GDP_i}}\right)}$ in equation (13) and, consequently, leads to more identifying variation in the instrument.

[12] The average number of origin countries within this group is 14 while the median is between 11 or 12 for countries of origin. These numbers are based on data of migrant stocks by destination and country of origin from the United Nations, Department of Economic and Social Affairs (2015). No correction has been made for the definition of migrants used to construct the migrant figures in the destination country; migrants are either defined as migrants by the country of their birth or their citizenship and for some countries the data includes the number of asylum seekers. We follow their classification of Sub-Saharan countries as all African countries excluding Algeria, Egypt, Libya, Morocco, Tunisia and Western Sahara.

[13] The interaction between islands and border is not added to the model because it is always zero because islands do not share borders and countries that share borders are not islands.

To make inferences in this framework we cannot correct the standard errors using the FR approach because $\hat{T}_i^{DMP}$ is generated from two auxiliary regressions instead of one.[14] To generate valid standard errors we use bootstrapping: First, we draw a random sample with replacement from the bilateral trade data, while ensuring that each of the reporting 98 countries has 161 observations, where 161 is the maximum number of possible partners a country can trade with. Based on this random sample, we estimate both auxiliary models whose fitted values are then used to construct the instrument for trade openness, $\hat{T}_i^{DMP}$. Finally, the income regression is estimated by 2SLS/IV. The bootstrap sampling and 2SLS estimation are repeated 1,000 times. The standard deviations in the sample of 1,000 observations of coefficient estimates from the 2SLS income regressions are the bootstrap standard errors of the point estimates of these coefficients. For completeness, we also bootstrap standard errors when $\hat{T}_i^{All}$ is used as the instrument for trade.

The first column under each model heading in Table 6 reports our IV estimates for the income regression when $\hat{T}_i^{All}$ is used as the instrument for trade. The coefficient estimates and the standard errors in curly brackets are identical to those in Table 2, while the standard errors in soft parentheses are bootstrapped. Table A.3 in the Appendix similarly displays these results for the additional ten models we consider. The bootstrapped standard errors are generally smaller than those based on the FR approach, implying that the estimated trade effects on income are often statistically more significant when the standard errors are bootstrapped than when they are not.

Comparing the performance of $\hat{T}_i^{All}$ and $\hat{T}_i^{DMP}$ in Table 6 and Appendix Table A.3 yields the following results. While the estimated trade effects tend to be similar in magnitude, they vary in statistical significance: $\hat{T}_i^{DMP}$ produces significant coefficient estimates in 11 out of the 14 cases, while $\hat{T}_i^{All}$ does so in only 8 of the 14 cases. More importantly, $\hat{T}_i^{DMP}$ produces larger *t*-statistics than $\hat{T}_i^{All}$ in 13 of the 14 cases (on average 17% higher). Thus, accounting for the exogenous variation in the probability of engaging in trade yields more precise estimates and improves the power of the instrument. These gains are important since most of the coefficients have gone from insignificance to significance by using $\hat{T}_i^{DMP}$ instead of $\hat{T}_i^{All}$ in the income regressions. Furthermore, these results have bearings for generated instruments in other applications, including the ones discussed in Section 4.2, as the power of valid

[14] FR obtain standard errors for $\hat{T}_i^{All}$ by adding to the IV variance-covariance matrix to the term $\frac{\partial \hat{\boldsymbol{b}}}{\partial \hat{\boldsymbol{a}}} \hat{\boldsymbol{\Omega}} \frac{\partial \hat{\boldsymbol{b}}}{\partial \hat{\boldsymbol{a}}'}$, where $\hat{\boldsymbol{b}}$ is the vector of estimated coefficients from the income regression; $\hat{\boldsymbol{a}}$ is the vector of estimates from the bilateral trade equation; and $\hat{\boldsymbol{\Omega}}$ is the variance-covariance matrix of $\hat{\boldsymbol{a}}$. For implementation, FR calculate the partial derivative $\frac{\partial \hat{\boldsymbol{b}}}{\partial \hat{\boldsymbol{a}}}$ numerically in four steps as follows: 1. Estimate $\hat{\boldsymbol{b}}$; 2. Add 0.001 to the first element of $\hat{\boldsymbol{a}}$, recompute $\hat{T}_i^{All}$, and run the IV regression, to obtain a new set of coefficients, $\hat{\boldsymbol{b}}^*$; 3. Construct the first column of $\frac{\partial \hat{\boldsymbol{b}}}{\partial \hat{\boldsymbol{a}}}$ as $\frac{(\hat{\boldsymbol{b}}^* - \hat{\boldsymbol{b}})}{0.001}$; 4. Repeat steps 2. and 3. for all the elements of a separately.

generated instruments can be enhanced by accounting for the exogenous variation in the probability of observing the outcome variable in the auxiliary regressions.

Table 6. Estimates of the Income Equation: FR *vs* DMP instruments

Second-stage regressions:	Model (1)		Model (2)	
	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$
Trade share$_i$	2.454***	2.393***	0.463	0.525*
	(0.719)	(0.701)	(0.294)	(0.275)
	[3.411]	[3.413]	[1.574]	[1.908]
	{0.686}***		{0.377}	
Observations	98	98	98	98
First-stage regressions:				
$\hat{T}_i$	6.818	7.806	7.606	8.759
	(1.356)	(1.536)	(1.931)	(2.154)
KP *rk* Wald *F*-stat	25.27	25.84	15.51	16.54
Partial R^2	0.284	0.317	0.282	0.319
Second-stage regressions:	Model (3)		Model (4)	
	IV-$\hat{T}_i^{ALL}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{ALL}$	IV-$\hat{T}_i^{DMP}$
Trade share$_i$	0.643*	0.727**	1.073*	0.993*
	(0.328)	(0.307)	(0.576)	(0.548)
	[1.958]	[2.365]	[1.861]	[1.814]
	{0.416}		{0.507}**	
Observations	98	98	98	98
First-stage regressions:				
$\hat{T}_i$	7.673	8.761	6.745	7.725
	(1.729)	(1.937)	(1.435)	(1.606)
KP *rk* Wald *F*-stat	19.70	20.47	22.08	23.14
Partial R^2	0.289	0.324	0.230	0.259

Notes. The dependent variable is log of real GDP per capita reported by PWT Mark 5.6 for the year 1985. Bootstrapped standard errors and *t*-statistics are in soft parentheses and square brackets, respectively. Standard errors corrected using the FR approach are in curly brackets. $\hat{T}_i^{All}$ is the predicted trade openness based on all possible bilateral trade shares. $\hat{T}_i^{DMP}$ is the weighted instrument we propose in Eq. (16). Model (1) controls for area and population (in logs). Models (2), (3) and (4) include distance to the equator, percentage of land in the tropics and continental dummies as control variables. The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic. Exogenous variables are included in the first-stage regressions but not shown. *, **, *** indicate significant at 10, 5 and 1 percent levels, respectively.

6. Concluding Remarks

The identification strategy suggested in the seminal paper of Frankel and Romer (1999) (FR) has become an increasingly popular method for creating instruments for variables that are outcomes of bilateral flows such as trade, immigration, FDI, currency unions, globalization etc. The method is appealing because geographic characteristics, which are used as instruments for bilateral flows, are exogenous. However, the FR method has a potential pitfall that is related to whether or not predicted unobserved or zero bilateral flows are included in the instruments – a choice that seems innocent and which is often not explicitly stated in most of the literature.

In this paper we have shown that an endogeneity bias arises if predicted unobserved or zero bilateral flows are excluded from the instrument set and that the results are often biased against the null hypothesis of no effects of trade on per capita income. The bias arises, in the case of the trade-income nexus, because the number of trading partners is positively correlated with per capita income – high-income countries have more trade partners than low-income countries. To show the significance of the bias, we created bilateral trade shares predicted from randomly generated geographical characteristics to form instruments for trade openness. We find that a significantly positive relationship between income and trade is spuriously created when *only* observed bilateral trade flows are included in the instrument set. However, the significance of randomly created trade openness in the income regression disappears once the IV-set includes the predicted bilateral trade for all possible trading partners, suggesting that the structural estimates can only be unbiased if predictions of all potential trade relationships are included in the IV-set.

To show explicitly that the coefficient of trade openness in the income regressions is influenced by the number of trade partners when the predictions for zero or missing observations are excluded from the instrument set, we decomposed the variation in the instrument for trade into average bilateral trade openness and the number of countries that country *i* trades with. Including the number of trade partners in the FR regression in which predictions for zero or missing observations are excluded from the instrument set renders the coefficient of trade openness insignificant, while the coefficient becomes significantly positive at the 1% level when average bilateral trade openness is controlled for. Based on data for trade costs we find that this relationship is driven by trade costs: Trade costs of low-income countries are often higher than those of high-income countries because of deficient infrastructure and, among other factors, this reduces the number of trading partners. These results suggest that the statistical significance of trade openness in the structural regressions, when zero or missing observations are excluded from the instrument set, are driven by the positive relationship between number of trade partners and per capita income and not by the exogeneous variation in trade openness.

From the analysis it follows that one should always include predictions for zero or missing observations from instruments, created by aggregating predicted values from auxiliary regressions, to ensure that the structural relationship is not an outcome of a significant correlation between the outcome variable and the probability of observing the dependent variable in the auxiliary regression; a correlation that we have shown is likely to exist in most applications of the FR approach. Furthermore, we suggest the power of valid instruments generated by aggregating fitted values from auxiliary regressions is enhanced by using exogenous weights based on the likelihood of observing the dependent auxiliary variable when the latter is endogenous to the outcome of interest.

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Appendix

A1. Data

Bilateral data set

The bilateral data set includes bilateral data for the 98 countries from the Mankiw (1992) sample and 161 partner countries, i.e., each country has 161 partners. Although relevant data are available for a larger set of partner countries, the analysis follows FR and limits partner countries outside the sample to those countries whose population is greater than 100,000.

The 98 countries in the Mankiw (1992) sample include: Algeria, Angola, Argentina, Australia, Austria, Bangladesh, Belgium, Benin, Bolivia, **Botswana**, Brazil, Burkina Faso, Burundi, Cameroon, Canada, Central African Republic, Chad, Chile, Colombia, Congo, Costa Rica, Denmark, Dominican Republic, Ecuador, Egypt, El Salvador, Ethiopia, Finland, France, Germany (unified), Ghana, Greece, Guatemala, Haiti, Honduras, Hong Kong, India, Indonesia, Ireland, Israel, Italy, Ivory Coast, Jamaica, Japan, Jordan, Kenya, South Korea, Liberia, Madagascar, Malawi, Malaysia, Mali, Mauritania, Mauritius, Mexico, Morocco, Mozambique, Myanmar, Nepal, Netherlands, New Zealand, Nicaragua, Niger, Nigeria, Norway, Pakistan, Panama, Papua New Guinea, Paraguay, Peru, Philippines, Portugal, Rwanda, Senegal, Sierra Leone, Singapore, Somalia, South Africa, Spain, Sri Lanka, Sudan, Sweden, Switzerland, Syria, Tanzania, Thailand, Togo, Trinidad & Tobago, Tunisia, Turkey, U.K., U.S.A., Uganda, Uruguay, Venezuela, Zaire, Zambia and Zimbabwe.

The 161 partner countries include the 98 countries listed in the previous paragraph and: Afghanistan, Albania, Bahamas, Bahrain, Barbados, Belize, Bhutan*, Brunei Darussalam, Bulgaria, Cambodia, Cape Verde, China, Comoros, Cuba, Cyprus, Czechoslovakia, Djibouti, East Timor*, Eritrea*, Equatorial Guinea, Fiji, French Polynesia*, Gabon, Gambia, Guinea, Guinea-Bissau, Guyana, Hungary, Iceland, Iran, Iraq, Kuwait, Laos, Lebanon, Libya, Lesotho, Luxembourg, Maldives, Malta, Mongolia, Namibia, New Caledonia, North Korea, Oman, Poland, Puerto Rico*, Qatar, Reunion, Romania, Sao Tome and Principe, Saudi Arabia, Solomon Islands, St. Lucia, St. Vincent & Grenadines, Suriname, Swaziland, Taiwan*, U.S.S.R., United Arab Emirates, Vanuatu, Vietnam, Western Samoa, Yemen and Yugoslavia.

In the country lists above, countries in bold font are non-reporting in the DOTS but enter our dataset because of the symmetry imposed on bilateral trade flows. There is no record of bilateral trade for countries that are starred.

Bilateral trade data from the DOTS for the year 1985 is used to construct symmetric bilateral trade flows. Bilateral trade shares are calculated by dividing bilateral trade in nominal terms by the destination country's GDP. The latter is the product of real GDP per capita (base year 1985) and a country's population, both from the Penn World Tables (PWT) Mark 5.6.

In addition, the bilateral data set contains data on area, bilateral distance, border and landlocked status from the CEPII *GeoDist* database. Population data are from the PWT Mark 5.6 and, when missing, the World Development Indicators (WDI).

Finally, data on island status and common religion is sourced from data used by Helpman et al.(2008). Island status is a dummy variable equal to 1 when both reporter and partner are island countries and zero otherwise. Common religion is a variable with values between 0 and 1, where larger values reflect the percent of the religious similarity between two bilateral trading partners. Helpman et al.(2008) constructed common religion as follows: (% Protestants in reporter country X % Protestants in partner country) + (% Catholics in reporter country X % Catholics in partner country) + (% Muslims in reporter X % Muslims in partner country).

Helpman et al. (2008) do not include data for Belgium, Luxembourg, and Botswana. For Belgium and Luxembourg we therefore use the data observations for Benelux replacing Benelux with either Belgium or Luxembourg. For the bilateral observation between Belgium - Luxembourg we use the bilateral observation Benelux – France, whereby we replace Benelux with Belgium, and France with Luxembourg. The shares of religious affiliation in France is the most similar to those of Luxembourg, according to the CIA World Factbook (Central Intelligence Agency, 2016). For Botswana a duplicate of the observations for South Africa are used. The bilateral observation for South Africa – Botswana is a duplication of the bilateral observation for South Africa – Angola where we substitute Botswana for Angola. Again, the choice of Angola is based on the CIA World Factbook; after South Africa, the most similar in terms of shares of the religious affiliations of its population is Angola.

Country data set

Real income per capita, trade openness and population data are taken from PWT Mark5.6. Area is sourced from CEPII *GeoDist*.

Data on the percentage of land or population in the tropics, and continents is from the Centre for International Development (CID), as used by Gallup et al. (1999). Latitude and distance to the equator are sourced from the CEPII *GeoDist*. Legal origin is from La Porta *et al*. (2008) and, when missing, from the CIA World Factbook (2016). The index of ethno-linguistic fractionalization is from Easterly and Levine (1997). Data on constraint on executive is from the Polity IV Project (2014). Finally, data on corruption and the quality of governance come from the International Country Risky Guide (ICRG) provided by the Political Risk Services Group based on Knack and Keefer (1995).

Table A.1 Overview of variables used in the analysis

Variable	**Description**
Real GDP per capita	Real GDP per capita, chain weighted, US $, base year=1985.
Population	Total population.
Area	Area in km^2.
Bilateral Trade	Sum of bilateral exports and imports, in millions of US $.
Distance	Distance between two main cities, weighted for the geographic distribution of the population within the country, in km.
Landlocked	Dummy variable set equal to 1 for landlocked countries.
Border	Dummy variable set equal to 1 for country pairs sharing a border.
Island	Dummy variable set equal to 1 for island states
Religion	Index. Equal to (% Protestants in country *i* x % Protestants in country *j*) + (% Catholics in country *i* x % Catholics in country *j*) + (% Muslims in country *i* % Muslims in country *j)*
Latitude	Calculated as the latitude of the main city, scaled to take values between -1 and 1.
Distance to the equator	Calculated using the absolute value of the latitude, scaled to take values between 0 and 1.
% Land in tropics	The percentage of land area located in the tropics.
Continental Dummies	Dummy variables for Latin America, Sub-Saharan Africa, and East Asia.

[continues]

Table A.1 Overview of variables used in the analysis

Variable	**Description**
% Population in tropics	The percentage of the population living in a tropical area.
ICRG index	An index constructed as the sum of five variables: corruption, bureaucratic quality and rule of law, each multiplied by 5/3, as well as repudiation of contracts and expropriation risk. The index is normalized to vary between 0 and 1.
Corruption	Assessment of corruption within the political system; rescaled to take values between 0 and 1.
Executive constraint	Index of the extent to which decision making power of the executive is constrained by institutionalized procedures.
Ethno-linguistic fractionalization	Index that measures the probability that two randomly selected people from a given country do not belong to the same ethno-linguistic group.
Legal origin	Variable that takes on 1 if a country's legal origin is English, 2 if it is French, 3 if it is German and 4 if it is Scandinavian.
High Regulation Cost	Dummy variable set equal to 1 if sum of number of procedures and number of days to start a new firm is greater than the median.
High Cost of Entry	Dummy variable set equal to 1 if relative cost (as a percentage of GNI per capita) is higher than the median relative cost
Own infrastructure	Index for the quality of infrastructure of road and rail density as well as telephone lines per capita
Transit infrastructure	Index for the quality of infrastructure of the transit country for landlocked country

A2. Additional estimates using actual data

Table A.2 reports estimates for ten additional specifications of the income equation each estimated by 2SLS/IV using $\hat{T}_i^{Pos}$ and $\hat{T}_i^{All}$ as instruments for trade. These specifications are the same as in Noguer and Siscart (2005). Standard errors for the IV regressions are adjusted to account for the fact that instruments depend on the parameters of the bilateral trade equation following the approach proposed by FR. Table A.2 further reports selected results from the first-stage.

Table A.3 reports estimates for the same ten additional specifications of the income equation using both $\hat{T}_i^{All}$ and $\hat{T}_i^{DMP}$ as instruments for trade, respectively. The standard errors for the IV regressions in parentheses are bootstrapped.

Table A.2 Estimates of the Income Equation using Actual Data: Additional Controls Included

	PANEL A									
	Model (5)		**Model (6)**		**Model (7)**		**Model (8)**		**Model (9)**	
	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$
Second-stage results:										
Trade share$_i$	0.693*	1.023***	0.613	1.078***	0.451	0.710**	0.524	0.909***	0.841*	1.110***
	(0.386)	(0.353)	(0.440)	(0.407)	(0.329)	(0.288)	(0.379)	(0.330)	(0.490)	(0.413)
Ln population$_i$	-0.030	0.001	0.067	0.108	0.006	0.028	-0.026	0.010	-0.024	0.017
	(0.077)	(0.081)	(0.085)	(0.088)	(0.066)	(0.066)	(0.073)	(0.076)	(0.097)	(0.090)
Ln area$_i$	0.146**	0.176**	-0.081	-0.033	0.026	0.053	0.060	0.097	0.124*	0.140**
	(0.070)	(0.071)	(0.083)	(0.082)	(0.063)	(0.063)	(0.069)	(0.069)	(0.069)	(0.070)
Latitude$_i$	0.609**	0.568**	0.058	0.010			0.212	0.169	0.296	0.280
	(0.273)	(0.287)	(0.328)	(0.339)			(0.260)	(0.271)	(0.379)	(0.396)
% Population in tropics$_i$	-2.012***	-1.979***			-1.304***	-1.290***	-1.480***	-1.447***	-1.293***	-1.276***
	(0.203)	(0.208)			(0.219)	(0.222)	(0.225)	(0.232)	(0.285)	(0.284)
Distance to equator$_i$					2.483***	2.431***				
					(0.368)	(0.370)				
% Land in tropics$_i$			-1.565***	-1.533***			-0.719***	-0.712***		
			(0.186)	(0.185)			(0.206)	(0.207)		
Sub-Saharan Africa$_i$									-0.865***	-0.839**
									(0.329)	(0.333)
East Asia$_i$									-0.413	-0.529
									(0.394)	(0.374)
Latin America$_i$									-0.123	-0.054
									(0.312)	(0.303)
Observations	98	98	98	98	98	98	98	98	98	98
First-stage results:										
$\hat{T}_i^{*}$	8.655***	9.554***	8.853***	9.659***	7.602***	8.487***	8.825***	9.649***	7.364***	8.597***
	(2.216)	(2.302)	(2.211)	(2.294)	(1.935)	(2.091)	(2.222)	(2.327)	(1.787)	(1.831)
Partial R^2	0.310	0.369	0.317	0.374	0.282	0.336	0.315	0.371	0.244	0.328
KP *rk* Wald *F*-stat	15.25	17.22	16.04	17.73	15.43	16.47	15.77	17.19	16.99	22.06

[continues]

Table A.2 Estimates of the Income Equation using Actual Data: Additional Controls Included

	PANEL B									
	Model (10)		**Model (11)**		**Model (12)**		**Model (13)**		**Model (14)**	
	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$	IV- $\hat{T}_i^{All}$	IV-$\hat{T}_i^{Pos}$
Second-stage results:										
Trade share$_i$	0.133	0.356	0.094	0.396	0.782**	0.895***	0.773*	1.099***	0.823**	1.097***
	(0.351)	(0.322)	(0.402)	(0.346)	(0.306)	(0.284)	(0.406)	(0.377)	(0.393)	(0.352)
Ln population$_i$	-0.066	-0.058	-0.043	-0.034	-0.007	0.005	0.032	0.062	0.021	0.051
	(0.053)	(0.054)	(0.058)	(0.058)	(0.077)	(0.077)	(0.078)	(0.083)	(0.087)	(0.091)
Ln area$_i$	0.074	0.108	0.066	0.112	0.132**	0.140**	0.146*	0.178**	0.137**	0.159**
	(0.070)	(0.069)	(0.083)	(0.077)	(0.059)	(0.060)	(0.076)	(0.077)	(0.069)	(0.070)
Latitude$_i$	0.255	0.287	0.450**	0.475**	0.500**	0.483**	0.477*	0.426	0.322	0.258
	(0.189)	(0.198)	(0.221)	(0.224)	(0.209)	(0.213)	(0.278)	(0.289)	(0.323)	(0.335)
% Population in tropics$_i$	-1.499***	-1.527***	-1.622***	-1.647***	-1.268***	-1.261***	-1.715***	-1.661***	-1.944***	-1.915***
	(0.182)	(0.180)	(0.203)	(0.198)	(0.207)	(0.209)	(0.254)	(0.255)	(0.221)	(0.226)
IGRC-Index$_i$	2.425***	2.259***								
	(0.343)	(0.354)								
Corruption$_i$			1.669***	1.520***						
			(0.278)	(0.277)						
Executive constraint$_i$					0.210***	0.210***				
					(0.027)	(0.028)				
Ethno-ling. fract.$_i$							-0.716**	-0.785**		
							(0.319)	(0.319)		
Legal Origin$_i$									0.230*	0.255**
									(0.119)	(0.119)
Observations	90	90	90	90	94	94	95	95	96	96
First-stage results:										
$\hat{T}_i^{*}$	6.812***	7.614***	6.996***	8.003***	8.063***	8.949***	8.786***	9.748***	8.895***	9.813***
	(1.708)	(1.903)	(1.679)	(1.842)	(2.675)	(2.859)	(2.204)	(2.297)	(2.220)	(2.277)
Partial R^2	0.238	0.279	0.228	0.281	0.273	0.328	0.319	0.383	0.334	0.399
KP *rk* Wald *F*-stat	15.90	16.02	17.36	18.88	9.08	9.80	15.89	18.01	16.05	18.58

Note. The dependent variable is log of real GDP per capita reported by PWT Mark 5.6 for the year 1985. Heteroscedastic consistent standard errors are in parentheses. Standard errors are corrected for the fact that the instrument depends on the parameters of the bilateral trade equation following FR. $\hat{T}_i^{Pos}$ is the predicted trade openness based only on predictions for positive observed bilateral trade shares. $\hat{T}_i^{All}$ is the predicted trade openness based on all possible observations, i.e., including predictions for observations of zero or missing bilateral trade shares. The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic. Exogenous variables are included in the first-stage regressions but not shown. *,**, *** indicates significant at 10, 5 and 1 percent, respectively.

Table A.3 Estimates of the Income Equation: FR vs DMP Instruments and Additional Controls Included

	PANEL A									
Second-stage results:	Model (5)		Model (6)		Model (7)		Model (8)		Model (9)	
	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$
Trade share$_i$	0.693**	0.736**	0.613*	0.705**	0.451	0.496*	0.524	0.588*	0.841	0.828
	(0.346)	(0.327)	(0.360)	(0.332)	(0.286)	(0.268)	(0.356)	(0.329)	(0.544)	(0.531)
	[2.004]	[2.249]	[1.701]	[2.124]	[1.578]	[1.850]	[1.473]	[1.785]	[1.545]	[1.560]
	{0.386}*		{0.440}		{0.329}		{0.379}		{0.490}*	
Observations	98	98	98	98	98	98	98	98	98	98
First-stage regressions:										
$\hat{T}_i$	8.655***	9.692***	8.853***	9.882***	7.602***	8.750***	8.825***	9.853***	7.364***	8.268***
	(2.216)	(2.361)	(2.211)	(2.348)	(1.935)	(2.153)	(2.222)	(2.369)	(1.787)	(1.903)
KP *rk* Wald *F*-stat	15.25	16.85	16.04	17.72	15.43	16.52	15.77	17.30	16.99	18.89
Partial R^2	0.310	0.344	0.317	0.350	0.282	0.319	0.315	0.348	0.244	0.271
	PANEL B									
Second-stage results:	Model (10)		Model (11)		Model (12)		Model (13)		Model (14)	
	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$	IV-$\hat{T}_i^{All}$	IV-$\hat{T}_i^{DMP}$
Trade share$_i$	0.133	0.183	0.094	0.145	0.782***	0.790***	0.773**	0.796**	0.823**	0.859***
	(0.327)	(0.303)	(0.552)	(0.628)	(0.290)	(0.287)	(0.345)	(0.321)	(0.334)	(0.313)
	[0.407]	[0.603]	[0.170]	[0.231]	[2.699]	[2.753]	[2.243]	[2.480]	[2.465]	[2.740]
	{0.351}		{0.402}		{0.306}**		{0.406}*		{0.393}**	
Observations	90	90	90	90	94	94	95	95	96	96
First-stage regressions:										
$\hat{T}_i$	6.812***	7.708***	6.996***	7.960***	8.063***	9.154***	8.786***	9.890***	8.895***	10.01***
	(1.708)	(1.850)	(1.679)	(1.802)	(2.675)	(2.982)	(2.204)	(2.338)	(2.220)	(2.349)
KP *rk* Wald *F*-stat	15.90	17.36	17.36	19.51	9.084	9.427	15.89	17.89	16.05	18.14
Partial R^2	0.238	0.267	0.228	0.257	0.273	0.304	0.319	0.357	0.334	0.372

Notes. The dependent variable is log of real GDP per capita reported by PWT Mark 5.6 for the year 1985. Bootstrapped standard errors and t-statistics are in parentheses and square brackets, respectively. Standard errors corrected using FR's approach are in curly brackets. $\hat{T}_i^{All}$ is the predicted trade openness based on all possible bilateral trade shares. $\hat{T}_i^{DMP}$ is the weighted instrument we propose in eq. (14). The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic. *,**, *** indicate significant at 10, 5 and 1 percent, respectively.

Online Appendix

Online Appendix A. PPML estimates

Table OA.1 reports estimates for the bilateral trade equation using the PPML technique. Because the bilateral trade equation includes only geographic variables that explain bilateral trade in a gravity model, this is following the literature on the estimation of the gravity equation for trade. The PPML method allows to obtaining consistent estimates in the presence of errors whose variance depends on regressors, which occurs when the original gravity equation is log-linearized (Santos Silva and Tenreyro, 2006). Also, the PPML method provides estimates based on all bilateral trade observations, including zeroes.

The estimates in Table OA.1 are obtained after transforming all missing observations of bilateral trade shares to zero. Estimates, available upon request, are not different if the missing observations are not converted to zero, i.e. excluding these observations from the estimation, or if only positive values of the dependent variable are used in the estimation. Thus, selection does not seem to be an issue in our application.

Estimates in Table OA.1 have the same sign but tend to be smaller in absolute value relative to those in Table 1 of the main text. Nonetheless the instruments generated from PPML predictions, $\hat{T}_{i,ppml}^{Pos}$ and $\hat{T}_{i,ppml}^{All}$, correlate almost perfectly and significantly with those obtained from OLS predictions.

Table OA.2 and OA.3 report the 2SLS/IV results for all fourteen specifications of the income equation using $\hat{T}_{i,ppml}^{Pos}$ and $\hat{T}_{i,ppml}^{All}$, as instruments for trade, respectively. When we consider all the estimates for the coefficient of trade openness we find it significant at least at the 10% level in five out of fourteen times when $\hat{T}_{i,ppml}^{All}$ is the instrument, and in twelve out of fourteen times when $\hat{T}_{i,ppml}^{Pos}$ is the instrument. This is in line with what we find and report in the main text based on instruments generated from OLS predicted bilateral shares.

Table OA.1 Estimation of the Bilateral Trade Equation using PPML

	Variable	Border interaction
Constant	-4.535***	1.397
	(0.722)	(2.814)
Ln $distance_{ij}$	-0.793***	0.182
	(0.059)	(0.446)
Ln $population_i$	-0.307***	-0.062
	(0.054)	(0.165)
Ln $population_j$	0.824***	0.081
	(0.043)	(0.198)
Ln $area_i$	-0.099**	-0.054
	(0.042)	(0.198)
Ln $area_j$	-0.191***	-0.142
	(0.048)	(0.247)
$Landlocked_{ij}$	-0.999***	0.525**
	(0.082)	(0.228)
Observations	15,778	
R^2	0.196	

Note. The dependent variable is τ_{ji}/GDP_i where all observations of bilateral trade share have a minimum value of zero, i.e. there are no missing observations for the 98 countries and their 161 possible trading partners. Column (1) reports the coefficient of the variable listed, and column (2) shows the coefficient of the interaction between the variable in the first column and border. Heteroscedasticity consistent standard errors are in parentheses. **, *** Significant at 5 and 1 percent, respectively.

Table OA.2 Estimates of the Income Equation using Actual Data and an instrument generated using estimates in Table OA.1.

	Model (1)			**Model (2)**		
Second-stage results:	OLS	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$	OLS	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$
Trade share$_i$	0.911***	2.620***	2.955***	0.578***	1.040**	1.182***
	(0.306)	(0.792)	(0.838)	(0.204)	(0.421)	(0.363)
Ln population$_i$	0.271***	0.393***	0.417***	0.106	0.143*	0.155**
	(0.102)	(0.137)	(0.147)	(0.072)	(0.079)	(0.079)
Ln area$_i$	-0.087	0.102	0.140	-0.087	-0.037	-0.022
	(0.088)	(0.135)	(0.138)	(0.065)	(0.076)	(0.073)
Distance to equator$_i$				-0.087***	4.031***	3.991***
				(0.065)	(0.335)	(0.343)
Obs.	98	98	98	98	98	98
R^2	0.145	-	-	0.600	-	-
First-stage results:						
$\hat{T}_i^*$	-	1.435	1.572	-	1.470	1.738
		(0.296)	(0.321)		(0.382)	(0.445)
Partial R^2	-	0.245	0.303	-	0.228	0.301
KP *rk* Wald *F*-stat	-	23.58	23.98	-	14.81	15.27

	Model (3)			**Model (4)**		
Second-stage results:	OLS	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$	OLS	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$
Trade share$_i$	0.636***	1.230***	1.551***	0.704***	1.346**	1.486***
	(0.205)	(0.473)	(0.440)	(0.254)	(0.568)	(0.502)
Ln population$_i$	0.072	0.121	0.148*	-0.037	0.059	0.080
	(0.076)	(0.082)	(0.086)	(0.104)	(0.121)	(0.113)
Ln area$_i$	-0.082	-0.017	0.017	0.040	0.083	0.092
	(0.070)	(0.086)	(0.084)	(0.065)	(0.073)	(0.071)
% Land in tropics$_i$	-1.580***	-1.521***	-1.489***			
	(0.167)	(0.170)	(0.174)			
Sub-Saharan Africa$_i$				-1.889***	-1.786***	-1.763***
				(0.206)	(0.219)	(0.214)
East Asia$_i$				-0.626*	-0.887**	-0.943**
				(0.340)	(0.409)	(0.392)
Latin America$_i$				-0.581**	-0.392	-0.351
				(0.221)	(0.258)	(0.241)
Obs.	98	98	98	98	98	98
R^2	0.547	-	-	0.594	-	-
First-stage results:						
$\hat{T}_i^*$	-	1.477	1.683	-	1.265	1.557
		0.350	0.394		0.287	0.333
Partial R^2	-	0.233	0.300	-	0.194	0.271
KP *rk* Wald *F*-stat	-	17.75	18.20	-	19.41	21.82

Notes. The dependent variable is log of real GDP per capita reported by PWT Mark 5.6 for the year 1985. Heteroscedastic consistent standard errors are in parentheses. Standard errors in the IV-regressions are corrected for the fact that the instrument depends on the parameters of the bilateral trade equation following FR. $\hat{T}_i^{Pos}$ is the predicted trade openness based only on predictions for positive observed bilateral trade shares. $\hat{T}_i^{All}$ is the predicted trade openness based on all possible observations, i.e., including predictions for observations of zero or missing bilateral trade shares. The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic. Exogenous variables are included in the first-stage regressions but not shown. *,**, *** Significant at 10, 5 and 1 percent, respectively.

Table OA.3 Estimates of the Income Equation using Actual Data and the "PPML instrument": Additional Controls Included

	PANEL A									
	Model (5)		**Model (6)**		**Model (7)**		**Model (8)**		**Model (9)**	
	IV- $\hat{T}^{All}_{i,ppml}$	IV- $\hat{T}^{Pos}_{i,ppml}$	IV- $\hat{T}^{All}_{i,ppml}$	IV- $\hat{T}^{Pos}_{i,ppml}$	IV- $\hat{T}^{All}_{i,ppml}$	IV- $\hat{T}^{Pos}_{i,ppml}$	IV- $\hat{T}^{All}_{i,ppml}$	IV- $\hat{T}^{Pos}_{i,ppml}$	IV- $\hat{T}^{All}_{i,ppml}$	IV- $\hat{T}^{Pos}_{i,ppml}$
Second-stage results:										
Trade share$_i$	0.452	0.951***	1.233**	1.569***	0.545	0.843***	0.563	1.008***	0.688	1.095**
	(0.487)	(0.369)	(0.500)	(0.479)	(0.400)	(0.321)	(0.450)	(0.352)	(0.591)	(0.475)
Ln population$_i$	-0.052	-0.005	0.122	0.152	0.014	0.039	-0.022	0.019	-0.047	0.015
	(0.080)	(0.078)	(0.092)	(0.100)	(0.068)	(0.067)	(0.076)	(0.076)	(0.111)	(0.097)
Ln area$_i$	0.123*	0.169**	-0.018	0.017	0.036	0.066	0.064	0.106	0.114	0.139**
	(0.074)	(0.072)	(0.086)	(0.084)	(0.068)	(0.065)	(0.073)	(0.071)	(0.070)	(0.070)
Latitude$_i$	0.639**	0.577**	-0.006	-0.041			0.208	0.158	0.305	0.281
	(0.271)	(0.283)	(0.346)	(0.367)			(0.259)	(0.273)	(0.373)	(0.397)
% Population in tropics$_i$	-2.036***	-1.986***			-1.299***	-1.282***	-1.477***	-1.438***	-1.302***	-1.277***
	(0.204)	(0.206)			(0.219)	(0.224)	(0.224)	(0.232)	(0.287)	(0.283)
Distance to equator$_i$					2.464***	2.404***				
					(0.375)	(0.387)				
% Land in tropics$_i$			-1.523***	-1.500***			-0.718***	-0.711***		
			(0.188)	(0.192)			(0.206)	(0.210)		
Sub-Saharan Africa$_i$									-0.879***	-0.840**
									(0.329)	(0.334)
East Asia$_i$									-0.346	-0.523
									(0.424)	(0.401)
Latin America$_i$									-0.163	-0.058
									(0.323)	(0.309)
Observations	98	98	98	98	98	98	98	98	98	98
First-stage results:										
$\hat{T}^*_i$	1.638***	1.934***	1.572***	1.838***	1.524***	1.775***	1.655***	1.942***	1.374***	1.652***
	(0.450)	(0.494)	(0.418)	(0.462)	(0.389)	(0.454)	(0.456)	(0.497)	(0.371)	(0.397)
Partial R^2	0.238	0.320	0.238	0.314	0.232	0.303	0.241	0.322	0.202	0.279
KP *rk* Wald *F*-stat	13.25	15.30	14.11	15.85	15.33	15.31	13.15	15.28	13.67	17.35

[continues]

Table OA.3 Estimates of the Income Equation using Actual Data and the "PPML instrument": Additional Controls Included (continued)

	PANEL B									
	Model (10)		**Model (11)**		**Model (12)**		**Model (13)**		**Model (14)**	
	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$	IV- $\hat{T}_{i,ppml}^{All}$	IV- $\hat{T}_{i,ppml}^{Pos}$
Second-stage results:										
Trade share$_i$	0.114	0.456	-0.006	0.460	0.416	0.710**	0.633	1.084***	0.670	1.079***
	(0.396)	(0.301)	(0.485)	(0.330)	(0.431)	(0.314)	(0.466)	(0.374)	(0.449)	(0.347)
Ln population$_i$	-0.067	-0.055	-0.045	-0.032	-0.046	-0.014	0.019	0.061	0.004	0.049
	(0.054)	(0.055)	(0.060)	(0.058)	(0.086)	(0.077)	(0.076)	(0.078)	(0.086)	(0.086)
Ln area$_i$	0.071	0.123**	0.051	0.122*	0.106*	0.127**	0.132*	0.177**	0.124*	0.158**
	(0.069)	(0.060)	(0.087)	(0.068)	(0.059)	(0.058)	(0.078)	(0.077)	(0.070)	(0.071)
Latitude$_i$	0.252	0.302	0.442**	0.480**	0.553***	0.510**	0.499*	0.428	0.357	0.263
	(0.188)	(0.199)	(0.222)	(0.224)	(0.207)	(0.204)	(0.280)	(0.290)	(0.318)	(0.328)
% Population in tropics$_i$	-1.497***	-1.540***	-1.614***	-1.653***	-1.290***	-1.272***	-1.737***	-1.664***	-1.961***	-1.917***
	(0.184)	(0.182)	(0.208)	(0.201)	(0.208)	(0.209)	(0.258)	(0.252)	(0.221)	(0.224)
IGRC-Index$_i$	2.439***	2.184***								
	(0.357)	(0.342)								
Corruption$_i$			1.718***	1.488***						
			(0.311)	(0.287)						
Executive constraint$_i$					0.213***	0.211***				
					(0.026)	(0.027)				
Ethno-ling. fract.$_i$							-0.687**	-0.782**		
							(0.325)	(0.315)		
Legal Origin$_i$									0.217*	0.253**
									(0.117)	(0.115)
Observations	90	90	90	90	94	94	95	95	96	96
First-stage results:										
$\hat{T}_i^*$	1.355***	1.592***	1.338***	1.637***	1.493**	1.821***	1.685***	1.999***	1.709***	2.002***
	(0.361)	(0.410)	(0.364)	(0.409)	(0.563)	(0.661)	(0.449)	(0.492)	(0.449)	(0.490)
Partial R^2	0.194	0.256	0.174	0.249	0.195	0.273	0.243	0.334	0.257	0.347
KP *rk* Wald *F*-stat	14.08	15.06	13.54	16.04	7.02	7.58	14.05	16.51	14.49	16.67

Notes. The dependent variable is log of real GDP per capita reported by PWT Mark 5.6 for the year 1985. Heteroscedastic consistent standard errors are in parentheses. Standard errors in the IV-regressions are corrected for the fact that the instrument depends on the parameters of the bilateral trade equation following FR. $\hat{T}_i^{Pos}$is the predicted trade openness based only on predictions for positive observed bilateral trade shares. $\hat{T}_i^{All}$ is the predicted trade openness based on all possible observations, i.e., including predictions for observations of zero or missing bilateral trade shares. The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic. Exogenous variables are included in the first-stage regressions but not shown. $^{*},^{**},^{***}$ Significant at 10, 5 and 1 percent, respectively.

Online Appendix B. Full results Monte Carlo Simulations

Table OB.1-OB.3 summarize 2SLS estimates for all fourteen specifications of the income equation using $\tilde{T}_i^{All}$ and $\tilde{T}_i^{Pos}$ as instruments for trade, respectively. These results are based on 1000 replications for each model.

Table OB.1 Estimates of the Income Equation using Randomized Instruments (1000 replications)

	Model (1)		**Model (2)**		**Model (3)**		**Model (4)**	
Second-stage results:	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$
Trade share$_i$	3.319	6.609	0.396	3.523	2.395	4.203	0.814	6.109
	(255.203)	(0.848)	(45.571)	(0.652)	(48.156)	(0.688)	(59.637)	(1.716)
	[10]	[1000]	[4]	[995]	[5]	[1000]	[8]	[987]
	{3}	{999}	{2}	{989}	{2}	{996}	{2}	{969}
Ln population$_i$	0.443	0.677	0.092	0.344	0.217	0.366	-0.021	0.773
	(18.165)	(0.060)	(3.672)	(0.053)	(3.967)	(0.057)	(8.938)	(0.257)
	[115]	[1000]	[4]	[960]	[2]	[942]	[1]	[951]
	{46}	{997}	{0}	{398}	{0}	{160}	{0}	{861}
Ln area$_i$	0.180	0.544	-0.107	0.232	0.109	0.305	0.047	0.402
	(28.271)	(0.094)	(4.937)	(0.071)	(5.228)	(0.075)	(4.001)	(0.115)
	[4]	[560]	[17]	[531]	[13]	[642]	[2]	[780]
	{1}	{24}	{2}	{29}	{2}	{67}	{0}	{191}
Distance to equator$_i$			4.209	3.344				
			(12.606)	(0.180)				
			[670]	[995]				
			{640}	{993}				
% Land in tropics$_i$					-1.406	-1.228		
					(4.752)	(0.068)		
					[667]	[998]		
					{634}	{995}		
Sub-Saharan Africa$_i$							-1.871	-1.021
							(9.571)	(0.275)
							[607]	[820]
							{564}	{718}
East Asia$_i$							-0.670	-2.822
							(24.235)	(0.697)
							[37]	[962]
							{18}	{893}
Latin America$_i$							-0.548	1.010
							(17.552)	(0.505)
							[60]	[203]
							{26}	{0}
Obs.	98	98	98	98	98	98	98	98

Notes. The table reports average values from 1000 replications. The standard deviation of this average is reported in parentheses. For the estimated coefficients, the number of replications that produce an estimate significant at least at the 10% level is in [square brackets] and the number of replications in which the estimate is significant at least at the 5% level is in {curly brackets}. The p-values of each coefficients are determined using standard errors that have been corrected for the fact that the instrument depends on the parameters of the bilateral trade equation following FR.

Table OB.2 Estimates of the Income Equation using Randomized Instruments: Additional Controls Included

	PANEL A									
	Model (5)		**Model (6)**		**Model (7)**		**Model (8)**		**Model (9)**	
	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$
Second-stage results:										
Trade share$_i$	3.541	4.102	-0.888	4.322	1.150	3.218	2.532	3.758	-6.162	5.685
	(38.602)	(0.720)	(95.792)	(0.738)	(20.272)	(0.593)	(56.133)	(0.669)	(195.755)	(1.985)
	[8]	[998]	[7]	[998]	[6]	[997]	[9]	[998]	[11]	[986]
	{2}	{992}	{2}	{992}	{1}	{991}	{2}	{992}	{2}	{960}
Ln population$_i$	0.238	0.291	-0.066	0.395	0.065	0.240	0.162	0.276	-1.087	0.712
	(3.628)	(0.068)	(8.478)	(0.065)	(1.714)	(0.050)	(5.250)	(0.063)	(29.725)	(0.301)
	[0]	[0]	[0]	[552]	[0]	[12]	[0]	[0]	[1]	[923]
	{0}	{0}	{0}	{1}	{0}	{0}	{0}	{0}	{0}	{733}
Ln area$_i$	0.408	0.460	-0.236	0.300	0.098	0.310	0.249	0.364	-0.308	0.422
	(3.560)	(0.066)	(9.846)	(0.076)	(2.084)	(0.061)	(5.272)	(0.063)	(12.060)	(0.122)
	[40]	[998]	[11]	[385]	[1]	[993]	[5]	[990]	[26]	[856]
	{13}	{979}	{2}	{11}	{0}	{956}	{0}	{860}	{7}	{339}
Latitude$_i$	0.259	0.190	0.215	-0.329			-0.014	-0.153	0.707	0.012
	(4.748)	(0.089)	(10.002)	(0.077)			(6.339)	(0.076)	(11.482)	(0.116)
	[244]	[0]	[0]	[0]			[0]	[0]	[0]	[0]
	{110}	{0}	{0}	{0}			{0}	{0}	{0}	{0}
% Population in tropics$_i$	-1.726	-1.670			-1.264	-1.146	-1.305	-1.199	-1.726	-0.993
	(3.873)	(0.072)			(1.160)	(0.034)	(4.888)	(0.058)	(12.123)	(0.123)
	[719]	[998]			[717]	[992]	[677]	[975]	[664]	[371]
	{685}	{998}			{684}	{981}	{642}	{908}	{611}	{148}
Distance to equator$_i$					2.342	1.925				
					(4.086)	(0.120)				
					[611]	[844]				
					{562}	{558}				
% Land in tropics$_i$			-1.666	-1.314			-0.684	-0.663		
			(6.462)	(0.050)			(0.975)	(0.012)		
			[731]	[998]			[691]	[634]		
			{705}	{998}			{627}	{168}		

[continues]

Table OB.2 Estimates of the Income Equation using Randomized Instruments: Additional Controls Included (continued)

	Model (5)		**Model (6)**		**Model (7)**		**Model (8)**		**Model (9)**	
	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$
Second-stage results:										
Sub-Saharan Africa$_i$									-1.537	-0.400
									(18.797)	(0.191)
									[462]	[4]
									{351}	{0}
East Asia$_i$									2.621	-2.511
									(84.792)	(0.860)
									[5]	[964]
									{0}	{882}
Latin America$_i$									-1.924	1.123
									(50.353)	(0.511)
									[0]	[135]
									{0}	{0}
Observations	98	98	98	98	98	98	98	98	98	98
First-stage results:										
$\tilde{T}_i^*$	5.591	28.950	5.127	29.581	5.492	31.760	5.563	29.846	5.487	21.384
	(27.723)	(5.795)	(28.213)	(5.646)	(27.969)	(6.582)	(28.165)	(5.951)	(25.398)	(4.898)
	[115]	[997]	[115]	[997]	[126]	[995]	[112]	[997]	[136]	[980]
	{52}	{987}	{49}	{992}	{51}	{979}	{52}	{986}	{63}	{943}
Partial R^2	0.012	0.109	0.012	0.115	0.012	0.117	0.012	0.112	0.013	0.072
	(0.017)	(0.031)	(0.016)	(0.031)	(0.017)	(0.033)	(0.017)	(0.031)	(0.017)	(0.027)
KP *rk* Wald *F*-stat	1.160	10.917	1.140	11.458	1.163	9.632	1.153	10.818	1.230	9.846
	<1>	<646>	<0>	<706>	<1>	<468>	<1>	<633>	<2>	<505>

[continues]

Table OB.2 Estimates of the Income Equation using Randomized Instruments: Additional Controls Included (continued)

	PANEL B									
	Model (10)		**Model (11)**		**Model (12)**		**Model (13)**		**Model (14)**	
	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$
Second-stage results:										
Trade share$_i$	-0.375	2.140	1.384	-4.425	0.869	2.898	-2.270	3.840	1.490	3.936
	(35.116)	(47.475)	(40.107)	(273.753)	(59.465)	(0.585)	(114.702)	(0.703)	(27.250)	(0.683)
	[2]	[507]	[1]	[891]	[11]	[994]	[7]	[998]	[8]	[998]
	{0}	{203}	{0}	{795}	{3}	{958}	{2}	{991}	{2}	{992}
Ln population$_i$	-0.084	0.005	-0.006	-0.172	0.003	0.219	-0.249	0.316	0.094	0.363
	(1.247)	(1.685)	(1.145)	(7.817)	(6.333)	(0.062)	(10.610)	(0.065)	(2.993)	(0.075)
	[0]	[0]	[0]	[0]	[1]	[0]	[0]	[5]	[0]	[119]
	{0}	{0}	{0}	{0}	{0}	{0}	{0}	{0}	{0}	{0}
Ln area$_i$	-0.003	0.379	0.262	-0.621	0.138	0.284	-0.154	0.449	0.191	0.391
	(5.329)	(7.204)	(6.095)	(41.604)	(4.270)	(0.042)	(11.323)	(0.069)	(2.224)	(0.056)
	[6]	[515]	[8]	[857]	[75]	[985]	[32]	[998]	[32]	[996]
	{0}	{240}	{2}	{726}	{21}	{866}	{9}	{981}	{7}	{959}
Latitude$_i$	0.180	0.548	0.556	0.078	0.487	0.191	0.957	-0.007	0.167	-0.399
	(5.139)	(6.947)	(3.301)	(22.534)	(8.678)	(0.085)	(18.102)	(0.111)	(6.308)	(0.158)
	[0]	[0]	[194]	[18]	[218]	[0]	[66]	[0]	[3]	[0]
	{0}	{0}	{32}	{1}	{106}	{0}	{7}	{0}	{0}	{0}
% Population in tropics$_i$	-1.435	-1.752	-1.730	-1.245	-1.262	-1.139	-2.213	-1.212	-1.872	-1.609
	(4.427)	(5.985)	(3.346)	(22.841)	(3.608)	(0.036)	(18.792)	(0.115)	(2.933)	(0.074)
	[663]	[907]	[725]	[986]	[736]	[998]	[610]	[976]	[711]	[998]
	{623}	{880}	{699}	{979}	{714}	{994}	{569}	{948}	{690}	{998}
IGRC-Index$_i$	2.804	0.929								
	(26.171)	(35.382)								
	[297]	[14]								
	{219}	{6}								
Corruption$_i$			1.033	3.897						
			(19.774)	(134.970)						
			[257]	[9]						
			{188}	{2}						

[continues]

Table OB.2 Estimates of the Income Equation using Randomized Instruments: Additional Controls Included (continued)

	Model (10)		**Model (11)**		**Model (12)**		**Model (13)**		**Model (14)**	
	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$	IV- $\tilde{T}_i^{All}$	IV- $\tilde{T}_i^{Pos}$
Second-stage results:										
Executive constraint$_i$					0.210	0.196				
					(0.395)	(0.004)				
					[769]	[999]				
					{745}	{998}				
Ethno-ling. fract.$_i$							-0.071	-1.367		
							(24.315)	(0.149)		
							[154]	[999]		
							{75}	{994}		
Legal Origin$_i$									0.290	0.508
									(2.432)	(0.061)
									[76]	[999]
									{23}	{995}
Observations	90	90	90	90	94	94	95	95	96	96
First-stage results:										
$\tilde{T}_i^*$	1.621	15.267	2.210	21.142	5.574	29.212	5.577	30.037	5.981	29.452
	(25.598)	(6.173)	(26.425)	(6.332)	(26.837)	(6.560)	(29.502)	(6.177)	(28.562)	(5.841)
	[124]	[509]	[127]	[886]	[114]	[976]	[118]	[996]	[121]	[997]
	{62}	{253}	{63}	{789}	{46}	{895}	{56}	{983}	{51}	{983}
Partial R^2	0.013	0.031	0.013	0.058	0.013	0.101	0.013	0.116	0.013	0.116
	(0.018)	(0.021)	(0.018)	(0.027)	(0.018)	(0.032)	(0.017)	(0.033)	(0.017)	(0.032)
KP *rk* Wald *F*-stat	1.178	2.927	1.170	6.202	1.152	6.039	1.171	11.219	1.176	10.620
	<1>	<3>	<1>	<76>	<1>	<21>	<3>	<669>	<2>	<611>

Notes. The table reports average values from 1000 replications. The standard deviation of this average is reported in parentheses. For the estimated coefficients, the number of replications that produce an estimate significant at least at the 10% level is in [square brackets] and the number of replications in which the estimate is significant at least at the 5% level is in {curly brackets}. The number of times the KP *rk* Wald *F*-stat is greater than 10 is in <angle brackets>. The p-values of each coefficient are determined using standard errors that have been corrected for the fact that the instrument depends on the parameters of the bilateral trade equation following FR. Exogenous variables are included in the first stage regressions but not shown.

Online Appendix C. Regression Decomposition Results

To determine how much each margin contributes to the variation of $\widehat{T}_i^{Pos*}$ we regress the logarithm of each component of $\widehat{T}_i^{Pos*}$ on the logarithm of $\widehat{T}_i^{Pos*}$. The coefficients from these regressions summarize the share of the overall variation due to each component and add up to one.

Table OC.1 Decomposition of $\widehat{T}_i^{Pos*}$ into extensive margin, N_i , and intensive margin, $\overline{\widehat{T}_i^{Pos}}$

	PANEL A				
	No Controls	**Model (1)**	**Model (2)**	**Model (3)**	**Model (4)**
$\ln N_i$	0.223	0.397	0.274	0.304	0.279
	(0.056)	(0.055)	(0.062)	(0.062)	(0.084)
$\ln \overline{\widehat{T}_i^{Pos}}$	0.777	0.603	0.726	0.696	0.721
	(0.056)	(0.055)	(0.062)	(0.062)	(0.084)
Additional Controls			Distance to Equator$_i$	%Land in tropics$_i$	Regional dummies
Observations		98	98	98	98
	PANEL B				
	Model (5)	**Model (6)**	**Model (7)**	**Model (8)**	**Model (9)**
$\ln N_i$	0.375	0.418	0.264	0.384	0.346
	(0.055)	(0.089)	(0.061)	(0.086)	(0.097)
$\ln \overline{\widehat{T}_i^{Pos}}$	0.625	0.582	0.736	0.616	0.654
	(0.086)	(0.89)	(0.061)	(0.086)	(0.097)
Additional Controls	Latitude$_i$ %Population in tropics$_i$	Latitude$_i$ % Land in tropics	%Population in tropics$_i$ Distance to equator$_i$	Latitude$_i$; % Population in tropics$_i$; % Land in tropics$_i$	Latitude$_i$;% Population in tropics$_i$; Regional dummies
Observations	98	98	98	98	98

[continues]

Table OC.1 Decomposition of $\hat{T}_i^{Pos*}$ into extensive margin, N_i , and intensive margin, $\overline{\hat{T}_i^{Pos}}$ (continued)

	PANEL C				
	Model (10)	**Model (11)**	**Model (12)**	**Model (13)**	**Model (14)**
ln N_i	0.355	0.346	0.439	0.405	0.420
	(0.075)	(0.078)	(0.085)	(0.088)	(0.087)
ln $\overline{\hat{T}_i^{Pos}}$	0.645	0.654	0.561	0.595	0.580
	(0.075)	(0.078)	(0.085)	(0.088)	(0.087)
Additional controls	Latitude$_i$; % Population in tropics$_i$; IGRC-Index$_i$	Latitude$_i$; % Population in tropics$_i$; Corruption$_i$	Latitude$_i$; % Population in tropics$_i$; Executive constraint$_i$	Latitude$_i$; % Population in tropics$_i$; Ethno-ling. fract.$_i$	Latitude$_i$; % Population in tropics$_i$; Legal Origin$_i$
Observations	90	90	94	95	96

Note. The coefficient for the log of $\hat{T}_i^{Pos*}$ is reported with heteroskedastic robust standard errors in parentheses. Models (1)-(14) control for area and population (in logs) as well as the additional control variables listed at the bottom of each panel.

Online Appendix D. Remaining Models Results: Disentangling the role of $\widehat{T}_i^{Pos*}$'s margins

Table OD.1 shows the results for ten additional specifications of the income equation each estimated by 2SLS/IV using $\widehat{T}_i^{Pos*}$. As in previous Appendices these additional specifications are the same as in Noguer and Siscart (2005).

The first column of each model in Table OD.1 reports selected results from Table A.2 in the paper. The remaining two columns report the results once we control for either the extensive or the intensive margin of $\widehat{T}_i^{Pos*}$ using the following composition:

$$\widehat{T}_i^{Pos*} = \sum_{j\in\Omega_{ij}} e^{ln\left(\frac{\widehat{\tau_{ij}}}{GDP_i}\right)} = N_i * \frac{\sum_{j\in\Omega_{ij}} e^{ln\left(\frac{\widehat{\tau_{ij}}}{GDP_i}\right)}}{N_i} = N_i * \frac{\widehat{T}_i^{Pos}}{N_i} = N_i * \overline{\widehat{T}_i^{Pos}}$$

where N_i is the number of countries that country *I* trades with (the extensive margin) and $\overline{\widehat{T}_i^{Pos}}$ is each country's average predicted bilateral trade openness (the intensive margin).

The pattern identified in the paper for the four basic models is also visible below and support the results reported in Table 4.

Table OD.1 Income Equation with additional controls: Disentangling the role of $\hat{T}_i^{Pos*}$'s margins

	PANEL A					
	Model (5)			**Model (6)**		
	Latitude$_i$ %Population in tropics$_i$			Latitude$_i$ % Land in tropics		
Second-stage results:						
Trade share$_i$	1.023***	-0.097	1.860***	1.078***	-0.154	1.831***
	(0.353)	(0.313)	(0.416)	(0.407)	(0.353)	(0.430)
N_i		0.020***			0.023***	
		(0.002)			(0.003)	
$\overline{\hat{T}_i^{Pos}}$			-1677.70***			-1471.01***
			(361.92)			(394.18)
Observations	98	98	98	98	98	98
First-stage results:						
$\hat{T}_i^*$	9.554***	8.893	11.170	9.659***	8.931	11.505
	(2.302)	(2.490)	(2.376)	(2.294)	(2.477)	(2.394)
Partial R^2	0.369	0.287	0.379	0.374	0.290	0.388
KP *rk* Wald *F*-stat	17.22	12.755	22.096	17.73	13.002	23.102

	PANEL B					
	Model (7)			**Model (8)**		
	%Population in tropics$_i$ Distance to equator$_i$			Latitude$_i$; % Population in tropics$_i$; % Land in tropics$_i$		
Second-stage results:						
Trade share$_i$	0.710**	-0.240	1.529***	0.909***	-0.114	1.696***
	(0.288)	(0.336)	(0.330)	(0.330)	(0.314)	(0.366)
N_i		0.019***			0.020***	
		(0.002)			(0.002)	
$\overline{\hat{T}_i^{Pos}}$			-1128.27***			-1537.91***
			(291.26)			(349.62)
Observations	98	98	98	98	98	98
First-stage results:						
$\hat{T}_i^*$	8.487***	1.942***	1.374***	9.649***	8.923***	11.494***
	(2.091)	(0.497)	(0.371)	(2.327)	(2.488)	(2.424)
Partial R^2	0.336	0.322	0.202	0.371	0.290	0.386
KP *rk* Wald *F*-stat	16.47	15.28	13.67	17.19	12.866	22.492

	Panel C					
	Model (9)			**Model (10)**		
	Latitude$_i$;% Population in tropics$_i$; Regional dummies			Latitude$_i$; % Population in tropics$_i$; IGRC-Index$_i$		
Second-stage results:						
Trade share$_i$	1.110***	0.082	2.056***	0.356	-0.241	1.294***
	(0.413)	(0.318)	(0.433)	(0.322)	(0.311)	(0.466)
N_i		0.020***			0.013***	
		(0.002)			(0.003)	
$\overline{\hat{T}_i^{Pos}}$			-1602.12***			-1189.40***
			(368.35)			(438.00)
Observations	98	98	98	90	90	90
First_stage results:						
$\hat{T}_i^*$	8.597***	8.225***	10.088***	7.614***	7.691***	9.189***
	(1.831)	(2.018)	(1.930)	(1.903)	(2.111)	(2.168)
Partial R^2	0.328	0.278	0.339	0.279	0.254	0.225
KP *rk* Wald *F*-stat	22.06	16.613	27.311	16.02	13.278	17.962

[continues]

Table OD.1 Income Equation with additional controls: Disentangling the role of $\hat{T}_i^{Pos*}$'s margins (continued)

	Panel D					
	Model (11)			**Model (12)**		
	Latitude$_i$; % Population in tropics$_i$; Corruption$_i$			Latitude$_i$; % Population in tropics$_i$; Executive constraint$_i$		
Second-stage results:						
Trade share$_i$	0.396	-0.411	1.417***	0.895***	0.124	1.390***
	(0.346)	(0.366)	(0.406)	(0.284)	(0.298)	(0.356)
N_i		0.017***			0.014***	
		(0.003)			(0.002)	
$\overline{\hat{T}_i^{Pos}}$			-1393.32***			-861.96***
			(421.05)			(324.54)
Observations	90	90	90	94	94	94
First-stage results:						
$\hat{T}_i^*$	8.003***	7.598***	10.323***	8.949***	8.288***	10.906***
	(1.842)	(2.038)	(2.012)	(2.859)	(2.925)	(3.178)
Partial R^2	0.281	0.233	0.272	0.328	0.247	0.337
KP *rk* Wald *F*-stat	18.88	13.896	26.333	9.80	8.031	11.774
	Panel E					
	Model (13)			**Model (14)**		
	Latitude$_i$; % Population in tropics$_i$; Ethno-ling. fract.$_i$			Latitude$_i$; % Population in tropics$_i$; Legal Origin$_i$		
Second-stage results:						
Trade share$_i$	1.099***	0.015	1.812***	1.097***	-0.006	1.822***
	(0.377)	(0.326)	(0.415)	(0.352)	(0.313)	(0.385)
N_i		0.019***			0.020***	
		(0.002)			(0.002)	
$\overline{\hat{T}_i^{Pos}}$			-1554.08***			-1592.50***
			(402.61)			(382.13)
Observations	95	95	95	96	96	96
First-stage results:						
$\hat{T}_i^*$	9.748***	9.096***	11.275***	9.813***	9.281***	11.311***
	(2.297)	(2.480)	(2.370)	(2.277)	(2.482)	(2.304)
Partial R^2	0.383	0.294	0.393	0.399	0.313	0.406
KP *rk* Wald *F*-stat	18.01	13.452	22.638	18.58	13.982	24.104

Notes. Heteroscedastic consistent standard errors are in parentheses. The standard errors in the second-stage are corrected for the errors created from the generated regressors using the approach devised by FR. $\hat{T}_i^{Pos}$ is the predicted trade openness based only on predictions for observations of actual positive bilateral trade. N_i and $\overline{\hat{T}_i^{Pos}}$ are *i*'s number of trading partners and average bilateral predicted trade openness, respectively. All models control for area and population (in logs) as well as the additional control variables listed below the column title in both the first and second stage. The KP *rk* Wald *F*-stat is the Kleibergen-Paap *rk* Wald *F*-statistic. *, **, *** Significant at 10, 5 and 1 percent, respectively.