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Robust Determinants of Bilateral Trade

Marianne Baxter
Boston University

Jonathan Hersh
Chapman University, hersh@chapman.edu

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Marianne Baxter[1]
Boston University and NBER

Jonathan Hersh[2]
Boston University

Abstract

What are the policies and country-level conditions which best explain bilateral trade flows between countries? As databases expand, an increasing number of possible explanatory variables are proposed that influence bilateral trade without a clear indication of which variables are robustly important across contexts, time periods, and which are not sensitive to inclusion of other control variables. To shed light on this problem, we apply three model selection methods – Lasso reguarlized regression, Bayesian Model Averaging, and Extreme Bound Analysis -- to candidate variables in a gravity models of trade. Using a panel of 198 countries covering the years 1970 to 2000, we find model selection methods suggest many fewer variables are robust that those suggested by the null hypothesis rejection methodology from ordinary least squares.

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[1] mbaxter@bu.edu, Department of Economics, 270 Bay State Road, Boston, MA 02215.
[2] jhersh@bu.edu, Department of Economics, 270 Bay State Road, Boston, MA 02215.

1. Introduction

In 1962, Tinbergen proposed that the flow of trade between two countries should be proportional to the size of the countries' economies and inversely proportional to their distance. In reference to Newton's law of universal gravitation, he dubbed this relationship as "gravity."Subsequently, countless empirical studies found gravity to be a robust relationship across a broad range of contexts and time periods. The model was so popular that it led Anderson (1979) to state that the gravity model was "the most successful empirical trade device of the last twenty-five years."

This model was placed on firm theoretical ground through the work of Anderson and van Wincoop (2003) and the large literature that followed[3] At the same time, there has been a revival of interest in empirical 'gravity' models that are motivated by policy questions such as "do currency unions matter?" or "do trade agreements/customs unions increase trade?" both of which remain relevant today. The problem of variable selection for empirical analysis of the gravity model is growing more complex as the availability of machine-readable databases expand along with statistical and computational methods for handling large datasets. It is tempting to include every possible empirical determinant of trade in the gravity model, although there are well known problems with "overfitting."[4] Further, variables that improve fit in-sample may not predict well when applied out of sample or to other datasets. If the empirical gravity model is to be used to inform policy it must balance in-sample and out-of-sample performance.

Our goal in this paper is to evaluate the robustness of commonly included measures of trade frictions, policy decisions, and country characteristics in determining the extent of bilateral trade. We use a panel of 198 countries from 1970 to 2000, and apply a standard empirical form of the gravity equation. To evaluate the robustness of variables included in the gravity equation we use three empirical methods: Bayesian Model Averaging; Lasso; and Extreme Bound Analysis[6] for the purposes of variable selection. Through these methods we learn which variables *should* be included in the gravity equation, that is which ones robustly predict trade flows.

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[4] Even, curiously, data on Eurovision scores (Felbermayr and Toubal, 2009).
[6] These methods are not entirely new in economics, with Varian (2014), Belloni and Chernozhukov (2013) advocating for the use of Lasso, and Fernandez, Ley, and Steel (2001) employing Bayesian Model Averaging in the context of cross-country growth regressions.

The rest of the paper proceeds as follows. Section 2 reviews the Anderson-van Wincoop (2003) model of the gravity equation, which has become the standard workhorse model used in empirical implementation, and summarizes relevant empirical research. Section 3 presents background on the three empirical methods used for variable selection. Section 4 introduces the data used in our analysis and section 5 contains the results of applying the three approaches to model selection to bilateral trade data. Section 6 concludes.

2. Methodology

Anderson (1979) was the first researcher to present theoretical foundations which rationalized the gravity model. His model rested on the assumption that each country produces a single, imperfectly substitutable good. Anderson and Van Wincoop (2003) extended the single-good framework of Anderson (1979) to an arbitrary number of goods. We use their model with some modifications to the specification of trade costs.

2.1 Model Description

The consumer's objective is:

$$(1) \qquad \max_{c_{ij}} \left\{ \left(\sum_i \beta_i^{\frac{1-\sigma}{\sigma}} c_{ij}^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}} \right\} \quad s.t. \ \sum_i p_{ij} c_{ij} = y_j$$

where c_{ij} is the consumption in region j of goods from exporting region i, p_{ij} is the price of region i goods for region j consumers, and y_j is nominal income in region j. The parameter β_i is a scale distribution parameter and σ is the elasticity of substitution between all goods. Trade costs enter the model through costs passed from exporter to importer. That is, t_{ij} is the trade cost factor between i and j, and given an exporter's supply price of p_i we can model the importer's supply price as $p_{ij} = p_i t_{ij}$. Next we let x_{ij} be the nominal value of exports from i to j. Since these exports are eventually consumed in region j we must have $x_{ij} = p_{ij} c_{ij}$. Finally, since each country consumes the value of its income, $y_i = \sum_j x_{ij}$. Maximization of equation (1) yields:

$$(2) \qquad x_{ij} = \left(\frac{\beta_i p_i t_{ij}}{\mathrm{P}_j} \right)^{(1-\sigma)} y_j$$

where $\mathrm{P}_j = \left[\sum_i \left(\beta_i p_i t_{ij}\right)^{1-\sigma}\right]^{\frac{1}{1-\sigma}}$ is the consumer price index in region j. In words the optimization condition states that exports from region i to j are related to the exporter's supply price and the trade cost factor divided by the destination country's CPI.

Imposing market clearing gives us

$$(3) \qquad y_i = \sum_j x_{ij} = \sum_j \left(\frac{\beta_i t_{ij}}{\mathrm{P}_j}\right)^{(1-\sigma)} = (\beta_i p_i)^{1-\sigma} \sum_j \left(\frac{t_{ij}}{\mathrm{P}_j}\right)^{1-\sigma} y_{ij} \ \forall\ i$$

Let $Y^W = \sum_j y_j$ denote world income. Summing over all countries gives the more tractable expression:

$$(4) \qquad x_{ij} = \frac{y_i y_j}{Y^W}\left(\frac{t_{ij}}{\Pi_{\mathrm{i}} \mathrm{P}_j}\right)^{1-\sigma}$$

where

$$(5) \qquad \Pi_i = \left(\sum_i \left(\frac{t_{ij}}{\mathrm{P}_j}\right)^{1-\sigma} \frac{y_j}{Y^W}\right)^{1/1-\sigma}$$

Anderson and van Wincoop (2003) propose one normalization that provides a solution to the set of equations (4) and (5) which is $\Pi_i = \mathrm{P}_i$. They note however that this is not innocuous[7]. Nevertheless, with this normalization we arrive at the most widely used form of the gravity equation:

$$(6) \qquad x_{ij} = \frac{y_i y_j}{Y^W}\left(\frac{t_{ij}}{\mathrm{P}_i \mathrm{P}_j}\right)^{1-\sigma}$$

The "gravity" elements--a negative relationship between trade and distance and a positive relationship between trade and GDP--are evident in equation (6). Trade flows between regions i and j are positively related to the product of the countries' GDP. Because t_{ij} is almost always parameterized to include distance, trade flows are inversely related to the distance between the

[7] The general solution is of the form $\mathrm{P}_i = \lambda \bar{\mathrm{P}}_i$ and $\Pi_i = \bar{\Pi}_i/\lambda$. The normalization is not innocuous in that in practice these multilateral resistance terms are estimated via country fixed effects. This is appropriate for cross-sectional estimation, but not for panel estimation. For more on panel estimation with the gravity model see Baier and Bergstrand (2007) and Egger and Nelson (2011).

two regions. The elements P_i and P_j are the "multilateral resistance" terms for regions i and j respectively. Though they are only indexed by i and j, note that both of them include the sum of all other regions' trade costs.

2.2 Empirical Specification of the Gravity Model

The estimating equation for the linear standard gravity equation is derived by taking the natural log of equation (6) and adding an error term:

$$\ln(T_{ij}) = k + \ln(y_i) + \ln(y_j) + (1-\sigma)t_{ij} + (1-\sigma)\mathrm{P}_i + (1-\sigma)\mathrm{P}_j + \epsilon_{ij} \tag{7}$$

where k is a constant term, and T_{ij} are the bilateral flows from region i to j (i's exports to j plus j's exports to i). The multilateral resistance terms P_{ij} can be accounted for using country-level fixed effects. The more troubling parameter is t_{ij}, the trade cost specification, which is not observed. In Anderson and van Wincoop (2003) the authors specify the trade cost as a function of bilateral distance and whether the trade flows occur between two different countries: $t_{ij} = b_{ij}d_{ij}^{p}$.

In the related empirical literature, researchers have specified t_{ij} to include (i) measures of cultural or ethnic closeness, such as having a common language or a common legal system; (ii) geographic considerations that affect the ease of moving goods, such as sharing a border, being landlocked, being an island; (iii) membership in the WTO and/or other regional trading groups; (iv) a host of policies that bear on exchange rate stability; the ease of currency convertibility, banking and exchange rate crises.

This is far from an exhaustive list of variables considered in the empirical gravity equation. Our goal in this paper is to address the problem of "model uncertainty" through application of three methods which are well-suited to this problem. We discuss these methods in the next section.

3. Statistical Methods

In this section we give a brief overview of the three methods used in the paper. These methods were developed in part to assist with the issue of selecting the optimal statistical model, thus they seem particularly well suited to this use.[8] Our empirical approach is to estimate equation (7) using panel regressions that include exporter, importer and year fixed effects. Note the variable selection mechanisms are not applied to the fixed effects which are used uniformly throughout the specifications.

3.1 Extreme Bound Analysis

Extreme Bound Analysis (EBA) was proposed by Leamer (1983, 1985) to address model uncertainty. EBA attempts to find which variables, in the set of candidate variables $\boldsymbol{X}$**,** are associated with an outcome variable yet robust to the inclusion of different control variables. As summarized by Leamer (2008):

> *"Extreme bounds analysis is a global sensitivity analysis that applies to the choice of variables in a linear regression. Rather than a discrete search over models that include or exclude subsets of the variables, this sensitivity analysis answers the question: how extreme can the estimates be if any linear homogenous restrictions on a selected subset of the coefficients are allowed?"*

The robustness of each coefficient is determined by whether the coefficient remains statistically significant and of the same sign in a reasonable number of estimated models. More formally, let $\boldsymbol{F}$ be the set of control variables that remain fixed in every model specification, which we call the "fixed" variables. The set $\boldsymbol{X}$ contains the variables that are the focus of the sensitivity analysis, which we refer to as the uncertain set of variables. Finally, let $\boldsymbol{U}_j \subseteq \mathbf{X}$ be the subset of variables which we use as control variables for a given specification j. Let $x \in \mathbf{X}$ be a singular control variable that we are focusing on with model j. The model we use to estimate the robustness of x has the form

(8) $$y = \beta_{0,j} + \beta_j x + \gamma_j \boldsymbol{F} + \Lambda_{\mathrm{j}} \boldsymbol{U}_j + \epsilon$$

where j indexes the regression models. We estimate this regression for each of the M possible models depending on the combinations of $\boldsymbol{U}_j$ that are possible. The number of elements in $\boldsymbol{U}_j$ is typically limited to three variables in the literature (see Levine and Renelt (1992)) though the number of elements to be included for each specification is in theory limited only by the size of **X**. In the present application, this specification is estimated for all subsets of **X** with the exception any subsets including x itself. This process yields a distribution of coefficient estimates and associated standard errors, which are used to estimate empirical confidence intervals at some desired level of significance. The "extreme bound" for the coefficient of variable x is given by [*a*,*b*], where a is the lowest value in any confidence interval and b is the highest value in any confidence interval. The variable x is robust if [*a*,*b*] does not contain the value zero. The variable is "fragile" if [*a*,*b*] contains zero.

3.2 Lasso Regression

The Lasso regression is a member of the family of regularized regressions which estimates a regression model with an added constraint that forces parsimony in the coefficient estimate (Tibshirani, 1996). These estimators are referred to as "shrinkage" estimators, so named because relative to OLS their coefficients are biased towards zero. The motivation for shrinking coefficients towards zero comes from the bias-variance tradeoff; by adding more parameters one can easily reduce within-sample error or bias. This comes at the expense of a larger estimator variance or out-of-sample error. Lasso regressions and other shrinkage estimators attempt to strike a balance between in-sample and out-of-sample error.

Formally, the Lasso estimator, β_{lasso} solves the minimization problem

$$(9) \quad \beta_{lasso} = \underset{\beta}{\operatorname{argmin}} \left\{ \frac{1}{2} \underbrace{\sum_{i=1}^{N} \left(y_i - \beta_0 - \sum_{j=1}^{K} x_{ij} \beta_j \right)^2}_{OLS\ Sum\ of\ squared\ residuals} \quad + \quad \underbrace{\lambda \sum_{j=1}^{K} \left| \beta_j \right|}_{Shrinkage\ factor} \right\}$$

where $\lambda \geq 0$ is a parameter that represents a penalty associated with the sum of the absolute values of the coefficients. The Lasso estimator adjusts all parameter estimates by the same absolute amount unless this adjustment would cause the parameter to change sign, in which case, the parameter is set to zero (Friedman, Hastie, and Tibshirani, 2001). Note that as $\lambda \rightarrow 0$, the parameter penalization decreases and $\beta_{lasso} \rightarrow \beta_{OLS}$. As $\lambda \rightarrow \infty$, variables are penalized more stringently and β_{lasso} converges to the zero vector.

Optimal λ^* is selected through cross-validation and comparing root mean squared error (RMSE) from a vector of possible $\hat{\lambda}$. The cross-validation algorithm for selecting λ^* is as follows: Sample data are split into K equally sized subsamples, or 'folds,' of equal size. Model estimation is performed using (K-1) of the folds and the resulting estimates are used to forecast or fit the data on the withheld fold. The average root mean squared error of this forecast is a function of λ. Thus, the ex-post optimal λ^* is the value of λ that minimizes this RMSE. In practice, however, researchers often choose the value of λ that corresponds to the more restrictive model associated with a one-standard-deviation increase in the cross-validation RMSE.[9] We follow this practice in our analysis.

Belloni and Chernozhukov (2013) discuss the Lasso estimator in the context of statistical inference. The original Lasso method (Tibshirani, 1996) was developed from the standpoint of prediction, which differs from the usual approach of applied economists who are concerned with parameter inference. Belloni and Chernozhukov develop an estimator they call the "post-Lasso" estimator, which they show to perform at least as well as the Lasso estimator with slightly less bias. The post-Lasso estimator is a two-step procedure. In step 1, a Lasso model is estimated over a large set of possible control variables. The variables which have non-zero coefficients are selected and retained for use in the second step. In step 2, an OLS model is fit using only the subset of variables that had non-zero coefficients in the first step. This method leans on the strengths of each approach: Lasso is useful for variable selection but presents biased estimates of coefficients.[10] OLS is unbiased and efficient, though cannot handle models with large number of covariates. In our analysis we present both the Lasso and the Post-Lasso estimates.

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[9] See Krstajic et al (2014) for more discussion on the selection of λ. The value is set to the RMSE minimizing value plus one standard error for the purposes of choosing "the simplest model whose accuracy is comparable with the best model." That is, while a more complicated model may perform better, the more parsimonious model performs comparable well enough to the more complicated one.

[10] Since Lasso estimation may shrink fixed effect coefficients, which should be included in any unbiased estimate, we employ a two step procedure. In the first step, we use Frisch-Waugh-Lovell (FWL) theorem (Frisch and Waugh, 1933; Lovell, 1963) to transform the dependent and independent variables to control for the level fixed effects. In the second step, the desired estimator is used on the FWL- transformed data series.

3.3 Bayesian Model Averaging

Bayesian model averaging (BMA) is an intuitive approach to model uncertainty where Bayes Rule is applied to the model and data, from which one can construct posterior parameter estimates. One advantage of BMA is that as in typical Bayesian estimation procedures, the output is a posterior distribution of possible parameter estimates, which can be more revealing than the point estimates returned by other methods. BMA is estimated as follows: First, all permutations of a linear regression model are estimated using the set of explanatory variables, $\boldsymbol{X}$. We refer to $\boldsymbol{X}_\alpha$ as a particular subset of variables in $\boldsymbol{X}$, and in that sense, each distinct $\boldsymbol{X}_\alpha$ is a separate model. In the second step, a posterior parameter vector is constructed using a weighted average of all parameters estimated from the set of estimated models in step 1. Because some models explain the data better than others, posterior parameters are a weighted function of parameter estimates using posterior model probabilities (PMP), which describe how well a given model (with an associated $\boldsymbol{X}_\alpha$) explain the data. If the dimension of $\boldsymbol{X}$ is K –that is we can choose from K possible explanatory variables to fit our model–this implies that BMA needs to estimate 2^K possible models to estimate every possible explanatory variable combination, a considerable computational undertaking. In practice, restricting estimation to a sample of the 2^K possible model computations reduces model estimation to a manageable size.

To give more structure to the problem, consider the problem of estimating a model of the form

(10) $$y = \beta_{0,\alpha} + X_\alpha \beta_\alpha + \epsilon_\alpha$$

where we must choose which set of variables $X_\alpha \in \boldsymbol{X}$ should be included in a given regression. Using Bayes Rule, we can calculate the posterior model probability–a measure of the reasonableness of the coefficients used–as

(11) $$p(M_\alpha|y, X) = \frac{p(y|M_\alpha, X)p(M_\alpha)}{p(y|M_\alpha)}$$

Where $p(M_\alpha|y, X)$ is the probability of the model given the data, or the posterior model probability; $p(y|M_\alpha, X)$ is the probability of the outcome variable given the model and the set of covariates and $p(M_\alpha)$ is the unconditional probability of the particular specification of the model, M_α. Using an application of the law of total probability we can rewrite the posterior model probability as

(12) $$p(M_\alpha|y,X) = \frac{p(y|M_\alpha,X)p(M_\alpha)}{\sum_{j=1}^{2^K} p(y|M_j,X)p(M_j)}$$

This leads to an expression for the model weighted posterior distribution for any estimator, β_k as

(13) $$p(\beta_k|y,X) = \sum_{\alpha=1}^{2^K} p(\beta_k|M_\alpha,y,X)p(M_\alpha|X,y)$$

The equation above shows that given the posterior model probability (PMP) we can estimate $p(\beta_k|y,X)$ –the probability that any estimator is included in the true model. The left hand side of equation is referred to as the posterior inclusion probability (PIP) and is reported a number between zero and one. The PIP reflects our relative confidence that the true model contains any particular variable. For example, if a variable has a PIP value of 1.0 this indicates that 100% of the weighted models include the variable β_k as a regressor, giving us relative confidence that the true model contains this variable. From the posterior distributions we also recover the posterior mean–the posterior average of the coefficient–and the posterior standard deviation, which give us the weighted average and the weighted standard deviation of the coefficient estimates across estimated model.

4. Data

Our panel covers the sample period of 1970 – 2000. Country coverage varies based on data availability. Regarding variables considered, we include a large set of candidate variables that the literature has suggested as measures of trade frictions, making attempts to use the data sources most commonly employed. However, when faced with a choice we decide in favor of variables that are measured over the entire sample period. Summary statistics statistics for the data used are presented in Table 1. Data sources are summarized in Appendix Table A-1.

4.1 List of Data Sources

Measurement of Trade Intensity

Real Bilateral Trade Flows For measures of trade intensity, we use the NBER-UN dataset of bilateral trade flows as described in Feenstra et al. (2005). The NBER-UN dataset offers several advantages: a long panel from 1962-2000, trade statistics covering all reported trading partners as collected by the United Nations, and construction using the more reliable import statistics when these are available. In the few cases where import statistics are not available, Feenstra, et al. use export measures as reported by the trading partner. Since these data primarily use import statistics, the trade intensity data measure CIF trade flows.

Gravity Variables

Distance The defining features of a gravity equation are a positive relationship between trading partners size and trade intensity and an inverse relationship between distance and trade intensity. Several measures of geographical distance have been proposed and used, with no consensus in the literature as to which one is preferred.[12] We consider four measures of distance, with a goal that the variable selection methods will provide evidence for which measure best explains trade volumes. Each distance measure is provided by the Centre d'Etudes Prospectives et d'Informations Internationales (CEPII) (Mayer, and Zignago, 2011). The first distance measure is the natural log of distance between most populated cities -- the most standard distance measure employed in the empirical gravity literature. The second is the natural log of distance between capitals. The next two measures were developed by Head and Mayer (2002). These measures are (i) the natural log of weighted distance and (ii) the natural log of CES-weighted distance. They calculate weighted distance as

(14) $$d_{ij} = \left[\sum_{k \in i} \left(\frac{pop_k}{pop_i}\right) \sum_{l \in j} \left(\frac{pop_l}{pop_j}\right) d_{kl}^{\theta}\right]^{1/\theta}$$

where pop_k measures the population of area k in country i. For simple weighted distance, θ is set to 1. However, with CES weighted distance, θ is set to -1, which intentionally corresponds to the most frequently measured elasticity between trade and distance. Intuitively, these weighted distance metrics measure distance along the dimensions that matter: since good will eventually need to travel to where demand is located, these measures attempt to account for different dispersions in population densities.

Product of GDPs Data on country GDP are from the Penn World Tables, version 7.1 (Heston, Summers and Aten 2012) and are expressed in constant US dollars. Our GDP product variable is constructed as the average of the logs of the two partners' levels of real GDP.

[12] See Disdier and Head (2008) for an illuminating meta-analysis on distance in gravity models.

Geographical Determinants of Trade
Contiguous, Island, and Landlocked For geographical determinants of trade, we look at three widely used variables in the literature: (i) an indicator variable for whether the trading partners are contiguous–that is they are adjacent to each other; (ii) an indicator for whether either trading partner is an island, and (iii) an indicator for whether either trading partner is landlocked.

Proxies for Cultural Distance
Next we consider variables which proxy for, or are directly related to, cultural distance between trading partners. These determinants of trade rest on the affinity principle: countries find it advantageous to trade trade with countries that similar to themselves. Some of these variables, such as language, can be thought of informative of reduced trade costs through easier contracting, or reduced transaction costs. Other cultural variables might proxy for shared demand systems across populations.

Share Official Language, 9%+ Speak Language A language indicator is often included in gravity models of trade. One way to justify its inclusion is in reducing contracting and coordinating costs between trading partners, what we refer to as the *direct* mechanism of reducing trade costs. Because language is a specialized skill, it is not necessary for the majority of population to speak the language in order to exploit this channel of reduced trade costs. Therefore we consider the indicator for whether 9% of the population share a common language as a test for the direct reduction of trade costs through language. There is some support in the literature for broadening the scope of this common covariate. Melitz and Toubal (2014) estimate a model which adds linguistic proximity, shared native language, and spoken language to the usual official-language indicator variable. They find that the inclusion of these variables results in trade impacts twice as large as with official language alone. The second language measurement we consider is whether the trading partners share an official language. This variable captures a sense of shared cultural background between trading partners, either through similarity of culture, or through shared historical past, during which one would have had much time to develop trading linkages.

Religious Distance We consider religious distance as a proxy for shared culture between trading partners. Lewer and van de Berg (2007) construct a series of indicator variables for shared majority religion and find trading partners who share religion have more trade. We take a slightly different approach and construct a continuous metric of similarity of religion that we define as religious distance. We parameterize religious distance as the Euclidean distance between the percent of the population in 16 different religious groups in the two countries, where these groups are defined by the World Religion Dataset[13]. A distance of 0 indicates that the trading partners have populations which have identical population fractions for each religious group; higher values of the distance variable indicate less religious similarity.

Factor Endowments

Human Capital, Physical Capital, and Arable Land Many theories of international trade predict that factor endowments should be correlated with trade.[14] To measure the factor endowment of human capital we use the Barro-Lee (2013) statistics on the average years of schooling for the population over the age of 15. For physical capital, we define factor endowment as a measure of physical capital per worker. Using data from the Penn World Tables, we calculate the value of capital stock measured at the current PPP exchange rate, divided by the number of employed persons in the economy. Finally, for the factor endowment for arable land is defined as arable land per worker, using data from the World Development Indicators. For each measure of factor endowments (human capital; physical capital; arable land), the factor intensity for the trading pairs i and j is defined as

$$f_t^{\{ij\}} = \ln(F_{it} * F_{jt}) \quad (15)$$

where F_{it} is the endowment of for country i in period t. Countries with similar factor endowments will have larger factor intensity measures.

[13] The World Religion Dataset is available at and gives the percent of population in each of the 16 different major religious groups for 192 countries covering 1945-2010. http://www.thearda.com/Archive/Files/Downloads/WRDNATL_DL2.asp

[14] The Heckscher-Ohlin model predicts higher trade for countries with dissimilar factor endowments. Models in the tradition of the "New Trade Theory" predict higher trade for countries with similar factor proportions. For our purposes, we wish only to consider whether factor endowments robustly predict trade. We do not propose our empirical analysis as a test of a particular model of international trade.

Impediments to Flows of Goods and Capital

WTO/GATT Membership, Regional Trade Agreements Multilateral agreements, such as the World Trade Organization (WTO) and the General Agreement on Tariffs and Trade (GATT), are one method by which countries can commit to lower impediments to the flow of goods and capital. These trade organizations are tasked with the goal of increasing world trade, thus it is natural to posit that membership in these organizations has a positive effect on trade volumes. Rose (2004) estimated the effect of WTO/GATT membership on trade, parameterizing membership as an indicator for whether either trading partner are included in a trade agreement, and an indicator for whether both partners are in the WTO/GATT. He finds positive effects of membership. Baier and Bergstrand (2006) use a panel framework to attempt to address the endogeneity of membership within a free trade agreement, and find that the trade gains from membership are even larger than those found by Rose. Subramanian and Wei (2007) find that WTO membership has a strong heterogeneous impact on trade, with effects largest when both trading partners are members, and further find that sectors which did not liberalize experienced no trade gains to WTO membership. We use WTO/GATT membership published by *Centre d'Etudes Prospectives et d'Informacions Internationales* (CEPII). A very large number of trading partners in our dataset are members of the WTO/GATT: 96%. We also include an indicator for membership in a regional trade agreement, the data for which is courtesy of de Sousa (2012).

Common Currency A shared currency between trading partners is widely believed to encourage trade. This was one of the main justifications for the introduction of the Euro in 1999. We use de Sousa's (2012) formulation of shared currency, which parameterizes the variable as equal to 1 if trading partners are part of an explicit or implied currency union. In an explicit currency union, the currency of one country circulates as legal tender in the second country. An implied currency union exists when one country maintains an explicit peg at a fixed rate of their currency to another country's currency. Note this does not include any other type of peg besides a fixed and maintained peg. Our summary tables show that 0.46% of trading partners in our sample share a common currency. The effect of a common currency on international trade has received more scrutiny than any other variable. Several influential papers using data from 2000 and earlier (i.e., not including the Euro zone) found that countries with a common currency enjoyed a level of trade from 110% higher to 577% higher, compared with countries that did not share a common currency.[15] In their meta-analysis of studies that estimated this parameter, Rose and Stanley (2005) consider 34 separate studies that overall present 754 estimates of the common currency effect. They find that the mean estimate implies a 136% increase in trade, while the median estimate implies a 70% increase in trade.

Capital Openness The degree to which capital can flow freely between countries may also affect trade. We utilize Chinn and Ito's (2007) index for financial liberalization, which is itself based on the IMF's *Annual Report on Exchange Arrangements and Exchange Restrictions* (AREAER). Their index is based on the series of binary indicator variables provided in the financial transactions of the AREAER, for a five year window in which the capital controls were not in effect. They define $share_{i,t} = \frac{\sum_{k,t\in \boldsymbol{K}} k_{i,t}}{card(\boldsymbol{K_t})}$ where $\boldsymbol{K_t}$ is the set of possible capital controls in year t. Their capital openness variable is the first standardized principal component of this share variable. We consider their openness index to be a parsimonious dimension reduction of a series of measures of capital controls projected into one dimension. Our summary tables show this variable has mean of 0.21 and varies from 0 (low financial openness) to 1 (high financial openness).

Exchange Rate Measurements

Exchange Rate Volatility, and Exchange Rate Regimes: Fixed Exchange Rate, Crawling Peg, or Moving Band Nominal exchange rate volatility has been shown to affect trade flows in models where firms set prices in advance (Broda and Romalis, 2003) and it has been tested empirically quite broadly. Nonetheless, Anderson and Van Wincoop (2004) in their review of the literature remark that there is "substantial consensus that the impact of exchange rate volatility on trade is very small at best, with even the sign uncertain (pg. 719.)" There are various ways to parameterize exchange rate volatility; we model exchange rate volatility as the residuals derived

[15] In roughly chronological order, these are Rose (2001): 235% higher; Rose and van Wincoop (2001), 136% to 297% higher; Frankel and Rose (2002) 371% higher; Glick and Rose (2002) 110% higher; and Barro and Tenreyo (2007), 577% higher.

from an $ARCH(1,3)$ process for yearly bilateral exchange rates. This variable shows a mean of 0.35 and a standard deviation of 1.8.

To measure the type of exchange rate regime, we use the IMF "coarse" classifications, as reported by Reinhart and Rogoff (2004) and subsequent updates. We define indicators for three exchange rate classifications: fixed exchange rate, crawling peg, and a moving band exchange rate regime. Each classification has two types: whether either trading partner employs this exchange rate regime, and whether both trading partner has this arrangement. In our sample, 49% of country pairs are characterized by at least one country belonging to a fixed rate regime, with both countries on a fixed-rate regime in 9.5% of country pairs. Regarding a crawling peg, 53% of the trading partners in our sample had at least one partner on a crawling peg exchange rate. Finally, 39% of the trading partners in our sample had at least one partner on a moving band exchange rate regime.

Crises Episodes

Indicators for Debt, Banking and Currency Crises Debt, banking and currency crises disrupt and depress economic activity in general, therefore it's likely that crises episodes have a large impact on trade flows between countries. We use the IMF's Systematic Banking Crises Database–which also contains data on currency and debt crises–as developed by Laeven and Valencia (2008) and updated in Laeven and Valencia (2012). The authors define a banking crisis to exist if two conditions are met:

> "1) Significant signs of financial distress in the banking system (as indicated by significant bank runs, losses in the banking system, and/or bank liquidations)
> 2) Significant banking policy intervention measures in response to significant losses in the banking system." (p. 4)

The authors record 147 banking crises since 1970. Their definition of a currency crisis is based on Frankel and Rose (1996). A currency crisis is defined as a nominal depreciation of the currency versus the US dollar of at least 30%. The authors find 218 events which qualify as currency crises during the time period of 1970-2011. The Laeven and Valencia definition of a debt crisis is based on information from Beim and Calomiris (2001), World Bank (2002), IMF reports and other agencies, and Sturzenegger and Zettelmeyer (2006). The authors find 66 events that qualify as sovereign debt crises during the period 1970-2011.

Crises events are rare by definition. Since the effect of crisis on trade may not be immediate, we define an indicator variable taking the value one if either trading partner experienced a crisis within the previous three-year window and zero otherwise. Using this definition, 5.6% of the sample is characterized by at least one partner experiencing a debt crisis. For banking crises, this number is 15%, and is 19% for currency crises.

5. Results

The main results are presented in Tables 2 and 3. All specifications include year, exporter, and importer fixed effects.[16] Table 2 presents the coefficient estimates for OLS, Lasso and Post-Lasso, while Table 3 presents the results for Bayesian Model Averaging and Extreme Bound Analysis. We consider a variable to be Lasso robust if it remains non-zero after Lasso Bayesian shrinkage, BMA robust if it has a posterior inclusion probability (PIP) of greater than 0.5, and EBA robust if the estimate upper bound and lower bound do not contain zero.

Table 2 compares OLS and Lasso estimates. Of the 31 covariates in the candidate set of variables (excluding the intercept),OLS regression finds that 26 of these variables are statistically significant at the 5% level. However, only 17 are Lasso robust. Table 3 shows that 18 are BMA robust and 19 are EBA robust.[18] Together, the three methods suggest a more parsimonious model of the determinants of bilateral trade than would be implied by standard application of OLS.

Figure 1 presents histograms of the distribution of estimated regression coefficients for the EBA method, where the vertical red line shows where zero sits in the distribution. These distributions can be highly informative; some variables, such as the landlocked indicator show a tight coefficient distribution, indicating across almost all reasonable specifications we can expect the coefficient estimate to lie within this range. Other variables, such as regional trade agreement,

[16] We present the results for alternative fixed effect specifications in Appendix tables A-2, A-3, and A-4.
[18] We consider a variable Lasso robust if it remains non-zero after Lasso Bayesian shrinkage, BMA robust if it has a posterior inclusion probability (PIP) of greater than 0.5, and EBA robust if the estimate upper bound and lower bound do not contain zero.

show a bimodal coefficient distribution, suggesting this parameter has heterogenous effects that may depend on other included covariates.

Figure 2 presents the posterior model probabilities from BMA, showing the most likely model specifications with their accompanying probabilities. The model with the highest estimated posterior model probability has a 17% posterior probability, and includes 19 variables (excluding the variables of banking crisis, crawling peg, moving band, fixed exchange rate, official common language, and currency crisis). The second most likely model has a 16% posterior probability, and includes all the variables in the previous model and includes a crawling peg indicator. The third most likely model 15% posterior model probability and includes all of the variables of the previous model, but includes an indicator for banking crises. Together, these three models have a cumulative probability of 48%. Note that after 70% cumulative model probability the models appear to fragment, with many models having small fractional posterior probabilities.
Figure 3 shows the shrinkage path of the Lasso coefficients. The y-axis presents the standardized coefficient value as the value of the shrinkage parameter, lambda, varies. The OLS solution corresponds to the left-most position on the x-axis. As the lambda parameter increases, and we move to the right on the x-axis, variables are shrunk towards zero. For any given value of lambda some coefficients will be estimated to be zero, thus for each value of lambda positive y-values correspond to variables selected via Lasso. The shrinkage path – that is the order in which variables are shrunk to zero -- is informative of which variables have the largest explanatory power. For example, for very large values of lambda, log of weighted distance remains while many other variables have been shrunk to zero.

Gravity Variables

Estimation via Lasso we find two out of the four candidate variables were not shrunk to zero: weighted distance and CES distance, with coefficients of -0.994 and -0.133 respectively. In comparison, OLS considers distance and weighted distance highly significant, with the log of distance having a puzzling positive coefficient. If we add the Lasso robust coefficients we get a combined elasticity of distance on trade of -1.127. This is slightly larger than the average elasticity of -0.907 as found in Disdier and Head’s meta-analysis of 1,467 gravity models. Disdier and Head find that papers using earlier data tend to have smaller coefficients, and an average coefficient size of 0.9, 0.96, and 0.95 in decades 1970s, 1980s and 1990s respectively. Because BMA and EBA methods are less robust to the inclusion of highly correlated variables, we chose only one of the two Lasso robust distance measures to test using BMA and EBA. Using Bayesian model averaging we estimate a coefficient on CES weighted distance of -1.113. The posterior inclusion probability (PIP) is 1, meaning that 100% of the weighted posterior models included distance in the final model. The posterior standard deviation of the estimated coefficient is 0.007, indicating a small amount of variation across models. Finally using EBA, we find an upper bound and lower bound range of (-1.34 to -1.1), within the range of significance suggested by EBA. Lasso shrinks the product of GDPs to an estimated 0.559 from the OLS estimate of 0.729. Using Post-Lasso, the estimate rises to 0.636. BMA shows the product of GDPs to be a tightly estimated 0.739, very close to the OLS estimate. This variable is also robust under EBA with an estimated range of (0.75, 0.99).

Geographical Determinants

All of the geographical determinants variables are robust according to the three methods used. OLS estimates the contiguous dummy’s coefficient as 0.614, while Lasso gives an estimate of 0.431. BMA agrees with the Lasso estimate, giving a mean estimate of 0.405 which is on the lower end of EBA’s estimate range from 0.37 to 0.69.

Proxies for Cultural Distance

Both language variables considered remain non-zero after Lasso shrinkage. The coefficient on official language is estimated at 0.066 and the coefficient on 9% speak is estimated at 0.296. Egger and Lassmann (2012), in a meta-analysis of 701 coefficients culled from 81 published articles, find an average coefficient of 0.49, considerably smaller than our estimate, even when one combines the two different language estimates. Our Post-Lasso estimate, is estimated at 0.047 for official language and at 0.327 for 9%+ population, also smaller than the literature average. The estimate from BMA show a posterior inclusion probability of 0.031, meaning only 3.1% of the weighted posterior models included this variable. EBA, however, shows robustness of official language, with an estimated coefficient range between 0.19 and 0.78. This variable’s counterpart, 9%+ population, however, is robust according to BMA with an estimated PIP of 1, and according to EBA which shows an estimated range of 0.21 and 0.76.

Both former colony and common colonizer appear strongly robust in the Lasso regression model, with coefficients of 0.738 and 0.319 respectively. The post-Lasso estimate highly significant with slightly larger coefficients of 0.867 and 0.394. This estimate is roughly on par with the coefficient estimated by Frankel and Rose (2002), and with the coefficient estimate of 0.45 in Glick and Rose (2002). The BMA and EBA show similar robustness of these covariates. Former colony is robust according to BMA with an estimated PIP of 1 and an estimated post-mean of 0.866. EBA gives the upper bound and lower bound range of (0.86,1.36). Common colonizer has an estimated PIP of 1 and a post mean estimate of 0.413, roughly similar to the post-Lasso estimate. The EBA estimate shows robustness with a rather large estimated range of (0.35 to 0.77). Though no meta-analysis exists for this coefficient, our estimate for former colony seems smaller than the coefficient on this covariate estimated previously, such as in Rose (2004) who estimates a coefficient of 1.28 for post-1970, or Rose and van Wincoop (2001) who find a coefficient of 1.74.

The estimated Lasso coefficient on common legal origin is 0.25, and has a post-Lasso coefficient of 0.286, which is nearly identical to the OLS estimate of 0.282. This estimate is similar in magnitude to others in the literature, such as 0.306 estimated by Head, Mayer and Ries (2010) or 0.410 estimated Felbermayr and Toubal (2009). The post-mean estimate from BMA is very similar in magnitude, estimated at 0.287, with an accompanying PIP of 1. The EBA range of (0.27,0.51) indicates this variable is considered robust according to that method. Religious distance has an OLS estimate of -0.209, and using Lasso we get a coefficient of -0.174. Given that this is an index, it’s hard to interpret the magnitude of this coefficient, but given that the standard deviation of this index varies is 0.69 in our sample, moving one standard deviation of religiously dissimilarity is predicted to decrease aggregate trade flows between partners by 11%[20]. The Post-Lasso coefficient estimate is -0.215 and is significant at the canonical levels. This variable is also robust according to BMA and EBA. BMA gives a posterior inclusion probability (PMP) of 1 with a post-mean coefficient of -0.216 and a standard deviation of 0.009. EBA further finds this variable robust and gives a range of (-0.3,-0.17). In comparison to other

[20] Assuming a marginal effect from 0 to 0.69.

work in the literature, our findings suggest a stronger effect of religious similarity than previous estimates (Linders et al., 2005) who estimate a coefficient of 0.22 for (binary) religious similarity between trading partners. Some of this difference may be coming from the continuous versus discrete parameterization of this variable, however when taken at face value our estimate implies a larger response to religious similarity and trade.

Factor Endowments

All three factor endowment variables – human capital, physical capital, and arable land -- are statistically significant using OLS with coefficients of 0.742, -0.129, and -0.231 respectively. Lasso selects only human capital and arable land, with coefficients of 0.389 and -0.15. Using BMA, all three variables have PIP of 1, and EBA finds all three robust. Human capital shows a BMA post-mean of 0.75, and an EBA range from (0.78, 1.37), consistent with the OLS coefficient estimate. Physical capital shows a BMA post-mean of -0.132 and an estimated EBA range of (-0.18, -0.09). Finally arable land shows a BMA post-mean of -0.229 and an estimated EBA range of (-0.41, -0.27).

Impediments to the Flows of Goods and Capital

WTO/GATT and common currency indicator are robust across all three methods. Exchange rate volatility is robust according to BMA, but not when using Lasso or EBA. Regional trade agreements and capital openness are not significant in any of the specifications. For capital openness, While OLS estimates a coefficient of -0.00298, Lasso estimation estimates a zero coefficient. This result is mirrored in the results for BMA, which estimates a zero PIP, and EBA, which estimates a range of coefficient values of (-0.21,0.04), which is not robust according to the method. This was a surprising result, as the degree to which capital can flow freely seems to a priori affect real trade flows. However, the appendix tables provide some guidance to answer this puzzle. Consider appendix table A-2, which presents the Lasso results varying fixed effect specifications. Note that capital openness is robust when either importer fixed effects or year fixed effects are not employed. This is also mirrored in the appendix tables A-3 and A-4, for BMA and EBA respectively. It appears that while capital openness is predictive of trade flows in the cross section, most of this variation is due to country-specific effects that are captured in the importer fixed effects. This suggests that although capital openness remains important, what matters more is the political and economic environment within a country that determines the degree of capital openness.

WTO/GATT membership looks strongly robust across methods. OLS estimates a significant coefficient of 0.335, Lasso estimates a coefficient of 0.171, and BMA estimates post-mean of 0.348. This compares to the coefficient estimated by Rose (2004) in column 4 of table 1 of 0.15, which is closer to the Lasso result than the OLS estimates. Regarding common currency, OLS estimates a coefficient of 0.448, which Lasso shrinks to 0.109. The BMA post-mean is 0.353 with a PIP of 1, and EBA estimates a range of (0.11, 0.84). Frankel and Rose (2002) estimate a coefficients on currency union membership which range from 1.36 to 1.55, which are substantially larger than our estimates.

Exchange Rate Measurements

Using OLS, all of the exchange rate variables are statistically significant from zero. However, there is large agreement across methods, showing only either crawling peg being robust. Lasso selects only either crawling peg indicator as robust and the rest are set to zero. Using BMA, exchange rate volatility, and either crawling peg have PIPs of 1 with estimated coefficients of -0.012 and 0.153 respectively. Both fixed exchange rate has a PIP of 0.893 with an estimated post-mean of 0.071 and either moving band has a PIP of 0.048. Using EBA only either fixed exchange rate and either crawling peg are robust, with estimated ranges of (-0.14, -0.02) and (0.06, 0.18) respectively. The differences in statistical robustness between OLS and the other methods are stark. We can only speculate as to the reason for the differences. Our hypothesis is that OLS may be fitting a significant amount of noise that it interprets as signal, which the other methods do not.

Crisis Measurements

Estimating using OLS we see that of the three crisis episodes considered—debt, banking, or currency—only banking crisis is significant at the standard levels, showing a positive coefficient of 0.0513. However, when estimating via Lasso and applying Bayesian shrinkage this variable is estimated at zero and thus is not considered robust according to Lasso. Using Bayesian Model Averaging, we see that the presence of a debt crisis has a PIP of 0, indicating no probability of inclusion in the true model. The PIP of banking crisis is on the cusp of robustness, showing a value of 0.481 and a post-mean of 0.021. Currency crisis shows a near-zero PIP of 0.006 and a post-mean indistinguishable from zero. Estimating via EBA, we see that neither debt crisis nor currency crisis are robust according to EBA. However, banking crisis is, showing a range of estimated coefficient values of (0.02,0.1). The positive coefficient on banking crisis is slightly puzzling, and given the window of this variable of 3 years, this may indicate that we are picking up the "rebound" period when trade returns to trend after a crisis.

To be sure, this is not to say that crisis episodes considered here do not necessarily have an impact on trade. When estimating trade flows *without* using year fixed effects (seen in tables A-2, A-3, and A-4) banking and currency crises are consistently negative and robust. Our results do not preclude the possibility that all worldwide trade is depressed during periods of banking and currency crises. That is to say, it is possible from viewing these results that all countries lose out during banking and currency crisis episodes, not just those that experience the crises themselves. There appears to be some support for this thesis, as shown in Shelburne (2010) who looks at trade decline during the global financial crisis from 2007-2010. How much is worldwide trade depressed? Our results indicate quite a lot. EBA shows the coefficient on banking crisis varies from -0.52 to -0.3, even when controlling for exporter and importer fixed effects. This translates to a marginal effect of -40% to -25.9% per trading partner, which indicates almost implausibly large aggregate declines. For currency crisis, the coefficient varies from -0.44 to -0.23 indicating marginal effects on trade of -35.6% to -20.5%.

6. Conclusion

How do the three variable selection methods refine the set of variables that should define the workhorse empirical gravity model? First, our result reject the robustness of roughly a fifth of the variables in the candidate set for which OLS does not reject the null hypothesis. Second, the set of robust variables is remarkably consistent across the three model selection methodologies.

Table 3 shows relative agreement across methods. Very few variables appear highly significant using one method while not very significant in others. In particular Lasso and EBA show very similar results qualitatively, differing in parameter inclusion significance for only 4 variables.

Table 4 show the results across methods. A mark in the table indicates that the variable is robust according to that particular method. Specifically, for lasso, a mark indicates a non-zero coefficient. For EBA, a mark indicates that the upper and lower bound do not include zero. For Bayesian Model Averaging, a mark indicates a 50% or great PIP. Overall, our results show that model selection methods that balance “fit” and “prediction” are straightforward to employ; give a consistent set of results, at least in the context of the gravity model; and that these methods represent the best current solution to the problem of variable selection in potentially a wide variety of contexts.

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Table 1: Summary Statistics

	count	*mean*	*sd*	*min*	*max*
Trade Intensity					
Ln of Real Bilateral Trade Flows	152,213	17.0	2.97	8.14	26.4
Gravity					
ln Dist	152,213	8.70	0.78	4.09	9.89
ln of Dist between Capitals	152,213	8.70	0.78	4.09	9.89
ln of Weighted Distance	152,213	8.71	0.77	4.74	9.89
ln of CES Weighted Distance	152,213	8.70	0.79	4.66	9.89
Product of GDPs	152,213	22.8	2.29	14.4	31.6
Geographical Determinants					
Contiguous	152,213	0.025	0.16	0	1
Either Island	152,213	0.042	0.20	0	1
Either Landlocked	152,213	0.19	0.39	0	1
Proxies for Cultural Distance					
Share Official Language	152,213	0.16	0.37	0	1
9%+ Speak Language	152,213	0.18	0.39	0	1
Former Colony	152,213	0.034	0.18	0	1
Common Colonizer	152,213	0.060	0.24	0	1
Common Legal Origin	152,213	0.37	0.48	0	1
Religious Distance	152,213	0.70	0.69	0	2.14
Factor Endowments					
Human Capital (product)	152,213	1.54	0.40	0.099	2.48
Physical Capital (product)	152,213	21.1	1.77	13.4	24.9
Arable Land (product)	152,213	-3.21	1.83	-14.3	2.13
Impediments to the Flows of Goods and Capital					
WTO/GATT	152,213	0.96	0.19	0	1
Regional Trade Agreement	152,213	0.051	0.22	0	1
Common Currency	152,213	0.0046	0.068	0	1
Capital Openness	152,213	0.21	0.26	0	1
Exchange Rate Measurements					
Exchange Rate Volatility	152,213	0.35	1.80	0.035	65.0
Either Fixed Exchange Rate	152,213	0.49	0.50	0	1
Both Fixed Exchange Rate	152,213	0.095	0.29	0	1
Either Crawling Peg Exch Rate	152,213	0.53	0.50	0	1
Both Crawling Peg Exchange Rate	152,213	0.090	0.29	0	1
Either Moving Band Exch Rate	152,213	0.39	0.49	0	1
Both Moving Band Exchange Rate	152,213	0.045	0.21	0	1
Crisis Measurements					
Debt Crisis 3yr Window	152,213	0.056	0.23	0	1
Banking Crisis 3yr Window	152,213	0.15	0.35	0	1
Currency Crisis 3yr Window	152,213	0.19	0.39	0	1

Table 2: OLS and Lasso

Variable	(1) OLS	(2) Lasso	(3) Post Lasso
ln Dist	0.500***	0	
ln of Dist between Capitals	0.201	0	
ln of Weighted Dist	-1.875***	-0.994	-1.690***
ln of CES Weighted Dist	0.0205	-0.133	0.534***
ln of Product of GDPs	0.729***	0.559	0.636***
Contiguous	0.614***	0.431	0.601***
Either Island	0.475***	0.337	0.476***
Either Landlocked	-0.531***	-0.211	-0.520***
Share Official Language	0.0646*	0.066	0.0470
9%+ Speak Language	0.311***	0.296	0.327***
Former Colony	0.855***	0.738	0.867***
Common Colonizer	0.396***	0.319	0.394***
Common Legal Origin	0.282***	0.25	0.286***
Religious Distance	-0.209***	-0.174	-0.215***
Human Capital (product)	0.742***	0.389	0.707***
Physical Capital (product)	-0.129***	0	
Arable Land (product)	-0.231***	-0.15	-0.249***
WTO/GATT	0.335***	0.171	0.353***
Regional Trade Agreement	-0.00572	0	
Common Currency	0.448***	0.109	0.481***
Capital Openness	-0.00298	0	
Exchange Rate Volatility	-0.0120***	0	
Either Fixed Exch Rate	0.0414**	0	
Both Fixed Exch Rate	0.0949***	0	
Either Crawling Peg Exch Rate	0.177***	0.073	0.130***
Both Crawling Peg Exch Rate	0.0814***	0	
Either Moving Band Exch Rate	0.0758***	0	
Both Moving Band Exch Rate	0.0871***	0	
Debt Crisis 3yr Window	-0.0159	0	
Banking Crisis 3yr Window	0.0513***	0	
Currency Crisis 3yr Window	-0.0142	0	
Constant	0.0668***	0.064	0.0667***
Observations	152,213	152,213	152,213

Notes: Dependent variable is the log of real bilateral trade flows for all regression specifications. All regressions include year, exporter, and importer fixed effects. For OLS, t statistics are presented in parentheses. Robust standard errors. T-statistics are hidden in this version of the table. *p<0.05, ** p <0.01, *** p<0.001

Table 3: Bayesian Model Averaging and Extreme Bound Analysis Baseline Results

	Bayesian Model Averaging			Extreme Bound Analysis	
	PIP	Post Mean	Post SD	UB to LB	Robust
ln of CES Weighted Dist	1	-1.113	0.007	(-1.34,-1.1)	y
Product of GDPs	1	0.736	0.016	(0.75,0.99)	y
Contiguous	1	0.405	0.031	(0.37,0.69)	y
Either Island	1	0.488	0.026	(0.46,0.77)	y
Either Landlocked	1	-0.514	0.047	(-0.67,-0.38)	y
Share Official Language	0.031	0.002	0.011	(0.19,0.78)	y
9%+ Speak Language	1	0.364	0.017	(0.21,0.76)	y
Former Colony	1	0.866	0.027	(0.83,1.36)	y
Common Colonizer	1	0.413	0.023	(0.35,0.77)	y
Common Legal Origin	1	0.287	0.011	(0.27,0.51)	y
Religious Distance	1	-0.216	0.009	(-0.3,-0.17)	y
Human Capital (product)	1	0.75	0.068	(0.78,1.37)	y
Physical Capital (product)	1	-0.132	0.012	(-0.18,-0.09)	y
Arable Land (product)	1	-0.229	0.018	(-0.41,-0.27)	y
WTO/GATT	1	0.348	0.025	(0.12,0.41)	y
Regional Trade Agreement	0	0	0	(-0.18,0.07)	n
Common Currency	1	0.353	0.062	(0.11,0.84)	y
Capital Openness	0	0	0	(-0.21,0.04)	n
Exchange Rate Volatility	1	-0.012	0.002	(-0.01,0)	n
Either Fixed Exch Rate	0.051	0.002	0.01	(-0.14,-0.02)	y
Both Fixed Exch Rate	0.893	0.071	0.031	(-0.1,0.1)	n
Either Crawling Peg ER	1	0.153	0.015	(0.06,0.18)	y
Both Crawling Peg ER	0.449	0.027	0.032	(-0.09,0.07)	n
Either Moving Band ER	0.924	0.048	0.02	(-0.02,0.11)	n
Both Moving Band ER	0.174	0.013	0.029	(-0.07,0.14)	n
Debt Crisis 3yr Window	0	0	0	(-0.08,0.04)	n
Banking Crisis 3yr Window	0.481	0.021	0.024	(0.02,0.1)	y
Currency Crisis 3yr Window	0.006	0	0.002	(-0.06,0.03)	n

Dependent variable is real bilateral trade flows between trading partners. All specifications include exporter, importer, year fixed effects. PIP is the “posterior inclusion probability” and reflects our relative confidence that the true model contains any particular regressor. Post Mean is the weighted average over the posterior estimates of the regressor. Post SD is the standard deviation of coefficient's posterior distribution. LB refers to highest value of the parameter in all of the models estimated, UB refers to the highest value of the parameter estimated. Leamer considers an estimate “robust” if its highest and lowest estimated value does not include zero.

Table 4: Summary of Variable Robustness Across Methods

	OLS	Lasso	BMA	EBA
ln Dist	▪		▪	▪
ln of Dist between Capitals			▪	▪
ln of Weighted Distance	▪	▪	▪	▪
ln of CES Weighted Distance		▪	▪	▪
Product of GDPs	▪	▪	▪	▪
Contiguous	▪	▪	▪	▪
Either Island	▪	▪	▪	▪
Either Landlocked	▪	▪	▪	▪
Share Official Language	▪	▪		▪
9%+ Speak Language	▪	▪	▪	▪
Former Colony	▪	▪	▪	▪
Common Colonizer	▪	▪	▪	▪
Common Legal Origin	▪	▪	▪	▪
Religious Distance	▪	▪	▪	▪
Human Capital (product)	▪	▪	▪	▪
Physical Capital (product)	▪		▪	▪
Arable Land (product)	▪	▪	▪	▪
WTO/GATT	▪	▪	▪	▪
Regional Trade Agreement				
Common Currency	▪	▪	▪	▪
Capital Openness				
Exchange Rate Volatility	▪		▪	
Either Fixed Exchange Rate	▪			▪
Both Fixed Exchange Rate	▪		▪	
Either Crawling Peg Exch Rate	▪	▪	▪	▪
Both Crawling Peg Exchange Rate	▪			
Either Moving Band Exch Rate	▪		▪	
Both Moving Band Exchange Rate	▪			
Debt Crisis 3yr Window				
Banking Crisis 3yr Window	▪		▪	▪
Currency Crisis 3yr Window				

Figure 1: Distributions of parameter estimates generated by Extreme Bounds Analysis

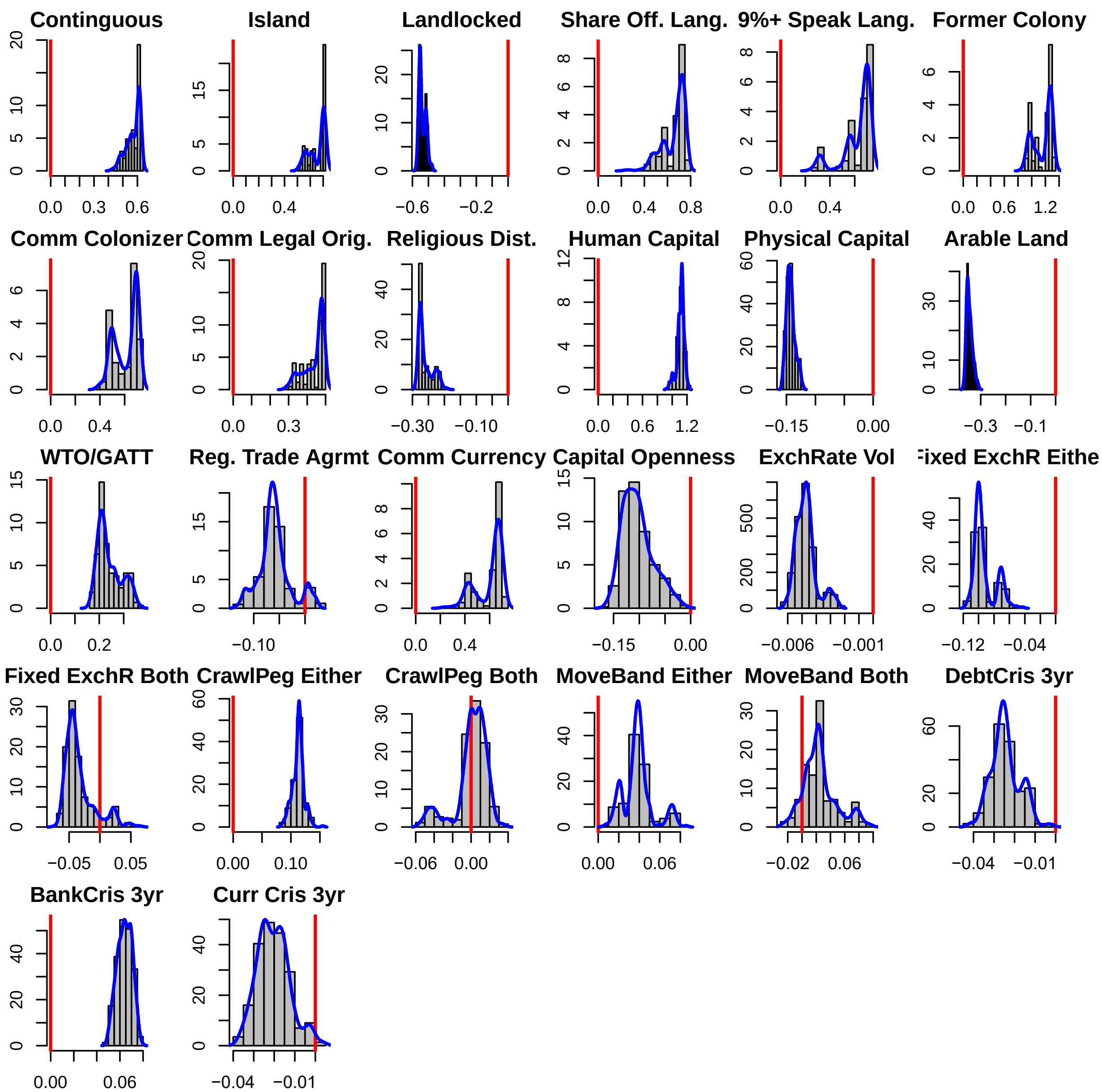


Figure shows histograms of coefficient probability densities from Extreme Bounds Analysis estimation. The vertical red line shows where zero lies on the x-axis. Blue lines show the kernel density smoothed histograms.

Figure 2: Bayesian Model Averaging, Posterior Model Probabilities

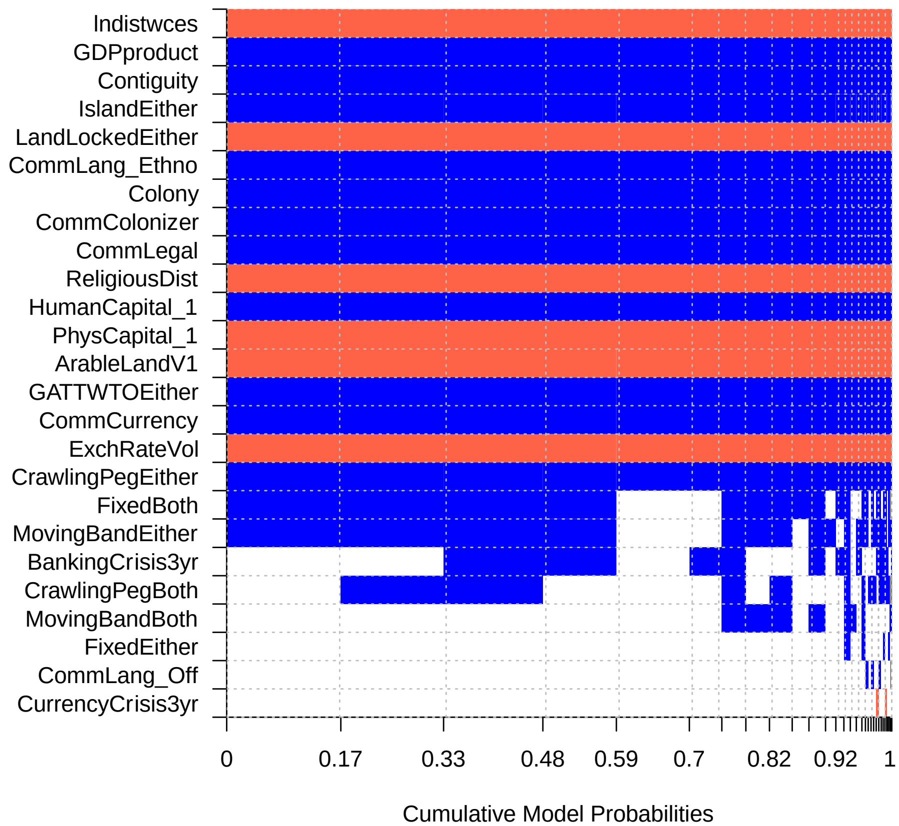
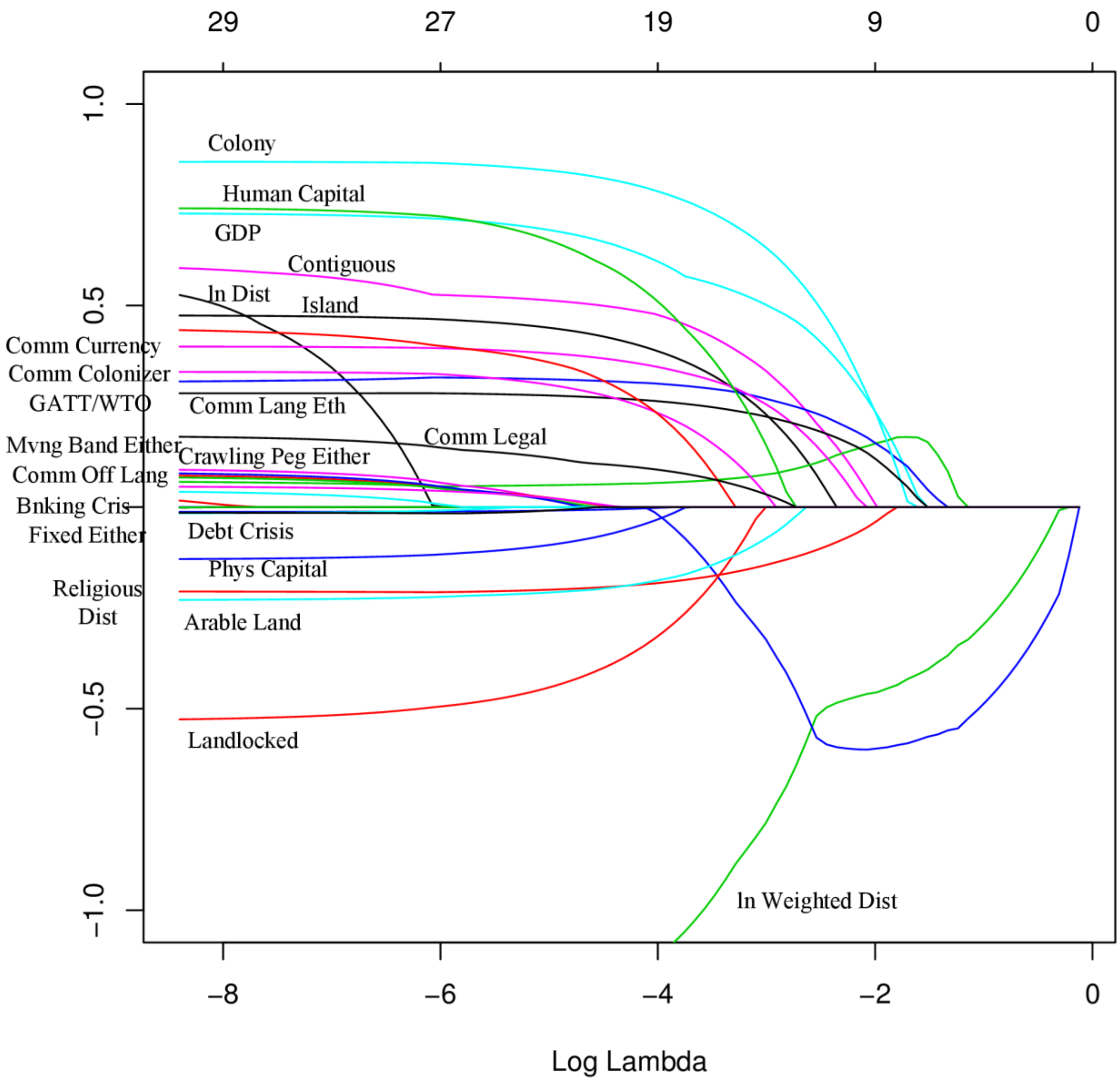


Figure shows posterior model probabilities and the associated variables included in the models. Variables shaded red have negative estimated coefficients; blue shading indicates positive estimated coefficients. Blank shading indicates variable not included in the given model.

Figure 3: Shrinkage Path for Lasso Estimation



APPENDIX TABLES

Table A-1: List of Data Sources

	Measure	Source	Citation
	Ln of Real Bilateral Trade Flows	NBER-UN	Feenstra et al. (2005)
Gravity			
1	Ln Distance)	CEPII	Mayer, T. & Zignago, S. (2011)
2	Product of Trading Partners GDPs	PWT 7.1	Heston, Summers, and Aten (2012)
Geographical Determinants			
3	Contiguous	CEPII	Mayer, T. & Zignago, S. (2011)
4	Either Island	CIA World Factbook	CIA World Factbook
5	Either Landlocked	CIA World Factbook	CIA World Factbook
Proxies for Cultural Distance			
6	Share Official Language	CEPII	Mayer, T. & Zignago, S. (2011)
7	9%+ Speak Language	CEPII	Mayer, T. & Zignago, S. (2011)
8	Former Colony	CEPII	Mayer, T. & Zignago, S. (2011)
9	Common Colonizer	CEPII	Mayer, T. & Zignago, S. (2011)
10	Common Legal Origin	CEPII	Mayer, T. & Zignago, S. (2011)
11	Religious Distance	World Religion	World Religion Dataset
Factor Endowments			
12	Human Capital (product)	Barro-Lee	Barro-Lee (2013)
13	Physical Capital	World Bank WDI	World Bank WDI
14	Arable Land (product)	World Bank WDI	World Bank WDI
Impediments to Flows of Goods and Capital			
15	WTO/GATT	CEPII	Mayer, T. & Zignago, S. (2011)
16	Regional Trade Agreement	de Sousa	de Sousa (2012a)
17	Common Currency	de Sousa	de Sousa (2012b)
18	Capital Openness	Chinn-Ito	Chinn and Ito (2007)
Exchange Rate Measurements			
19	Exchange Rate Volatility	Author's Estimates	
20	Either Fixed Exch Rate	R&R	Reinhart and Rogoff (2004)
21	Both Fixed Exch Rate	R&R	Reinhart and Rogoff (2004)
22	Either Crawling Peg Exchange Rate	R&R	Reinhart and Rogoff (2004)
23	Both Crawling Peg Exchange Rate	R&R	Reinhart and Rogoff (2004)
24	Either Moving Band Exchange Rate	R&R	Reinhart and Rogoff (2004)
25	Both Moving Band Exchange Rate	R&R	Reinhart and Rogoff (2004)
Crisis Measurements			
26	Debt Crisis 3yr Window	IMF Financial Crises	Laeven and Valencia (2012)
27	Banking Crisis 3yr Window	IMF Financial Crises	Laeven and Valencia (2012)
28	Currency Crisis 3yr Window	IMF Financial Crises	Laeven and Valencia (2012)

Table A-2: Lasso Estimation, Varying Fixed Effects

	(1)	(2)	(3)	(4)	(5)
lambda.1se	0.02211	0.02526	0.02024	0.01907	0.02834
(Intercept)	1.189	0.122	0.322	0.063	0.064
ln Distance	0	0	0	0	0
ln of Dist between Capitals	0	0	0	0	0
ln of Weighted Dist	0	-0.001	0	-0.001	-0.994
ln of CES Weighted Dist	-0.854	-1.045	-0.89	-0.937	-0.133
Product of GDPs	0.802	0.763	0.845	0.919	0.559
Contiguous	0.548	0.283	0.657	0.584	0.431
Either Island	0.612	0.596	0.626	0.314	0.337
Either Landlocked	-0.423	-0.673	-0.341	-0.037	-0.211
Share Official Language	0.222	0	0.188	0.388	0.066
9%+ Speak Language	0.192	0.292	0.241	0.016	0.296
Former Colony	1.066	1.077	0.9	0.832	0.738
Common Colonizer	0.105	0.158	0.211	0.304	0.319
Common Legal Origin	0.122	0.192	0.107	0.175	0.25
Religious Distance	-0.132	-0.123	-0.186	-0.178	-0.174
Human Capital (product)	-0.346	-0.4	-0.462	1.06	0.389
Physical Capital (product)	0.232	0.213	0.248	0.095	0
Arable Land (product)	-0.046	-0.031	-0.002	-0.11	-0.15
WTO/GATT	0.357	0.186	0.277	0.377	0.171
Regional Trade Agreement	0.394	0.292	0.215	0.273	0
Common Currency	0.5	0.165	0.329	0.388	0.109
Capital Openness	0.555	0.042	0.231	0.694	0
Exchange Rate Volatility	0.001	0	0	0	0
Either Fixed Exch Rate	0	0	-0.013	0	0
Both Fixed Exch Rate	0.081	0	0.037	0.013	0
Either Crawling Peg ER	0	0.012	0	0.011	0.073
Both Crawling Peg ER	-0.048	0	0	0	0
Either Moving Band ER	0.029	0	0.004	0	0
Both Moving Band ER	0	0	0	0	0
Debt Crisis 3yr Window	0	0	0	0	0
Banking Crisis 3yr Window	-0.348	-0.268	-0.278	0	0
Currency Crisis 3yr Window	-0.273	-0.225	-0.221	-0.056	0
Exporter FEs	No	Yes	Yes	Yes	Yes
Importer FEs	No	No	Yes	No	Yes
Year FEs	No	No	No	Yes	Yes
N	152213	152213	152213	152213	152213
R^2	56%	50.40%	49.70%	54%	26.30%

Table A-3: Bayesian Model Averaging, Varying Fixed Effects

	(1)			(2)			(3)		
	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD	PIP	Post Mean	Post SD
ln of CES Weighted Dist	1	-0.883	0.008	1	-0.943	0.008	1	-1.113	0.007
Product of GDPs	1	0.861	0.003	1	0.932	0.003	1	0.736	0.016
Contiguous	1	0.734	0.035	1	0.664	0.033	1	0.405	0.031
Either Island	1	0.736	0.028	1	0.379	0.026	1	0.488	0.026
Either Landlocked	1	-0.368	0.018	0.992	-0.08	0.019	1	-0.514	0.047
Share Official Language	1	0.189	0.029	1	0.416	0.016	0.031	0.002	0.011
9%+ Speak Language	1	0.268	0.027	0	0	0	1	0.364	0.017
Former Colony	1	0.942	0.03	1	0.892	0.028	1	0.866	0.027
Common Colonizer	1	0.273	0.026	1	0.368	0.023	1	0.413	0.023
Common Legal Origin	1	0.122	0.012	1	0.2	0.011	1	0.287	0.011
Religious Distance	1	-0.227	0.009	1	-0.202	0.008	1	-0.216	0.009
Human Capital (product)	1	-0.788	0.026	1	1.132	0.029	1	0.75	0.068
Physical Capital (product)	1	0.299	0.006	1	0.085	0.006	1	-0.132	0.012
Arable Land (product)	0.589	-0.008	0.008	1	-0.125	0.004	1	-0.229	0.018
WTO/GATT	1	0.439	0.028	1	0.484	0.027	1	0.348	0.025
Regional Trade Agreement	1	0.276	0.026	1	0.309	0.025	0	0	0
Common Currency	1	0.484	0.073	1	0.574	0.069	1	0.353	0.062
Capital Openness	1	0.314	0.025	1	0.715	0.024	0	0	0
Exchange Rate Volatility	0.201	0.002	0.003	0.519	0.005	0.005	1	-0.012	0.002
Either Fixed Exch Rate	1	-0.088	0.017	0.966	0.056	0.016	0.051	0.002	0.01
Both Fixed Exch Rate	1	0.114	0.02	1	0.149	0.02	0.893	0.071	0.031
Either Crawling Peg ER	0	0	0	1	0.105	0.013	1	0.153	0.015
Both Crawling Peg ER	0.53	-0.041	0.042	0.017	0.001	0.005	0.449	0.027	0.032
Either Moving Band ER	0.56	0.028	0.027	1	0.063	0.013	0.924	0.048	0.02
Both Moving Band ER	0	0	0	0.026	0.002	0.011	0.174	0.013	0.029
Debt Crisis 3yr Window	0	0	0	0	0	0	0	0	0
Banking Crisis 3yr Window	1	-0.309	0.015	0.351	-0.016	0.024	0.481	0.021	0.024
Currency Crisis 3yr Window	1	-0.26	0.014	1	-0.079	0.014	0.006	0	0.002
Exporter FEs		Yes			Yes			Yes	
Importer FEs		Yes			No			Yes	
Year FEs		No			Yes			Yes	

Dependent variable is bilateral trade flows between trading partners. **PIP** is the "posterior inclusion probability" and reflects our relative confidence that the true model contains any particular regressor. For example, if PIP = 1 this indicates that in 100% of the weighted models include this variable as a regressor. **Post Mean** is the weighted average over the posterior estimates of the regressor. **Post SD** is the standard deviation of coefficient's posterior distribution

Table A-4: Extreme Bound Analysis, Varying Fixed Effects

	(1)		(2)		(3)	
	UB to LB	Robust	UB to LB	Robust	UB to LB	Robust
(Intercept)	(0.03,0.12)	y	(-0.01,0.07)	n	(0.05,0.08)	y
ln of CES Weighted Dist	(-1.18,-0.93)	y	(-1.2,-0.94)	y	(-1.34,-1.1)	y
Product of GDPs	(0.82,0.96)	y	(0.89,1.07)	y	(0.75,0.99)	y
Contiguous	(0.52,1.04)	y	(0.38,0.99)	y	(0.37,0.69)	y
Either Island	(0.69,1.18)	y	(0.52,1.18)	y	(0.46,0.77)	y
Either Landlocked	(-0.64,-0.36)	y	(-0.38,-0.02)	y	(-0.67,-0.38)	y
Share Official Language	(0.31,0.83)	y	(0.4,0.87)	y	(0.19,0.78)	y
9%+ Speak Language	(0.14,0.77)	y	(0.01,0.78)	y	(0.21,0.76)	y
Former Colony	(0.99,1.54)	y	(0.89,1.44)	y	(0.83,1.36)	y
Common Colonizer	(0.11,0.66)	y	(0.06,0.81)	y	(0.35,0.77)	y
Common Legal Origin	(0.11,0.43)	y	(0.08,0.48)	y	(0.27,0.51)	y
Religious Distance	(-0.34,-0.16)	y	(-0.44,-0.15)	y	(-0.3,-0.17)	y
Human Capital (product)	(-1,0.47)	n	(1,1.89)	y	(0.78,1.37)	y
Physical Capital (product)	(0.17,0.38)	y	(0.07,0.36)	y	(-0.18,-0.09)	y
Arable Land (product)	(-0.08,0)	n	(-0.18,-0.09)	y	(-0.41,-0.27)	y
WTO/GATT	(0.05,0.48)	y	(0.25,0.85)	y	(0.12,0.41)	y
Regional Trade Agreement	(0.06,0.53)	y	(0.17,0.74)	y	(-0.18,0.07)	n
Common Currency	(0.39,1.24)	y	(0.31,1.31)	y	(0.11,0.84)	y
Capital Openness	(0.25,0.84)	y	(0.85,1.54)	y	(-0.21,0.04)	n
Exchange Rate Volatility	(-0.02,0.01)	n	(-0.01,0.01)	n	(-0.01,0)	n
Either Fixed Exch Rate	(-0.12,0.06)	n	(-0.15,0.14)	n	(-0.14,-0.02)	y
Both Fixed Exch Rate	(0.07,0.33)	y	(-0.06,0.25)	n	(-0.1,0.1)	n
Either Crawling Peg ER	(-0.07,0.13)	n	(-0.04,0.14)	n	(0.06,0.18)	y
Both Crawling Peg ER	(-0.15,0.06)	n	(-0.16,0.09)	n	(-0.09,0.07)	n
Either Moving Band ER	(-0.03,0.13)	n	(-0.06,0.17)	n	(-0.02,0.11)	n
Both Moving Band ER	(-0.07,0.17)	n	(-0.11,0.22)	n	(-0.07,0.14)	n
Debt Crisis 3yr Window	(-0.27,0.04)	n	(-0.27,0)	y	(-0.08,0.04)	n
Banking Crisis 3yr Window	(-0.52,-0.3)	y	(-0.21,-0.01)	y	(0.02,0.1)	y
Currency Crisis 3yr Window	(-0.44,-0.23)	y	(-0.28,-0.06)	y	(-0.06,0.03)	n
Exporter Fes	Yes		Yes		Yes	
Importer Fes	Yes		No		Yes	
Year Fes	No		Yes		Yes	

Dependent variable is real bilateral trade flows. The doubtful set of parameters is every parameter listed, except for log of distance and product of two countries GDP. LB refers to highest value of the parameter in all of the models estimated, UB refers to the highest value of the parameter estimated. Leamer considers an estimate “robust” if its highest and lowest estimated value does not include zero.