THREE ESSAYS ON TRADE GRAVITY MODEL

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The undersigned, appointed by the Dean of the Graduate School, have examined the dissertation entitled

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ABSTRACT

In this dissertation, I present my study on the gravity model which is a commonly used tool in international economics.

In chapter 1, I revisit the gravity models, both the “old” one with which McCallum (1995) finds the famous “border puzzle,” and the “new” one introduced by Anderson and van Wincoop (2003), who argue that this “border puzzle” was solved by estimating a theoretically-motivated gravity model. We examine the role of multilateral resistance and its relationship with the actual price index. We also extend the AvW gravity model to have non-tradable goods integrated. Then we use data simulations to test the performances of the gravity models.

In chapter 2, we revisit the question of how to measure the effect of language on international trade. More specifically, we present new data and suggest a corresponding estimation technique that gauges by how much language matching facilitates trade between two countries after their distance and incomes are controlled for. This is the first time that a complete set of world languages is used in the study of international trade. We employ a matching model, and integrate it into the traditional gravity setting. We find that the average language depression ratio is 0.31, which is large and economically significant.

In chapter 3, we try to indentify the mechanisms through which ethnic networks facilitate international trade. We create an entirely new data set that extends the data from Rauch and Trindade (2002) on ethnic Chinese networks to a panel of about 40 years. We combine it with data on the quality of national legal institutions from Knack and Keefer (1995) and on languages from chapter 2 of this dissertation. We integrate those variables in a modified gravity framework based on Anderson and van Wincoop (2003) to estimate direct and interaction effects between our variables of interest. We find that Chinese networks have a generally strong and robust influence on trade. We find weak evidence that language and networks are substitutes. In stark contrast to the previous literature, we find strong evidence that networks are complements to institutions, rather than substitutes in overcoming international transaction costs.

Chapter 1

The Price is Right! Borders, Prices, and Anderson and van Wincoop's Multilateral Resistances

1. INTRODUCTION

We attempt in this chapter to make advances in both the theoretical foundation and the estimation technique of the gravity model. This model receives its name from the physical law of gravity, since it explains trade flows between any two regions as functions of their economic "masses" and of the trade costs between them, the latter generally proxied by distance. The model is frequently augmented by other variables intended to account for transaction costs, such as institutional quality or language similarity. As we shall argue, the gravity model, even after some recent and notable advances, is riddled with unexamined assumptions which are likely to make the estimated coefficients biased and the resulting inferences problematic. We shall draw upon a list of such unexamined assumptions, and based on the theory will propose some ways to advance its estimation technique.

One famous inference of the gravity model, and arguably one of its most robust ones, is the so-called "border puzzle." This is the fact that the simple existence of an international border between two regions seems to depress trade between them to a fraction of what it could be without the border. It has been named one of the major puzzles in international economics.[1] We will therefore focus our attention on this puzzle, and in particular we will critique and attempt to improve upon the methodology of the seminal contribution by Anderson and van Wincoop (2003) (hereafter AvW), who claim to have "solved" the border puzzle, and of the extensive literature that has followed on

1 For an example of the border puzzle, see McCallum (1995), who finds that, after controlling for determinants of trade such as GDP and the distance between the trading pair, trade between two Canadian provinces is about 22 times larger than trade between a Canadian province and a US state. Obstfeld and Rogoff (2000) call McCallum's (1995) results one of the "the six major puzzles in international macroeconomics."

that paper's footsteps to propose a more streamlined dummy variable procedure, an example of which can be found in Feenstra (2002, 2003).[2]

AvW start from a constant elasticity of substitution (CES) utility function and then derive the gravity model based on that specification.[3] The main contribution of their paper is to derive the "multilateral resistances" (henceforth, MRs) of each trading region, and providing a computational solution for them. They argue that previous approaches to the gravity model were misspecified, because they did not account, or accounted incorrectly, for the fact that trade flows from one region to another region naturally depend on either region's alternative trading opportunities. If, for example, both regions have a relative dearth of alternatives, which in AvW's language will cause their MRs to be relatively high, then the two regions will trade more with each other. AvW find that, with the inclusion of MRs, trade compression due to the presence of an international border between the US and Canada is reduced from a factor of 16 or so to a factor of 10.

Importantly, one consequence of AvW is that simply using region dummies instead of the MRs is a consistent, if relatively inefficient, method for estimating the gravity model. This is the route that has been taken by much of the recent literature. However, there are

[2] We focus on AvW due to its enormous impact. A Google Scholar search (performed on 3-26-2009) of papers containing the word "gravity," reveals that AvW had 1225 citations, followed by Anderson (1979) and Bergstrand (1985). No other article had more than 1000 citations, and only five articles altogether had received more than 300 citations. Our focus on Feenstra's (2002, 2003) dummy variable approach is due to it being the most widely used gravity estimation procedure, while being fully consistent with AvW's results, making it the "state-of-the-art" of gravity, and thus a well-justified departure point for further advances.

[3] We shall discuss their other assumptions below, some of the most important of which are: goods are differentiated by country of origin; each country has one unique output; each country's supply-curve is vertical; trade costs between any bilateral pair are symmetric. For a more detailed critique on the last point, see Balistreri and Hillbery (2007). For other derivations of the gravity model, see Anderson (1979) and Deardorff (1998). Eaton and Kortum (2002) use a Ricardian approach (and in particular do not make an Armington assumption) to derive a model very similar to gravity. Helpman, Melitz and Rubinstein (2008) also derive such a model assuming that there are fixed-costs to trading.

several reasons to be cautious about using region-specific dummy variables. First, note that in panel estimation, each region's MRs *may* change over time and so using fixed effects instead is an inconsistent method. Perhaps more importantly, note that one important point about AvW's work is that its structural estimation would allow us to potentially identify any causes of trade flows, by appropriately extending the model. This would include any country-specific causes, such as institutions or ethnic networks. Since dummy variables, by their very nature, absorb not only the country-specific MRs, but any other country-specific variables, they preclude such identification. In sum, we would like to keep the structural approach of AvW's, while at the same time questioning the validity of their conclusions.

Thus AvW, either with MRs or dummies, will be the departure point for our research, but a departure point only it must be. We shall attempt in this work to move considerably beyond what the current literature has already accomplished. Our approach is to begin by listing below all the assumptions (hidden and otherwise) that seem to enter all gravity models. As we shall see, there are many such assumptions, and not all of them seem tenable either from a theoretical or from a practical point of view, or both. We will address the question of the likely relative impact of each assumption, while not attempting to address every assumption in full. Doing so for even just one of them would be enough for one whole chapter, and in fact this chapter is the first in what we hope to become a fecund research agenda!

One issue in particular will deserve most of the attention in the chapter, which is the possible impact of non-traded goods. Stemming from our discussion, we highlight here the main conclusions of the chapter: Consumer price indices (henceforth CPIs) are likely to be better indicators of the actual opportunities faced by each region than the MRs. Note that AvW derive the MRs formally as consumer price-indices (CPIs), while at the same time arguing that practical considerations prevent a full identification of MRs with CPIs. As an example, they mention the possibility that each region may exhibit home bias, making MRs (which also capture home bias) and CPIs (which do not) become different from each other. But note that any argument that MRs are different from CPIs actually is an argument in favor of including CPIs in the estimation (either in addition or possibly even instead of MRs), in order to avoid omitted variable bias. In fact this is at the very core of AvW's model, whose main idea is that we should take all consumers' opportunities into account. This raises questions about the importance of MRs and favors the use of CPIs. At the very least, it suggests that caution should be used in adopting the AvW methodology and in interpreting the MRs. One further reason for caution originates in AvW's method of calculating MRs. Given that they reject the use of price indices to ascertain consumers' trading opportunities, and that MRs are in themselves unobserved, they propose a computational approach to solve for MRs with the help of other observable variables, namely each region's income-shares and all of the trade costs. By construction, this implies that MRs are dependent only on those variables and implies that each region's trading opportunities (what the MRs purport to measure) are determined by no internal variables at all, with the single exception of the region's GDP!

To see what we think is problematic here, we use the following thought experiment. Consider a model in which a small region produces one traded good and one non-traded good. Suppose that the productivity in the non-traded good were to exogenously rise by a factor of two. If prices simply decrease by the same factor, then the region's nominal income does not change. If the region is small enough, any general equilibrium impact on the other regions will be negligible, and trade costs (by assumption) also do not change. In other words, all of the variables that enter the calculation of the MRs do no change, implying that MRs will also not change. But, depending on the preferences, the region's trade may definitely change, either because consumers import fewer tradable goods and substitute into the cheaper non-tradable, or because the income effect of the cheaper prices allows them to import more goods. In either case, that would be an effect that the AvW procedure would totally ignore! This is our reason to study non-traded goods, the main conclusion being that prices indices can potentially cause less bias than MRs (and whether they do or not is left as an empirical question). This is in spite of the fact that the MRs were expressly designed to reduce bias.

One conclusion form this discussion regards the absolute necessity to test the model. AvW argue persuasively for a more structural approach to estimating gravity. In their model they impose a large number of theoretical restrictions, not all of which are explicitly stated. Even within the strict confines of their model, out of seven possible parameter estimates, they only estimate two, impose the other four with the values suggested by theory and do not report the last one. It thus becomes vital to test the model. If the model is rejected by the data, then the general argument for the need of structural estimation remains true, but the inferences to be drawn from any particular rejected model certainly do not! In this chapter, we take the more conventional reverse approach and fill the gap that they left by testing their model: we estimate all parameters of the model instead of imposing any, and find that the data rejects the theory. Furthermore, one implication of the theory that is very easy to test is that the CPI and the MRs should be positively correlated. We test for this correlation and find the evidence lacking. We also compare the results of their methodology and of using directly a newly generated region-specific set of CPIs. In particular, we take the following three steps: we estimate their model using actual price data for Canadian provinces and US states. We replicate the procedure with price-data and calculated MRs for a multi-country data-set with preferential trade-agreements, and we finally simulate a two-country world similar to the US and Canada and compare the validity of common estimation procedures with each other. We find that estimation with price data instead of MR does not fit the data as well, but leads to even lower estimates of border effects. Simulation results suggest that parameter estimates using the AvW method are biased even if the data was generated by the model AvW employed to derive their estimation method.

2. THE GRAVITY MODEL BEFORE AND AFTER ANDERSON AND VAN WINCOOP

Before AvW's paper, most research using the gravity model took an atheoretical approach, by simply assuming that trade flows are log-linear in the economic masses of the two trading partners and in the distance between them. This basic equation might also be augmented by a variety of proxies for trade barriers or trade enhancers, such as common language, the presence of ethnic networks, the quality of institutions, and so on.

After AvW's contribution, one can speak of an "old" gravity model (defined as anything before AvW), and of the "new" gravity proposed in AvW's model. In this section, we assess both how much AvW has advanced the literature and what remains to be done. It will be useful to organize the discussion around the following problem, which the two models solve in different ways, and which is AvW's main contribution: suppose that we have a good measure for trade costs between any two regions in the sample of interest, including for within-region trade costs. An increase in any two regions' bilateral trade costs will of course lower trade between them. However, one must also consider the alternative trading opportunities of both regions, and these will reflect an impact from all trade costs that involve these two regions. Thus what matters is not only the trade cost required to export from region i to region j, say, but how that cost compares to all the costs incurred in exporting from i to other regions, and to the cost of exporting from other regions to j. Some of the old gravity literature either ignored the problem of these "global effects" of trade costs, or attempted an atheoretical fix by calculating a weighted trade cost indicator called "remoteness." AvW calculate instead the theory-mandated "Multilateral Resistances" (MRs) to take these global effects into account.[4]

To preview our conclusions, we will argue that using remoteness as in the "old" gravity models implies accepting a series of assumptions, not many of which have been examined in the previous literature. However, many of the same assumptions are uncritically adopted by AvW in their "new" gravity model, which at best implies the crucial need to test their model, and at worst invalidates their claim that they have "solved the border puzzle."

[4] Thus AvW's contribution is not about a better proxy for trade costs. They posit trade costs as a reduced-form function of distance and a border dummy, just as previous literature, and notably McCallum (1995), have done. Rather their contribution is to deduce a formula that allows the calculation of the MRs from the bilateral trade costs.

2.1 The "Old" Gravity Model

As an example of old gravity, we review the model estimated by McCallum (1995), because that was the paper that provided the puzzle that AvW strive to solve.

McCallum (1995) collected trade data between US states and Canadian provinces, as well as between the provinces, and ran a simplified version of the following regression:[5]

$$\ln x_{ij} = \alpha_1 + \alpha_2 \ln y_i + \alpha_3 \ln y_j + \alpha_4 \ln d_{ij} + \alpha_5 \delta_{ij} + \alpha_6 \gamma_{ij} + \varepsilon_{ij}, \qquad \textbf{(1-1)}$$

where x_{ij} is the value of exports from region i to region j; y_i represents region i's income; d_{ij} is the distance between the two regions; δ_{ij} is a border dummy that takes a value of one if regions i and j are both Canadian provinces, and zero otherwise; γ_{ij} is also a border dummy, taking a value of one if regions i and j are both US states, and zero otherwise; the α's are parameters to be estimated; and ε_{ij} is a stochastic disturbance.

The same model with "remoteness" would be:

$$\ln x_{ij} = \alpha_1 + \alpha_2 \ln y_i + \alpha_3 \ln y_j + \alpha_4 \ln d_{ij} + \alpha_5 \delta_{ij} + \alpha_6 \gamma_{ij} + \alpha_7 REM_i + \alpha_8 REM_j + \nu_{ij}, \qquad \textbf{(1-2)}$$

where the "remoteness" variables for regions i and j (REM_i and REM_j, respectively) can be obtained thus:

$$REM_i = \sum_{j=1}^{N} d_{ij} \frac{y_j}{y^W}. \qquad \textbf{(1-3)}$$

In this equation N is in principle the total number of regions (states or provinces) plus the total number of other regions of the world (other countries), and y^W is the total

5 McCallum did not need the US-US dummy because he had no state-to-state trade data. Note that in this and other equations, we use the AvW's notation throughout.

income of the world. In words, REM_i is the average distance between one region in the sample and all of its trading partners, weighted by each trading partner's economic size.

Keith Head (2003) proposes a more theoretically correct equation for remoteness:

$$REM_i^H = \left(\sum_{j=1}^{N} y_j / d_{ij} \right)^{-1} . \tag{1-4}$$

This would have the advantage that regions that are very far from region i have a negligible effect on region i's remoteness. By contrast, AvW calculate remoteness as:

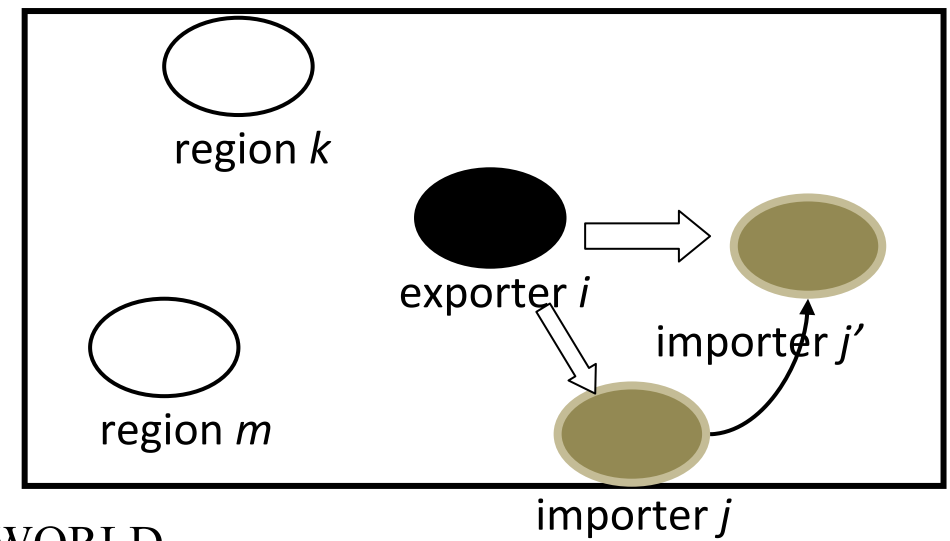
$$REM_i^{AvW} = \sum_{j=1}^{N} d_{ij} / y_j \,. \tag{1-5}$$

This has the counterintuitive implication that a small distant economy would have a large impact on region i's remoteness, while a large close-by economy would have a small impact.

The intuitive reason for including remoteness in the model can be explained with the aid of a thought experiment. Consider the exports from region i to region j. Suppose that we move the importing region j in such a way that its remoteness increases, while keeping the two regions' bilateral distance and GDPs unchanged. This is illustrated in figure 1-1, where each oval is one region, and region j becomes region j' upon this movement. Since bilateral trade costs do not change, while average trade costs for imports into j increase, exports from i to j go up, as illustrated by the thicker block arrow, thus implying that the importer's remoteness REM_j enters positively in the regression ($\alpha_8 > 0$). Once consequence of this intuitive reasoning is that it would be important to include all trading partners of the importing region in the calculation of its remoteness.

Suppose for example, that region j is Florida. If in the calculation of its remoteness one only includes US states and Canadian provinces one would conclude that Florida is a remote region. However, in the context of world trade, Florida is not so remote, since it is close to many Latin American countries.

Importantly, the story delineated above relies on many assumptions. First, there must be a degree of substitutability between region i's goods and the goods from other regions such as k. If, for example, there was no substitutability at all, there would be no effect. Consumers that moved with their region to a far-flung area of the world would simply resign themselves to paying higher prices for other regions' goods, but would not import more from region i. Second, the elasticity of trade costs to distance is the same across all goods. Otherwise, one would expect that as region j "moves" it may indeed increase its imports of some of region i's goods, namely those goods whose trade costs are more highly elastic with distance, but not all. Depending on how different goods enter in the utility function, which determines their weight (a weight that could well vary for different country pairs), the response of aggregate trade to distance could be very complicated. Third, in order to include only the average distance between other regions and region j, instead of every single bilateral distance, the substitutability between region i's goods and a third region k's goods must be identical to the substitutability between region i's goods and another region m's goods. To see this, suppose for example that region i's goods and region m's goods are closer substitutes than region i's goods and most other regions' (such as k's). Then exports from i to j might even decrease in spite of the fact that j would increase its remoteness as it moves to the periphery of the world, because by doing so j also moves closer to region m, and substitutes m's goods for i's goods.



WORLD

Figure 1-1 Remoteness

Switching now to the exporter, any impact of the *exporter*'s remoteness on trade flows seems more mysterious, at least under the usual assumptions of the gravity model.[6] Suppose that we now "move" the exporter *i* to the southeast corner of figure 1-1, making it more remote but keeping its distance to the importer *j*. Unlike the previous example, *no* costs of producing or transporting goods to the importer *j* change at all, from *any* region. If competitive pricing were the norm both in the product markets and in the transport markets, then *all* prices in region *j* remain constant and exports from *i* to *j* would hardly change at all!

However, the exporter's remoteness often enters regressions such as equation (1-2) significantly. It seems that the only way in which it can affect trade flows is if either the

6 Head (2003), for example, argues for the inclusion of only the importer's remoteness.

producers or the exporters from the exporting region have some pricing power. For example they may respond to their higher average cost to place goods globally by lowering prices in region j, in which case the exporter's remoteness would enter the equation positively. It is also conceivable that they take more advantage of market j by increasing prices there, and the exporter's remoteness would enter negatively. We leave the sign of the exporter's remoteness as an empirical question, but what seems certain is that if there is no pricing power, then the exporter's remoteness should not enter at all.

2.2 The "New" Gravity Model of AvW, with non-Traded Goods

We endorse AvW's criticism of the remoteness variable as lacking in sufficient theoretical foundation.[7] However, AvW do not discuss the relative importance of all of the assumptions that make up the remoteness variable and enter the gravity equation. They do derive a theory-based gravity model (see also the earlier contributions by Anderson 1979, and Deardorff 1998), but in doing so they simply take one set of assumptions as given, and extract conclusions from it. This would seem to make it crucial that they test the model, which they do not do.

Note that there are two ways to think about the validity of a model: to test it, and to see whether its assumptions are reasonable. As discussed in the introduction, the assumption of all goods to be traded goods may be a potential source for bias. Therefore, we want to examine how robust the model and its estimates are to inclusion of non-traded goods. To pursue this goal, in this subsection we derive a model similar to AvW, except that we allow for non-traded goods. AvW will then be easily shown to be a special case

[7] However, we point the reader to the extremely interesting paper by Keith Head (2003), which is the proverbial exception to the rule.

of that model. The starting point, as is standard in the literature, is to abstract from any disaggregation issues, and simply assume that each country produces only one traded good, and one non-traded good. Following AvW, and many others, we use constant elasticity of substitution (CES) preferences. Then, the upper tier utility function for region j is given by:

$$U_j\left(C_j, N_j\right) = \left[B_T^{(1-\psi)/\psi}\, C_j^{(\psi-1)/\psi} + B_{NT}^{(1-\psi)/\psi}\, N_j^{(\psi-1)/\psi}\right]^{\frac{\psi}{\psi-1}}. \qquad \textbf{(1-6)}$$

Here BT and BNT are demand weights placed on the traded and non-traded goods, respectively; ψ is the elasticity of substitution between traded and non-traded goods; N_j is the quantity of the non-traded good consumed; and C_j is the composite traded good, given by:

$$C_j\left(c_{1j}, \dots, c_{ij}, \dots, c_{nj}\right) = \left[\sum_{i=1}^{n} \beta_i^{(1-\sigma)/\sigma} c_{ij}^{(\sigma-1)/\sigma}\right]^{\frac{\sigma}{\sigma-1}}. \qquad \textbf{(1-7)}$$

In this equation, c_{ij} is region j's consumption of region i's tradable good (exports from i to j), σ stands for the elasticity of substitution that is common to all tradable goods pairs, βi is a weight parameter placed on region i's good by all consumers, and n is the total number of regions. Note that we allow for the elasticity of substitution between traded and non-traded goods to be different from the elasticity of substitution between traded goods. We will assume that both elasticities are larger than one. It is not unreasonable to imagine, for example, that $1<\psi<\sigma$, that is, all tradables are more substitutable than tradables and non-tradables are. It is straightforward to show that the unit cost of the composite traded good is given by:

$$P_j(p_{1j}, \dots, p_{ij}, \dots, p_{nj}) = \left[\sum_{i=1}^{n} \beta_i^{1-\sigma} p_{ij}^{1-\sigma}\right]^{1/(1-\sigma)}, \qquad \textbf{(1-8)}$$

where the p_{ij} are the trade cost-inclusive prices of region i's good in region j. These prices have two components, the producer prices pi from each region i, and the trade costs from region i to region j, denoted as t_{ij}, and therefore are given by:

$$p_{ij} = p_i t_{ij}. \qquad \textbf{(1-9)}$$

The price indices of equation (1-8) are crucial to AvW's approach. Their main argument is that these are the correctly specified measures for the global trade cost effects, as opposed to the atheoretical remoteness. AvW call these price indices the Multilateral Resistance terms (MRs).[8] Importantly, as we shall see, the calculation of the price indices is very different when non-traded goods are ignored.

We can now take the price indices, and combine them with the price of the non-traded good (denoted by πj), to obtain the price index for region j in the standard fashion as:

$$I_j(P_j, \pi_j) = \left[B_T^{1-\psi} P_j^{1-\psi} + B_{NT}^{1-\psi} \pi_j^{1-\psi}\right]^{1/(1-\psi)}. \qquad \textbf{(1-10)}$$

It is important to note that consumers optimize based on this overall price index, not on the traded goods price index. In other words, it is this price index that represents the overall opportunities to region j's consumers, precisely what the MRs are supposed to do in AvW's work.

Given this set-up, it is straightforward to show that region j's imports from region i are:

$$x_{ij} = \left[\frac{\beta_i p_i t_{ij}}{P_j}\right]^{1-\sigma} \left(B_T P_j / I_j\right)^{1-\psi} y_j, \qquad \textbf{(1-11)}$$

8 It is important to note that AvW explicitly dismiss the notion that these should be treated in the same way as price indices. We address this question below.

where $x_{ij} = p_{ij}c_{ij}$ is the value of exports from region *i* to region j.

The next step in the derivation is to assume trade balance for region i in order to eliminate the taste and cost parameters $\beta_i p_i$.[9] Since region *i*'s tradable good expenditures are $(B_T P_i/I_i)^{1-\psi} y_i$, we obtain:

$$(B_T P_i/I_i)^{1-\psi} y_i = \sum_{j=1}^{n} x_{ij} = B_T^{1-\psi} (\beta_i p_i)^{1-\sigma} \sum_{i=1}^{n} \left(t_{ij}/P_j\right)^{1-\sigma} \left(P_j/I_j\right)^{1-\psi} y_j, \qquad \textbf{(1-12)}$$

where the first and second terms are regions i's total value of imports and exports, respectively. It is straightforward, if cumbersome, to solve these equations for the terms $(\beta_i p_i)^{1-\sigma}$, and then plug the solutions back into the trade flows (equation 1-11) and into the definitions of the tradable goods price index (equation 1-8). Since AvW have done the analogue of this (minus the non-traded goods), we omit the steps here. Note that equation (1-12), in one stroke, allows the elimination of two non-measurable quantities: each country's production costs (p_i), and the taste parameters (β_i). Thus, the methodology is biased toward placing the burden of explaining international and inter-regional trade flows onto trade costs, and not onto each country's relative cost parameters and differences (or asymmetry) in preferences. We pause for a moment to note how much against the spirit of standard trade theories that is! We also follow AvW in assuming symmetric trade costs, that is we set $t_{ij} = t_{ji}$.[10] With all these assumptions in place, the trade flows in equation (1-11) become:

9 Anderson (1979) considers the possibility of trade imbalances, and models them in a reduced form as a function of each region's income and population. We shall also list balanced trade as one of the assumptions to be examined, but here we follow AvW in assuming balanced trade.

10 For a discussion on how AvW's results depend critically on the last assumption, see Balistreri and Hillberry (2007). We shall not pursue this issue here, except as added heft to the general argument on the fragility of conclusions to be drawn from one particular set of assumptions.

$$x_{ij} = \frac{y_i y_j}{y^W} t_{ij}^{1-\sigma} P_i^{\sigma-1} B_T^{(\psi-1)/2} P_j^{\sigma-1} B_T^{(\psi-1)/2} \phi_i \phi_j, \qquad \textbf{(1-13)}$$

where ϕ_i is region *i*'s expenditure share of tradable goods, given by $\phi_i = (B_T P_i / I_i)^{1-\psi}$, and the tradable goods price indices can be now found as the solutions to:

$$\frac{1}{P_j^{\sigma-1} B_T^{(\psi-1)/2}} = \sum_{i=1}^{n} P_i^{\sigma-1} B_T^{(\psi-1)/2} \theta_i t_{ij}^{1-\sigma} \phi_i\,, \quad j = 1, \ldots, n. \qquad \textbf{(1-14)}$$

Equations (1-13) and (1-14) are a computable gravity model that includes non-tradable goods. One possible approach would be to measure trade costs directly, that is, to consider t_{ij} as *data* to be obtained. Then the methodology would be to use equations (1-14) to solve for $P_j^{\sigma-1} B_T^{(\psi-1)/2}$, then insert the solutions into the estimation of equation (1-13). However, this is not the approach that AvW follow. For the application to the border puzzle, in which they use US and Canadian data, they follow most of the literature to date and assume a simple functional form of the trade costs on the distance and on the border dummy:

$$t_{ij} = b^{1-\delta_{ij}} d_{ij}^{\rho} \qquad \textbf{(1-15)}$$

Here, *b* is a constant that will represent the magnitude of the border effect, and ρ is the elasticity of trade costs with respect to distance.

The interpretation of equation (1-13) is straightforward. Common to old gravity models, it says that bilateral trade is proportional to the economic masses of the two regions and, given equation (1-15), that it is deterred by the distance between them, and by any international border that might exist between them. Note that, since we assume throughout that $\sigma > 1$, and this will be confirmed empirically, the price indices enter positively in trade. The intuition for $P_j^{1-\sigma}$ enhancing exports to region j is that a generally high price level in region j means that, at given levels of the trade barriers between i and j, region i's good becomes more attractive to region j's consumers. Note that this is precisely the same as the intuitive reason for the inclusion of the remoteness. Moreover, as we shall argue below, many of the same assumptions that underlie the informal justification for including the remoteness variable are also implicitly adopted by the far more formal theory here. The intuition for including the exporter's MR is more difficult to understand, but can be traced back to market clearance and the assumption of balanced trade, about which we shall also have more to say.

Computationally, the estimatable equations are derived from equations (1-13) and (1-14), after substituting from equation (1-15), yielding:

$$\ln\left(\frac{x_{ij}}{y_i y_j}\right) = k + a_1 \ln d_{ij} + a_2\left(1-\delta_{ij}\right) + \ln\left(P_i^{\sigma-1} B_T^{(\psi-1)/2}\right) + \ln\left(P_j^{\sigma-1} B_T^{(\psi-1)/2}\right) + \ln\phi_i + \ln\phi_j + \varepsilon_{ij} \tag{1-16}$$

where the tradable goods price indices are the solutions to:

$$\left(P_j^{\sigma-1} B_T^{(\psi-1)/2}\right)^{-1} = \sum_{i=1}^{n}\left(P_i^{\sigma-1} B_T^{(\psi-1)/2}\right)\theta_i e^{a_1 \ln d_{ij} + a_2\,(1-\delta_{ij})}\,\phi_i, \quad j = 1, \dots, n. \tag{1-17}$$

In equations (1-16) and (1-17), we include the tradable expenditure share, as implied by the theory. Note that the exclusion of the tradable share (which would include it in the error term) is likely to cause bias. For example a region with low tradable goods price index will ceteris paribus tend to trade more on average with other regions and will therefore have a high tradable share.

An allied concern is that the tradable expenditure share itself might suffer from endogeneity problems. Fortunately there is an easy solution for this. It is straightforward to show that instead of the procedure described by equations (1-16) and (1-17), an equivalent procedure that does not substitute out each region's price index would be:

$$\ln\left(\frac{x_{ij}}{y_i y_j}\right) = \tag{1-18}$$

$$k + a_1 \ln d_{ij} + a_2\left(1-\delta_{ij}\right) + \ln P_i^{\sigma-\psi} + \ln P_j^{\sigma-\psi} + \ln I_i^{\psi-1} + \ln I_j^{\psi-1} + \varepsilon_{ij}.$$

where the tradable goods price indices are the solutions to:

$$P_j^{1-\sigma} = \sum_{i=1}^{n} P_i^{\sigma-\psi} \theta_i e^{a_1 \ln d_{ij} + a_2\,(1-\delta_{ij})} I_i^{\psi-1}, \quad j = 1, \dots, n. \tag{1-19}$$

Equations (1-18) and (1-19) may well be the best way to estimate the gravity model under the assumption of non-tradable goods. For all variables to be exogenously determined in these equations (including the price indices I_i and I_j), all that we need is for prices and trade costs to be set competitively. That is a strong assumption, but not more so than is usually accepted. (We leave an exploration of the impact of market power for the gravity model for future investigation.) Under such assumption the price indices from each region should be included in the estimation without worry of endogeneity.

We now specialize this model to a model with tradable goods only, by making $\phi_i = 1,\ \forall i$, and $B_T = 1$. This allows the derivation of the AvW model as:

$$x_{ij} = \frac{y_i y_j}{y^W} t_{ij}^{1-\sigma} P_i^{\sigma-1} P_j^{\sigma-1}, \tag{1-20}$$

where the price indices are given as the solutions of:

$$P_j^{1-\sigma} = \sum_{i=1}^{n} P_i^{\sigma-1} \theta_i t_{ij}^{1-\sigma}, \quad j = 1, \dots, n. \tag{1-21}$$

From equations (1-20) and (1-21), after taking logs and substituting from equation (1-15), AvW obtain the estimation procedure given by:

$$\ln\left(\frac{x_{ij}}{y_i y_j}\right) = k + a_1 \ln d_{ij} + a_2(1-\delta_{ij}) + \ln P_i^{\sigma-1} + \ln P_j^{\sigma-1} + \varepsilon_{ij}, \qquad \textbf{(1-22)}$$

where the parameters to be estimated are $a_1 = (1-\sigma)\rho$ and $a_2 = (1-\sigma)\ln b$ (plus a constant k), and the MRs are the solution to the following equation:

$$P_j^{1-\sigma} = \sum_{i=1}^{n} P_i^{\sigma-1}\theta_i e^{a_1 \ln d_{ij} + a_2\,(1-\delta_{ij})}, \quad j = 1, \dots, n. \qquad \textbf{(1-23)}$$

Equations (1-22) and (1-23) constitute AvW's model. It is instructive to compare this model with the more general model with non-tradable goods, given either by equations (1-16) and (1-17), or by equations (1-18) and (1-19). Note that, even ignoring the taste parameters B_T (which could with a reasonable choice of units be made equal to one), the tradable goods price indices are given by very different equations depending on whether we include non-tradables in the model or not, and the difference is likely to matter. With non-tradables, the tradable-goods price index should include either the tradable expenditure shares ϕ_i, as in equation (1-17), or each region's price index, as in equation (1-19). These are likely to better represent a better overall picture of all of the consumers' opportunities, which is the very logic that led AvW to derive their model. But note that their MRs (equation 1-23) do not include any internal information from the region, if exception is made for the region's GDP-share. We have calculated both AvW's MRs (that is, the solutions to their methodology) and the trade-adjusted price indices from our methodology. We show the results on table 1-1, and here simply note that they look very different.

Table 1-1. AvW MRs and PIs

State/Province	GDP	Area	MR	PI	c
Alabama	82998	52423	1.03	1.18	0.85
Arizona	84951	114006	1.74	2.00	1.03
California	843100	163707	1.11	2.82	1.56
Florida	300681	65758	0.96	1.58	0.69
Georgia	170903	59441	0.93	1.21	0.99
Idaho	22399	83574	1.67	1.56	1.21
Illinois	312349	57918	0.83	1.76	1.19
Indiana	129667	36420	0.86	1.30	0.98
Kentucky	79915	40411	0.90	1.14	1.10
Louisiana	94656	51843	1.28	1.32	0.88
Maine	25075	35387	1.29	1.41	1.01
Maryland	124551	12407	0.81	1.71	0.65
Massachusetts	174041	10555	0.82	5.74	0.84
Michigan	217347	96810	0.93	2.14	1.04
Minnesota	114637	86943	1.19	1.67	1.26
Missouri	118301	69709	1.00	1.00	1.00
Montana	16085	147046	1.79	1.64	0.98
New Hampshire	27156	9351	0.99	2.95	0.79
New Jersey	243886	8722	0.78	0.85	0.78
New York	541113	54475	0.69	3.02	0.50
North Carolina	168550	53821	0.93	1.27	0.90
North Dakota	12724	70704	1.63	1.32	0.98
Ohio	256593	44828	0.83	1.45	1.05
Pennsylvania	283093	46058	0.71	2.02	0.86
Tennessee	116658	42146	0.97	1.14	1.11
Texas	452986	268601	1.15	1.20	1.29
Vermont	12971	9615	1.11	2.06	0.73
Virginia	169972	42769	0.85	1.53	0.55
Washington	136403	71303	1.22	1.86	1.40
Wisconsin	117651	65503	1.04	1.52	1.18
Alberta	56278	255541	3.56	1.14	4.71
British Columbia	62915	364764	2.15	1.91	3.95
Manitoba	16719	250116	3.72	1.09	3.25
New Brunswick	9464	28150	3.25	1.23	2.83
Newfoundland	6388	156453	6.18	1.52	2.24
Nova Scotia	12398	21345	3.36	1.52	2.20
Ontario	194311	415598	1.79	1.91	2.64

Prince Edward Island	1633	2185	4.06	1.23	1.80
Quebec	107121	595391	2.01	1.23	3.19
Saskatchewan	15338	251366	2.8	0.75	2.32

Notes: Since MR, PI and c are all relative values, we chose a common base (Missouri) for them in order to show differences between them more clearly.

Second, note that the actual gravity equation must include these expenditure shares. Furthermore, not including them is likely to result in bias. The reason is that the price indices themselves are likely to be correlated with the trade expenditure shares.

2.3 Assumptions, Old and New

To organize our discussion, we list in table 1-2 some of the assumptions of the old gravity models, stating which ones AvW also seem to accept (implicitly, in most cases). We do not intend this to be an exhaustive list. Nor do we intend to address each of the issues raised by every assumption in detail. Rather, the table serves a dual purpose. First, it motivates a whole research agenda, and we are certainly motivated to pursue some of the relevant questions in separate projects! By showing that the model is riddled with assumptions, both hidden and explicit, we aim to encourage further research on the relative importance of each assumption. Second, the table puts into context the assumptions that we do examine in further detail in this chapter.

Table 1-2. Gravity Assumptions

OLD GRAVITY ASSUMPTIONS	ADOPTED BY AVW?	NOTES
1. Two aggregate goods from two different regions are substitutable.	Yes.	See equation (1-15).
2. All goods from all regions have the same elasticity of trade costs with respect to distance.	Yes.	See equation (1-15).
3. There is quasi-symmetry among goods from different countries.[11]	Yes.	
4. Exporters cannot charge different mark-ups across markets.	Yes.	See equation (1-9).[12]
5. Each region trades only one good.	Yes.	
6. A region's overall trade is balanced.	Yes.	See equation (1-12).
7. Some combination of distance and border dummies is a good proxy for trade costs.	Yes.	
8. All goods are tradable.	Yes.	
9. A region's geography can be adequately represented by the situation of a principal city.	Yes.	

One main conclusion of the table is that any inferences to be drawn from any gravity model, old and new alike, need to be treated with caution. At the very least, this list implies that any such model should be tested before it is applied. Also, the table opens up

[11] We call it "quasi" because the parameter β_i allows for different weights to be placed on goods from different countries. The symmetry stems from the fact that all good pairs have the same elasticity of substitution. In practice, the weights β_i cannot be distinguished from quality, and therefore will be lumped with prices into what AvW call "scaled prices," that is, $\beta_i p_i$.

[12] AvW implicitly assume either competitive markets (if p_i in equation 9 is understood as cost) or at least constant price mark-ups of trade-inclusive marginal costs across different regions.

a whole research agenda. The general criterion on how to handle each of the assumptions is to look for those that seem to be in direct contrast with observational evidence, and that are likely to have the biggest impact on price indices and thus may cause omitted variable bias in the estimation. So to a large extent which assumption is likely to be most important is an empirical question, and we hope to address such empirical questions in the near future. For the purpose of this chapter, we focus in particular on the assumption that all goods are tradable. In particular, we pursue both a theoretical approach, in that we allow for non-traded goods above and draw theoretical conclusions from that, and we will also pursue a simulation approach, as explained below.

Taking the assumptions in turn, we shall have little to say in this chapter that relates to many of the assumptions on the list: for example, we will follow the extant literature in proxying for trade costs through a simple formula of distance and border barriers;[13] and we shall consider aggregate quantities only.

We will explore the consequence of assuming that all goods are tradable. We have already relaxed assumption 8 above, one main conclusion being that the presence of non-tradables changes the estimation procedure radically. Furthermore, as we have argued, the best procedure is likely to be one which uses each region's price indices. Suppose that there is a nontradable good produced in the region, and that good is to some extent substitutable with all of the tradable goods. Note that the very reason for why consumers respond to MRs in the AvW model is because these represent in some way a general price level of each region. With a nontradable good, though, the general price level must include the price of nontradables. But with nontradable goods present in the model that

[13] In chapter 3, however, we do analyze a more complete set of factors influencing trade cost.

price level is no longer akin to the MRs, since the latter only include costs of trade! We take up this insight in the next section, where we simulate and estimate a model with one non-tradable good per region, based on the theory described above. We will agree with AvW that MRs are not ultimately the same as PIs but we will draw the opposite conclusion from them, that is, the regression should use PIs.

For now let us just note two main features of their model. First, it is a necessary consequence of the assumptions that the MRs are consumer price indices, and we shall exploit this feature in what follows. Second, the model predicts parameter values that AvW simply accept as correct representations of reality and thus can be imposed onto the empirical analysis. In particular, the GDPs of regions i and j enter identically and with unit elasticity.

We begin our empirical analysis with the first point above. In particular, we begin by reproducing AvW's results to calculate the MRs directly with their method. Then we calculate state- and province-level CPIs and we compare their role in the gravity estimation with the use of calculated MRs.

3. DATA DESCRIPTION

We have obtained the state- and provincial-level trade data that AvW use.[14] These data have information on state-to-state, state-to-province and province-to-province trade

[14] We are grateful to Jim Anderson for providing the data. See AvW for the data description.

data for 1993, as well as distances between each region (state or province) pair and GDPs for each region. In our sample, there are 30 states and 10 provinces.[15]

In order to obtain the US state-level CPI, we have purchased the "ACCRA cost of living index" for year 1993, for 303 U.S. cities, which are shown on table 1-3 in appendix. These data are published by the Council for Community and Economic Research (C2ER, formally known as ACCRA). We normalized the data so that the average is set at 100. In order to get a state level price index from the city level price indices, we adopted the admittedly unsophisticated procedure of simply averaging the cities in each state. There are data for each quarter in 1993, and we use the first quarter's data. Note that there is no information on New Jersey or Maine (among those that are in the AvW sample), so we drop these two states from the sample.[16]

There are no Canadian province-level price comparisons. Instead, there are city-level price comparisons, obtainable from Statistics Canada (STATCAN). The cities available are listed on table 1-4 in appendix, along with the province to which they have been associated. We have 11 Canadian cities' price index for the year 2000. For the 10 provinces we are interested in, each province has a representative city's price index available, except Ontario, which has price indices for two cities. Given this almost one-to-one correspondence, and given that most of the Canadian population is urban, we simply regard the representative city's price index as the province-level price index. For Ontario, the average of the two cities' price index is used. Thus, we have CPI data for 10

[15] For computational reasons, AvW aggregated small states into one entity, and we followed their example.

[16] One alternative to dropping the data related to the two states is to replace CPI data with the MRs calculated from the AvW procedure. It turns out that the two treatments make no difference in our regressions later.

provinces for 2000. In order to deflate from 2000 to 1993, there are two options available. The first option assumes that all provinces have the same inflation rate over the seven years, implying that the relative price index does not change overtime. However, since we do have province-level inflation rates from 1993 to 2000, it is feasible to let province-level price indices diverge. We shall use both options in the chapter.

Finally, we merge the 10 provinces' price indices with the 38 states' price indices (the 40 states in AvW minus New Jersey and Maine), using the two countries' exchange rate and PPP in 1993.

4. RESULTS

In order to study the different competing models, we first replicate estimation results of the models above with our data as described in section 3. The results are presented in table 1-5. Since these are the standard results from the literature, we do not discuss them in detail here. The only purpose of table 1-5 is to use the estimated parameter shown as simulation parameters, as discussed below.

Table 1-5. Simulated Models

Model Name	Model Description	Model Parameters	Data Generation
1A	Old gravity, no remoteness control, actual data	α_1=-10.90 α_2=1.13 α_3=0.97 α_4=-1.11 α_5=2.75 α_6=0.4	Equation (1-1)
3A	Old gravity, with remoteness control given by equation (3), actual data	α_1=-11.28 α_2=1.11 α_3=1.02 α_4=-1.16 α_5=2.69 α_6=0.44 α_7=-0.15 α_8=0.61	Equation (1-2)
22A	AvW model, actual data	k=-17.07 a_1= -0.79 a_2=-1.65	Equation (1-22)
16A	Model with non-traded goods, actual data	k=-15.64 a_1= -0.79 a_2=-1.71	Equation (1-16)

Notes: Models with their name ending in A use actual data on GDPs, distances, and border dummies. For each row in the table there is also a corresponding model with its name ending in S, which uses simulated GDPs, distances and border dummies, but use the same model parameters as its corresponding A model. The model parameters were obtained by regressing each model with the actual data. In each case, the data are inputted into the relevant data-generating equation to generate the fitted trade flows. These are then used to generate appropriate distributional parameters for the normal distribution of the random disturbances, which are then used to generate the simulated trade flows. In each case the mean is chosen as zero and the standard deviation is chosen as some percentage of the mean fitted values (generally 20%, but we will experiment with other standard deviations).

The goal of this chapter is to assess the empirical performance of each competing model. In order to do so, we will simulate trade data in two ways. First, we shall take the real right-hand side data for each of the models of interest (for example, equation 1-1) and generate artificial trade data by adding random disturbances. These are the models with name ending in "A," listed on table 1-5.

Since this only varies the left-hand side of each model, we go a step further in this procedure. For each of the models with name ending in A, there will be a corresponding model with name ending in "S," for which we generate random GDPs, distances, and border dummies for an artificial "North America," as described in detail below. Only then do we input those data into the relevant data-generating equation to generate the simulated trade flows.

For either type of model, we generate the simulated trade flows in two steps. First, for each model we calculate the fitted trade flows. These allow us to calculate appropriate parameters for a normal distribution for the random disturbances, which then enables us to generate the simulated trade flows. Note that all model parameters are the same across the "A" and the "S" models, and in particular they all come from table 1-5, that is, they are the real parameters obtained from regressing the corresponding model with real data. However, the distributional parameters are not common, since they are generated by the fitted values in each case.

To generate the simulated trade flows for models 22A and 22S, we first input the (actual or simulated) data, plus the parameters a_1 and a_2 into equation (1-23), and solve for each of the $P_i^{\sigma-1}$. We use these values, plus data on distances and borders, to generate the data from equation (1-22). Similar procedures are used for models 16A and 16S.

As described above, in order to obtain the appropriate parameters for table 1-5, we first estimate each model with our actual real world data. We then use the parameters from that regression to generate simulated trade flows. As examples for our first step, table 1-6 reports the results from reproducing the old gravity model 3A and the new gravity model 22A using our actual real world data.

Table 1-6. The Old Gravity Model and the AvW Model

Variable	**Model 3A (Similar to McCallum 1995)**	**Model 22A (Similar to AvW 2003)**
Constant	-11.28 (0.44)	-16.96 (0.04)
ln y_i	1.11 (0.02)	1
ln y_j	1.02 (0.02)	1
ln d_{ij}	-1.16 (0.04)	-0.87 (0.03)
CA-CA dummy	2.69 (0.11)	
US-US dummy	0.44 (0.06)	
REM_i	-0.15 (0.11)	
REM_j	0.61 (0.11)	
$a_2=(1-\sigma)$ ln b		-1.63 (0.07)
R^2	0.86	0.81

Notes: the dependent variable is trade flows among US states and Canadian provinces. Standard errors are reported in parentheses.

Note that in the process of estimating models 22A and 22S we have obtained either the actual or the simulated MRs raised to an exponent related to the elasticity of substitution. Below, we will follow AvW in assuming an elasticity of substitution to calculate the actual MRs. Here, however, all that we need is the values of $P_i^{\sigma-1}$ for all i, not the MRs themselves.

As described in the introduction to this section, for models with their names ending in S, we have generated artificial data for a simulated "North America." This was done to test how robust each the methodology is in a different world, not just with the actual GDPs and locations of the real states and provinces. The simulated world was generated as follows. We started out with a rectangle, representing "North America," with assumed length = 2,664 Km and width = 4,432 Km. The length is approximately the distance between Brownsville, Texas and Winnipeg, Manitoba. We chose Brownsville because it is the Southernmost city in Texas and because it is at about the same latitude as Miami, the Southernmost metropolitan area in the United States with population over one million. Winnipeg was chosen because it is the single largest city in Canada that is close to due north of Brownsville. The width of the rectangle is approximately the distance between Seattle and Halifax, Nova Scotia, which were chosen for similar reasons.[17] We then randomly generated locations (x_1,y_1), (x_2,y_2), … (x_i,y_i), ….(x_n,y_n), in the rectangle, with uniform distribution, where n is the number of regions, and (x_i,y_i) is the economic center of region i measured from the lower left corner of the rectangle. Since we have 41 regions, we simply pick the 10 Northernmost among them to be "Canada" and the

[17] All distances were checked with maps.google.com, accessed on 3/7/2009. Note that the distances are *not* geographic distances, but actual travel distances. However, we chose the "walking" option, which yields the best approximation to the geographic distance.

remaining ones to be the "United States." All bilateral distances can then be calculated as $d_{ij} = \sqrt{(x_i - x_j)^2 + (y_i - y_j)^2}$. We also need to calculate the internal distance of each region. A correct procedure would take into account an actual partition of the North American rectangle into the different regions (note that we only have the location of the main city for each region, not the region itself). It would also require that we assume or generate a distribution of the population within each region, and then calculate the expected distance between two random members of that population.[18] We avoid these complications, and follow AvW in using a shortcut similar to Wei (1996). For both the models with real data and the models with simulated data (the A and the S models), we calculate the internal distance of each region as equal to 1/4 of the average distance from that region's main city to the four closest cities. Finally, for each region we also generate random GDPs, using normal distributions with mean=\$207,743k and variance=\$226,805k for states, and mean = \$48,256k and variance = \$61,348k for provinces (which are the actual means and variance of the provinces and states).

We have thus generated simulated data from several models. We will test how the different empirical methodologies behave, using these artificially generated worlds. In particular, we are interested in questions such as the following. Suppose that the data in the real world was actually generated by AvW's model, that is, AvW's model captures the main features of the real world well; then how bad are old gravity estimates? In

[18] This would be important, for example, in order to determine the impact of distance and of regionalism on trade. Note that the procedure implied above would also have the implication that the theoretically correct distance *between* regions is not just the distance between their main cities. Rather it would be the calculated expected distance between two inhabitants of the two regions. Consideration of all such issues will be left for future research. Here, we simply extend the usual shortcut taken by researchers to calculate the distance between regions to include a similar shortcut for the distance within regions, as explained in the text.

particular, how different are the border effects implied by using the old gravity model, perhaps augmented with a remoteness control, and the border effects implied by using AvW's methodology?

We first assume that the data generating process resembles an old gravity world, using equation (1-2) without remoteness. Using this artificial data, we estimated the old gravity model (equation 1-2), and the new gravity model as represented by AvW, equation (1-22) subject to the constraint of equation (1-23). The results are reported in table 1-7.

Table 1-7. Model 1S

Variable	**MODEL 1S** **Old Gravity**	**MODEL 1S** **New Gravity**
Constant	-16.14 (0.69)	-16.82
ln y_i	0.99 (0.04)	1
ln y_j	0.85 (0.04)	1
ln d_{ij}	-1.09 (0.04)	-0.85
CA-CA dummy	2.48 (0.16)	
US-US dummy	0.49 (0.09)	
(1-σ) ln b		-1.41
R^2	0.61	0.35

Implied CA-CA border effect	11.9	
Implied US-US border effect	1.6	

Notes: the dependent variable is the trade flows generated by the model heading the column. In all cases we have generated the data 30 times. The parameter estimates reported are the means of the 30 trials. The standard deviations of the 30 trials are reported in parentheses. The implied border effect is the exponential of the corresponding dummy variable for the old gravity estimations, and it is calculated as in table 1-8 below for the new gravity estimations.

We now discuss the results of the opposite exercise. We assume that AvW's model is a sufficiently accurate representation of the world, and we use the data thus generated to estimate both old and new gravity models. Specifically, after we simulated either model 16A or 16S, we have used the resulting data in the following five regressions:

Regression	**Equation**
1. New gravity (AvW's model, with estimated MRs)	(1-22), (1-23)
2. New gravity (AvW's model, with true MRs)	(1-22), with true MRs instead of estimated from (1-23).
3. New gravity with dummies instead of MRs	(1-24)
4. Old gravity with remoteness	(1-2), with remoteness calculated by (1-3)
5. Old gravity without remoteness	(1-1)

Estimation 1 listed above is simply to use AvW's methodology in order to estimate the gravity model on data that were generated by assuming that AvW's model is the true model of the world. Obviously we expect the model to perform quite well! In estimation 2, we use AvW's true MRs. For estimation 3, we have used AvW's and Feenstra's (2002) suggestion to simply estimate the gravity model with MRs replaced by dummies for each region. Thus we estimate:

$$\ln x_{ij} = k + \ln y_i + \ln y_j + a_1 \ln d_{ij} + a_2(1 - \delta_{ij}) + c_1\gamma_1 + c_2\gamma_2 + \cdots + c_n\gamma_n + \varepsilon_{ij} \tag{1-24}$$

Here, the variables γ_1, γ_2, …, γ_n are dummies, where the typical dummy variable takes on the value $\gamma_i = 1$ if region i is the exporter or importer, and otherwise $\gamma_i = 0$. Finally, estimations 4 and 5 are the old gravity estimation, with and without remoteness, respectively. For each of the two models (22A or 22S), we let the standard deviation of the disturbance iterate in increments of 0.1, between 0 and 2.5, thus taking values: 0, 0.1, 0.2,…, 2.4, 2.5. Note that a standard deviation of 1.3 is approximately 20% of the mean of the simulated trade flows, and that a standard deviation of 2.5 is approximately 46% of the simulated trade flows. For each value of the standard deviation we have simulated each model three times.

Table 1-8 below lists regressions on the simulated data in which the standard deviation of the disturbances is around 20% (between 18% and 22%) of the mean trade flows. All values in the table are the average of seven different regressions.

Table 1-8 – AvW Model's Performance with Different Estimations

Variable	**Parameters used for simulation** **MODEL 22S**	**Regression 1** **New Gravity**	**Regression 2** **New Gravity** **True MRs**	**Regression 3** **New Gravity** **Dummy**	**Regression 4** **Old Gravity** **REM**	**Regression 5** **Old Gravity** **No REM**
Constant	-17.07	-17.04 (0.04)	-17.05 (0.04)	-16.68 (0.50)	-14.72 (0.63)	-13.56 (0.55)
ln y_i	1(fixed)	1(fixed)	1(fixed)	1(fixed)	0.80 (0.03)	0.79 (0.03)
ln y_j	1(fixed)	1(fixed)	1(fixed)	1(fixed)	0.82 (0.03)	0.80 (0.03)
ln d_{ij}	-0.79	-0.80 (0.03)	-0.76 (0.04)	-0.74 (0.05)	-0.75 (0.04)	-0.70 (0.04)
CA-CA dummy					2.28 (0.14)	2.38 (0.14)
US-US dummy					1.02 (0.08)	0.97 (0.07)
REM_i					0.41 (0.17)	
REM_j					0.46 (0.17)	
(1-σ) ln b	-1.65	-1.61 (0.07)	-1.62 (0.06)	-1.66 (0.08)		
R^2		0.41	0.46	0.45	0.65	0.65
Implied CA-CA border effect	13.4*	12.8*	12.9*	13.7**	9.8***	10.8
Implied US-US border effect	2.0*	2.0*	2.0*	2.2**	2.8***	2.6

Notes: * The implied CA-CA border effect is calculated as $b^{\sigma-1}P_{CA}^{\sigma-1}/P_{US}^{\sigma-1}$, where $P_{CA}^{\sigma-1}$is the average $P^{\sigma-1}$of provinces, and $P_{US}^{\sigma-1}$is the average $P^{\sigma-1}$of states. The implied US-US border effect is calculated as $b^{\sigma-1}\,P_{US}^{\sigma-1}/P_{CA}^{\sigma-1}$. ** The implied CA-CA border effect is calculated as $b^{\sigma-1}\,e^{c_{CA}}/e^{c_{US}}$, where $C_{CA}$is the average c of provinces, and $c_{US}$is the average c of states. The implied US-US border effect is calculated as $b^{\sigma-1}\,e^{c_{US}}/e^{c_{CA}}$. *** 9.8 = exp(2.28), 2.8 = exp(1.02). However, they are not the implied border effects. To calculate the implied border effects that are comparable with those in AvW, we also need the average REM for states and the average REM for provinces.

Some findings can be gleaned from table 1-8. First, note that the old gravity model fits the data better than the new gravity, even though we emphasize that all data were generated by assuming that new gravity is the true data generating process of the world. Even more surprising, note that the implied border effect as estimated by the McCallum model is *smaller* than the border effect implied by AvW! This is especially surprising in light of AvW's claim to have "solved" the border puzzle, and would indicate that, if anything, the border effect estimated in the old gravity is biased *down*. Finally, note that the use of remoteness within the old gravity does lower the estimate of the CA-CA dummy, although not by much. Comparing these results with the real world data suggests that the AvW model may miss out on essential features of the real world in its original form – and therefore we cautiously propose that the AvW model may not be a viable candidate to model the real world data generating process. Consequently, the race for solving the border puzzle is still on.

Table 1-9 presents a different way to look at problems with the AvW estimation. We have simulated model 22S (that is, the regular AvW with simulated data), for different standard deviations (SD) of the disturbance, as a proportion to the mean log trade (LMEAN). Specifically, we have simulated 75 times for each of SD=0.1LMEAN, SD=0.2LMEAN, and SD=0.3LMEAN, for a total of 225 simulations. We then use AvW's estimation on these data. Again, we emphasize that the data generator and the estimator are the same model.

Table 1-9. Regression Results, AvW for Different Disturbance Levels

	True Value	**Population disturbance SD = 0.1 of trade mean**	**Population disturbance SD = 0.2 of trade mean**	**Population disturbance SD = 0.3 of trade mean**
a1	-0.79	-0.80 (0.02)	-0.79 (0.03)	-0.80 (0.04)
a2	-1.65	-1.63 (0.04)	-1.63 (0.07)	-1.62 (0.10)
R^2	1	0.72	0.43	0.25

Notes: Values in the table are average of 75 regressions.

This table shows that the model that was used to produce the data becomes remarkably less efficient as the standard deviations increase. This fact is perhaps not very surprising, but what may be surprising is how bad the fit becomes.

A separate but related question is on the possible biases of the estimation. To shed some light on possible biases, we have calculated percentage deviations ("actual bias" of the estimates) of the estimated coefficients as follows: $\%\text{deviation}\ (\mathrm{C})\ = 100\,(\hat{\mathrm{C}} - \mathrm{C}_0)/\mathrm{C}_0$, where C stands for any estimated parameter, $\hat{\mathrm{C}}$ is the estimated parameter, and C_0 is the "true" parameter on which the data generation was based. Figure 1-2 shows a scatter plot of these deviations for the distance parameter a1 (vertical axis), against the relative size of the standard deviation of the disturbances divided by mean trade volume. Note that we have allowed these to vary widely. In the figure we have 225 simulations. Note that the figure is suggestive of a potential upward bias in the parameter.

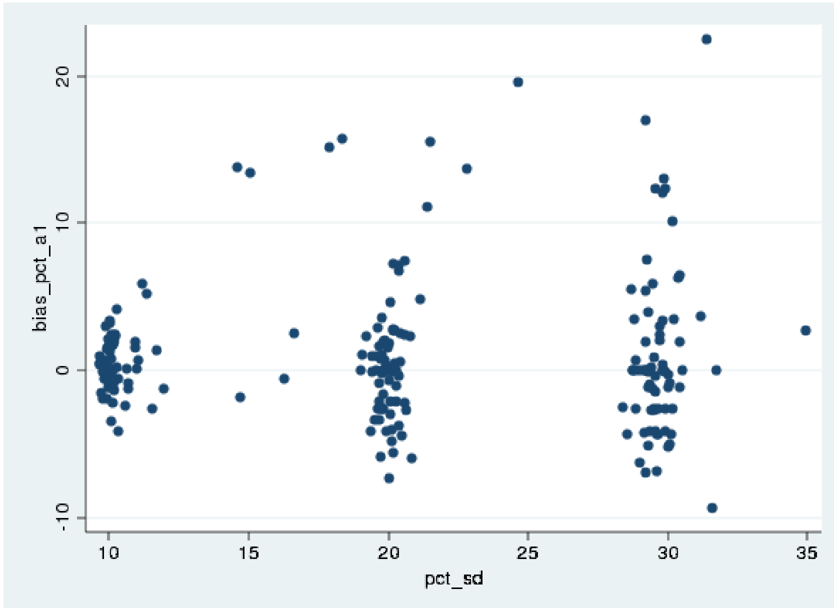


Figure 1-2 Bias in a1 to Disturbance Level

Figure 1-3 shows the corresponding pattern for the border variable a_2. As shown in the figure, there is some suggestion of a downward bias. In essence we begin to conjecture that the reason that AvW "solved" the border puzzle is that the estimation itself biases the border effect downward.

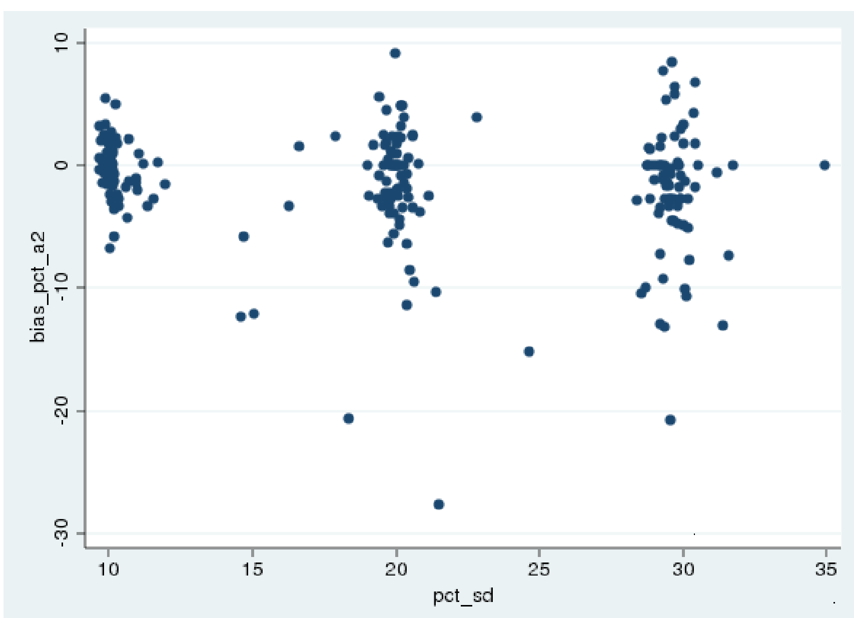


Figure 1-3 Bias in a2 to Disturbance Level

Table 1-10 makes some of the same points. It lists the mean %deviation (as defined above) for the distance parameter a_1 and the border parameter a_2.

Table 1-10. Mean of %Deviation of AvW parameters.

Population Disturbance Level	0.1	0.2	0.3
Mean of %Deviation in a_1	1.32	0.47	0.85
Mean of %Deviation in a_2	-1.35	-1.10	-1.97

The evidence presented in this table seems to suggest that the distance parameter is upward biased and the border parameter is downward biased. Note that for each disturbance level, we simulated 75 samples, and therefore there is reason to believe that this is a consistent pattern. In other words, AvW regression tends to over-estimate the distance elasticity but under-estimate the border effect, and therefore to solve the latter!

In figure 1-4, we plot the $\%\text{deviation}\ (a_2)$ relative to $\%\text{deviation}\ (a_1)$. Given the results above, it is not surprising that these seem to be negatively correlated. Since trade costs in their simplistic specification as a function of distance (equation 1-15) are almost assured to be mis-specified, and since the estimation of the distance elasticity may have an impact on the estimation of the border dummy, it is fair to question whether AvW's methodology is the best approach to estimating the border effect.

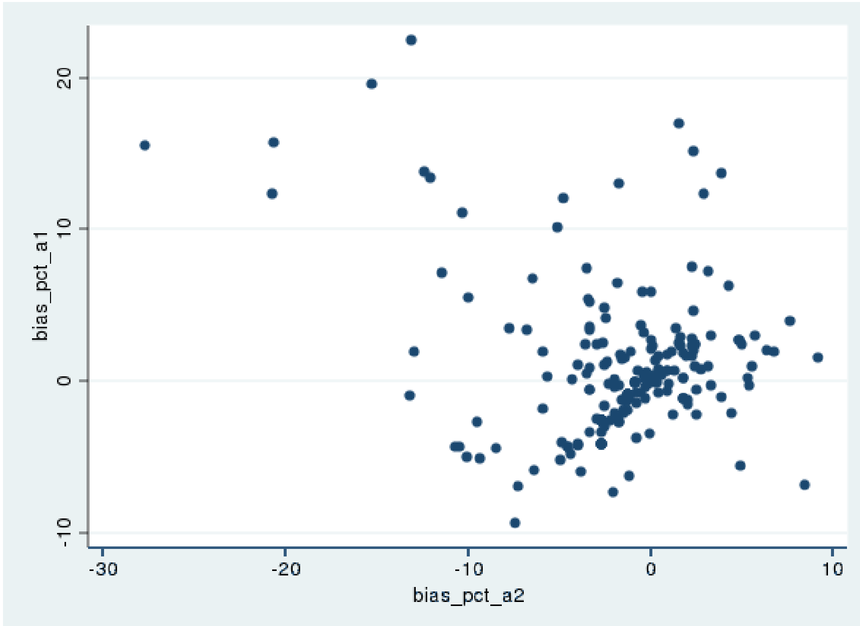


Figure 1-4 Bias in a1 to Bias in a2

We have argued in the theoretical section that the presence of non-traded goods might complicate the estimation procedure proposed by AvW, and in particular, might be a source for bias in that estimation. To explore this issue, we simulate data for model 16S, that is, our model with non-tradable goods, where GDPs are simulated as before with means and standard deviations close to the actual values of North America, and at the distances are calculated based on simulated locations. Furthermore we calculated ϕ_i in equation (1-16) based on the fitted trade data. Finally we used a true $a_1 = -0.78$, and a true $a_2 = -1.72$, which are the estimates of the estimation based on equations (1-16) and (1-17), that is, our model with non-nontradables.

For each level of the disturbance SD (0%, 10%, 20%, and 30%) we generate 20 samples. We then perform the following regressions:

Regression	Equation
1. New gravity, non-tradables	(1-16), (1-17)
2. New gravity (AvW's)	(1-22), (1-23)
3. New gravity with dummies instead of MRs	(1-24)
4. Old gravity without remoteness	(1-1)
5. Old gravity with remoteness	(1-2), with remoteness calculated by (1-3)

Table 1-11. Regression Results (data generated by non-tradable model).

	True Value	No disturbances		Population disturbance SD = 0.1 of trade mean		Population disturbance SD = 0.2 of trade mean		Population disturbance SD = 0.3 of trade mean	
		AvW-NonT	**AvW**	**AvW-NonT**	**AvW**	**AvW-NonT**	**AvW**	**AvW-NonT**	**AvW**
a_1	-0.78	-0.78 (0.00)	-0.78 (0.01)	-0.79 (0.02)	-0.78 (0.02)	-0.82 (0.03)	-0.78 (0.03)	-0.87 (0.04)	-0.78 (0.04)
a_2	-1.72	-1.72 (0.00)	-1.64 (0.02)	-1.68 (0.04)	-1.63 (0.04)	-1.69 (0.07)	-1.65 (0.07)	-1.69 (0.11)	-1.65 (0.10)
R^2	1	1	0.92	0.76	0.71	0.41	0.44	0.20	0.27
Average $P_j^{\sigma-1}$ or $P_j^{\sigma-1}B_T^{(\psi-1)/2}$ of states		1.56	0.81	1.47	0.82	1.18	0.83	0.80	0.81
Average $P_j^{\sigma-1}$ or $P_j^{\sigma-1}B_T^{(\psi-1)/2}$ of provinces		3.64	1.97	3.54	2.07	2.52	1.86	1.93	2.06
Implied border effect of CA-CA		13.0	12.5	12.9	12.9	11.6	11.7	13.1	13.2
Implied border effect of US-US		2.4	2.1	2.2	2.0	2.5	2.3	2.2	2.0

Notes: Values in the table are average of 20 regressions. a_1 is the coefficient of log distance. a_2 is the coefficient of border dummy. The Implied border effect of CA-CA is calculated as $e^{-a2}\frac{average\ P_j^{\sigma-1} of\ provinces}{average\ P_j^{\sigma-1} of\ states}$ for regular AvW and as $e^{-a2}\frac{average\ P_j^{\sigma-1}B_T^{(\psi-1)/2} of\ provinces}{average\ P_j^{\sigma-1}B_T^{(\psi-1)/2} of\ states}$ for the nontradable model.

The implied border effect of US-US is calculated as $e^{-a2}\frac{average\ P_j^{\sigma-1} of\ states}{average\ P_j^{\sigma-1} of\ provinces}$ for regular AvW and as $e^{-a2}\frac{average\ P_j^{\sigma-1} B_T^{(\psi-1)/2} of\ statets}{average\ P_j^{\sigma-1} B_T^{(\psi-1)/2} of\ provinces}$ for nontradable model.

Table 1-11 lists the results. We can observe from table 1-11 that if a model with non-tradable goods is a good approximation of the world, then the regular AvW seems to systematically under-estimate the distance elasticity a_1, and the bias seems to increase with the imprecision of the sample. More interestingly, it also tends to underestimate the border elasticity a_2, which again might go a long way in explain why AvW have "solved" the border puzzle, but for the wrong reasons!

Turning now to regression-based results, we have already presented on table 1-1 above the results from our calculation of the MRs, based on AvW's procedure (column labeled MR). It also presents the price indices that we constructed (column labeled PI). A simple "eyeball" comparison between the two columns already suggests that they do not resemble each other.

Table 1-12 reinforces this idea. It shows the correlation for the two variables in the sample. Note that the correlation between MR and PI is negative. This is an especially surprising (and from the point of view of the economic justification and reasoning behind the AvW methodology, especially worrisome) conclusion. Recall that the intuition of AvW's methodology would lead to a least a *positive* correlation between the two.

Table 1-12. Correlations Among the Variables

	GDP	Area	c	MR	PI	GDP/Area	Area/GDP
GDP	1.0000						
Area	0.0366	1.0000					
c	-0.2513	0.7033	1.0000				
MR	-0.4305	0.3118	0.6830	1.0000			
PI	0.3010	-0.1357	-0.2123	-0.2363	1.0000		
GDP/Area	0.3721	-0.3274	-0.3744	-0.3914	0.3435	1.0000	
Area/GDP	-0.3606	0.4065	0.5119	0.8139	-0.1850	-0.3128	1.0000

We have also performed a regression analysis of the alternative use of PIs versus MRs, which is described in tables 1-13 and 1-14. First note that we used the exact same specification as AvW, however, we allow the regression to choose the parameter values on the MR and the PI. Most notably, the coefficient on the border dummy is more than one third smaller when using actual PI data instead of MR. This indicates, at least in a preliminary fashion that the use of *actual* versus calculated PI is one possible avenue for solving the border puzzle.

Table 1-13. Gravity Equation Using MRs

The dependent variable is the GDP weighted trade volume in natural log.

a2	-1.28** (0.06)
a1	-1.23** (0.04)
log_MR_ex	0.48** (0.05)
log_MR_im	0.90** (0.05)
Constant	-7.90** (0.27)
R^2	0.53

Notes: * and ** indicate %5 and %1 significance level.

Table 1-14. Gravity Equation Using PIs

The dependent variable is the GDP weighted trade volume in natural log.

a2	-0.76** (0.06)
a1	-1.05** (0.04)
log_PI_ex	-0.34** (0.08)
log_PI_im	-0.23** (0.08)
Constant	-9.43** (0.28)
R^2	0.44

Notes: * and ** indicate %5 and %1 significance level.

8. CONCLUSION

In this chapter we have attempted to construct a critique of Anderson and van Wincoop's (2003) gravity model, and in particular their "solution" of the border puzzle. Of the many assumptions that pervade the theory of the gravity model, we chose to examine more closely in the theoretical section the assumption on the non-existence of non-traded goods, both because that assumption seems to be particularly at odds with the real world, and because our theoretical conjectures led us to posit that the assumption might be driving some bias in the estimation methodology. The conclusion that we drew from that exercise was that ignoring non-traded goods is done at the researcher's peril, because that means ignoring some of the trading opportunities of consumers in each trading region, which is precisely what AvW attempt to do.

The main avenue for the empirical part of the investigation was a series of simulations in which we assumed several possible "worlds" and used the simulated data on the different competing models. We can cautiously conclude after these exercises that AvW's methodology, while having introduced an arguably better way to account for each trading region's global trading opportunities, may itself have introduced its own source of bias. In particular we have found that the methodology seems to under-estimate the border effect, both in the case when the real world data generating process includes non-traded goods and (much more surprisingly) even in the case where the data generating process is AvW's model itself. Obviously, more research is needed on this point, we conjecture that the bias may come from a non-trivial interaction between the two estimated parameters (the distance elasticity and the border effect) in the context of non-linear estimation.

Chapter 2

Language and International Trade

1. INTRODUCTION

Languages play an important role in international trade. One example of additional trade costs that occur when language differences exist is for hiring translators. And there are many more channels through which language differences may raise trade costs of international trade.

Anderson and van Wincoop (2004) discussed trade costs as follows:

"*Trade costs, broadly defined, include all costs incurred in getting a good to a final user other than the marginal cost of producing the good itself: transportation costs, policy barriers, information costs, contract enforcement costs, costs associated with the use of different currencies, legal and regulatory costs, and local distribution costs.*"

Among these costs, language difference tends to cause higher information costs, contract enforcement costs, legal and regulatory costs. Therefore, the existence of language differences causes higher trade costs, thus reducing trade flow.

Language may also act as a proxy for culture. For example, if two groups of people speak the same language, it is very likely that they share a similar culture. Therefore, each group may have higher demand for goods produced by the other group than goods produced by different language speakers. In this way, language similarities promote trade. Or in other words, a difference in language reflects a culture barrier, which depresses trade.

Various studies[19] show that language differences substantially depress international trade. Many empirical studies in international trade add language variables into estimation as a control. A commonly used specification is the traditional gravity equation as shown below.

$$logT_{xm} = k + \alpha_x logY_x + \alpha_y logY_y + \rho logDistance_{xm} + \sum_{i=1}^{I} \beta_i \, logz_{xm,i} + \varepsilon_{xm}$$

[19] For example, Eaton & Kortum (2002), Hummels (2001), Melitz (2008), Rauch and Trindade (2002) and so on.

T_{xm} is the trade flow from the exporting country to the importing country. Y_x and Y_m are GDP's of the exporter and the importer. $Distance_{xm}$ is the distance between the two countries. $Z_{xm,i}$ could be any variable that constitutes a trade barrier from the exporter to the importer. A language variable is usually added as one of the z's. It frequently takes the form

$$\log Language_{xm} = \begin{cases} 1 & the\ two\ countries\ share\ an\ official\ language \\ 0 & otherwise \end{cases}.$$

So the coefficient estimate of log (Language) measures how much bilateral trade is promoted if the exporter and importer happen to have an official language in common.

Eaton & Kortum (2002) studied trade between 19 OECD countries in 1990. They used a dummy variable for a common official language as described above, in a more complex model. They found that if two countries happened to share an official language, their bilateral trade costs were 6% lower on average.

Hummels (2001) studied trade between 160 countries in 1994. His findings about language are that "*... importers will pay a 4 percent premium to trade with partners of a common language and a 2 percent premium to trade with adjacent countries.*" This implies that trading partners that share a common official language are preferred, either because of lower trade costs or because they offer goods that are more desirable because of cultural similarity of the trading partners.

Melitz (2008) in his analysis of world trade finds that a country pair with a common language traded 68% more than one without a common language.

Rauch and Trindade (2002) also found "*that the coefficient on LANGUAGE ... [is] positive and significant for the organized exchange and reference price commodity groups in 1990 for the conservative aggregation (and for the reference priced commodity group for the liberal* *aggregation*.)", though they used a language variable constructed in a different way other than the commonly used language dummy. Up to nine major languages were collected for each country, which was a big improvement in language information. Then they constructed a new variable called language matching probability, which is the probability that a randomly picked person from the exporting country happens to speak a common language with a randomly picked person from the importing country.

This chapter differs from all above researches in both data and model. We used 349 major languages in the world, which is the most complete language data collection that we are aware of in economics. They were picked because each had at least 1 million speakers. The total population speaking one of these languages accounted for 94% of the world's population. Besides the improvement in language information, we also used a matching model, and integrated it into the traditional gravity model.

The almost complete set of languages and the matching model together will enable us to answer the questions below. In answering them, we always take the trade between two countries which speak the same language as the benchmark.

- If two countries have no common language at all, by how much will trade be depressed?
- For any two countries in the world, by how much will their trade be affected by their languages?

Then next section describes our model. Then we will introduce the construction of our language data as well as a general description of all other data used. In section 4 we will present our regression results and section 5 concludes.

2. MODEL

In a traditional gravity model setting, the trade flow from a country to another country is predicted by their GDPs and distance as in the equation below.

$$T_{xm} = \mathrm{k}\frac{\mathrm{Y}_{\mathrm{x}}^{\alpha_{\mathrm{x}}}\mathrm{Y}_{\mathrm{m}}^{\alpha_{\mathrm{m}}}}{\mathrm{dist}_{\mathrm{xm}}^{\rho}} \qquad \textbf{(2-1)}$$

where T_{xm} is the trade flow from the exporting country x to the importing country m. Y_x is the GDP of the exporting country, Y_m is the GDP of importing country, and $dist_{xm}$ is the distance between the two countries. Also, in equation (2-1), k, α_x, α_m and ρ are parameters to be estimated.

A country may have one or more languages. A country's total population can be regarded as the sum of the different groups of people who speak different languages, where the main assumption would be that everyone has one primary language. Thus, we divide all inhabitants of the country into language groups, which can be thought of as (homogeneous) trading blocs, just as previous studies have divided the U.S. population by regions. However, we are aware of the situation of bilingual speakers, who can potentially cause a double-counting problem. We avoid this problem by only using every person’s first language (or what is called mother language). Since people only have one first language, the sum of all language populations is exactly the same as the total population. The fact that second languages are not counted may have some impact on the model, and we will discuss it later and revise the model so that that impact is minimized.

Suppose, for example, that there are n languages in the exporting country: A_1, A_2, ..., A_n, with corresponding population shares a_1, a_2, ..., a_n, as shown in the following table.

Exporting Country:

Language	A_1	A_2	...	A_n
Population Share	a_1	a_2	...	a_n
Group	1	2	...	N

Notes: $0 \leq a_i \leq 1, i = 1,2, \ldots, n$, and

$\sum_{i=1}^{n} a_i = 1$

Analogously, the importing country has m languages (which may or may not be the same): $B_1, B_2, \ldots, B_m$. The population share of each language is $b_1, b_2, \ldots, b_m$ correspondingly.

Importing Country:

Language	B_1	B_2	...	B_m
Population Share	b_1	b_2	...	b_m
Group	1	2	...	m

Notes: $0 \leq b_j \leq 1, j = 1,2, \ldots, m$, and

$\sum_{j=1}^{m} b_j = 1$

The driving assumption of this chapter is that the trade flow from the exporting country to the importing country is the sum of all trade flows from each group in the exporting country to each group in the importing country.[20] This implies the following equation:

$$T_{xm} = \sum_{i=1}^{n} \sum_{j=1}^{m} T_{ij}$$

where T_{xm} represents as before the trade flow from the exporting country to the importing country, and T_{ij} is the trade flow from language group i in the exporting country to language group j in the importing country.

[20] We will discuss the situation of bilingual speakers after equation 2 is introduced.

Following a traditional gravity model, and applying it to each linguistic group in turn, the trade flow from group i in the exporting country to group j in the importing country is predicted by the following gravity formula:

$T_{ij} = \mathrm{k}\frac{\mathrm{Y}_\mathrm{i}^{\alpha_\mathrm{x}}\mathrm{Y}_\mathrm{j}^{\alpha_\mathrm{m}}}{\mathrm{dist}_\mathrm{ij}^{\rho}}$, if group i and j speak the same language;

$T_{ij} = \mathrm{k}\frac{\mathrm{Y}_\mathrm{i}^{\alpha_\mathrm{x}}\mathrm{Y}_\mathrm{j}^{\alpha_\mathrm{m}}}{\mathrm{dist}_\mathrm{ij}^{\rho}}\beta$, if group i and j speak different languages,

where β is a parameter with $0 \leq \beta \leq 1$ that measures how much language difference depresses trade.

In this chapter we are mostly concerned with this parameter β. The smaller its value is, the more language matters in international trade. Conversely, the bigger its value is, the less language matters in international trade. Once we know the value of β, we are able to tell exactly how much their bilateral trade will fall if two countries do not share any language, as compared to trade in which the trading pair share one single language.

Finally, we are able to predict trade flow from the exporting country to the importing country by summing up the trade flow from groups in the exporting country to groups in the importing country, obtaining:

$$T_{xm} = \sum_{\mathrm{i}=1}^{\mathrm{n}}\sum_{\mathrm{j}=1}^{\mathrm{m}}\mathrm{T_{ij}} = \sum_{\mathrm{i,j}}\mathrm{k}\frac{\mathrm{Y}_\mathrm{i}^{\alpha_\mathrm{x}}\mathrm{Y}_\mathrm{j}^{\alpha_\mathrm{m}}}{\mathrm{dist}_\mathrm{ij}^{\rho}}\beta^{1-\delta_\mathrm{ij}} \qquad \textbf{(2-2)}$$

with the parameter δ_{ij} defined as:

$$\delta_{ij} = \begin{cases} 1 & if\ groups\ i\ and\ j\ speak\ the\ same\ language \\ 0 & otherwise \end{cases}.$$

The fact that only the first language is used in the model does have some potential impact on the true value of β. Let us start the discussion from an easy example. Suppose that people who speak English as their second language are distributed into each language group proportionally to its group population. Then these people will facilitate international trade between all groups, and at the same magnitude level. As a result, the true value of β will be brought up. There is no need to change the model in this kind of situation. However, in reality, the situation is likely to be more complex where second languages are distributed unevenly in different language groups. For example, British English-speaking people are more likely to learn French as their second language than to learn Chinese. So the true value of β may be higher than average for some particular group pairs, and it may be lower than average for some other group pairs. Taking this kind of fact into consideration, we know that the estimate of β will be the average for all different language groups. We hope that the abundance of language information we use will enable us to get a consistent estimate of β.

We are going to use the following two assumptions about GDP and distance to rewrite the equation above (equation 2-2) into a more straightforward form.

$dist_{ij} = dist_{xm}, \forall i, \forall j$ .... Assumption 2-1

$Y_i = a_i{*}Y_x,\ Y_j = b_j{*}Y_m, \forall i, \forall j$ .... Assumption 2-2

Assumption 2-1 states that the distances between groups from different countries are the same as distances between these countries. Assumption 2-2 means that a group's share of GDP in its country is the same as its population share.

It is possible that some language groups reside in some particular regions within a country so that these groups are geographically more distant or closer to other countries. However, three considerations favor the use of assumption 2-1. First, data are not available for capturing the geographical information of different language speakers within every country. Second, distances between two groups residing in different countries are very similar to the distances between the two countries. If there are differences, they are relatively small and can be expected to balance each other on average. Third, and reinforcing the previous point, this issue diminishes with increasing sample size. Since we are using all reasonably large language groups in all countries and they are treated indifferently from each other, our sample size is large enough to consider this issue to be of minor concern.

Assumption 2-2 also has some strong implications. It is actually quite likely that per-capita GDPs differ between ethnic groups. However, it would be impossible to collect per-capita data for all major 349 languages in all countries. Moreover, some minority language groups may actually be more affluent (like Mexican immigrants in the US). Consequently, we treat all language groups indifferently in our estimation, and we hope that this does not cause much bias to the estimates of beta.

With the two assumptions, equation (2-2) can be written as:

$$T_{xm} = \mathrm{k}\frac{\mathrm{Y}_{\mathrm{x}}^{\alpha_{\mathrm{x}}}\mathrm{Y}_{\mathrm{m}}^{\alpha_{\mathrm{m}}}}{\mathrm{dist}_{\mathrm{xm}}^{\rho}}\sum_{\mathrm{i,j}}\mathrm{a}_{\mathrm{i}}^{\alpha_{\mathrm{x}}}\mathrm{b}_{\mathrm{j}}^{\alpha_{\mathrm{m}}}\beta^{1-\delta_{\mathrm{ij}}} \tag{2-3}$$

or

$$T_{xm} = \mathrm{k}\frac{\mathrm{Y}_{\mathrm{x}}^{\alpha_{\mathrm{x}}}\mathrm{Y}_{\mathrm{m}}^{\alpha_{\mathrm{m}}}}{\mathrm{dist}_{\mathrm{xm}}^{\rho}}\mathrm{TLE}_{\mathrm{xm}},$$

with

$$\mathrm{TLE}_{\mathrm{xm}} = \sum\nolimits_{\mathrm{i,j}}\mathrm{a}_{\mathrm{i}}^{\alpha_{\mathrm{x}}}\mathrm{b}_{\mathrm{j}}^{\alpha_{\mathrm{m}}}\beta^{1-\delta_{\mathrm{ij}}}.$$

$$\delta_{ij} = \begin{cases} 1 & \textit{if groups i and j speak the same language} \\ 0 & \textit{otherwise} \end{cases}$$

We call TLE the total language effect on trade.

So far, we have successfully decomposed T_{xm} into the traditional gravity prediction and the total language effect. One can easily see this by comparing the equation (2-3) with (2-1).

The value of TLE_{xm} depends on the shares of the population in both countries that speak a certain language. It also depends on the parameters α1, α2 and β. To see this, we decompose the formula for TLE to separate those groups that share a common language from those that do not.

$$\mathrm{TLE}_{xm} = \overbrace{\sum\nolimits_{i,j} a_i^{\alpha_x} b_j^{\alpha_m}}^{\text{If } A_i \text{ and } B_j \text{ are the same language}} + \overbrace{\sum\nolimits_{i,j} a_i^{\alpha_x} b_j^{\alpha_m} \beta}^{\text{If } A_i \text{ and } B_j \text{ are two different languages}}$$

TLE is 1 if both populations in two countries exclusively speak one and the same language. It is zero if no one in a country pair shares a common language. In all other cases the TLE is between zero and one.

Since our parameter of interest is β, we can attempt to estimate it directly with equation (2-3). However, due to the non-linear nature of equation (2-3), we expect better results if we simplify it further before we start estimating it. We thus suggest two alternative approaches to simplify our estimation procedure.

Method 1.

One way to simplify equation (2-3) is to use the following assumption.

$\alpha_x = \alpha_m = 1$ ……….. Assumption 2-3

The values of α_x and α_m appeared to be frequently quite close to 1 in the empirical literature. In the AvW gravity model (Anderson and van Wincoop (2003)), α_x and α_m are fixed by theory to be 1. [21] Thus, with assumption 2-3 we simply follow these authors by analogy.

With assumption 2-3, equation (2-3) becomes

$$T_{xm} = \mathrm{k}\frac{\mathrm{Y_x Y_m}}{\mathrm{dist}_{\mathrm{xm}}^{\rho}}\mathrm{TLE_{xm}} \tag{2-4}$$

with

$$\mathrm{TLE_{xm}} = \textstyle\sum_{\mathrm{i,j}} \mathrm{a_i b_j} \beta^{1-\delta_{\mathrm{ij}}}.$$

$$\delta_{ij} = \begin{cases} 1 & if\ groups\ i\ and\ j\ speak\ the\ same\ language \\ 0 & otherwise \end{cases}.$$

or,

$$\underbrace{\mathrm{TLE_{xm}} = \quad \textstyle\sum_{\mathrm{i,j}} \mathrm{a_i b_j}}_{If\ A_i and\ B_j\ are\ the\ same\ language} \quad + \quad \underbrace{\textstyle\sum_{\mathrm{i,j}} \mathrm{a_i b_j} \beta}_{If\ A_i and\ B_j\ are\ two\ different\ languages}$$

$\sum_{\mathrm{i,j}} \mathrm{a_i b_j}$ (if A_i and B_j are the same language) is the probability that a randomly picked person from the exporting country happens to speak the same language as a randomly picked person from the importing country. We therefore call it language matching probability.

This enables us to write down the equation which will be used in regression analysis:

$$lnT_{xm} - lnY_x - lnY_m = k - \rho lnDist_{xm} + ln\sum_{\mathrm{i,j}} \mathrm{a_i b_j} \beta^{1-\delta_{\mathrm{ij}}} + \varepsilon_{\mathrm{xm}} \tag{2-5}$$

[21] The AvW gravity model is a very influential model which gives a theoretical foundation to the traditional gravity model. It predicts trade in the form of $Trade_{xm} = Y_x Y_m / (Y^w {t_{xm}}^{\sigma-1})\ {P_x}^{\sigma-1} {P_m}^{\sigma-1}$, where t_{xm} is the bilateral resistance to trade and measures as a function of distance, language matching and so on, P_x and P_m are multilateral resistances for the exporting and importing country.

With FTA added, the equation is extended to

$$lnT_{xm} - lnY_x - lnY_m = k - \rho lnDist_{xm} + \gamma FTA_{xm} + ln\sum_{i,j} a_i b_j \beta^{1-\delta_{ij}} + \varepsilon_{xm} \quad \textbf{(2-6)}$$

Method 2.

An alternative, arguably more careful way to simplify the estimation process without applying assumption 2-3 is to use a two-step regression approach.

Step 1: Use trade observations where TLE is a constant to estimate α_x and α_m based on equation (2-1).

If TLE is a constant, then equation (2-3) simply becomes equation (2-1) with a potentially different constant, but the same elasticities (α_x and α_m). Equation (2-1) can be written as a simple linear equation which is easy to estimate. There are two extreme situations where TLE is a constant.

Extreme case 1: TLE = 1

This is the case when there is only one language in the exporting country, and only one language in the importing country, and the two languages are the same. In this case, the two countries have perfect language matching, and TLE = 1.

Extreme case 2: TLE = β

This is the case when there is only one language in the exporting country, and only one language in the importing country, but the two languages are different. In this case, the two countries have no language matching at all, and TLE = β.

Extreme case 1 rarely exists in the actual data. However, extreme case 2 exists in quite a substantial number of country pairs. So we are going to use trade observations between these countries pairs to do step 1.

The step 1 equation for the regression is:

$$lnT_{xm} = k + \alpha_x \, lnY_x + \alpha_m \, lnY_m - \rho \, lnDist_{xm} + \varepsilon_{xm} \tag{2-7}$$

With FTA added, the equation is extended to

$$lnT_{xm} = k + \alpha_x \, lnY_x + \alpha_m \, lnY_m - \rho \, lnDist_{xm} + \gamma FTA_{xm} + \varepsilon_{xm} \tag{2-8}$$

Step 2: Estimate β (along with k and ρ) based on (2-3), with α_x and α_m replaced by step 1 estimates.

The step 2 equation for this regression then becomes:

$$lnT_{xm} - \widehat{\alpha_x} lnY_x - \widehat{\alpha_m} lnY_m = k - \rho \, lnDist_{xm} + ln \sum_{i,j} a_i^{\widehat{\alpha_x}} b_j^{\widehat{\alpha_m}} \beta^{1-\delta_{ij}} + \varepsilon_{xm} \tag{2-9}$$

With FTA added, the equation is extended to

$$\begin{aligned} lnT_{xm} - \widehat{\alpha_x} lnY_x - \widehat{\alpha_m} lnY_m \\ = k - \rho \, lnDist_{xm} + \gamma FTA_{xm} + ln \sum_{i,j} a_i^{\widehat{\alpha_x}} b_j^{\widehat{\alpha_m}} \beta^{1-\delta_{ij}} + \varepsilon_{xm} \end{aligned} \tag{2-10}$$

The 2-step regressions enable us to estimate β without adopting assumption 2-3.

We are not able to tell which of the two methods is better between since they both have weaknesses that need to be weighed against each other. Method 1's weakness is of course its dependence on assumption 2-3. Method 2's weakness is that only a proportion of our observations are used in step 1. In short, if we have prior information that allows us to believe that assumption 2-3 holds or almost holds, then method 1 is a better choice. However, if any or both of the "true" parameter estimates for α_x and α_m are far away from 1, then method 2 may be a better choice.

3. DATA

3.1 Language

We use the data for 349 major languages around the world. These languages were chosen because they are the set of languages that have at least 1,000,000 speakers. People who speak these languages account for 94% of the total world population.

The language data comes from the Ethnologue project which is run by SIL International (Summer Institute of Linguistics). It describes itself as follows:

"The Ethnologue database has been an active research project for more than fifty years. It is probably the most comprehensive listing of information about the currently known languages of the world. Thousands of linguists and other researchers all over the world rely on and have contributed to the Ethnologue database."

Ethnologue distinguishes a language from a dialect by the following criteria.

"Two related varieties are normally considered varieties of the same language if speakers of each variety have inherent understanding of the other variety at a functional level (that is, can understand based on knowledge of their own variety without needing to learn the other variety).

Where spoken intelligibility between varieties is marginal, the existence of a common literature or of a common ethnolinguistic identity with a central variety that both understand can be a strong indicator that they should nevertheless be considered varieties of the same language.

Where there is enough intelligibility between varieties to enable communication, the existence of well-established distinct ethnolinguistic identities can be a strong indicator that they should nevertheless be considered to be different languages."

Ethnologue records the exact population of a language's speakers in each country where it is still in use. The language population is defined as the population that uses this language as its first language. Language population data were unfortunately not collected in a single year, actually, this process took years. However, most of the latest updates of these major 349 languages were published around the year 1995. For some languages, the population data in some countries comes without a time stamp. We also treat them as 1995 data.

This is the first time (as far as we know) that such detailed language information[22] is put into use in international trade research. Previously, most researchers used a dummy variable indicating whether the exporting country and the importing country share a common official language. Rauch and Trindade (2002) used a language variable that measures the probability of language matching (the probability that a randomly selected person from the exporting country happens to speak the same language as a randomly selected person from the importing country). So we consider our current work to be rather substantial improvement in measuring the effects of language on trade. We expect that the abundance of language information helps to achieve a better understanding toward the relationship between language and international trade.

A slight inconvenience in the Ethnologue language data is that each country is only identified by its name, not by any standard country codes, such as the ISO 3-letter, or NBER-UN 6-digit country code. So we have to map country names in Ethnologue to country codes used in other datasets.[23]

3.2 World trade flow

Trade data comes from the NBER-United Nations world trade data. It is constructed from the United Nations trade data by Feenstra et.al (2004). It has US$ values of trade flows for all

[22] We have populations for 1447 language groups all around the world for these 349 major languages.

[23] Some country names in Ethnologue are different from those in PWT 6.1, but easily indentifyable. They include: USA, South Korea, Vietnam and Hong Kong.

exporter / importer pairs (if available) both at the disaggregate 4-digit SITC[24] level as well as at the aggregate level. We used the aggregate data, where each observation is the total trade flow in 1995 from an exporting country to an importing country.

Feenstra et.al (2004) constructed the dataset in the following way: data are collected from both the importing and exporting country. The former is preferred when both are available, under their assumption that the trade flows reported by the importer are more accurate than reports by the exporters.

The country code system in this data is unique. It originates from the 5-digit (United Nations) Standard Classification of Customs Areas and Territories, adapted to match the 6-digit classification complied in the World Trade Database by Statistics Canada.

3.3 GDP

Our data source of GDP's is the Penn World Table 6.1. PWT6.1 contains every country's real GDP (PPP, in US$) and other variables. However, since we want nominal GDP (in US$) instead of real GDP, we multiply a country's real GDP (PPP) with its PPP to get the value of its nominal GDP in its national currency first, then divide it by the exchange rate to convert the nominal GDP into US$.

PWT uses an ISO 3-letter country code. Again, we need to map the ISO 3-letter country code to the NBER-UN 6-digit country code.

[24] Standard International Trade Classification, revision 2.

3.4 Distance

Distance data between countries comes from the CEPII25 who calculated geodesic distances using the great circle method, between the latitudes and longitudes of the most important cities/agglomerations (in terms of population).

Distances are measured in kilometers. ISO codes are provided in 2-letter, 3-letter and 3-digit format for indentifying countries. These standard country codes give us convenience when integrating the data.

3.5 Free Trade Agreements (FTA)

Data on preferential trade agreements is from Baier and Bergstrand (2007). A dummy variable is used to indicate whether two countries are in any kind of preferential trade agreement or not.

[25] CEPII is a French research center in international economics.

4. REGRESSION RESULTS

We are now in the position to estimate the effect of language on trade with the two different methods described above. Table 2-1 presents the results.

Table 2-1 -- Regression Results

	Reg1.1 (Method 1)	**Reg1.1a (Method 1, with FTA)**	**Reg1.2 (Method 2, Step 1)**	**Reg1.2a (Method 2, Step 1, with FTA)**	**Reg1.3 (Method 2, Step 2)**	**Reg1.3a (Method 2, Step 2, with FTA)**
k	-17.02 (0.20)	-17.01 (0.20)	-15.19 (0.35)	-15.17 (0.35)	-13.64 (0.19)	-13.68 (0.21)
α_x	1 (fixed)	1 (fixed)	0.94 (0.01)	0.93 (0.01)	0.94 (fixed)	0.94 (fixed)
α_m	1 (fixed)	1 (fixed)	0.87 (0.01)	0.86 (0.01)	0.87 (fixed)	0.86 (fixed)
ρ	0.94 (0.02)	0.94 (0.02)	0.87 (0.02)	0.84 (0.02)	0.93 (0.02)	0.90 (0.02)
β	0.37 (0.04)	0.37 (0.04)			0.31 (0.03)	0.31 (0.03)
γ		-0.01 (0.10)		0.46 (0.13)		0.41 (0.10)
R^2	0.214	0.214	0.634	0.635	0.222	0.223

Method 1 and method 1a (both under the assumption that $\alpha_x = \alpha_m = 1$) yield estimate of $\beta = 0.37$. Method 2 and method 2a (relaxing the assumption about α's, but using less observations in step 1) provide estimates of $\beta = 0.31$. Between the 2 estimates, we prefer the second one because the estimate of α_m is quite substantially different from 1. In other words, we prefer method 2 because it avoids assumption 2-3 which turns out to be false. So, we prefer the estimate of $\beta = 0.31$ to the one of $\beta = 0.37$.

The similarity in the estimated β of regression1.1 and regression 1.3 eases our worry about the possible bias in α_x and α_m estimated in regression 1.2. Even if the worst case of method 2 happens, namely that regression 1.2 gives slightly biased estimates of α_x and α_m because it does not include all observations, the estimate of β will not be affected much by such a small bias in α_x and α_m. Thus, overall we feel more confident about method 2.

Note that the R^2 in regression 1.1 and regression 1.3 are much smaller than in regression 1.2. Actually, the R^2 tend to be large if α_x and α_m are not fixed, but they tend to be small if α_x and α_m are fixed. Anderson and van Wincoop (2003) found a similar pattern for trade between U.S. states and Canadian provinces (see Table 1 in Anderson and van Wincoop 2003). The gravity equation is so commonly used not only because of its simple form, but also because it is able to give large R^2, as regression 1.2 shows. However, R^2 tend to be much smaller if α_x and α_m are fixed. However, our main interest – estimating β – has little connection with income elasticity and the resulting R^2. Consequently, we need not concern ourselves with this drop in R^2, since it will not affect our estimation of β.

From the above estimate of β, we know that language differences between 2 groups of people (in different countries) reduces their bilateral trade to 31% of what it could be should these people speak the same language. This language depression ratio (about 1/3) is statistically significant, large and economically important.

Finally, we can now derive the effect of language similarities on trade at the country level by appropriately aggregating groups. Note that due to the fact that we analyze the effect of language at the group level, we are able to calculate the effect of language on trade for each country pair individually, conditional on whether this country is an import or exporter.

In the extreme cases where two countries have perfect language matching or complete language difference, trade flows between those with perfect language matching tend to be 3 times of that of two countries where there is no language overlap, after the differences in GDPs, distances and FTAs are controlled for.

In the more usual cases where countries have both some language matching and some language differences between them, we calculate some exemplary TLE's for selected country pairs in table 2-2 below.

Table 2-2 -- Some Examples of Total Language Effect (TLE)

Exporter	Importer	TLE
USA	UK	0.93
USA	Germany	0.50
USA	Canada	0.87
UK	USA	0.97
Germany	USA	0.52
Canada	USA	0.85

Notes: TLE's are not symmetric due to the fact that $\alpha_x > \alpha_m$.

Based on the table above, we are able to compare the TLE between the USA and the UK with that between the USA and Germany. Actually, the fact that the USA had a higher degree of language matching with the UK than with Germany caused the USA exports to be 86% higher to the UK than to Germany.

5. CONCLUSIONS

In this chapter, we studied the language effect in international trade by using a new model and a newly created more complete language dataset. We found that the language depression ratio is 0.31, which implies that trade between two groups whose languages differ is only 31% of trade between two groups whose languages are the same. We found these effects to be substantial and varying strongly across countries. For example, the USA, the UK and Germany are all OECD countries. However, USA exported 86% more to the UK than to Germany due to language relevant factors after GDPs, distances and FTAs are controlled for. How much does our estimated effect differ from previously found ones? To answer this question, we used the "old" language variable (the common official language dummy) in order to find out what the "old" language variable would tell us about language effects, as in the following equation:

$$\ln T_{xm} = k + \alpha_x \ln Y_x + \alpha_m \ln Y_m - \rho \ln Dist_{xm} + \gamma FTA_{xm} + \theta * CommonOfficialLanguage + \varepsilon_{xm}. \quad \textbf{(2-11)}$$

Here, e^{θ} shows the difference caused by a common official language. Situations where a country-pair has no common official language is used as the base by default. However, we play a trick here by switching the base to situations where a country-pair share a common official language, for example, the USA, Canada and the UK all share a common official language. The following table compares the importance of the language effect for both our measure (TLE) and the old language measures.

Table 2-3 – Comparison of Language Effects

Exporter	**Importer**	**TLE (our findings)**	**TLE (under the old settings)**
USA	UK	0.93	1
USA	Germany	0.50	0.47
USA	Canada	0.87	1
UK	USA	0.97	1
Germany	USA	0.52	0.47
Canada	USA	0.85	1

Under the old setting, the USA exported %112 more to the UK than to Germany due to the fact that the USA and the UK share a common official language. By comparing our findings with the "would be" findings using the previously used methodology, we can see that our findings are not astonishingly big. However, we believe that our findings are more precise, since they are not only based on a more complete set of language information, they also allow to gauge the effect for each country-pair individually, not only for the two rough groups that either share or do not share a common official language.

Chapter 3

Ethnic Networks in Trade: What Do They Bridge?

1. INTRODUCTION

A growing literature suggests that social networks provide a wide variety of services to those conducting international trade transactions. For example, Rauch and Casella (2003), as well as Rauch and Trindade (2002) highlight that networks help promote international trade by lowering information costs and providing legal services. Greif (1993) argues that legal enforcement through networks can be quite effective as the continued membership in the network involves repeated interaction. In other words, the threat of exclusion from the network may be sufficient to deter a trader who is a member of the network to default on any contract, since that would exclude him from any future profit stream. Another mechanism for the interaction between social networks and international trade has to do with the impact that ethnic networks have on cultural and linguistic barriers between countries (see for instance Gould 1994, who also identifies the possibility that ethnic networks enhance trade simply through similarity of preferences). As analyzed in the previous chapter, a large number of studies show the importance of language similarities for trade, so networks can add value by supplying language intermediation.

Alternatively, legal enforcement can also be provided by the legal institutions in each country of the trading pair. Berkowitz et. al. (2006) study the effect of domestic legal institutions on trade, and find that institutions seem to be providing legal services similar to those provided by ethnic networks. In particular, they find that legal institutions not only lower international transaction costs, they also lower domestic transaction costs, which specially benefits differentiated products that tend to have longer supply chains than commodities.

These two lines of research, the one based on ethnic networks and the one focused on institutions, both find statistically significant and economically highly important results. Note that both the quality of legal institutions and the presence of networks are variables that can be directly or indirectly influenced by governmental policy. Given the importance of institutions, and of the several ways that ethnic networks can impact trade, an important yet unanswered question is what the relative importance of the different mechanisms is in countries where both networks and institutions have an important presence. In other words, if a government has the opportunity to influence either of the two variables, which of the two should it sponsor, if any? Or should it sponsor both at the same time? This is the question that we address in this chapter. In particular, we assess the relative impact of institutions versus ethnic (Chinese) networks, and their interaction.

In doing so, we shall also ask some subsidiary questions, all of which have to do with the main question of the relative importance of the different mechanisms. First, are the sometimes surprisingly strong results an artifact of omitted variable bias, since in past work they have been mutually omitted from empirical analysis? Or are these strong results still present when networks, institutions, and other potential substitutes for networks (like common language) are jointly taken into account? Second, are these effects as uniformly strong as they seem to be? For example, do networks still promote trade when countries share languages and have good quality institutions? That is, do they provide legal and information services that formal institutions and shared languages cannot substitute for? Or do networks deploy their power only in the absence of a common shared language or high quality legal institutions?

While the literature has consistently argued that networks provide value, it is far from obvious that they do so in all circumstances. To see this, consider the mechanism of how networks and institutions provide their services. Networks reduce search costs, since potential partners only need to search within the network, where every potential partner is viable. Outside the network there is not only a larger number of potential partners that need to be analyzed, there is also the possibility of engaging in a business relationship with a partner that does not prove viable in the long run. Thus, networks can lower international transaction costs and in that way they promote trade. However, intermediation is costly and networks need to be maintained. Moreover, in order to remain in good standing within the network, contract fulfillment of transactions within the network may require higher levels of effort for a supplier, possibly increasing production costs. This is in contrast to high quality legal institutions, which actually *lower* production costs by enabling producers to more efficiently outsource, which allows those producers to concentrate on the slice of the value chain that they are best at. Consequently, if substitutes are readily available, the extra service provided by networks may not outweigh its incremental costs. Therefore, even if additional services could be provided by networks, they may not be worth the extra effort, even if the costs of network formation have already been sunk. In such a situation, networks would not provide any benefit. It follows that networks may not impact trade equally across different trading partners, across different types of goods, and under some circumstances may not impact trade at all. In sum, which of the described cases is the relevant case is strictly an empirical question. Our aim in this chapter is to resolve this empirical question for aggregate trade.

Two other consequences of this discussion may not be quite as obvious. First, legal institutions and language may only supply very basic enforcement and information services. The literature generally argues that networks can substitute for the lack of these basic services. However, networks may still offer benefits in excess of those basic services. In the remainder of this chapter, we will call them *residual network services*, since they cannot be supplied easily outside of a network. In fact, those residual network services itself may be *complementary* to the basic services. To see this, consider first the effect of high quality legal institutions: as shown by

Moenius and Berkowitz (2008), they help increase the size of the differentiated products sector, both in terms of value as well as the number of industries that provide sophisticated, differentiated products. Highly sophisticated products may require a much higher level of legal services than an average differentiated product may require.[26] For international trade to take place in highly complex products, a larger segment of this differentiated products sector may demand more specialized legal services and trust of the kind networks are able to provide. If this is the case, residual legal services as provided by networks may be complementary to general legal services as provided by institutions.

Second, information services and legal services themselves may be complementary to each other. Since high quality legal institutions help shift an economy towards production of differentiated products, there is not only a larger number of firms that may benefit from information services, but those information services may become more valuable, since it may be harder to find the right partner when the number of potential partners increases.

In sum, we conclude that the precise nature of the services that networks provide in international trade (for example, information versus legal services), their relative value, as well as the interaction among the different types of services, all raise questions that remain empirically unresolved.

This chapter will shed some light on those questions for the case of the overseas ethnic Chinese network. It identifies the relative contributions of legal services and information services through Chinese networks after taking the quality of legal institutions and shared language into

[26] Moenius and Berkowitz (2008) show that not only do higher quality legal institutions increase trade in differentiated products, they also show that the higher the quality of legal institutions in a country, the more important is the effect on domestic transaction costs and the less important is the effect on international transaction costs.

account, thus identifying the residual services as contributed by the overseas Chinese network. It also analyzes whether these residual services are complementary to basic legal services, and under which conditions Chinese networks substitute for the lack of quality of legal services. Finally, it will provide some insight on whether legal services and information services are complements or substitutes to each other.

In order to do so, we extend the model as specified in Anderson and van Wincoop (2003) (henceforth noted as AvW). More precisely, we build on the trade cost specification that AvW suggest, but extend it so that it more closely resembles the notion of trade costs that they discuss. In particular, we will investigate information as well as legal and regulatory costs. As outlined above, various scholars in the past have identified the importance of these costs. In what follows, we integrate the approaches by Rauch and Trindade (2002), chapter 2 and a modified version of Berkowitz et. al. (2006) into AvW's methodology. In doing so, we strive to make two contributions. First, we analyze the relative contribution of information services and legal services to trade. Specifically, we use legal institutions and language differences as a benchmark to investigate conditions under which ethnic Chinese networks substitute or complement legal institutions or language similarities. Second, we put the alternative method developed in chapter 1 to work with a more complete specification of trade costs as in the AvW model. This has two advantages. First, we can analyze country-specific trade-cost variables, which either can be done only to a limited degree in AvW's multilateral resistance approach,[27] or those country-specific factors simply have to be absorbed in country dummies, removing them from the analysis

[27] Note that any country-specific trade cost factors have to be included in the calculation of Multilateral Resistance Terms in the AvW approach. Since this requires the solution of non-linear equations, only a limited number of additional factors can be included to ensure that a global optimum is found. Moreover, practical considerations, namely limitations in computing power, require that no more than about 40 countries be included in the calculations.

entirely. Second, we will be able to provide a case that allows us to see how much omitted variable bias is introduced by leaving out price-terms (as a substitute for MR) versus specifying trade costs incompletely.

To accomplish our tasks, we add three variables that we will analyze in the context of the amended AvW model: ethnic Chinese population as a proxy for the ethnic Chinese social networking services; the quality of legal institutions; and newly constructed variables that gauge language differences across countries (see chapter 2 for details). We estimate several specifications and include interaction effects to identify potential complementary or substitutive relationships. In accord with the previous literature, we find that ethnic Chinese networks do increase trade substantially. However, Chinese networks may have no value at all in relationships where traders share the same language. Most surprisingly, though, they have a higher effect on trade in countries with high quality legal institutions. Our evidence suggests that they either do not substitute for the lack of quality legal institutions, or complementary effects outweigh substitutive effects entirely. Thus, ethnic networks are able to deploy their full power in countries with high quality institutions that do not share a common language. This suggests that the relationship between legal institutions and networks is complementary rather than substitutive, which is in stark contrast to the previous literature. One might now expect that networks simply have a smaller effect on lowering international transaction costs in countries where those institutions are especially poor. Similarly surprising, though, they seem to have no effect at all in those countries. Finally, we also find that incompletely specifying trade costs leads to about the same amount of omitted variable bias in our estimation as leaving out the price terms in the amended AvW model.

The chapter is organized as follows: In section two, we discuss the economic relationship between our variables of interest. Then we present our estimation strategy, followed by a discussion of the data and the results. Section six discusses some robustness checks before we draw conclusions from our analysis.

2. ECONOMIC EFFECTS OF NETWORKS, LANGUAGE DIFFERENCES AND INSTITUTIONS

Before integrating the three variables of interest in our model, we need to lay out their effect on international transaction costs. Beginning with ethnic networks, recall that overseas Chinese are generally assumed to provide two types of services: information and legal services. We will first discuss how Chinese networks can substitute for the lack of reliable legal institutions, but also which additional legal services they may provide. Similarly, we then analyze how Chinese networks can substitute for language differences, and also which additional language-related services they may offer.

As discussed earlier, we will focus on the international transaction cost effects of ethnic networks and institutions. Berkowitz et. al. (2006) also identify this international transaction cost effect of legal institutions, but they emphasize that there is an even more important domestic transaction cost effect, which they label as a production cost effect of legal services. However, this production cost effect of legal services is absorbed by domestic prices in the AvW model, and we therefore need not concern ourselves here with such effect. We therefore only model the international transaction cost effects of legal services as identified by Anderson and Marcoulier (2001) and Berkowitz et. al. (2006).

All contracts are incomplete (Hart and Moore 1999), since not all possible states of nature that may influence outcomes can be accounted for. Legal institutions generally ensure that contracts are fulfilled as written and that conflicts that may arise through incomplete contracts are resolved in the spirit of the contract. However, legal institutions cannot ensure that a company delivers the best quality and service that they actually could, given the specification in the contract. For example, a company will only have incentives to deliver as few defective parts per batch as specified in its contract, not as few as it actually is able to, even if it could do so with little extra effort. When contractual relationships run into difficulties, the contract is – naturally – the first line of defense for either partner, regardless of who or what caused the problem, even if it is socially optimal to find the best joint outcome instead of reverting to the contractual stipulation. More generally, suppliers have little incentives to deliver more than whatever is specified in the contract, even if different processes that are hard to monitor could yield better outcomes. These examples illustrate aspects of business relationships that could benefit from cooperation under unforeseeable or hard to monitor circumstances. This level of cooperation, however, is closer to the concept of trust than to that of legal enforcement. Legal institutions can only negatively sanction certain behavior, so they cannot enforce previously unspecified cooperation. Networks can provide services similar to those of legal institutions, but they can also provide higher level services that are closer to trust since they can inflict sanctions and offer rewards. As discussed before, the higher the complexity of a product and thus the higher its outsourcing requirements, the more it benefits from both high quality basic legal services as well as higher level legal services that foster cooperation under unforeseen circumstances. To distinguish the latter from basic services, we will from now on call them *cooperation services*. The following scheme illustrates the relationship.

Provided by Legal Systems

Low Level Legal Services — High Level Cooperation Services

Provided by the Network

Similar arguments can be made about language: language is arguably an acceptable proxy for basic cultural similarity. The German-speaking Swiss, Austrians, and Germans themselves all share more similarities amongst each other than the Germans do with the French, or even with the Swiss whose mother tongue is French or Italian. The question is how deep this understanding is – does it cover knowledge about business culture and negotiation styles and strategies? The British would likely disagree that Americans or Australians have a very similar business culture to their own. But they would most likely agree that they have a closer level of understanding with Americans and Australians than with the Chinese or Japanese. In simple schematic terms, this can be illustrated in a similar manner as before:

Provided by Language

Translation / Basic Culture — Business Culture, Negotiation

Provided by the Network

This discussion implies that the overseas Chinese may be able to provide more comprehensive services that reduce international transaction costs than potential substitutes, whether they are good institutions or linguistic and cultural similarity. Moreover, they may be able to provide those on both the legal as well as the informational dimension, while the possible substitutes could only cover one dimension each. Consequently, if legal institutions on the one hand and shared language on the other are indeed substitutes for network services, we can identify the conditions under which Chinese networks should be most valuable, and their effect on trade thus should be strong. We do so in the following simple taxonomy:

Table 3-1. The trade effects of networks: a taxonomy.

Language / Legal quality	Different	Same
High	Medium	Weak
Low	Strong	Medium

For example, when languages are different and the quality of legal institutions is low, then the effect of Chinese networks on trade should be high. If legal services, language and networks are actually complements, the cells indicating strong and weak effects would be reversed. Cell contents would need to be rearranged if either legal services or language similarities had a substitutive while the other had a complementary relationship with networks. Finally, networks could be substitutes for legal institutions when legal quality is low and complements to them when it is high. In short, the pattern of estimated effects of networks will allow us to learn which services are most important under which conditions, and thus whether those variables have complementary or substitutive relationships to each other.

These are the relationships between legal services, language, and networks that we will try to identify below. To identify the relationships, we will estimate both direct effects and interaction terms of our variables of interest. Before inspecting our estimation method more closely, we need to point out that networks also provide information services that are not covered by our discussion above, such as simply providing information about possible trading partners. We would expect these to be always complementary to legal or cultural services. We will need to keep this effect in mind when we discuss our results.

3. ESTIMATION

As discussed above, our variables of interest all affect international trade costs. First, recall the specification of trade costs in the AvW model. The "iceberg" cost is given by:

$$t_{ij} = b^{1-\delta_{ij}} d_{ij}^{\rho} \quad \textbf{(3-1)}$$

Since AvW are mainly concerned with border effects, b is a constant that gauges the size of the border effect. In our context below, it will measure a trade block effect. ρ is the elasticity of trade costs with respect to distance. The variable $\delta_{ij} = 1$ if region i and j are in the same country; otherwise it is 0. d_{ij} is the distance between the two regions. From this set of assumptions, we noted in chapter 1 that AvW deduce the gravity model to be estimated as:

$$\ln\left(\frac{x_{ij}}{y_i y_j}\right) = k + a_1 \ln d_{ij} + a_2\left(1 - \delta_{ij}\right) - \ln P_i^{1-\sigma} - \ln P_j^{1-\sigma} + \varepsilon_{ij} \quad \textbf{(3-2)}$$

where the parameters to be estimated are $a_1 = (1-\sigma)\rho$ and $a_2 = (1-\sigma)\ln b$ (in here, σ is the elasticity of substitution, assumed to be common to all goods pairs). AvW do not have price data, they therefore impute the price indices ($P_i^{1-\sigma}$ and $P_j^{1-\sigma}$) by replacing them with what they call Multilateral Resistance Terms (MR). They do so by solving the following n equations for the price indices $P_j^{1-\sigma}$:

$$P_j^{1-\sigma} = \sum_{i=1}^{n} P_i^{\sigma-1}\theta_i t_{ij}^{1-\sigma}, \quad j = 1, \ldots, n, \tag{3-3}$$

where θ_i is the share of country i GDP in world GDP.

Trade costs take a prominent role in determining the values of MR. As AvW already point out, it is of high importance to specify trade costs correctly in order to avoid omitted variable bias. We therefore expand their trade cost specification in the following way. We follow the previous work cited above and assume that higher quality legal institutions both in the exporting and importing country imply lower international transaction costs. We assume further that Chinese residents in a country can help enhance trade with the partner country. The resulting trade cost equation reads as

$$t_{ij} = b^{1-\delta 1_{ij}} d_{ij}^{\rho} l^{1-\delta 2_{ij}} I_i^{\beta 1} I_j^{\beta 2} CN_i^{\beta 3} CN_j^{\beta 4} \tag{3-4}$$

Here, $\delta 1_{ij}$ is a trade agreement dummy, $\delta 2_{ij}$ is a language dummy, I_i and I_j are the measures of institutional quality and CN_i and CN_j are the populations of Chinese ethnicity in the two countries in the trading pair. $\boldsymbol{\beta}1$ and $\boldsymbol{\beta}2$ are the elasticities of trade costs with respect to the quality of legal institutions, where higher quality institutions imply a lower probability of uncompensated contractual problems. Similarly, $\boldsymbol{\beta}3$ and $\boldsymbol{\beta}4$ are the elasticities of trade costs with respect to the number of ethnic Chinese in a country. Each elasticity measures jointly how many customers the Chinese residents in a country can serve and how beneficial this service is in terms of costs of trade reductions, where it is assumed that a larger number of ethnic Chinese implies a higher number of mediated cross border relationships. This assumption is reasonable as long as the population of ethnic Chinese is small relative to total population in each country. The corresponding estimation equation is then:

$$\ln\left(\frac{x_{ij}}{y_i y_j}\right) = k + a_1 \ln d_{ij} + a_2\left(1 - \delta 1_{ij}\right) + a_3\left(1 - \delta 2_{ij}\right) \tag{3-5}$$

$$+b_1 \ln I_i + b_2 \ln I_j + b_3 \ln CN_i + b_4 \ln CN_j - \ln P_i^{1-\sigma} - \ln P_j^{1-\sigma} + \varepsilon_{ij}$$

where the additional parameters to be estimated are $a_3 = (1-\sigma)\ln l$ and $b_1 = (1-\sigma)\beta 1$, and analogously for b_2, b_3 and b_4. Instead of calculating MR as specified in (3-3), with trade costs as in (3-4), we use actual price data as suggested in chapter 1, which allows us to use a larger cross-section as well as extend the analysis to a panel. Consequently, most variables in (3-5) receive additional time-indices. We include interaction terms between institutions, our language variable and our Chinese population data in this estimation to identify potential complementarities or substitutive relationships between our variables of interest.

Internationally comparable price data are available relative to the US from the Penn World Tables[28] in the form of purchasing power parity exchange rates. In our estimation, we would like to have the (relative) prices of the complete basket of all goods as consumed in each country. Call the prices of these baskets in country *i* and in country *j* the price indices P_i and P_j, respectively. In order to make the prices of these bundles comparable, we convert their values to US dollars. We can normalize the foreign price indices relative to the US by dividing them by the price of this bundle in the United States. If we want to express it in percentage terms, we can multiply it by 100. The resulting price index for country *i* has the following form (and analogously for country *j*):

[28] See data description below for details.

$$\left(\frac{\frac{P_i}{P_{US}}}{\frac{FC_i}{\$}}\right) \times 100$$

FC stands for foreign currency. The term in the numerator is the definition of Purchasing Power Parity, while the term in the denominator is the exchange rate, and the whole term is exactly the price index that the Penn World Tables provide. However, these are not exactly the same as the price indices as in our model. While the exchange rate is necessary to make the price indices comparable, neither the normalization nor the change into percentage values is necessary. However, since this normalization and the change into percentages is done for all price indices, this does not affect their value as control variables in the estimation, since the unnecessary additional terms are absorbed into the constant and year dummies in our panel estimation. These, as well as the parameters on the price variables themselves, however, have to be therefore interpreted taking these changes into account.

We will estimate various versions of the following equation:

$$\ln\left(\frac{x_{ijt}}{y_{it}y_{jt}}\right) = k_t + a_1 \ln d_{ij} + a_2\left(1 - \delta 1_{ijt}\right) + a_3\left(1 - \delta 2_{ij}\right) \quad \textbf{(3-6)}$$

$$+ b_1 \ln I_{it} + b_2 \ln I_{jt} + b_3 \ln CN_{it} + b_4 \ln CN_{jt} + b_5 \ln P_{it} + b_6 \ln P_{jt} + \varepsilon_{ijt}$$

Our discussion in section 2 suggests one more approach to address possible dependencies between legal institutions and language on the one hand and ethnic Chinese networks on the other: one can simply sort countries of high and low quality institutions that share or do not share a language and then re-estimate our model. Since only few countries share languages, we cannot split our sample in four groups. Instead, we first divide our data in those groups that share a language and those who do not. We then estimate (3-6) using additional interaction terms that separate out the effects of networks and institutions for those groups. We repeat the exercise for countries with weak legal institutions, this time interacting a dummy for low quality legal institutions with networks and institutional quality itself.

4. DATA

We spent considerable effort to collect data on ethnic Chinese population shares. These were collected from the yearbooks published by the Taiwanese government, who keep track of ethnic Chinese all over the world. The quality or legal institutions is measured by the data from the International Country Risk Guide (ICRG) as described in Knack and Keefer (1995). Language data is from the Ethnologue project which is described in chapter 2. Data on preferential trade agreements is from Baier and Bergstrand (2007). GDP and price levels are from the Penn World Table 6.1. Trade data comes from Feenstra et. al. (2005), while the usual gravity controls were provided by the CEPII and are described in Mayer and Zignago (2006). Table 3-2 lists descriptive statistics of the original datasets we use.

Table 3-2. Statistics of Data Sources

Original Data	**Year Range**	**Countries**	**Country Code System**	**Unit of value**	**Mean**	**Std. Dev.**
Ethnic Chinese	1959-1999 (except 1985, 1976, 1974 and 1960-1964)	144	Country names	1 person	0.26 mln	0.95 mln
Quality of Legal Institutions	1982-1997	135	World Bank Code	0.1 (min = 0, max = 6)	3.46	1.65
Language	1995 (approximately)	225	ISO	Language matching probability (min = 0, max = 1)	0.03	0.16
Free Trade Agreement	1960, 1965, 1970, ..., 2000	96	Country names	Dummy (1 if in FTA, 0 otherwise)	0.02	0.15
GDP	1950-2000	173	ISO	$1,000	88 mln	46 mln
Price Level	1950-2000	173	ISO	Percentage of US	57	40
Trade	1962-2000	201	NBER	$1,000	0.2 mln	2.0 mln
Distance	Unvarying	224	ISO	Km	8,482	4,704

Notes:

- Trade volumes are in nominal US$. GDPs are in nominal US$ too. PWT6.1 provides PPP-GDPs by default. To get nominal GDP, we divided PPP-GDP by PPP first for nominal GDP in national currency value and then divided it by exchange rate for nominal GDP in US$.
- Price level of GDP is the PPP (of GDP) divided by the exchange rate times 100. It is the percentage of PPP over exchange rate.

Due to the fact that our data-sets cover different time-periods and frequencies, we needed to decide on which data to include in the final data-set. To avoid interpolation of data, we chose to only use data for the largest commonly available time-span at the minimum provided frequency available for all countries in the original data-sources, which is five years, and chose data as closely matched as possible if necessary. Since network size, institutional quality and participation in trade agreements in each country only change at a moderate pace, we believe this cautious selection allows for more conservatively estimated results than all other options available.[29] Moreover, this allows us to construct a panel without missing observations. We also exclude countries whose major population are ethnic Chinese in order to avoid potential colinearity between ethnic Chinese population and language dummy. Finally, with a total of 13,038 for the three years available we believe to have sufficient observations to identify any effects our variables of interest may have on trade. Table 3-3 lists descriptive statistics of the final dataset.

29 Baier and Bergstrand (2007) take a similar approach (5-year interval) when studying the effect of free trade agreements.

Table 3-3. Statistics of the Final Dataset

Variable	Years	Countries	Country Code System	Unit of value	Mean	Std. Dev.
Ethnic Chinese	1985, 1990, 1995	91	ISO	1 person	0.29 mln	1.11 mln
Quality of Legal Institutions	1985, 1990, 1995	91	ISO	0.1 (min = 0, max = 6)	3.65	1.68
Language	1985, 1990, 1995	91	ISO	Language matching probability (min = 0, max = 1)	0.05	0.20
Free Trade Agreement	1985, 1990, 1995	91	ISO	Dummy (1 if in FTA, 0 otherwise)	0.05	0.21
GDP	1985, 1990, 1995	91	ISO	$1,000	229 mln	823 mln
Price Level	1985, 1990, 1995	91	ISO	Percentage	60	39
Trade	1985, 1990, 1995	91	ISO	$1,000	0.45 mln	3.3 mln
Distance	Unvarying	91	ISO	Km	7,752	4,417

Notes:

- Total observations: 13,038
- There are 91 countries as exporters while 90 of them as importers (Russia's importing flow is missing).
- Ethnic Chinese data in 1985 is missing despite of the fact that the data is available in most years. We used 1986's ethnic Chinese instead. We did so because of the two following considerations. One consideration is that if we again drop year 1985, there would be a loss of 1/3 in observations. The other is that ethnic Chinese populations did not change a lot in one year.

Recall that we need to identify countries with weak legal institutional quality. We do that in the following way: as can be seen from table 3-2, the index-values for legal quality range from 0 to 6. We arbitrarily select, for example, a cut-off value for legal quality of 3, so that a country is assumed to have good quality legal institutions if the legal quality index is greater than 3, and weak legal institutions otherwise. In this case, this implies that 64% of our trade observations are assumed to stem from countries with good institutions. We provide results for this and various other cut-off values when we discuss robustness checks of our results.

Similarly, we identify countries with large language similarities. In order to do so, we use the language matching variable described in chapter 2, and arbitrarily select a cut-off value as follows: we call a country-pair to have a high level of matching languages if the language matching probability is greater than 0.8, and call it a low level of language matching otherwise. 4% of our observations are between trade partners with good language matching. Although this appears to be a small fraction, it is still larger than utilizing the common official language dummy which has been generally used by scholars. Note that a language matching probability of 0.8 is impressively large: For example, if 90% of the population in the exporting country speaks English and the rest French, and 90% of the population in the importing country speaks English and the rest German, then the language matching probability of the 2 countries is 0.81. As in the case of legal institutions, we provide results for various other cut-off values in our section on robustness checks.

5. RESULTS

Before studying how networks can substitute or complement other trade cost factors, we study the main effect of each of the variables. The results are presented in table 3-4.

Table 3-4. Transaction Cost Effects of Institutions and Networks

	Reg 4.1	**Reg 4.2**	**Reg 4.3**	**Reg 4.4**
Distance	-0.89** (0.02)	-0.88** (0.02)	-0.92** (0.02)	-0.91** (0.02)
FTA	0.35** (0.07)	0.26** (0.07)	0.31** (0.07)	0.24** (0.07)
Language Dummy	0.57** (0.07)	0.62** (0.07)	0.62** (0.07)	0.65** (0.07)
Exporter Institutions		0.09** (0.01)		0.08** (0.01)
Importer Institutions		0.07** (0.01)		0.06** (0.01)
Chinese Population Exporter			0.10** (0.01)	0.09** (0.01)
Chinese Population Importer			0.05** (0.01)	0.04** (0.01)
Year dummy 1990	-0.53** (0.03)	-0.44** (0.04)	-0.56** (0.03)	-0.48** (0.04)
Year dummy 1995	-0.71** (0.03)	-0.81** (0.03)	-0.74** (0.03)	-0.83** (0.03)
Price Level Exporter	0.0003 (0.0004)	-0.0023** (0.0004)	0.0004 (0.0004)	-0.0014** (0.0004)
Price Level Importer	-0.0033** (0.0004)	-0.0046** (0.0004)	-0.0028** (0.0004)	-0.0041** (0.0004)
Constant	-17.53** (0.17)	-18.01** (0.18)	-17.42** (0.17)	-17.87** (0.18)
R^2 adjusted	0.229	0.235	0.235	0.240

Notes: * and ** represents significance at the 5% and 1% level. The dependent variable is the logarithm of the GDP weighted trade.

We first note that our control for distance is within reasonable order of magnitude of the results found in other studies, and it is stable across specifications. Prices and year dummies are statistically significant in our more complete specifications. Our language variable is also stable and enters at high levels of statistical significance. Our institutional variables also enter our regression with high statistical significance. Their effect on exporter-related transaction costs is higher than on importer-related transaction costs, consistent with the findings in Berkowitz et.al. (2006) that legal services matter more for exporters than importers (see also Anderson and Marcoulier 2001). The Chinese network variables also enter strongly in our regression, consistent with Rauch and Trindade (2003). Interestingly, they enter with a similar pattern as institutions, which suggests that they might work in a similar way as institutions in promoting trade. Coefficients of networks and institutions do not change significantly when entered jointly in the regression. The free trade agreement variable, however, which only plays the role of a control in our study, varies quite substantially across specifications: once institutions are added, its coefficient drops one quarter in size, and it drops even further once our Chinese network variables are additionally included in the regression. Since the FTA variable takes the role of the border dummy in the AvW regression, we wonder whether omitted variable bias, similar to the omission of price variables as argued by AvW, may affect some of the estimated coefficients if institutional variables are excluded from the regression. We will investigate this issue further when we discuss the robustness of our results. We summarize as a first result that our network, institutional and language variables all enter strongly and in a relatively stable manner in our regressions.

Next, we investigate whether any of the discussed substitutive relationships between networks and language or networks and institutions exist. We do so by studying the interaction terms between our variables of interest. The results are presented in table 3-5.

Table 3-5. Complementary and Substitutive Relationships between Language, Institutions, and Networks

	Reg 5.1	Reg 5.2	Reg 5.3	Reg 5.4	Reg 5.5
Distance	-0.91** (0.02)	-0.91** (0.02)	-0.91** (0.02)	-0.91** (0.02)	-0.91** (0.02)
FTA	0.24** (0.07)	0.24** (0.07)	0.23** (0.07)	0.25** (0.07)	0.24** (0.07)
Language Dummy	0.65** (0.07)	0.66** (0.08)	0.14 (0.23)	0.65** (0.07)	0.09 (0.23)
Exporter Institutions	0.08** (0.01)	0.08** (0.01)	0.08** (0.01)	0.08** (0.01)	0.07** (0.01)
Importer Institutions	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.05** (0.01)
Chinese Population Exporter	0.09** (0.01)	0.09** (0.01)	0.09** (0.01)	0.02 (0.03)	0.02 (0.03)
Chinese Population Importer	0.04** (0.01)	0.04** (0.01)	0.04** (0.01)	-0.01 (0.03)	-0.02 (0.03)
Year dummy 1990	-0.48** (0.04)	-0.47** (0.04)	-0.48** (0.04)	-0.47** (0.04)	-0.48** (0.04)
Year dummy 1995	-0.83** (0.03)	-0.83** (0.03)	-0.83** (0.03)	-0.84** (0.03)	-0.84** (0.03)
Price Level Exporter	-0.0014** (0.0004)	-0.0014** (0.0004)	-0.0015** (0.0004)	-0.0014** (0.0004)	-0.0014** (0.0004)
Price Level Importer	-0.0041** (0.0004)	-0.0041** (0.0004)	-0.0041** (0.0004)	-0.0041** (0.0004)	-0.0040** (0.0004)
Interaction language Chinese importer		0.02 (0.23)			-0.14 (0.24)
Interaction language Chinese exporter		0.11 (0.23)			-0.25 (0.24)
Interaction language institution importer			0.12* (0.05)		0.13** (0.05)
Interaction language Institution exporter			0.02 (0.05)		0.04 (0.05)
Interaction institution Chinese importer				0.01 (0.01)	0.02 (0.01)
Interaction institution Chinese exporter				0.02* (0.01)	0.02* (0.01)
Constant	-17.87** (0.18)	-17.87** (0.18)	-17.79** (0.18)	-17.81** (0.18)	-17.74** (0.18)
R^2	0.241	0.241	0.241	0.241	0.242
R^2 adjusted	0.240	0.240	0.240	0.241	0.241

First, we note that our general gravity controls, namely distance, trade agreements, prices, and year-dummies, all are statistically significant. Next, we note that with these regressions, we cannot identify with sufficient precision whether networks can substitute for a common language– none of the coefficients related to the interaction terms between language and networks are significant, and they also change sign as additional terms are included. However, most interestingly, we find a significant positive interaction term between networks and institutions for the exporter, but not for the importer. This indicates that networks and institutions act as complements, not substitutes in lowering international transaction costs and thus promoting trade. This, at first sight, suggests the opposite of previous findings (e.g. Greif 1993) which argue that networks substitute effectively for legal institutions. Note, however, that our empirical analysis is not capable of testing this hypothesis in general, since we cannot effectively insulate the legal services that networks provide from their information services. More precisely, high quality institutions increase the number of varieties of complex goods (Moenius and Berkowitz 2008), which makes information services of networks more valuable. At the same time, they bring about products of higher level of complexity, which thus may require more advanced legal services than those networks are able to provide. This automatically suggests that networks may still be able to substitute for legal institutions in those countries where legal quality is low. We will take this question on in the context of our robustness checks. In passing, we note that we also controlled for possible relationships between language and legal institutions, but view this strictly as a control and therefore do not attempt to explain the coefficients found. Summarizing this second set of results, we find no statistically significant interaction between language and networks, but a substantial complementarity between networks and institutions for the exporter. While this does not allow us to reject the hypothesis that networks substitute for legal institutions, this possible substitutive relationship is strongly dominated by the complementary relationship on average. We wonder whether these results are stable across all levels of language matching probability and quality of institutions. We turn to this question in the next section.

6. ROBUSTNESS-CHECKS AND DISCUSSION

Recall that we did not find a precisely measured coefficient on the interaction between language and networks. We will now attempt to shed more light on this issue. First, we replaced our language dummy with the language matching variable developed in chapter 2. However, our results remain unchanged. We then wondered whether our cut-off point for language-overlap is too demanding which leaves us with a possibly too small number of observations. We therefore repeat our analysis with different language cut-offs. The results are presented in table 3-6, which lists the cut-off matching probability for the language dummy, how many observations are affected, as well as the results of the estimation.

Table 3-6. Robustness-Check: Different Cut-Offs for Language Variable.

Cut-off Lang. Matching Probability >	0.8	0.6	0.4	0.2	0.1	0.05	0.01	0
N of Obs. where Lang. Dummy ==1	493	673	705	762	793	979	1513	6275
	Reg 6.1	**Reg 6.2**	**Reg 6.3**	**Reg 6.4**	**Reg 6.5**	**Reg 6.6**	**Reg 6.7**	**Reg 6.8**
Distance	-0.91** (0.02)	-0.91** (0.02)	-0.91** (0.02)	-0.90** (0.02)	-0.89** (0.02)	-0.89** (0.02)	-0.90** (0.02)	-0.90** (0.02)
FTA	0.23** (0.07)	0.25** (0.07)	0.24** (0.07)	0.23** (0.07)	0.22** (0.07)	0.23** (0.07)	0.23** (0.07)	0.26** (0.07)
Language Dummy	0.12 (0.23)	0.24 (0.20)	0.23 (0.19)	0.47** (0.18)	0.61** (0.18)	0.63** (0.17)	0.81** (0.15)	0.82** (0.10)
Exporter Institutions	0.08** (0.01)	0.08** (0.01)	0.08** (0.01)	0.08** (0.01)	0.09** (0.01)	0.09** (0.01)	0.09** (0.01)	0.11** (0.01)

Importer Institutions	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.08** (0.01)
Chinese Population Exporter	0.09** (0.01)	0.09** (0.01)	0.09** (0.01)	0.09** (0.01)	0.09** (0.01)	0.09** (0.01)	0.09** (0.01)	0.10** (0.01)
Chinese Population Importer	0.04** (0.01)	0.05** (0.01)	0.05** (0.01)	0.05** (0.01)	0.05** (0.01)	0.04** (0.01)	0.05** (0.01)	0.06** (0.01)
Year Dummy 1990	-0.48** (0.04)	-0.48** (0.04)	-0.48** (0.04)	-0.48** (0.04)	-0.47** (0.04)	-0.47** (0.04)	-0.46** (0.04)	-0.46** (0.04)
Year Dummy 1995	-0.83** (0.03)	-0.83** (0.03)	-0.83** (0.03)	-0.83** (0.03)	-0.83** (0.03)	-0.82** (0.03)	-0.81** (0.03)	-0.80** (0.03)
Price Level Exporter	-0.0014** (0.0004)	-0.0014** (0.0004)	-0.0013** (0.0004)	-0.0014** (0.0004)	-0.0014** (0.0004)	-0.0014** (0.0004)	-0.0017** (0.0004)	-0.0018** (0.0004)
Price Level Importer	-0.0040** (0.0004)	-0.0040** (0.0004)	-0.0040** (0.0004)	-0.0040** (0.0004)	-0.0041** (0.0004)	-0.0041** (0.0004)	-0.0044** (0.0004)	-0.0045** (0.0004)
Interaction language Chinese importer	-0.12 (0.24)	-0.38* (0.19)	-0.44** (0.18)	-0.40* (0.17)	-0.33 (0.17)	-0.21* (0.10)	-0.09 (0.07)	-0.05 (0.03)
Interaction language Chinese exporter	-0.23 (0.24)	-0.43* (0.19)	-0.51** (0.18)	-0.49** (0.19)	-0.41** (0.17)	-0.50** (0.10)	-0.17* (0.07)	-0.02 (0.03)
Interaction language institution importer	0.13* (0.05)	0.09* (0.04)	0.08* (0.04)	0.06 (0.04)	0.04 (0.04)	0.03 (0.04)	0.01 (0.03)	-0.06** (0.02)
Interaction language Institution exporter	0.03 (0.05)	0.07 (0.04)	0.08 (0.04)	0.03 (0.04)	0.00 (0.04)	0.00 (0.04)	-0.08** (0.03)	-0.08 (0.02)
Constant	-17.80** (0.18)	-17.86** (0.18)	-17.88** (0.18)	-17.98** (0.18)	-18.03** (0.18)	-18.08** (0.18)	-17.98** (0.18)	-18.18** (0.19)
R2	0.241	0.245	0.245	0.245	0.245	0.246	0.244	0.243
R2 adjusted	0.240	0.244	0.244	0.244	0.244	0.245	0.244	0.242

We are most interested in the interaction term between the language dummy and our network variables. We observe a consistent pattern of negative coefficients. These are statistically significant for most cut-off values, except for cut-off at 0.8 and 0. Before we even attempt to interpret these results, we would like to emphasize again that these estimates are still based on quite small numbers of observations. Nevertheless, they do indicate that language and networks can be substitutes. For country-pairs that do not share a language, networks always have a positive effect on trade. As the language similarity increases starting from zero, networks' effect on trade is taken over by the effect of language similarity, and their substitutive relationship disappears when the two countries have very high language similarities. We cautiously conclude that – all else equal – a shared language may render networks as ineffective.

Next, we reexamine the somewhat surprising result that networks and legal institutions are complements, not substitutes. We employ a similar method as in the case of the language variables. For this, we identify cut-off levels for the quality of legal institutions as described in the data-section. We choose cut-off levels from 1.5 to 4 and see whether networks have a higher effect in countries with weak legal environments. We restrict ourselves to cases where institutions are weak in both the exporting and importing country. The results are presented in table 3-7.

Table 3-7. Robustness-Check: Are Networks More Effective in Weak Institutional Environments?

cut-off >	1.5	2	2.5	3	3.5	4
count both inst weak ==1	149	624	640	1560	1720	3318
	Reg 7.1	**Reg 7.2**	**Reg 7.3**	**Reg 7.4**	**Reg 7.5**	**Reg 7.6**
Distance	-0.91** (0.02)	-0.91** (0.02)	-0.91** (0.02)	-0.91** (0.02)	-0.91** (0.02)	-0.92** (0.02)
FTA	0.24** (0.07)	0.24** (0.07)	0.24** (0.07)	0.25** (0.07)	0.27** (0.07)	0.31** (0.07)
Language Dummy	0.65** (0.07)	0.66** (0.07)	0.66** (0.07)	0.65** (0.07)	0.65** (0.07)	0.70** (0.07)
Exporter Institutions	0.08** (0.01)	0.08** (0.01)	0.08** (0.01)	0.06** (0.01)	0.05** (0.01)	0.02 (0.01)
Importer Institutions	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.06** (0.01)	0.03* (0.01)
Chinese Population Exporter	0.09** (0.01)	0.10** (0.01)	0.10** (0.01)	0.09** (0.01)	0.09** (0.01)	0.10** (0.01)
Chinese Population Importer	0.04** (0.01)	0.05** (0.01)	0.05** (0.01)	0.05** (0.01)	0.05** (0.01)	0.05** (0.01)
Year Dummy 1990	-0.47** (0.04)	-0.47** (0.04)	-0.47** (0.04)	-0.48** (0.04)	-0.48** (0.04)	-0.47** (0.04)
Year Dummy 1995	-0.83** (0.03)	-0.83** (0.03)	-0.83** (0.03)	-0.83** (0.03)	-0.82** (0.03)	-0.81** (0.03)
Price Level Exporter	-0.0014** (0.0004)	-0.0014** (0.0004)	-0.0014** (0.0004)	-0.0012** (0.0004)	-0.0012** (0.0004)	-0.0014** (0.0005)
Price Level Importer	-0.0040** (0.0004)	-0.0040** (0.0004)	-0.0041** (0.0004)	-0.0043** (0.0004)	-0.0043** (0.0004)	-0.0047** (0.0005)
Weak Institution Dummy	2.15** (0.83)	-0.65* (0.26)	-0.56* (0.26)	-0.06 (0.16)	-0.12 (0.15)	-0.44** (0.13)
Interaction Weak Institution Dummy Institution Exporter	-0.88 (0.50)	0.45** (0.12)	0.38** (0.12)	0.19** (0.05)	0.14** (0.05)	0.11** (0.03)
Interaction Weak Institution Dummy Institution Importer	-1.33* (0.61)	0.06 (0.12)	0.05 (0.12)	-0.22** (0.05)	-0.18** (0.05)	-0.05* (0.03)
Interaction Weak Institution Dummy Chinese Exporter	-0.76 (0.44)	-0.17** (0.04)	-0.16** (0.04)	-0.02 (0.03)	-0.01 (0.03)	-0.04 (0.02)
Interaction Weak Institution Dummy Chinese Importer	-0.19 (0.52)	-0.10** (0.04)	-0.10** (0.04)	-0.02 (0.03)	-0.03 (0.03)	-0.02 (0.02)
Constant	-17.85**	-17.85**	-17.84**	-17.71**	-17.60**	-17.28**

	(0.18)	(0.18)	(0.18)	(0.19)	(0.19)	(0.20)
R^2	0.242	0.243	0.243	0.243	0.243	0.245
R^2 adjusted	0.241	0.242	0.242	0.242	0.243	0.244

To our surprise, not even at the lowest level of legal quality did we find an indication that networks had a higher effect on trade when institutions are weak – to the contrary, their effect was measurably weaker and likely zero for all of the cut-off samples analyzed. If networks have a zero measurable effect in weak legal environments, this implies that neither legal services, whether basic or advanced, nor information services are of measurable value to increase trade in such environments, which rejects the hypothesis that networks can substitute for lack of quality legal institutions in international transactions. Note that we can only identify international transaction cost effects of networks. Consequently, there might still be a possibility that networks have a positive effect on national transaction costs, or possibly even have a positive effect on trade in differentiated goods exports in this country. Due to the fact that countries with low quality legal institutions generally only have a small differentiated goods sector, we may not be able to identify the positive effect of networks due to its small share in overall trade. However, these possible effects are beyond the scope of our study and we can confidently reject the hypothesis that networks have a positive effect on trade in countries with weak legal institutions on average.

One final step is missing in order to complete the robustness analysis of our results. Since we employ a modified version of the AvW model that has previously not been used, it is well in place to investigate the influence of the price variables and time dummies that this estimation technique calls for. To do so, we re-estimate our baseline equation (3-6), but include prices and year-dummies in a step-wise manner. The results are presented in table 3-8.

Table 3-8. The Influence of the Correct Price Specification on Other Parameter Estimates

	without	**w year-d**	**w prices**	**w y and p**
Distance	-0.92** (0.02)	-0.91** (0.02)	-0.92** (0.02)	-0.91** (0.02)
FTA	0.20** (0.07)	0.13 (0.07)	0.36** (0.07)	0.24** (0.07)
Language Dummy	0.64** (0.07)	0.70** (0.07)	0.57** (0.07)	0.65** (0.07)
Exporter Institutions	0.02* (0.01)	0.07** (0.01)	0.04** (0.01)	0.08** (0.01)
Importer Institutions	-0.04** (0.01)	0.01 (0.01)	0.02 (0.01)	0.06** (0.01)
Chinese Population Exporter	0.08** (0.01)	0.10** (0.01)	0.07** (0.01)	0.09** (0.01)
Chinese Population Importer	0.05** (0.01)	0.06** (0.01)	0.03** (0.01)	0.04** (0.01)
Year Dummy 1990		-0.58** (0.03)		-0.48** (0.04)
Year Dummy 1995		-0.85** (0.03)		-0.83** (0.03)
Price Level Exporter			-0.002** (0.000)	-0.001* (0.000)
Price Level Importer			-0.005** (0.000)	-0.004** (0.000)
Constant	-17.93** (0.18)	-17.89** (0.18)	-17.80** (0.18)	-17.87** (0.18)

We find that only some of our variables and controls are affected by the inclusion of prices and year-dummies: parameter estimates on language and networks almost do not react, while importer's institutions as well as trade agreements react substantially – from insignificant to strongly significant and easily changing parameter estimates by a factor 2 or more. While one may speculate whether those two groups of variables operate at different margins that influence trade, with only one of them directly responding to – or influencing – prices, we think that this clearly calls for more research in the future to find out which analysis requires the inclusion of prices (and multilateral resistances) and which may not. But a general requirement is clearly at least questioned by those results.

Thus, our analysis provides us with two substantial insights: common language and networks are substitutes for each other, while institutions and networks are actually complements. However, the substitutive relationship is somewhat sensitive to the chosen cut-off value of when we say that two countries share a common language, and it relies on a relatively small number of observations. However, too stringent requirements lead to an econometric inability to identify effects. This does not only call for more careful inspection of the language variables that have become standard use in gravity models, it calls for more careful analysis of variables that affect international transaction costs in general: different groups, products and environments may make more or less intensive use of the services such a variable may measure. This calls for more disaggregate analysis, which we intend to undertake in the future.

Our analysis also reminds us that any important variable that is missing from an econometric specification can cause omitted variable bias, not only price terms. The analysis above shows that this bias can be as large as the bias caused by the omission of price-terms. It also shows that not all estimated coefficients suffer from the omission of prices from the analysis. The McCallum (1995) results pointed at a high level of trade resistance from the sheer existence of a border, which was puzzling because there existed a common prior that borders should not have such a large effect. The solution led to the general requirement to include multilateral resistance terms or their equivalents, namely country dummies, into all gravity estimations. The lack of a common prior, however, should not distract us from finding – and including in our analysis – the factors that are important to control for, whether puzzling or not. It should also not lead to a general requirement to include certain controls, even if no omitted variable bias may be expected.

7. CONCLUSION

Ethnic networks like the overseas Chinese have been identified to provide a variety of services in international trade: from translation services and general information services, to legal services, their importance has been argued about by different authors. We unify those approaches and identify the relative importance of these effects by analyzing potential substitutes to those network services. We find that networks, language and institutions have significant effects on lowering international transaction costs, and their estimated effects are – on average – independent of whether they enter regressions jointly or separately. However, the effects of networks are not uniform: We find that a common shared language can potentially substitute for the presence of networks. Contrary to our initial expectations, we find that networks do not seem to substitute for legal services on average, not even in the weakest of all legal environments. Rather, they seem to be complementary to legal services provided by legal institutions, suggesting that information services and cooperation services seem to be of much higher importance, which can be most efficiently used by countries with good legal institutions that provide a large variety of complex goods. We interpret this as evidence for networks to provide some services that legal institution cannot completely substitute for, while some networks services can be substituted for by a common language. We also find that the new gravity controls play an important role in identifying the size of substitute effects, but not the effects of our network variables themselves. We emphasize that any variables that may cause omitted variable bias should be included in regression analysis, not only price variables.

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APPENDIX

Table 1-3. U.S Cities Where Price Data Were Collected

STATE	CITY (METRO AREA)
Alabama	Birmingham-Hoover AL Metro
Alabama	Cullman AL Micro
Alabama	Decatur AL Metro
Alabama	Dothan AL Metro
Alabama	Florence-Muscle Shoals AL Metro
Alabama	Gadsden AL Metro
Alabama	Huntsville AL Metro
Alabama	Mobile AL Metro
Alabama	Montgomery AL Metro
Alabama	Tuscaloosa AL Metro
Alaska	Anchorage AK Metro
Alaska	Fairbanks AK Metro
Alaska	Juneau AK Micro
Alaska	Kodiak AK Micro
Arizona	Flagstaff AZ Metro
Arizona	Ketchikan AK Micro
Arizona	Lake Havasu City-Kingman AZ Micro
Arizona	Phoenix-Mesa-Scottsdale AZ Metro
Arizona	Prescott AZ Metro
Arizona	Phoenix-Mesa-Scottsdale AZ Metro
Arizona	Tucson AZ Metro
Arizona	Yuma AZ Metro
Arkansas	Fayetteville-Springdale-Rogers AR-MO Metro
Arkansas	Fort Smith AR-OK Metro
Arkansas	Hot Springs AR Metro
Arkansas	Jonesboro AR Metro
Arkansas	Little Rock-North Little Rock AR Metro
California	Bakersfield CA Metro
California	Los Angeles-Long Beach-Glendale CA Metro Div.
California	Riverside-San Bernardino-Ontario CA Metro
California	Riverside-San Bernardino-Ontario CA Metro
California	Riverside-San Bernardino-Ontario CA Metro

California	Riverside-San Bernardino-Ontario CA Metro
California	San Diego-Carlsbad-San Marcos CA Metro
California	Visalia-Porterville CA Metro
Colorado	Colorado Springs CO Metro
Colorado	Denver-Aurora CO Metro
Colorado	Fort Collins-Loveland CO Metro
Colorado	Fort Collins-Loveland CO Metro
Colorado	Grand Junction CO Metro
Colorado	Pueblo CO Metro
Colorado	NonMetro US
Colorado	NonMetro US
Connecticut	Hartford-West Hartford-East Hartford CT Metro
Connecticut	New Haven-Milford CT Metro
Delaware	Dover DE Metro
Delaware	Wilmington DE-MD-NJ Metro Div.
DC	Washington-Arlington-Alexandria DC-VA-MD-WV Metro Div.
Florida	Jacksonville FL Metro
Florida	Miami-Miami Beach-Kendall FL Metro Div.
Florida	Orlando FL Metro
Florida	Tallahassee FL Metro
Florida	Tampa-St. Petersburg-Clearwater FL Metro
Florida	West Palm Beach-Boca Raton-Boynton Beach FL
Georgia	Americus GA Micro
Georgia	Atlanta-Sandy Springs-Marietta GA Metro
Georgia	Atlanta-Sandy Springs-Marietta GA Metro
Georgia	Atlanta-Sandy Springs-Marietta GA Metro
Georgia	Augusta-Richmond County GA-SC Metro
Georgia	Bainbridge GA Micro
Georgia	Columbus GA-AL Metro
Georgia	Douglas GA Micro
Georgia	LaGrange GA Micro
Georgia	Macon GA Metro
Georgia	Moultrie GA Micro
Georgia	Rome GA Metro
Georgia	Tifton GA Micro
Georgia	Valdosta GA Metro
Georgia	NonMetro US
Idaho	Boise City-Nampa ID Metro

Idaho	Idaho Falls ID Metro
Idaho	Pocatello ID Metro
Illinois	Bloomington-Normal IL Metro
Illinois	Champaign-Urbana IL Metro
Illinois	Chicago-Naperville-Joliet IL Metro Div.
Illinois	Chicago-Naperville-Joliet IL Metro Div.
Illinois	Chicago-Naperville-Joliet IL Metro Div.
Illinois	Danville IL Metro
Illinois	Davenport-Moline-Rock Island IA-IL
Illinois	Decatur IL Metro
Illinois	Freeport IL Micro
Illinois	Peoria IL Metro
Illinois	Quincy IL-MO Micro
Illinois	Rockford IL Metro
Illinois	Springfield IL Metro
Indiana	Anderson IN Metro
Indiana	Bloomington IN Metro
Indiana	Evansville IN-KY Metro
Indiana	Fort Wayne IN Metro
Indiana	Indianapolis IN Metro
Indiana	Michigan City-La Porte IN Metro
Indiana	Michigan City-La Porte IN Metro
Indiana	Muncie IN Metro
Indiana	Plymouth IN Micro
Indiana	Richmond IN Micro
Indiana	South Bend-Mishawaka IN-MI Metro
Indiana	Warsaw IN Micro
Iowa	Ames IA Metro
Iowa	Cedar Rapids IA Metro
Iowa	Des Moines IA Metro
Iowa	Dubuque IA Metro
Iowa	Fort Dodge IA Micro
Iowa	Mason City IA Micro
Iowa	Sioux City IA-NE-SD Metro
Iowa	Waterloo-Cedar Falls IA Metro
Kansas	Garden City KS Micro
Kansas	Lawrence KS Metro
Kansas	Manhattan KS Micro

Kansas	Salina KS Micro
Kentucky	Bowling Green KY Metro
Kentucky	Clarksville TN-KY Metro
Kentucky	Lexington-Fayette KY Metro
Kentucky	Louisville KY-IN Metro
Kentucky	Murray KY Micro
Kentucky	Owensboro KY Metro
Kentucky	Paducah KY-IL Micro
Kentucky	NonMetro US
Louisiana	Alexandria LA Metro
Louisiana	Baton Rouge LA Metro
Louisiana	Lake Charles LA Metro
Louisiana	Monroe LA Metro
Louisiana	New Orleans-Metairie-Kenner LA Metro
Maryland	Cumberland MD-WV Metro
Maryland	Hagerstown-Martinsburg MD-WV Metro
Maryland	Ocean Pines MD Micro
Massachusetts	Boston-Quincy MA Metro Div.
Michigan	Ann Arbor MI Metro
Michigan	Holland-Grand Haven MI Metro
Michigan	Lansing-East Lansing MI Metro
Michigan	Niles-Benton Harbor MI Metro
Michigan	Warren-Farmington Hills-Troy MI Metro Div.
Minnesota	Minneapolis-St. Paul-Bloomington MN-WI Metro
Minnesota	Minneapolis-St. Paul-Bloomington MN-WI Metro
Minnesota	Rochester MN Metro
Minnesota	St. Cloud MN Metro
Mississippi	Laurel MS Micro
Missouri	Columbia MO Metro
Missouri	Jefferson City MO Metro
Missouri	Joplin MO Metro
Missouri	Kansas City MO-KS Metro
Missouri	Kennett MO Micro
Missouri	Kirksville MO Micro
Missouri	Poplar Bluff MO Micro
Missouri	St. Joseph MO-KS Metro
Missouri	St. Louis MO-IL Metro
Missouri	St. Louis MO-IL Metro

Missouri	Springfield MO Metro
Missouri	NonMetro US
Montana	Billings MT Metro
Montana	Bozeman MT Micro
Montana	Great Falls MT Metro
Montana	Missoula MT Metro
Nebraska	Hastings NE Micro
Nebraska	Kearney NE Micro
Nebraska	Lincoln NE Metro
Nebraska	Omaha-Council Bluffs NE-IA Metro
Nevada	Carson City NV Metro
Nevada	Reno-Sparks NV Metro
New Hampshire	Manchester-Nashua NH Metro
New Mexico	Albuquerque NM Metro
New Mexico	Carlsbad-Artesia NM Micro
New Mexico	Clovis NM Micro
New Mexico	Farmington NM Metro
New Mexico	Hobbs NM Micro
New Mexico	Las Cruces NM Metro
New Mexico	Roswell NM Micro
New Mexico	Santa Fe NM Metro
New York	Albany-Schenectady-Troy NY Metro
New York	Binghamton NY Metro
New York	Glens Falls NY Metro
New York	Jamestown-Dunkirk-Fredonia NY Micro
New York	New York-White Plains-Wayne NY-NJ Metro Div.
New York	Rochester NY Metro
New York	Syracuse NY Metro
New York	Utica-Rome NY Metro
North Carolina	Burlington NC Metro
North Carolina	Charlotte-Gastonia-Concord NC-SC Metro
North Carolina	Charlotte-Gastonia-Concord NC-SC Metro
North Carolina	Fayetteville NC Metro
North Carolina	Goldsboro NC Metro
North Carolina	Greenville NC Metro
North Carolina	Hickory-Lenoir-Morganton NC Metro
North Carolina	Kill Devil Hills NC Micro
North Carolina	Raleigh-Cary NC Metro

North Carolina	Rockingham NC Micro
North Carolina	Statesville-Mooresville NC Micro
North Carolina	Winston-Salem NC Metro
North Carolina	NonMetro US
North Dakota	Fargo ND-MN Metro
North Dakota	Minot ND Micro
Ohio	Akron OH Metro
Ohio	Canton-Massillon OH Metro
Ohio	Cincinnati-Middletown OH-KY-IN Metro
Ohio	Cleveland-Elyria-Mentor OH Metro
Ohio	Dayton OH Metro
Ohio	Mansfield OH Metro
Ohio	Mount Vernon OH Micro
Ohio	Parkersburg-Marietta-Vienna WV-OH Metro
Ohio	Toledo OH Metro
Ohio	Youngstown-Warren-Boardman OH-PA Metro
Oklahoma	Ardmore OK Micro
Oklahoma	Bartlesville OK Micro
Oklahoma	Lawton OK Metro
Oklahoma	McAlester OK Micro
Oklahoma	Oklahoma City OK Metro
Oklahoma	Stillwater OK Micro
Oklahoma	Tulsa OK Metro
Oklahoma	NonMetro US
Oregon	Bend OR Metro
Oregon	Klamath Falls OR Micro
Oregon	Portland-Vancouver-Beaverton OR-WA Metro
Oregon	Salem OR Metro
Pennsylvania	Allentown-Bethlehem-Easton PA-NJ Metro
Pennsylvania	Erie PA Metro
Pennsylvania	Harrisburg-Carlisle PA Metro
Pennsylvania	Lancaster PA Metro
Pennsylvania	Philadelphia PA Metro Div.
Pennsylvania	Pittsburgh PA Metro
Pennsylvania	Scranton-Wilkes-Barre PA Metro
Pennsylvania	Williamsport PA Metro
Pennsylvania	York-Hanover PA Metro
Pennsylvania	York-Hanover PA Metro

Pennsylvania	Youngstown-Warren-Boardman OH-PA
South Carolina	Charleston-North Charleston SC Metro
South Carolina	Columbia SC Metro
South Carolina	Florence SC Metro
South Carolina	Greenville SC Metro
South Carolina	Myrtle Beach-Conway-North Myrtle Beach SC Metro
South Carolina	Spartanburg SC Metro
South Carolina	Sumter SC Metro
South Dakota	Sioux Falls SD Metro
South Dakota	Vermillion SD Micro
Tennessee	Chattanooga TN-GA Metro
Tennessee	Clarksville TN-KY Metro
Tennessee	Cleveland TN Metro
Tennessee	Dyersburg TN Micro
Tennessee	Jackson TN Metro
Tennessee	Johnson City TN Metro
Tennessee	Kingsport-Bristol-Bristol TN-VA Metro
Tennessee	Knoxville TN Metro
Tennessee	Memphis TN-MS-AR Metro
Tennessee	Morristown TN Metro
Tennessee	Nashville-Davidson-Murfreesboro TN Metro
Texas	Abilene TX Metro
Texas	Amarillo TX Metro
Texas	Austin-Round Rock TX Metro
Texas	Beaumont-Port Arthur TX Metro
Texas	Brownsville-Harlingen TX Metro
Texas	College Station-Bryan TX Metro
Texas	Corpus Christi TX Metro
Texas	Dallas-Plano-Irving TX Metro Div.
Texas	El Paso TX Metro
Texas	Fort Worth-Arlington TX Metro Div.
Texas	Fort Worth-Arlington TX Metro Div.
Texas	Houston-Sugar Land-Baytown TX Metro
Texas	Kerrville TX Micro
Texas	Killeen-Temple-Fort Hood TX Metro
Texas	Lubbock TX Metro
Texas	McAllen-Edinburg-Mission TX Metro
Texas	Midland TX Metro

Texas	Odessa TX Metro
Texas	San Antonio TX Metro
Texas	Tyler TX Metro
Texas	Waco TX Metro
Texas	Wichita Falls TX Metro
Utah	Cedar City UT Micro
Utah	Provo-Orem UT Metro
Utah	St. George UT Metro
Utah	Salt Lake City UT Metro
Vermont	Barre VT Micro
Virginia	Kingsport-Bristol-Bristol TN-VA Metro
Virginia	Lynchburg VA Metro
Virginia	Richmond VA Metro
Virginia	Roanoke VA Metro
Virginia	Virginia Beach-Norfolk-Newport News VA-NC Metro
Virginia	Washington-Arlington-Alexandria DC-VA-MD-WV Metro Div.
Washington	Bellingham WA Metro
Washington	Kennewick-Richland-Pasco WA Metro
Washington	Olympia WA Metro
Washington	Seattle-Bellevue-Everett WA Metro Div.
Washington	Spokane WA Metro
Washington	Tacoma WA Metro Div.
Washington	Wenatchee WA Metro
Washington	Yakima WA Metro
West Virginia	Charleston WV Metro
West Virginia	Hagerstown-Martinsburg MD-WV Metro
Wisconsin	Appleton WI Metro
Wisconsin	Eau Claire WI Metro
Wisconsin	Fond du Lac WI Metro
Wisconsin	Green Bay WI Metro
Wisconsin	Janesville WI Metro
Wisconsin	La Crosse WI-MN Metro
Wisconsin	Madison WI Metro
Wisconsin	Manitowoc WI Micro
Wisconsin	Marinette WI-MI Micro
Wisconsin	Milwaukee-Waukesha-West Allis WI Metro
Wisconsin	Stevens Point WI Micro
Wisconsin	Wausau WI Metro

Wisconsin	Wisconsin Rapids-Marshfield WI Micro
Wyoming	Casper WY Metro
Wyoming	Cheyenne WY Metro
Wyoming	Gillette WY Micro
Wyoming	Laramie WY Micro

Table 1-4. Canadian Cities Where Price Data Were Collected

PROVINCE	**CITY**
Newfoundland and Labrador	St. John's
Prince Edward Island	Charlottetown-Summerside
Nova Scotia	Halifax
New Brunswick	Saint John
Quebec	Montréal
Ontario	Ottawa
Ontario	Toronto
Manitoba	Winnipeg
Saskatchewan	Regina
Alberta	Edmonton
British Columbia	Vancouver

VITA

Wei Wu, born in China in 1977, attended Nankai University in 1994 and earned a bachelor of science in Electronics. After graduation, he worked in the main research center of Huawei Technologies. From 2004, he studied at the University of Missouri and was about to graduate in May 2009 as a fresh Ph.D. in Economics.