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Understanding Interstate Trade Patterns

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Understanding Interstate Trade Patterns

Hakan Yilmazkuday[†]

Abstract

This paper models and estimates bilateral trade patterns of U.S. states in a CES framework and identifies the elasticity of substitution across goods, elasticity of substitution across varieties of each good, and the good-specific elasticity of distance measures by using markup values obtained from the production side. Compared to empirical international trade literature, the elasticity of substitution estimates are lower across both goods and varieties, while the elasticity of distance estimates are higher. Although home-bias effects at the state level are significant, there is evidence for decreasing effects over time.

JEL Classification: F12, R12, R32

Key Words: Trade Patterns; Elasticity of Substitution; Elasticity of Distance; the United States

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1. Introduction

The elasticity of substitution and elasticity of distance are two key parameters used by policy makers to derive quantitative results in international or intranational trade, because the effects of a policy change are evaluated by converting policy changes into price effects through these parameters. Therefore, there is no question that the measurement of these parameters is of fundamental importance in economic modeling where they connect quantities to prices. In empirical trade studies, especially the famous and successful gravity models, usual subproducts of an empirical analysis are some measures of these elasticities; however, in a typical gravity model estimation, one cannot identify the elasticity of substitution (across goods and/or varieties) and the elasticity of distance at the same time. This paper proposes a new approach by considering markups in the production side to estimate the elasticity of substitution across goods, the elasticity of substitution across varieties of each good, and the good-specific elasticity of distance measures, all identified in the empirical analysis.

A monopolistic-competition model consisting of a finite number of regions and a finite number of goods is employed in a constant elasticity of substitution (CES) framework. Each region consumes all varieties of each good, while it produces only one variety of each good. On the consumer side, as is standard in a CES framework, bilateral trade of a variety of a good across any two regions depends on the relative price of the variety and total demand of the good in the destination (importer) region. Similarly, total imports of a good in a region depends on relative price of the good and total demand of all goods in the region. On the production side, having market power in the production of a variety of each good results in positive markups in each region. In equilibrium, markups at the good level are connected to good-specific elasticities of substitution at the good level.

We show that the simple CES framework is sufficient to estimate/calculate all structural parameters in the model when trade, distance, and markup measures are known. The estimated parameters correspond to: a) elasticity of substitution across varieties of a good, each produced in a different region; b) elasticity of substitution across goods, each consisting of different varieties; c) elasticity of distance, which governs good-specific trade costs; and d) heterogeneity of individual tastes, measuring geographic barriers and the so-called home-bias.

The key innovation is to bring in additional data for markups at the good level and use this to aid in identification of all types of elasticities mentioned above. The chain of logic is as follows: (1) Elasticities of substitution at the good level are estimated by markup data. (2) Elasticities of distance at the good level are identified through combining markups and bilateral trade estimates at the good level. (3) For each region, good-level source prices are calculated using markups and source fixed effects in the bilateral trade estimation. (4) For each destination, composite price indices and total imports are calculated at the good level. (5) Elasticity of substitution across goods is estimated using composite price indices and total imports.

In the related literature, the gravity models are popular mostly due to their empirical success.¹ When the theoretical background of gravity type studies is considered, Anderson (1979) is the first one to model gravity equations. The main motivation behind Anderson's (1979) gravity model is the assumption that each region is specialized in the production of only one good.² Despite its empirical success, as Anderson and van Wincoop (2003) point out, the specialization assumption suppresses finer classifications of goods, and thus makes the model useless in explaining the trade data at the disaggregate level. Another deficiency of Anderson's (1979) gravity model is the lack

¹Deardorff (1984) reviews the earlier gravity literature. For recent applications, see Wei (1996), Jensen (2000),

Rauch (1999), Hummels and Levinsohn (1995), and Evenett and Keller (2002).

 $2 \text{In the Appendix of his paper, Anderson (1979) extends his basic model to a model in which multiple goods are.}$ produced in each region.

of a production side. Bergstrand (1985) bridges this gap by introducing a one-factor, one-industry, N -country general equilibrium model in which the production side is considered.³

The main deficiency of the gravity models is that they cannot identify elasticity of substitution across varieties of each good, elasticity of substitution across goods, and the elasticity of distance at the same time, which may lead to biased empirical results in a policy analysis. Moreover, none of the gravity papers mentioned above empirically deal with the trade patterns within a country comprehensively, although, according to the U.S. trade data, intranational trade volume is more than 6 times international trade volume, on average, between 1993 and $2007⁴$ Recently, Wolf (2000), Hillberry and Hummels (2002, 2003), and Millimet and Osang (2007) bridge this gap by analyzing the interstate trade patterns within the U.S. However, these studies use aggregate-level (i.e., total-bilateral) trade data and cannot capture good-specific policy implications. Besides, these intranational studies also use gravity frameworks, and thus, they cannot distinguish between different elasticities, as mentioned above, either. On the other hand, this paper uses good-level bilateral trade data within the U.S. and can distinguish between such elasticities crucial to U.S. policy makers.

³Also see Suga (2007) for a monopolistic-competition model of international trade with external economies of scale, Lopez et al. (2006) for an analysis on home-bias on U.S. imports of processed food products, and Gallaway et al. (2003) for an empirical study to estimate short-run and long-run industry-level U.S. Armington elasticities.

⁴Intranational trade data are the sum of all state-level imports and exports volume obtained from Commoditiy

Flow Survey compiled by the Bureau of Transportation Statistics for the U.S. over the years of 1993, 1997, 2002, 2007. International trade data are the sum of international exports and imports volume obtained from U.S. Census Bureau, Foreign Trade Division, for the same years. The long-run ratio of intranational to international trade volume (which is 6.42) is calculated by taking the average across year-specific ratios which are 8.62 in 1993, 4.06 in 1997, 7.06 in 2002, and 5.94 in 2007.

2. The Model

An economy consisting of a finite number of regions and a finite number of goods is modeled. Each region consumes all varieties of all goods but produces only one variety of each good. To focus on trade implications of the model, in many instances, the irrelevant details are skipped. Each good is denoted by $j = 1, ..., J$. Each variety is denoted by i which is also the notation for the region producing that variety. The analysis is made for a typical region r , and the total number of regions is R. In the model, generally speaking, $H_{d,s}^j$ stands for variable H where d is related to destination and s is related to source in terms of good j; H_r^j stands for variable H in region r in terms of good j; H_r stands for the variable H in region r; H^j stands for the variable H in terms of good j.

2.1. Individuals and Firms

The representative agent in region r maximizes utility of a composite index of goods given by:

$$
C_r \equiv \left(\sum_j \left(\gamma_r^j\right)^{\frac{1}{\varepsilon}} \left(C_r^j\right)^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}
$$

where C_r^j is given by:

$$
C_{r}^{j} \equiv \left(\sum_{i} \left(\theta_{r,i}^{j}\right)^{\frac{1}{\eta^{j}}} \left(C_{r,i}^{j}\right)^{\frac{\eta^{j}-1}{\eta^{j}}} \right)^{\frac{\eta^{j}}{\eta^{j}-1}}
$$

where $C_{r,i}^j$ is the variety i of good j imported from region i; $\varepsilon > 0$ is the elasticity of substitution across goods; $\eta^j > 1$ is the elasticity of substitution across varieties of good j; γ_r^j and $\theta_{r,i}^j$ are taste parameters.

The optimal allocation of any given expenditure within each variety of goods yields the following demand functions:

$$
C_{r,i}^{j} = \theta_{r,i}^{j} \left(\frac{P_{r,i}^{j}}{P_r^{j}}\right)^{-\eta^{j}} C_r^{j}
$$
 (2.1)

and

$$
C_r^j = \gamma_r^j \left(\frac{P_r^j}{P_r}\right)^{-\epsilon} C_r \tag{2.2}
$$

where

$$
P_r^j \equiv \left(\sum_i \theta_{r,i}^j \left(P_{r,i}^j\right)^{1-\eta^j}\right)^{\frac{1}{1-\eta^j}}
$$
(2.3)

is the price index of good j (which is composed of different varieties), and

$$
P_r \equiv \left(\sum_j \gamma_r^j \left(P_r^j\right)^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}
$$
\n(2.4)

is the cost of living index in region r . Last four equations imply that the total value of imports of region r in terms of good j can be written as follows:

$$
P_r^j C_r^j = \sum_i P_{r,i}^j C_{r,i}^j \tag{2.5}
$$

and that the total expenditure in region r for all goods can be written as follows:

$$
P_r C_r = \sum_j P^j_r C^j_r
$$

Region r produces variety r of good j (for all j) with the following profit maximization problem:

$$
\max_{P_{r,r}^j} Y_r^j \left[P_{r,r}^j - Z_r^j \right]
$$

subject to

$$
P_{r,r}^j Y_r^j = \sum_i P_{i,r}^j C_{i,r}^j
$$

where Y_r^j is the level of output for good j in region r, $P_{r,r}^j$ is the factory-gate price of good j in region r, Z_r^j is the marginal cost of production of good j in region r (of which details are irrelevant for the empirical analysis of this paper), $P_{i,r}^j C_{i,r}^j$ is the value of exports of good j of region r to region *i* (i.e., the symmetric version of Equation 2.1 multiplied by $P_{i,r}^j$). The first order condition for this problem is as follows:⁵

$$
Y_r^j \left[1 - \frac{\eta^j}{P_{r,r}^j} \left(P_{r,r}^j - Z_r^j\right)\right] = 0
$$

which implies that:

$$
P_{r,r}^j = \left(\frac{\eta^j}{\eta^j - 1}\right) Z_r^j
$$

where $\frac{\eta^j}{n^j-1}$ $\frac{\eta^j}{\eta^j-1}$ represents a good-specific (gross) markup. Under the assumption of constant-returnsto-scale production function, one can also write:

$$
\underbrace{Y_r^j P_{r,r}^j}_{\text{Total Revenue}} = \underbrace{\left(\frac{\eta^j}{\eta^j - 1}\right)}_{\substack{Markup\\ \text{Markup}}} \underbrace{Y_r^j Z_r^j}_{\text{Total Cost}}
$$

which is a relation between total revenue, total costs, and markups. If we take the sum across regions (i.e., across r) in both sides, we obtain:

$$
\left(\frac{\eta^j}{\eta^j - 1}\right) = \frac{\sum_r Y_r^j P_{r,r}^j}{\sum_r Y_r^j Z_r^j}
$$
\n(2.6)

which is a useful expression to estimate good-specific (gross) markups when data are available for the sum of total revenues and total costs in all regions at the good level.

2.2. Implications for Trade

Trade is subject to "iceberg-melting" trade costs across regions:

$$
P_{r,i}^{j} = P_{i,i}^{j} \tau_{r,i}^{j}
$$

= $P_{i,i}^{j} (D_{r,i}^{j})^{\delta^{j}}$ (2.7)

where $P_{r,i}^{j}$ is the price of variety i of good j in region r (i.e., the destination), $P_{i,i}^{j}$ is the price of variety *i* of good *j* in region *i* (i.e., the source), $\tau_{r,i}^j$ represents gross trade costs, $D_{r,i}^j$ is the distance

⁵Notice that the producer takes the composite consumption index of good j (i.e., C_r^j 's), and the composite price index of good j (i.e., P_r^j 's) in each region as given in the optimization problem, because the producer is assumed to be too small to have an effect on these aggregate-level variables.

of shipment for good j from region i to region r, and, finally, $\delta^j > 0$ is good-specific elasticity of distance. Approximation of $\tau_{r,i}^j$'s with $(D_{r,i}^j)^{\delta^j}$'s in the second line is a common practice to connect trade costs to distance, especially in the absence of an international border as in this paper (see Anderson and van Wincoop, 2004).

According to Equations 2.1 and 2.7, an expression for the value of bilateral trade, measured at the source, can be obtained at the good level:

$$
X_{r,i}^{j} = \theta_{r,i}^{j} (P_{i,i}^{j})^{1-\eta^{j}} ((P_{r}^{j})^{\eta^{j}} C_{r}^{j}) ((D_{r,i}^{j})^{-\delta^{j}\eta^{j}})
$$
\n(2.8)

where $X_{r,i}^j = P_{i,i}^j C_{r,i}^j$ is the value of eXports of region i to region r in terms of good j measured in region i (i.e., the source). Equation 2.8 suggests that bilateral trade between regions i and r is negatively affected by source prices and distance (because $\eta^j > 1$ and $\delta^j > 0$), while it is positively a§ected by total demand at the destination.

Now, consider the following expression:

$$
M_r^j = \gamma_r^j \left(\frac{P_r^j}{P_r}\right)^{1-\varepsilon} P_r C_r \tag{2.9}
$$

which is just another representation of Equation 2.1 where $M_r^j = P_r^j C_r^j$ represents the value of total iMports of region r in terms of good j measured in region r (i.e., the destination). When the value of exports measured at the source are known at the variety level (i.e., when $X_{r,i}^j$'s are known), the left hand side of Equation 2.9 can be calculated (through Equations 2.5, 2.7, and 2.8) as follows:

$$
M_r^j = \sum_i X_{r,i}^j \left(D_{r,i}^j \right)^{\delta^j}
$$
 (2.10)

which suggests through Equation 2.8 that total imports of a region depends on the geographical location (i.e., remoteness) of the region (due to trade costs) and source prices in all regions.

3. Data

For the bilateral trade analysis, state-level Commodity Flow Survey (CFS) data obtained from the Bureau of Transportation Statistics for the United States for the year 2007 are used. CFS depicts both source and destination states for the value of shipments (i.e., exports) that are measured at the source (i.e., $X_{r,i}^j$'s) together with the average distance of shipment *observed* between these states at the good level (i.e., $D_{r,i}^j$'s). Shipment values and distance measures within the same state (i.e., $X_{r,r}^j$'s and $D_{r,r}^j$'s) are also provided. This is a perfect match to test the model of this paper, especially through Equation 2.8. A typical sample from CFS data is the value and average shipment distance of Alcoholic Beverages (of which SCTG code is 8) from New York to California. In CFS, shipments traversing the U.S. from a foreign location to another foreign location (e.g., from Canada to Mexico) are not included.⁶ CFS captures data on shipments originating from select types of business establishments (102,369 establishments out of 753,699) located in all states of the U.S.; however, due to data availability, Alaska, District of Columbia and Hawaii are excluded. Although there are not any zero-trade flows in CFS in 2007, CFS does not publish some of the trade data, since they do not meet publication standards due to high sampling variability or poor response quality. In this paper, such data are treated as missing observations, and they are simply ignored in the empirical analysis, because any attempt to approximate or remedy these observations may result in biased empirical results. The sample size for bilateral trade of each good will be provided during the empirical analysis, below.

The disaggregated-level exports data cover 2-digit Standard Classification of Transported Goods (SCTG) commodities. SCTG codes, good descriptions, and descriptive statistics for the value of

⁶Shipments that are shipped through a foreign territory with both the origin and destination in the U.S. are included in the CFS data. The mileages calculated for these shipments exclude the international segments (e.g., shipments from New York to Michigan through Canada do not include any mileages for Canada).

shipments are given in Table 1. There are 38 good categories in Table 1 where, for each good, descriptive statistics have been calculated after pooling the bilateral value of shipments for all source and destination states. As is evident, "Electronic & other electrical equipment & components & o¢ ce equipment" has the highest total value of shipments, while "Calcareous monumental and building stone" has the lowest total value of shipments; mean and median values are also in line with total values of shipments. The minimum value of bilateral trade across states for each good is about 1 million U.S. dollars, while the maximum value ranges between \$451 million and \$98,409 million. Although standard deviation of bilateral trade across states differs across goods, the coefficients of variation, which control the scale effects in the standard deviation, are close to each other (i.e., the regional distributions of bilateral trade are similar across goods); exceptions of high coefficients of variation are "Coal and petroleum products, nec" (for which California and Texas are main suppliers) and "Basic chemicals" (for which Louisiana and Texas are main suppliers).

Descriptive statistics for the shipping distances are given in Table 2. The total miles of shipment within the U.S. range between 35 thousand and 1.7 million miles across goods. Mean and median miles of shipment, on average, are about 800 miles, which corresponds to a typical shipping distance between any two states. Minimum shipping distances are, on average, about 15 miles, mostly representing shipments within the same state, while maximum shipping distances are, on average, about 3,145 miles. Both standard deviation and coefficient of variation measures are similar, indicating similar distributions of bilateral shipping distances across goods.

According to Equation 2.6, gross markups at the good level are calculated/estimated using the total cost and total revenue in the production of each good at the national level (i.e., for the U.S.). The data for total cost and total revenue obtained from the U.S. Census Bureau for 2007 are available for industries classified according to the North American Industrial Classification System (NAICS), while CFS trade data are classified according to SCTG; a mapping between NAICS

and SCTG is provided in Table 3. Gross markup for each individual NAICS code in Table 3 is calculated, and their average is taken within each row to calculate the corresponding markup for SCTG code/good. Using the definition of gross markups (i.e., $\eta^{j}/(\eta^{j}-1)$'s), the elasticities of substitution across varieties of each SCTG good (i.e., η^j 's) are calculated; they are depicted in the last row of Table 3. As is evident, η^{j} 's range between 1.61 and 5.99 with an average value of 3.01; therefore, the gross markups range between 1.20 and 2.65 with an average value of 1.50. Since the intranational studies within the U.S. such as Wolf (2000), Hillberry and Hummels (2002, 2003), and Millimet and Osang (2007) use gravity equations, they cannot estimate for the elasticity of substitution and the elasticity of distance at the same time, so the elasticities of substitution across goods in this paper are compared with the results in empirical international trade literature. It is found that the estimates of this paper for the elasticity of substitution are lower on average. In particular, Hummelís (2001) estimates range between 4.79 and 8.26, the estimates of Head and Ries (2001) range between 7.9 and 11.4, the estimate of Baier and Bergstrand (2001) is about 6.4, Harrigan's (1996) estimates range from 5 to 10, Feenstra's (1994) estimates range from 3 to 8.4, the estimate by Eaton and Kortum (2002) is about 9.28, the estimates by Romalis (2007) range between 6.2 and 10.9, the (mean) estimates of Broda and Weinstein (2006) range between 4 and 17.3, and the estimates of Simonovska and Waugh (2011) range between 3.47 and 5.42.

4. Estimation Methodology

If trade data were measured at the destination (rather than at the source as in this paper), it would be possible to estimate/identify elasticity of distance (i.e., δ^{j} s), elasticity of substitution across varieties of each good (i.e., η^j 's), and the elasticity of substitution across goods (i.e., ε) through using two estimations, one at the variety level (i.e., Equation 2.8) and one at the good level (i.e., Equation 2.9). However, having the value of trade measured at the source requires the use of the model and a two-step estimation process to connect the value of trade at the source to the value measured at the destination; a two-step estimation process allows us to distinguish between δ^{j} 's, η^{j} 's and ε . In the first step, the empirical power of the model is tested for bilateral trade at the variety level (i.e., Equation 2.8), and estimates of the multiplication $\eta^j \delta^j$ is obtained. Using Equation 2.6 and production data at the industry level for the U.S., the elasticity of substitution across varieties of each good (i.e., η^j 's) are obtained, therefore good specific distance elasticities (i.e., δ^{j} 's), together with source prices at the variety level (i.e., $P_{r,r}^{j}$'s), are identified; these are used to obtain good-specific price indices (i.e., P_r^j 's) according to Equations 2.3 and 2.7. Second, the empirical power of the model is tested for total imports of a region (i.e., the value of imports of all varieties) at the good level, and the elasticity of substitution across goods (i.e., ε) is estimated.

4.1. Estimation of Bilateral Trade at the Good Level

Taking the log of both sides in Equation 2.8 results in the following log-linear expression for the bilateral good-level trade values:

$$
\underbrace{\log(X_{r,i}^j)}_{\text{Value of Bilateral Trade}} = \underbrace{\log((P_{i,i}^j)^{1-\eta^j})}_{\text{Source Effects}} + \underbrace{\log((P_r^j)^{\eta^j} C_r^j)}_{\text{Destination Effects}} - \underbrace{\delta^j \eta^j \log(D_{r,i}^j)}_{\text{Trade Costs}} + \underbrace{\log(\theta_{r,i}^j)}_{\text{Residuals}}
$$
(4.1)

where value of trade is measured at the source (to be consistent with the data) and estimation can be achieved for each good separately, because all the right-hand-side variables are good specific. As is evident, when the estimation is achieved at the good level, the source effects will correspond to log $((P_{i,i}^j)^{1-\eta^j})$, the destination effects will correspond to log $((P_i^j)^{\eta^j} C_r^j)$, trade costs will be measured by $\log \left(\left(D_{r,i}^{j}\right)^{-\delta^{j}\eta^{j}}\right)$, and the log of taste parameters log $\left(\theta_{r,i}^{j}\right)$ will correspond to residuals. When Ordinary Least Squares (OLS) is used as an estimation methodology, employing taste parameters as residuals brings two restrictions both of which are consistent with the model: (i) the

sum of log $(\theta_{r,i}^j)$'s is zero (i.e., the multiplication of $(\theta_{r,i}^j)$'s is one); (ii) log $(\theta_{r,i}^j)$'s are orthogonal to trade costs, source effects, or destination effects (i.e., taste parameters will capture the pattern of trade that cannot be explained by trade costs, source effects, or destination effects). Such a strategy is not new to this paper: Hillberry et al. (2005) also use taste parameters as model residuals and show that models rely heavily on these parameters to explain the pattern of trade. In this context, the analysis of this paper will also shed light on the role of these taste parameters through simply investigating the explanatory power of regressions.

4.2. Estimation of Total Imports at the Good Level

According to Equation 4.1, when $D_{r,i}^j$ and η^j are known for all i, r, j (which is the case in this paper as explained in the data section), $P_{i,i}^j$'s and δ^j 's can be identified for all i and j through estimated source effects and trade costs, respectively, which can be put together to construct the right hand side of Equation 2.3:

$$
P_r^j \equiv \left(\sum_i \theta_{r,i}^j \left(P_{i,i}^j \left(D_{r,i}^j\right)^{\delta^j}\right)^{1-\eta^j}\right)^{\frac{1}{1-\eta^j}}
$$
(4.2)

where we have used Equation 2.7 to connect source prices to destination prices and estimated residuals of Equation 4.1 to calculate $\theta_{r,i}^j$'s.

Now, consider the log version of Equation 2.9 that represents log value of total imports of region r in terms of good j measured in region r :

$$
\underbrace{\log\left(M_r^j\right)}_{\text{Equation 2.10}} = (1 - \varepsilon) \underbrace{\log\left(P_r^j\right)}_{\text{Equation 4.2}} + \underbrace{\log\left(\left(P_r\right)^{\varepsilon} C_r\right)}_{\text{Resional Effects}} + \underbrace{\log \gamma_r^j}_{\text{Residuals}} \tag{4.3}
$$

where the left hand side (i.e., M_r^j 's) can be calculated using bilateral trade (i.e., $X_{r,i}^j$'s), distance (i.e., $D_{r,i}^j$'s), and estimated elasticities of distance (i.e., δ^j 's) through Equation 2.10, and the first right hand side variable, which is both good and region specific, is calculated through Equation 4.2.

This is a useful expression to estimate the elasticity of substitution across goods (i.e., ε). Although Equation 4.1 can be estimated for each good separately, Equation 4.3 can only be estimated for the pooled sample due to regional effects (i.e., $\log((P_r)^{\varepsilon} C_r)$'s) that are common across all goods.

Since P_r^j 's are generated using estimated parameters and predicted residuals from a prior regression (i.e., Equation 4.1), there is a generated regressor problem (Pagan, 1984); i.e., the OLS standard errors are invalid. Following Efron and Tibshirani (1993), we employ bootstrap techniques to obtain standard errors that explicitly take into account the presence of generated regressors. In particular, for each bootstrap b , (i) we resample (with replacement) the bilateral good-level trade values by using the fitted values and residuals in Equation 4.1, (ii) estimate Equation 4.1 with the resampled left hand side, (iii) use the estimated parameters and predicted residuals from this regression to generate $P_r^j(b)$'s by using Equation 4.2, and (iv) estimate Equation 4.3 using $P_r^j(b)$'s to estimate $\varepsilon(b)$. We repeat this exercise 1000 times and compute the bootstrap standard error of ε as follows:

$$
\text{S.E.}(\varepsilon) = \left(\frac{1}{1000} \sum_{b=1}^{1000} (\varepsilon(b) - \varepsilon)^2\right)^{\frac{1}{2}}
$$

where ε is the original OLS coefficient estimated by Equation 4.3.

5. Empirical Results

Estimation results for bilateral trade at the good level (i.e., Equation 4.1) are given in Table 4. As is evident, the coefficients in front of distance (i.e., $\delta^j \eta^j$'s) are highly significant in all but one estimations, and they range between 0.67 and 2.09 with an average of 1.25; "Transportation Equipment" has the lowest value, while "Mixed Freight" has the highest value followed by "Pharmaceutical Products" and "Wood Products". Compared to the aggregate-level estimates by gravity equations in the literature (i.e., studies focusing on bilateral trade across U.S. states for the

sum of all goods), $\delta^j \eta^j$ estimates are mostly higher on average. In particular, by using CFS trade data in 1993 and the minimum driving distance in miles between the largest city in each state, Wolf (2000) estimates $\delta^j \eta^j$'s ranging between 0.75 and 1.02; using CFS trade data in 1997 and the actual shipping distances, Hillberry and Hummels (2003) estimate $\delta^j \eta^j$'s ranging between 0.88 and 1.06; using CFS trade data in 1993 and 1997 and distance measure of Wolf (2000), Millimet and Osang (2007) estimate $\delta^j \eta^j$'s ranging between 0.71 and 1.05 in their baseline gravity regressions.

Substituting the elasticity of substitution across varieties (i.e., η^j 's) into the estimated $\delta^j \eta^j$'s results in identifying the elasticities of distance, δ^j 's. Such implied δ^j 's are depicted in Table 4. As is evident, δ^{j} 's range between 0.18 (for "Log and Other Wood in the Rough") and 0.84 (for "Pharmaceutical Products") with an average of 0.45. The differences across goods are mostly attributable to modes of transportation: e.g., according to the U.S. level report of CFS, 30 percent of "Log and Other Wood in the Rough" is shipped by private trucks, and almost none of it is shipped by parcel, U.S.P.S. or courier; on the other hand, 31 percent of "Pharmaceutical Products" are shipped by parcel, U.S.P.S. or courier, and only 11 percent of it is shipped by private trucks. The average value of $\delta = 0.45$ is higher than the distance elasticity estimates in the international trade literature about 0.3 (see Hummels, 2001; Limao and Venables, 2001; Anderson and van Wincoop, 2004). This difference may be due to using different frameworks or data sets, as well as the mode of transportation for interstate trade which may be different from the one for international trade (e.g., water transportation for international trade versus highway transportation for interstate trade).

Since we assigned taste parameters (i.e., $\theta_{r,i}^j$) as model residuals, recall that they capture the pattern of trade that cannot be explained by trade costs, source effects, or destination effects. In this context, the goodness of fit of the model is 100% for each good. Nevertheless, R-bar squared values in Table 4 still provide useful information: they depict which portion of the sum of squares of the left hand side of the log-linear model can be explained by trade costs, source effects, or destination effects, after normalizing for the number of explanatory variables on the right hand side. On average, about 94 percent of the sum of squares of bilateral trade is explained by the modeled economic behavior (i.e., by trade costs, source effects, or destination effects) and only 6 percent is explained by taste parameters. Trade patterns that are affected most by tastes belong to "Log and Other Wood in the Rough", while trade patterns that are affected least by tastes belong to "Electronic & other electrical equipment & components & office equipment"; this makes perfect sense, since the former category consists of products of which quality change depending on natural advantages/disadvantages of a state, and the latter category consists of products that can be produced almost anywhere with similar qualities. High R-bar squared measures are against the results of Hillberry et al. (2005) who show that in 33 of the 46 commodity groups, variables other than taste parameters (i.e., modeled economic behavior) explain less than 20 percent of the variation in bilateral trade.

Using taste parameter $\theta_{r,i}^j$ estimates from the residuals, we can also analyze whether or not there is a home-bias in preferences. The measure that we use for home-bias at the good level is as follows:

$$
HB_j = \sum_{r} \left(\frac{\theta_{r,r}^j}{\left(\sum_{i \neq r} \theta_{r,i}^j\right) / (R-1)} \right) / R \tag{5.1}
$$

where HB_j represents home bias for good j (calculated as the average home-bias for good j across states), $\theta_{r,r}^{j}$ is the taste parameter of region r for good j produced at home, $\theta_{r,i}^{j}$ is the taste parameter of region r for good j produced in another state, and R is the total number of states (including region r). The denominator inside the big parenthesis of Equation 5.1 is the average taste parameter in region r for varieties of good j coming from other regions; hence, the big parenthesis represents the home bias of region r for good j ; when we take the average across all regions, we have the measure of home bias for good j (i.e., HB_j). Calculated HB_j values for the U.S. are given in Table 4 under the column "Home Bias" and range between 0.96 (for "Electronic & other electrical equipment & components & office equipment") and 7.53 (for "Calcareous monumental or building stone") with an overall average of 2.51. This average number is lower than intranational home-bias estimates in the literature through dummy variables in gravity frameworks: Wolf's (2000) home-bias estimates range between 3.12 and 4.39 for 1993; Hillberry and Hummels (2003) estimate home-bias as 2:69 for 1997. Since CFS trade data of this paper belong to 2007, this may also be taken as an indicator of decreasing home-bias effects through time.

Using taste parameter $\theta_{r,i}^j$ estimates from the residuals, we can also measure home-bias in preferences in each state (calculated as an average of home-bias across goods). The measure that we use for home-bias at the state level is as follows:

$$
HB_r = \sum_{j} \left(\frac{\theta_{r,r}^j}{\left(\sum_{i \neq r} \theta_{r,i}^j\right) / (R-1)} \right) / J \tag{5.2}
$$

where the notation is almost the same as in Equation 5.1; the only difference is taking the average across goods rather than regions in the final stage, so we divide the overall summation by total number of goods J. Calculated HB_r values for each state are given in Figure 1 on the U.S. map. As is evident, highest home-bias estimates belong to West Virginia (7.10), Wyoming (6.93), Mississippi (6.21), and Virginia (5.27), while lowest estimates belong to California (0.54), Oregon (0.73), Washington (0.74), and Texas (0.79). The average home bias across states is 2.48, which is, as expected, very close to the average home bias across goods.

Having the results from the Örst-step estimation, we can now estimate Equation 4.3. Estimation of total imports at the good level (with a sample size of 1754) result in an elasticity of substitution across goods estimate of $\varepsilon = 1.09$ with a bootstrap standard error of (0.03), a twosided 95% bootstrap percentile method confidence interval of $(1.03, 1.14)$, and an R-bar squared value of 0.95. This significant estimate is consistent with the view that when goods are aggregated, the elasticity of substitution decreases; i.e., goods are much less substitutable across each other compared to varieties of each good. Estimated $\varepsilon = 1.09$ is also significantly lower than the elasticity of substitution estimates in the literature discussed above.

6. Conclusions

This paper has introduced a simple CES framework to investigate intranational bilateral trade across U.S. states. The key innovation is the identification of the elasticity of substitution across varieties of each good, elasticity of substitution across goods, and elasticity of distance in the empirical analysis. As expected, the elasticities of substitution across varieties are much higher than the elasticity of substitution across goods, because goods are much less substitutable across each other compared to varieties of each good. Compared to the existing literature, the elasticity of substitution estimates are lower, and the elasticity of distance measures (thus, trade costs) are higher in this paper. The lower elasticities of substitution in this paper likely arise through a specific mechanism that more aggregated studies are unable to account for. Spatial matching of supply and demand is part of the distance elasticity in aggregate studies, and presumably, the disaggregation by industry in this study is removing part of this effect. The average elasticity of distance is less than the estimate that would arise from aggregated data, if spatial matching of supply and demand is important. In other words, disaggregation is key to achieving identification and getting at the true parameter.

Besides providing identification solutions, this paper also investigates home-bias effects and show that they are significant at the U.S. state level. Using historical home-bias measures from earlier studies (that use data from 1993 and 1997), it is safe to claim that home-bias effects are decreasing through time. Nevertheless, when home-bias effects are compared across goods and across states, they are significantly dispersed; much remains to be learned from such dispersions.

References

- [1] Anderson, J.E., (1979), "A Theoretical Foundation for the Gravity Equation", American Economic Review, 69(1): 106-116.
- [2] Anderson, J.E., and Wincoop, E.V., (2003), "Gravity with Gravitas: A Solution to the Border Puzzle", American Economic Review, 93(1): 170-192.
- [3] Anderson, J.E., and Wincoop, E.V., (2004), "Trade Costs", *Journal of Economic Literature*, 42: 691-751.
- [4] Bergstrand, J.H., (1985), "The Gravity Equation in International Trade: Some Microeconomic Foundations and Empirical Evidence", The Review of Economics and Statistics, 67(3): 474- 481.
- [5] Broda, C., and Weinstein, D.E., (2006), "Globalization and the Gains from Variety", Quarterly Journal of Economics, 121(2): 541-585.
- [6] Deardorff, A. V. (1984): "Testing Trade Theories and Predicting Trade Flows," in Handbook of International Economics, Volume I, ed. by R. Jones and P. Kenen. Amsterdam: North-Holland.
- [7] Eaton, J., and Kortum, S., (2002), "Technology, Geography and Trade", *Econometrica*, 70(5): 1741-1779.
- [8] Evenett, S. J., and W. Keller (2002): "On Theories Explaining the Success of the Gravity Equation," Journal of Political Economy, 110, 281-316.
- [9] FAF (2010), Freight Analysis Framework (FAF) Version 2.2, User Guide. Federal Highway Administration (FHWA), U.S. Department of Transportation (USDOT). http://ops.fhwa.dot.gov/freight/freight_analysis/faf/faf2userguide/index.htm. Access on October 8th, 2010.
- [10] Gallaway, Michael P. , McDaniel, Christine A., and Rivera, Sandra A., (2003), "Short-run and long-run industry-level estimates of U.S. Armington elasticities", North American Journal of Economics and Finance 14: 49–68.
- [11] Harrigan, J., (1996), "Openness to Trade in Manufactures in the OECD", Journal of International Economics, 40: 23-39.
- [12] Head, K. and Ries, J., (2001), "Increasing Returns versus National Product Differentiation as an Explanation for the Pattern of U.S.-Canada Trade", American Economic Review, 91(4): 858-876..
- [13] Hillberry, R., and Hummels D., (2002), "Explaining Home Bias in Consumption: The Role of Intermediate Input Trade", NBER Working Paper No 9020.
- [14] Hillberry, R., and Hummels D., (2003), "Intranational Home Bias: Some Explanations", The Review of Economic and Statistics, 85(4):1089-1092.
- [15] Hummels, D., (2001), "Toward a Geography of Trade Costs", mimeo.
- [16] Hummels, D., and J. Levinsohn (1995): "Monopolistic Competition and International Trade: Reconsidering the Evidence," Quarterly Journal of Economics, 110: 799–836.
- [17] Lopez, Rigoberto A., Pagoulatos, Emilio, Gonzalez, Maria A., (2006), "Home bias and U.S. imports of processed food products", North American Journal of Economics and Finance 17: 363–373.
- [18] Millimet, D., Osang, T., (2007), "Do state borders matter for U.S. intranational trade? The role of history and internal migration", *Canadian Journal of Economics*, 40(1): 93-126(34).
- [19] Pagan, A., (1984), "Econometric issues in the analysis of regressions with generated regressors", International Economic Review, $25(1)$: $221-247$.
- [20] Romalis, J., (2007), "NAFTA's and CUSFTA's Impact on International Trade", The Review of Economics and Statistics, 89(3): 416-435.
- [21] Simonovska, I. and Waugh, M.E., (2011), "The Elasticity of Trade: Estimates and Evidence", NBER Working Paper No: 16796.
- [22] Suga, N., (2007), "A monopolistic-competition model of international trade with external economies of scale", North American Journal of Economics and Finance 18: 77–91.
- [23] Wei, SJ, (1996), "Intranational versus International Trade: How Stubborn are Nations in Global Integration?", NBER Working Paper No: 5531.
- [24] Wolf, H., (2000), "Intra-National Home Bias in Trade", Review of Economics and Statistics, 82(4): 555-563.

Table 1 ‐ Descriptive Statistics for the Values of Shipments

Notes: The values of shipments are in million U.S. dollars. For each SCTG good, descriptive statistics have been obtained by pooling the value of shipments for all source and destination states. SD stands for standard deviation, and CV stands for coefficient of variation calculated by dividing the standard error by the mean of pooled data for each good.

Table 2 ‐ Descriptive Statistics for Shipping Distances

Notes: The shipping distance measures are in miles. For each SCTG good, descriptive statistics have been obtained by pooling the shipment distances for all source and destination states. SD stands for standard deviation, and CV stands for coefficient of variation calculated by dividing the standard error by the mean.

Table 3 ‐ Elasticities of Substitution (η**) through Mapping between SCTG and NAICS**

Notes: NAICS stands for North American Industrial Classification System. SCTG stands for Standard Classification of Transported Goods.The source for the mapping is FAF (2010). SCTG good-specific elasticities of substitution (η) are averages of the elasticities of substitution calculated using total revenue and
total cost of the relevant NAICS industries. The source for to 2007. Dash (‐) between any two NAICS codes corresponds to all industries ranging between the two NAICS codes.

Table 4 ‐ Estimation Results for Bilateral Trade at the Good Level

Notes: ** and *** indicate significance at the 1% and 0.1% levels, respectively. Std Err stands for standard errors of estimated δη's. Estimation of δη's is by OLS at the good level. All regressions include fixed effects for source and destination states that are not shown. η's have been borrowed from Table 3.

