Cultural and Geographic Proximity in the United States Automotive Industry*

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Abstract

Using data on supply relationships in the United States automotive industry, I measure the value of cultural proximity between upstream suppliers and downstream assemblers. I find that foreign-owned assemblers value contracting with suppliers from their continent of origin at a level equivalent to a nearly 100% reduction in physical distance. Domestic assemblers value this form of cultural proximity much less. Both domestic and foreign owned assembler firms value contracting with suppliers with whom they have a previous relationship at a level equivalent to a 100% reduction in physical distance.

*The views expressed in this article are those of the author. They do not necessarily represent those of the Federal Trade Commission or any of its Commissioners. This paper is based on Chapter 1 of my PhD dissertation and I thank my PhD advisors Steve Berry, Phil Haile, and Peter Schott for their support and comments. Thanks to Nathan Wilson and Devesh Raval for their comments on this draft and to Steven Wingett of Supplier Business for discussing the details of the Supplier Business dataset with me.

1 Introduction

One of the most well established facts in economics is that closer proximity between parties facilitates trade. It has long been known that this relationship holds for geographic proximity, and recent work has illustrated that this relationship holds for cultural proximity as well (Head and Mayer, 2014; Melitz and Toubal, 2014). While physical proximity helps facilitate the physical flow of goods, cultural proximity helps facilitate the flow of information and the formation of trust.

Much of this research has focused on international trade (e.g., Combes et al., 2005). However, there are important differences between trade within the same country and trade between countries that could lead to differential effects of cultural proximity. For example, within the same country trading firms may have more similar workforces and similar regulatory environments such that cultural proximity is less important than it would be for international trade.

In this paper, I estimate the value of cultural proximity in vertical supply relationships within the United States automotive industry and show that cultural proximity can remain important even when trading firms are located within the same country. Using data on supplier-assembler contracting and establishment locations from 1999-2008, I estimate supplier firms' variable cost functions. Using the estimated parameters, I quantify the cost advantage provided by cultural proximity by measuring the marginal rate of substitution between cultural proximity and physical distance to an assembler.

Across multiple metrics, I find that cultural proximity significantly reduces costs. Since distance costs are non-linear, I report marginal rates of substitution measured at a 60 mile distance between the trading firms. Supplier firms' marginal rate of substitution imply that the benefit to an Asian supplier of supplying an Asian assembler is cost equivalent to being 800 miles closer together. For European assemblers, the benefits of a European supplier are equivalent to 400 miles of proximity and for North American owned assemblers and suppliers, these benefits are equivalent to 40 miles of proximity. Further, for firms that used to be vertically integrated or who previously contracted with each other these benefits are equivalent to approximately 500 miles of proximity. With the exception of North American suppliers and assemblers, these are all equivalent to an approximately 100% reduction in distance. By way of comparison, Atalay et al. (2019) find that across all manufacturing firms, the benefits of contracting within a firm as opposed to outside of it are equivalent to a 40% decrease in distance. Therefore, these magnitudes are large.[1]

These results are robust across a variety of dimensions. My results are consistent when I allow effects to vary across the beginning and end of the sample period, geographic location of assembler, suppliers' proximity, and the type of part. While I find that cultural proximity is far more valuable than physical proximity across almost all parts, for some parts that are supplied on a just-in-time basis cultural proximity's relative value is much closer to zero.

Supplier firms are likely to locate their plants geographically closer to assembler firms with whom they are likely to do business. To the extent that this is not captured by my observed measures of cultural proximity, the distance between the plants may be endogenous and the coefficient on distance may be too large in magnitude. However, to the extent that this is a concern, my results on the relative importance of cultural proximity should be conservative.

In finding that cultural proximity drives trading in the automotive industry, I corroborate the findings of Schmitt and Van Biesebroeck (2013), who analyze the European automotive supplier market and find that geographic and cultural proximity improve the likelihood of a supplier firm obtaining a contract from an assembler. Outside of the automotive industry, Head and Mayer (2014) survey numerous articles that show that common language and colonial links increase international trade between two countries. Chaney (2014) presents a theoretical model where contacts between firms can overcome the barriers that inhibit trade.

The paper proceeds as follows. In Section 2, I outline relevant background of the industry. In Section 3, I discuss the data and provide motivating statistics for the estimation. In Section 4, I discuss my theoretical model and estimation strategy. In Section 5, I show results and in Section 6, I conclude by discussing some of the mechanisms that could be driving my results and paths for future research.

[1] The results of Schmitt and Van Biesebroeck (2013) imply a similar magnitude to my results. They find that for automotive suppliers and assemblers in Europe, being of the same nationality is valued more than twice as much as having plants located within 700km of each other.

2 Background

Many of the parts used by the major automobile manufacturers (referred to in this paper as assemblers) to produce cars come from a large network of suppliers. These suppliers are frequently categorized into tiers, reflecting their locations in the "river" of production. The suppliers that supply the assembler directly are known as tier-one, the suppliers that supply the tier-one are tier-two, and so on. A supplier could be a tier-one for one car model and a tier-two for another.

Contracts between an assembler and a tier-one supplier are typically made through a competitive bidding process.[2] These contracts are typically put up for bidding at the introduction of a new car model, and the contract will last for the duration of the model, typically 4-8 years. While the contract is usually long-term, the purchase orders for specific quantities and prices are negotiated on a more short-term basis (e.g., Hellerstein and Villas-Boas, 2010).

Even though contracts are usually tendered on a per-model basis, many suppliers have assemblers with whom they frequently do business. However, even while many supplier firms have "primary customers", supplier firms typically attempt to have a diverse portfolio of assemblers that they supply and try to obtain contracts from a range of different assemblers (Jauchius et al., 2004). Typically, even from a given plant, suppliers will supply multiple assemblers.[3]

The importance of the geographic proximity of suppliers to assemblers is a result of multiple features of the industry. Over the past 30 years, just-in-time inventory control, where a part is delivered to the assembler soon before it is needed on the assembly line, has become a dominant logistics model (Klier and Rubenstein, 2008). In this type of system, proximity to suppliers is important for flexibility and reliability of supply (KPMG, 2005). Additionally, since many of these parts are bulky, the cost of shipping these products can be

[2] This section is largely based on Ben-Shahar and White (2006) and reflects conversations with people in the industry.

[3] Using data from the Elm International Database, which is used in Klier and Rubenstein (2008), I compute the approximate number of customers per supplier plant. The median number of customers per supplier plant is 4 and the first quantile is 2. While some of the customers listed in these data are other downstream suppliers, most are assemblers.

high. Furthermore, it may be that closer proximity leads to better quality control through lower monitoring costs (Bray et al., 2019).

3 Data

In this section, I outline my main sources of data and then present motivating descriptive statistics.

3.1 Data Sources

Supply Network I use the "Who Supplies Whom" (WSW) dataset from Supplier Business for data on the automotive supplier network.[4] This dataset contains a list of supplier-model-part combinations, and I use a version of this dataset that contains 18,000 such combinations from models produced in North America between 1999 through 2009. Throughout the paper, I will refer to a model-part combination as a "market", since the assumption is that is the level at which an assembler solicits bids for contracts from suppliers.

While the data has rich coverage of the industry, it is not comprehensive. The data is obtained by contacting many of the largest suppliers to find out which car models they are newly supplying. During the time period covered by my data, the suppliers had incentives to report to Supplier Business any new contracts, since there was a chance that their company would be featured in Automotive News as a supplier to a new model. These data includes at least some parts from car models accounting for 60% of 2007 US production.[5]

Since these data are not a comprehensive list of all supply relationships, it is not possible to know for a given car model the full set of supplier choices for an assembler. In an effort to construct this, I supplement the WSW data with information on all firms in Automotive News "Top 150 North American Automotive Suppliers" from 1994 and 1999-2008. Of the 183 firms in the "Top 150 Supplier" list in any of those years, 128 of them appear in the WSW data.

[4] This dataset is also used by Fox (2018), Schmitt and Van Biesebroeck (2013), and Bray et al. (2019)

[5] I compute this looking at all car models in the WSW data from between 2002-2007, and see what share of production from those models is covered in the 2007 production data. The 2002-2007 window is appropriate since many car models are in production for multiple years.

The WSW data lists 525 separate supplier firms. However, out of the 18,000 supplier-model-part combinations in the data, 11,434, or 64% are supplied by the "Top 150" firms. For parsimony and consistency, I treat any of the "Top 150" firms as a choice for an assembler looking to outsource that part. Conversely, any firm not on that list is treated as in the outside option.

For this paper, I winnow the WSW data to eliminate model-part combinations where there is missing or incomplete information on the year, part, or model of the car. I eliminate all model-part combinations after 2008, since, as discussed below, I do not have supplier location information for that year in my data. I also eliminate models that are made in Canada or Mexico, and from parts where no firm in the "Top 150" dataset is categorized as making it.[6] After imposing these restrictions, I have a dataset of 12,941 contracts, of which 7,728 were won by a firm in the "Top 150" of firms.[7]

Other Data For supplier locations, I use the National Establishment Time Series (NETS) from 1990-2008.[8] This is an establishment-level panel dataset containing establishment location from all sectors of the economy. In order to obtain a dataset of automotive supplier manufacturing plants, the data was winnowed using a process described in appendix Section A.1.

Both to be consistent with my approach for the production network data and to focus on the largest suppliers, I again winnow these data to focus on the firms in the "Top 150 Supplier" lists discussed above.

I supplement these data on firms with information on assembler locations and production levels, supplier and assembler firm characteristics, and information on parts. This information is summarized in appendix Section A.

[6]This last restriction only implicates less than 0.1% of contracts.

[7]In Section A.6, I show that the set of contracts in WSW is fairly representative of the US automotive industry, but Asian assemblers are somewhat underrepresented and European assemblers are somewhat over represented. I also show there that there is no obvious selection in which contracts were won by a "Top 150" firm.

[8]This is constructed by Walls and Associates using Dun and Bradstreet data.

Statistic	Mean	Median	St. Dev.	Min	Max
North American Supplier	0.57	1	0.50	0	1
Asian Supplier	0.08	0	0.28	0	1
European Supplier	0.35	0	0.48	0	1
Same Contintent	0.56	1	0.50	0	1
Historic Ties	0.05	0	0.22	0	1
Previous Contract	0.86	1.00	0.32	0.00	1.00
Distance (100s miles)	1.83	0.87	2.72	0.00	20.79

(a) Winning Supplier Firms

Statistic	Mean	Median	St. Dev.	Min	Max
North American Supplier	0.62	1	0.48	0	1
Asian Supplier	0.14	0	0.34	0	1
European Supplier	0.24	0	0.43	0	1
Same Contintent	0.49	0	0.50	0	1
Historic Ties	0.01	0	0.12	0	1
Previous Contract	0.67	1.00	0.41	0.00	1.00
Distance (100s miles)	2.26	1.25	3.12	0.00	34.88

(b) Losing Supplier Firms

Table I Characteristics of Contracts

Note: Tables are based on full data set, except for the "Previous Contract" row, which is only based on data from 2005-2008. "Winning Firms" are the firms that are listed in the WSW data as obtaining the contract. "Losing firms" are firms that make the part and have a US plant open in the model year. The listed distance is to the supplier firm's plant located closest to the factory where the model is manufactured.

3.2 Descriptive Statistics

In the top panel of Table I, I show summary statistics for the contracts won by the "Top 150" firms. These show that 57% of these contracts were won by North American suppliers, 35% by European suppliers, and 8% by Asian suppliers. 56% of these contracts were won by supplier firms of the same continent of origin as the assembler and 1% were won by supplier firms where they had historical ties with the assembler. 90% of the contracts in 2005 and later were won by supplier firms who had at least one contract with the assembler between 1999 and 2004. Finally, the mean distance from the assembler plant to the closest supplier plant of the winning firm was 183 miles.

In the bottom panel of Table I, I show the summary statistics for the losing firms. An observation here is a firm/contract unit, where a firm is included as a choice for that contract if they are coded as making that part and have a US plant opened in the model year. Comparing these results to the winning firms, a few patterns emerge. First, the firms that win lose the contracts have their closest plant on average 43 miles farther than the winning firm. Second, these firms are seven percentage points less likely to be of the same continent of origin as the winner, four percentage points less likely to have historical ties and twenty percentage points less likely to have a previous contract with the assembler.

These descriptive statistics values preview some of the estimation results – geographically and culturally proximal firms are more likely to win contracts. However, to quantify the trade-offs firms make between these two, I develop a model of supplier and assembler contracting.

4 Empirical Model

I model assembler firms' procurement decisions (i.e., choice of supplier) using a second-price auction (SPA) framework. This approach allows me to recover supplier firm costs based on the assemblers' choice of supplier.

4.1 Primitives

There are two types of firms in the model: upstream supplier firms, indexed by f, and downstream assembler firms, indexed by a. The number of suppliers and assemblers is fixed. Supplier firm f has the capabilities to produce parts, indexed by p, in the set $\mathcal{P}_f$. Conversely, the set of firms that make the part p is denoted $\mathcal{F}_p$. The set of parts that firms produce is taken as given. Firm f produces these parts in a set of plants $\mathcal{I}_f$, indexed by i. This set of plants has N_f elements, which is taken as given.

The cost for plant i to supply one unit of part $p(r)$ to model $m(r)$ is given by:

$$C_{ri} \equiv \bar{C}_r + \bar{C}_{ri} + \epsilon_{ri} + \eta_{rf}$$

$\bar{C}_r$ is the component of costs that is constant across all plants that produce the part, and includes the costs of materials and the capital necessary to build this part. $\bar{C}_{ri}$ varies by plant, and includes transportation costs, local labor costs, productivity differences, and relationship-specific human capital between the supplier and assembler. Both $\bar{C}$ components are observed by all supplier firms and by the assembler.

There are two idiosyncratic components of supplier plant costs: ϵ_{ri} and η_{rf}. ϵ_{ri} is a contract/supplier *plant* specific cost. When assemblers award contracts to supplier firms, its realization is unobserved, but its distribution is known by the assembler and the other supplier firms. η_{rf} is a contract/supplier *firm* cost. Examples of these costs include personal relationships and specialized skills at both the supplier plant and supplier firm levels.

4.2 Procurement

I make three main assumptions on supplier firms' costs and assemblers' procurement mechanism.

Assumption 1 *Costs are additively separable across contracts.*

Assumption 2 *Contracts are awarded in a second-price auction.*

Assumption 3 *The set of contracts ($\mathcal{R}$) and the quantity needed for each contract (ψ_r) are taken as given.*

Assumption 1 implies that a supplier firm's costs to supply a given contract are unaffected by any other contract it obtains.[9] Assumption 2 provides a mapping from firms' costs to the winning firm for a given contract.[10] Assumption 3 implies that the composition of a car and the quantity of cars produced is inelastic with respect to the price of parts for the car.

[9] This is admittedly a strong assumption, however, it greatly simplifies the empirical analysis, by allowing me to avoid modeling the interdependence across contracts. Also, this assumption is bolstered by two facts about the industry. First, the capital needed to produce a part for a given model is frequently unique to that model and owned by the assembler (not the supplier). Second, within the WSW data, in cases where multiple parts are listed for the same model within the same narrow part category, in over 60% of cases these parts are supplied by different firms. That indicates that even within the same car model and narrow part group, many different firms are producing the parts. Both of these facts notwithstanding, without a formal model it is not possible to know the precise extent of these complementarities.

[10] The use of second-price auction pricing (Bertrand pricing) to introduce imperfect competition into a model of product sourcing is used in Bernard et al. (2003) in the context of international trade.

These three assumptions imply that a supplier firm obtains a contract r when it has the lowest cost of any supplier firm to produce part $p(r)$ for model $m(r)$:

$$C_{rf} \leq C_{rf'} \forall f' \in \mathcal{F}_{p(r)} \tag{1}$$

4.3 Estimation

The empirical implication of the assembler procurement portion of the model is that the low-cost supplier firm for a given part obtains the contract to produce it. Therefore, the model yields a simple formulation for suppliers' variable costs to supply a given contract. The probability of firm f being the low-cost firm for contract r is:

$$P_{rf} = Pr(\bar{C}_{rf} + \eta_{rf} < \bar{C}_{rf'} + \eta_{rf'} \forall f' \neq f \in \mathcal{F}_{pt}) \tag{2}$$

where η is unobserved to the econometrician. I assume that $-\eta_{rf}$ is distributed independent type-I extreme value ("logit") across markets and firms. Therefore, the probability of firm f winning contract r takes the familiar multinomial logit form:[11]

$$P_{rf} = \frac{\exp(-\bar{C}_{rf})}{\sum_{f' \in \mathcal{F}_{p(r)t}} \exp(-\bar{C}_{rf'})}$$

Supplier firms' costs ($\bar{C}_{rf}$) have both (supplier) firm level and location components. The supplier firm components are independent of location, while the location components depend on the supplier plant used to supply the contract. The major supplier firm level components of interest are the cultural proximity components discussed above: whether suppliers and assemblers are of the same continent of origin, whether they have a historical relationship, and whether they have previously contracted together.

The major supplier plant level covariate of interest is distance, for which I will use the crow-flies distance between the supplier and assembler plants. I assume that transportation costs are a natural log function of distance. This functional form allows for diminishing marginal value of distance as the plants are farther apart from each other. As robustness,

[11] Schmitt and Van Biesebroeck (2013) and Bray et al. (2019) run similar multinomial logit estimations on the same data set.

I also estimate a piecewise linear function, with kinks at 60 miles (approximately one hour drive time) and 400 miles (approximately one day drive time).

In the estimation, I make two different assumptions about which supplier plant i supplies a given contract. In the first approach, I follow the model and assume that $-\epsilon_{ri}$ is distributed type-I extreme value.[12] Therefore, firms have uncertainty over which supplier plant will be the lowest cost to supply that part, and when bidding on a contract, they take expectations over that uncertainty. In the second, I assume that a supplier always supplies a given contract from the supplier plant that is closest to the assembler plant where the car model is made.

The "outside-option" is absorbed in the assembler-specific constant term in the estimation. This is when a supplier that is not in the top 150 Automotive News suppliers in any of the years listed above or a supplier that has no US plants obtains the contract to produce a given part for a given car. In order to control for any changes in the value of the outside option over the sample period, a linear time trend is included.

Using the conditional independence of the P_{rf}, the likelihood to estimate the variable cost parameters is given by

$$\mathcal{L}(x;\alpha,\beta,\gamma) = \prod_r \prod_f P_{rf}(x;\beta), \tag{3}$$

where β are the parameters of the cost function.

5 Results

5.1 Main Findings

I first show results from the 2005-2008 time period only, since for those years I can include the "previously contracted" covariate. Then, excluding that covariate, I show results for the whole time period from 1999-2008.

In Table II, I show the variable cost estimates using the 2005-2008 data. Column 1 and 2 show the results for the "closest plant" specification, while columns 3 and 4 shows the

[12] The variance of $-\epsilon_{ri}$ is $\lambda^2 \frac{\pi^2}{6}$, where $\frac{\pi^2}{6}$ is the variance of the standard type-I extreme value distribution.

results for the "all plant" specification. The results from the "closest plant" and "all plant" specifications are largely similar, and for the remainder of this section, I will focus on the closest plant specification.

The coefficients all have the expected signs – variable costs are lower when firms are located geographically closer together and when they are culturally more proximal. The results show that the relative importance of cultural proximity along the dimension of continent of origin is highest for Asian assemblers followed by Europeans and then North Americans. In contrast, the importance of having a previous contract is similar for assemblers of different continents of origin. The coefficient for distance falls between the specification that include the previous contract covariates and those that do not. This is consistent with there being some endogeneity of distance that is absorbed by the previous contract variables.

In Figure 1, I show the marginal rate of substitution (MRS) between cultural proximity and physical proximity for the main "cultural proximity" measures that I consider. I compute these marginal rates of substitution at a 60 mile distance (roughly an hour drive).

For a contract from a North American assembler, having a North American supplier is cost equivalent to under 40 miles of proximity. For a European assembler, having a European supplier is cost equivalent to approximately 420 miles of proximity. For an Asian assembler, having an Asian supplier is worth approximately 800 miles of proximity. Having a supplier with which assemblers have had a historical relationship is worth approximately 510 miles of proximity and having a previous contract is worth between 500-600 miles of proximity. With some exceptions, cultural proximity seems much more important than physical proximity in firms' costs.

One concern is that supplier firms locate plants primarily in response to assemblers' decision to contract with them. This could potentially bias the transportation costs to be larger (in absolute value) than they actually are. To the extent that this is a concern, it likely strengthens the results of the paper that cultural proximity is much more important than physical proximity. To the extent that the transportation costs are biased away from zero, the marginal rate of substitution between cultural and physical proximity is biased towards zero.

	Closest Plants		All Plants	
	(1)	(2)	(3)	(4)
Log Distance (in 100s of Miles)	-0.186	-0.121	-0.143	-0.107
	(0.02)	(0.011)	(0.01)	(0.01)
Asian Supplier and Assembler	1.881	1.438	1.722	1.414
	(0.114)	(0.115)	(0.115)	(0.115)
European Supplier and Assembler	1.101	0.748	1.028	0.752
	(0.105)	(0.117)	(0.105)	(0.116)
NorAm Supplier and Assembler	0.019	0.078	0.029	0.076
	(0.084)	(0.085)	(0.084)	(0.085)
Historical Connection	0.594	0.893	1.016	0.906
	(0.066)	(0.067)	(0.066)	(0.067)
Previous Contract- Asian Assembler		0.85		0.89
		(0.087)		(0.086)
Previous Contract- European Assembler		0.8		0.82
		(0.122)		(0.122)
Previous Contract- NorAm Assembler		1.017		1.068
		(0.06)		(0.059)

Table II Variable Cost Estimation Results

Note: All estimations include supplier and assembler indicator variables and a linear time trend.

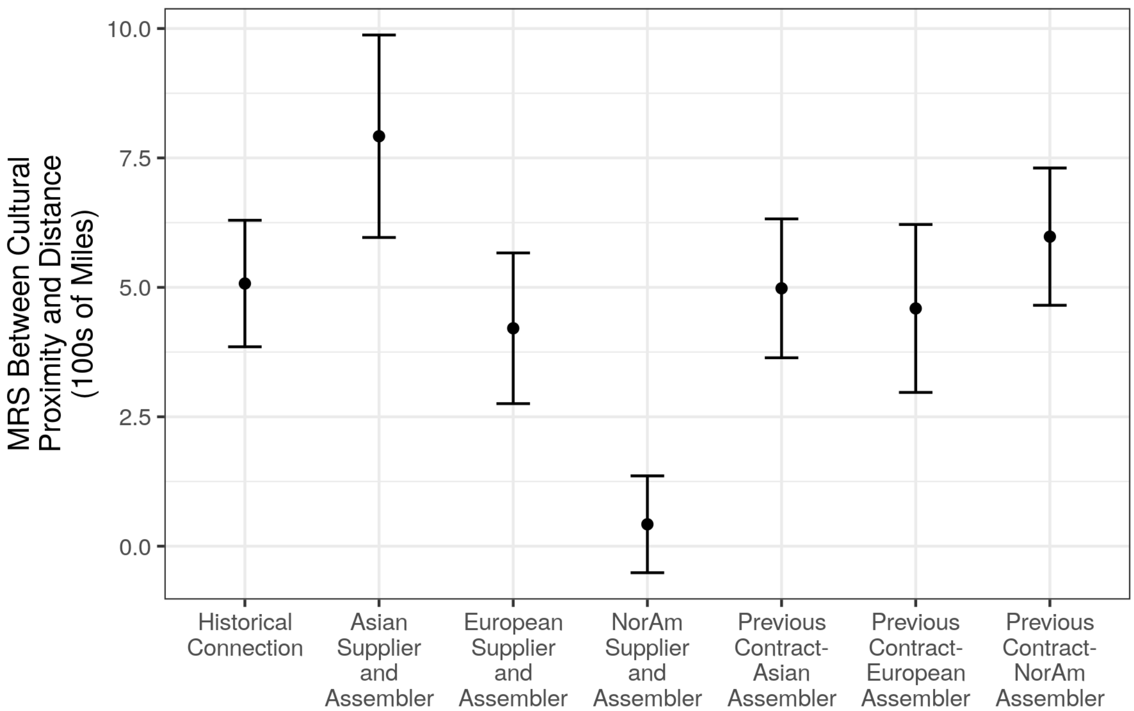


Figure 1 Marginal Rates of Substitution Between Cultural and Physical Proximity at One Day Drive

Note: Bars represent 95% confidence intervals. Uses estimation results from Table II column (2).

5.2 Robustness

Next, I explore heterogeneity in these marginal rates of substitution across four dimensions: time period, geographic location of assembler, proximity to assembler, and type of part.[13] Except where specified, these estimates are pooled over the full time period. Because of that, these figures do not include the "previous contract" variables, since that requires a split sample to estimate. Overall, these results confirm the main result that cultural proximity is much more important than physical proximity for assembler firms in their choice of supplier.

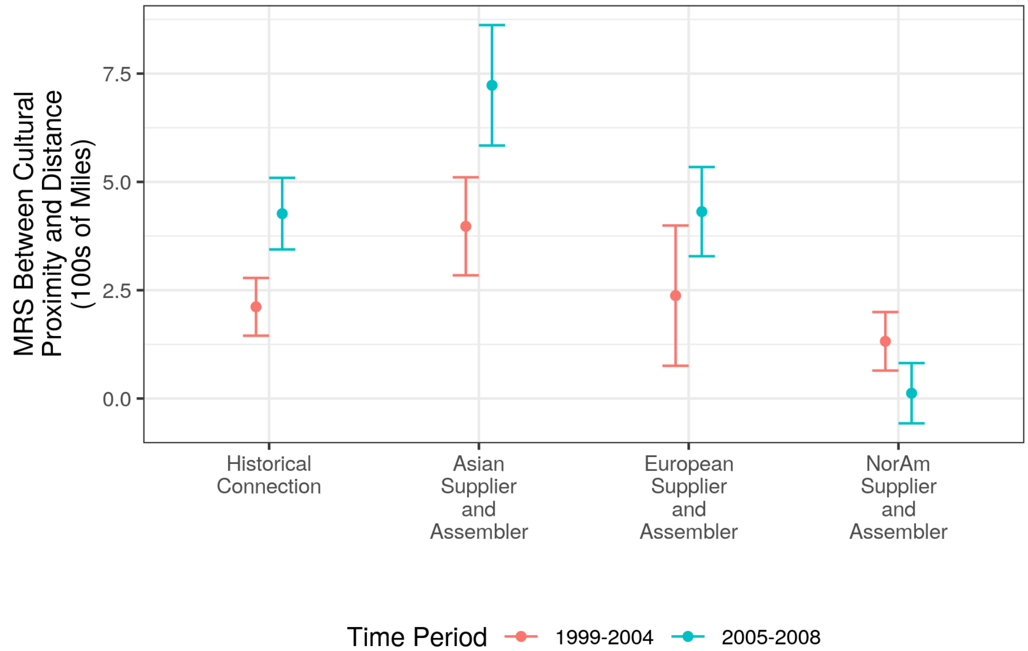
Time Period In Figure 2a, I display the MRS from dividing the data into two time periods: 1999-2004 and 2005-2008. The broad patterns in the data are similar across the two periods, but there is some evidence that Asian assemblers' preferences for Asian suppliers increased over time.

Geography In Figure 2b, I display the MRS from estimates that exclude assembly plants located in Michigan and compare that to the estimates on the full dataset. One may think that assemblers in middle of the industry's major industrial cluster have different preferences for proximal suppliers than other ones. However, there is no substantive difference between the estimates.

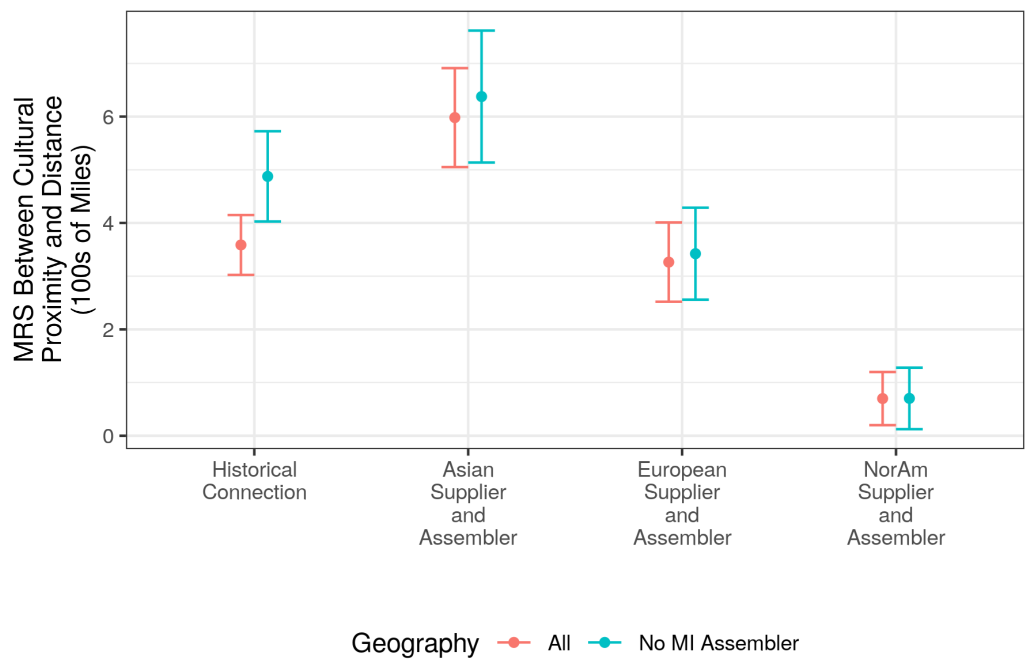
Proximity to Assembler In order to study the differences in MRS across different distances between the supplier and assembler plant, it may be important to have a more flexible functional form for transportation costs than the natural logarithm. Therefore, I estimate a piecewise linear function with kinks at 60 miles and 400 miles (my measures of "hour distance" and "day distance" respectively). I display the results from these piecewise linear distance functions in Figure 3, with the results at an hour distance in Figure 3a and the results from a days distance in Figure 3b.

The order of magnitude of the difference in y axis between Figure 3a and Figure 3b illustrates the decreasing importance of physician proximity relative to cultural proximity as

[13]The full results tables corresponding to these graphs are in the appendix.



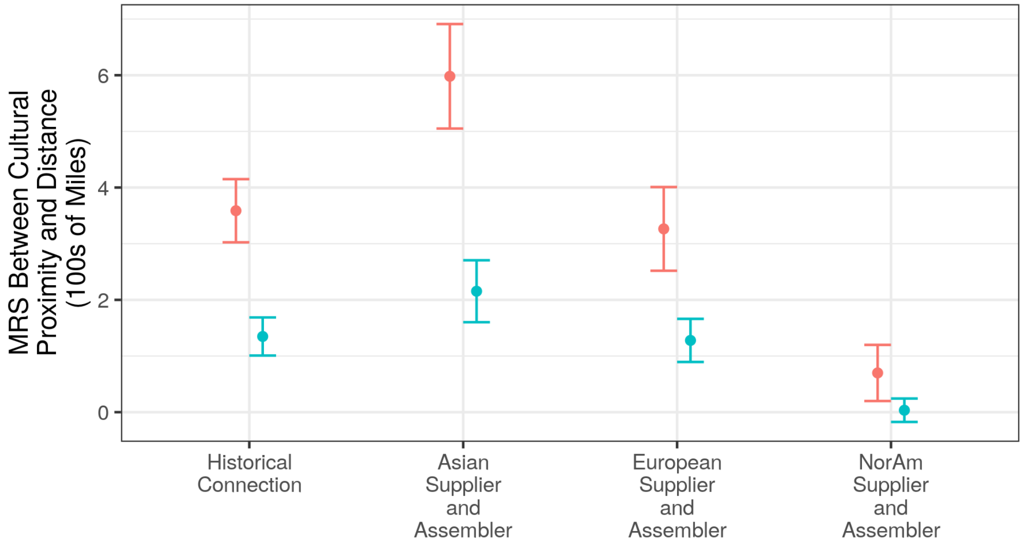
(a) Time Period



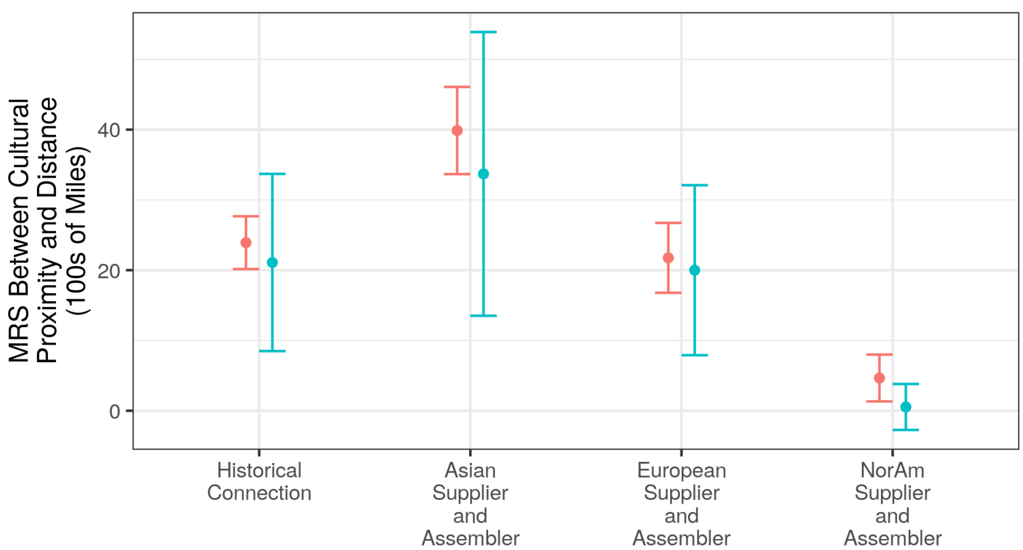
(b) Assembler Location

Figure 2 MRS: Time Period and Assembler Location

Note: Bars represent 95% confidence intervals. Uses estimation results from appendix tables Table IV and Table V.



(a) Hour Distance



(b) Day Distance

Figure 3 MRS at Varying Distances

Note: Bars represent 95% confidence intervals. Uses estimation results from appendix table Table VI and computes the marginal rate of substitution at 60 miles (1 hour) and 400 miles (1 day). "PW" indicates a piecewise linear transportation cost while "Log" indicates logarithmic transportation costs.

physical proximity increases. This finding is true for the piecewise linear specification and the log specification.

These figures also illustrate the potential bias at smaller distances from using the more parsimonious log function. The results for the piecewise linear specification for 0-60 miles ("hour") are all below those of the logit, which suggests that the log specification may somewhat overstate the MRS at some shorter distances. Nevertheless, even for the piecewise linear function, distance is worth approximately 100 miles of distance for many of the measures of cultural proximity.

Type of Part In Figure 4, I show the MRS at one hour of travel for parts with different shipping costs. I measure these shipping costs in two ways. First, I include an interaction between distance and parts weight to value ("WTV") ratio. Second, I separately estimate the model for the six parts that are likely to be supplied on a just-in-time ("JIT") basis.[14] In Figure 4, I show the MRS from the first weight to value estimation, calculated at the 10th and 90th percentile of the weight to value distribution. I also show the MRS from the separate estimation of the JIT parts.

The results from the WTV estimation show little difference across the WTV distribution. While the transportation costs are slightly higher for higher WTV parts, this difference is not economically significant and makes no difference in the estimated MRS. However, the results from the JIT parts estimation suggests that for some particularly time sensitive parts, the MRS is close to zero. Nevertheless, I am cautious in interpreting this as a true zero, since the distance coefficient here may be biased away from zero (i.e., overstate the importance of distance) due to the endogeneity of plant locations discussed above. Nevertheless, this result illustrates that distance is relatively more important for this subset of parts.

[14] This is described in appendix Section A.3.

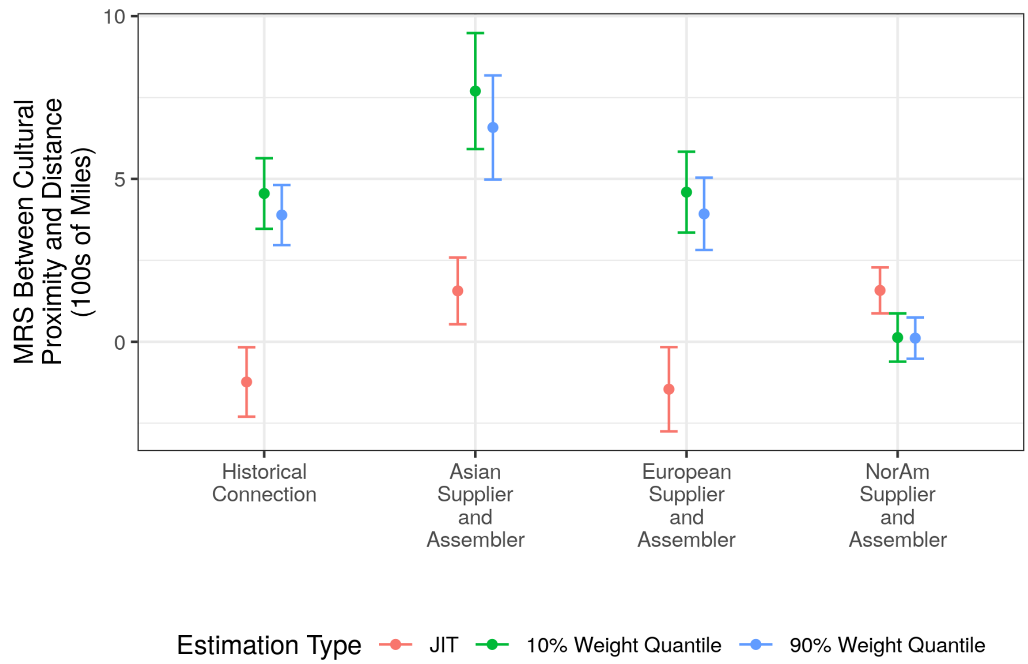


Figure 4 MRS: Different Size Parts

Note: Bars represent 95% confidence intervals. Uses estimation results from appendix Table VII and VIII. The marginal rate of substitution is computed at 60 miles (1 hour).

6 Discussion/Conclusion

Using detailed data on automotive supply relationships on cars produced within the United States, I find that downstream automotive firms strongly value cultural proximity in their choice of suppliers. These results are robust to focusing on different time periods, assembler plants, and specifications for transportation costs. While this paper focuses on the automotive industry, it is likely that many similar considerations apply in other industries with supply chain linkages as well.

My results point to future research into understanding both the mechanism why cultural proximity is important and the dynamics of cultural proximity.

Mechanism This paper leaves open the question of why assembler firms contract with suppliers with whom they have a high level of cultural proximity. There are at least three possibilities each of which is relevant to a different part of the contracting process: production costs, contracting costs, and search costs.

Production costs might be lower between firms that are culturally proximal due to easier communication between the firms making it easier for the downstream firm to monitor the upstream one. Recent research shows that geographic proximity can increase product quality in this industry (Bray et al., 2019). It is possible that cultural proximity does as well.

Beyond production efficiencies, the smoother communication that cultural proximity fosters may lower contracting costs. This increase in communication could foster longer term relationships between firms. Helper and Henderson (2014) suggest that part of the reason for Japanese automotive manufacturers success were their "patterns of managerial practice that center around dense networks of communication and joint problem solving". The long-term relationships that are necessary for this to be successful could be fostered by cultural proximity.

If culturally proximal firms typically provide some efficiency benefit for the assembler, that may also function as a screening mechanism for the assembler in their choice of firm to contract with. This is consistent with research that in the presence of search costs, individuals may optimally only consider those choices that are ex-ante most likely to be optimal (Caplin et al., 2019). Therefore, to the extent that there are efficiencies in choosing a culturally proximal supplier, search costs could further increase the probability of a culturally proximal supplier being chosen.

Dynamics This paper treats cultural proximity as static and as a function of readily observable characteristics: historical relationships and national origins. However, in reality, cultural proximity may evolve over time as firms work together and develop relationships. In this research, I find that assembly firms have an increased probability of contracting with suppliers with whom they have previously contracted. However, I leave open whether this is because they like to do business with firms with whom they have previously done business (structural state dependence) or that they repeatedly do business with suppliers that they particularly like (preferences).

The idea that cultural proximity can be developed over time links to recent models in international trade that highlight the importance of contacts between firms in driving trading relationships (Chaney, 2014). As firms make contact with their trading partners and become more familiar with them more firms can become culturally proximal. This also has the implication that as networks of contacts diffuse, national origin may become less important over time. In this paper, I show that over the decade of the 2000s, preferences for cultural proximity did not decline among US assembly firms. However, it is possible that the types of effects predicted by these models may take many years to develop.

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A Data Appendix

A.1 Supplier Plant Data

This section describes how the NETS data was processed.

First, I manually evaluated the detailed industry coding used in the NETS database, and selected codes that were related to the automotive supplier industry.[15] These industry codes are assigned on a yearly basis and any plant that contains a relevant industry code in any year is included in the dataset. This yields approximately 56,000 plant locations (spanning all years).

A second level of winnowing is performed to include only plants that belong to firms that are likely to be primarily supplying assemblers. I construct a list of this set of firms by using the list of the top 150 automotive suppliers by North American revenue that is constructed on an annual basis (since 1994) by Automotive News.[16] I use the union of the set of firms on the list from 1999-2008 (and 1994), which yields approximately 280 firms. Of these firms, 228 were able to be matched to the NETS data.[17]

Finally, in order to attempt to ensure that only manufacturing plants and not warehouses or sales offices are included in the analysis, establishments are only included in the dataset if they have more than 50 employees and are within 1 kilometer of a site listed within the EPA's Facility Registry Service ("FRS"), which lists places of environmental interest within the United States.[18] The employee restriction is based upon the assumption is that sales offices and warehouses, and not manufacturing plants, would be the establishments with a small number of employees.[19] This reduces the number of plant locations (from 1999-2008) to approximately 2.6 thousand and the number of firms to approximately 200.

A.2 Matching Firms

I attempt to match all firms in the Automotive News "Top 150 North American Automotive Suppliers" from 1994 and 1999-2008 to three datasets: NETS, WSW, and the Elm International Database. I match firms to the NETS database using a manual match on the name of the headquarters, "trade name" of the headquarters, name of plant, and "trade name" of the plant. If the name in any of those fields (or crucial part of the name) matches the name, I manually inspect the result list. If the firm matches the headquarters name, it is considered a match. If it matches the "trade name" of the headquarters, and there is nothing in the headquarters name that conflicts with it, that is considered a match. If a company name or company trade name matches, the headquarters code is inspected to see what other plants are in that firm and a determination is made whether or not to include it.

The match to WSW and Elm is made on the basis of a manual text search on the names for the firm in each of the databases.

[15] This is a "nine digit" SIC coding scheme and is therefore more detailed than the standard SIC coding scheme. A list of these codes can be obtained from the author upon request.

[16] Note that these firms could have parent companies from any continent – Asia, Europe, or North America.

[17] One reason why firms may not match is that they have no plants in the United States and either have plants in Canada or Mexico and/or supply the North American industry from plants abroad.

[18] I use the FRS downloaded from https://www3.epa.gov/enviro/html/fii/downloads/state_files/national_combined.zip on 2/2/18.

[19] In the Elm International Database (described in footnote 20), only 10% of automotive supplier manufacturing plants are listed has having less than 50 employees.

A.3 Parts

The WSW database contains a variety of different methods of categorizing parts, based on area of car (e.g., interior), broad system (e.g., body parts), and specific part (e.g., handles/latches). These were in turn manually categorized on the basis of the system and specific part into 152 part groups (this example would be in the latch/handle group, which would include handles and latches from all different systems of the car). Any firm in WSW, NETS, or Elm International (which is merged to the other data) that is listed as making a part within a given narrow part category in any of its plants is considered to have the capability of making that part.[20] I describe these merges below.

Since transportation costs may differ by characteristics of the parts, such as the weight or the use of just-in-time inventory control for that part, parts are grouped in two different ways. The first grouping of parts categorizes as "JIT" 6 parts that are either heavier or more important in just-in-time sequencing. These parts are body panels, doors, frame, glass, seats, and seat frames.[21] The second grouping of parts uses data from the United States trade statistics to obtain a weight by value measure for each part. This is described more below. The expectation is that, independent of assembly line sequencing and the associated just-in-time concerns, parts that have a higher weight by value are more expensive to ship.[22]

Merges In addition to these categories, the WSW dataset contains the part name "as reported by the supplier." These part names are more specific than the general categories, and these supplier reported part names are used as guides in the merges that follow. The baseline categories described above are manually matched to the 9-digit SIC codes in the NETS data. The Elm International dataset contains a listing of parts made in each supplier plant. Using the supplier reported part names from WSW as guides, these are merged to the baseline categories above. Finally, parts are merged to the HS codes from the United States import data (downloaded from http://www.som.yale.edu/faculty/pks4/sub_international.htm and http://cid.econ.ucdavis.edu/). I match the HS codes in the trade data to the main categories that I delineated. An HS code is assigned to a main category if it matches a SIC code from at least one plant that is from a firm that is classified as making that part. If there is no match within that set, then I search over all HS codes and try to find a match. This match was also done manually using the "supplier reported" part names from WSW and the commodity description from the HS dictionary as guides.

Weight By Value The weight by value measure is constructed by using the import data described above. For each category match, I compute the weight by value by summing up the value and weight (in kg) over imports from all countries for that given part. I then deflate the value into year 2000 dollars, and aggregate the value and weight data over all years. Dividing the aggregated weight by the aggregated value, I obtain the weight by value measure used in the paper (which is in units of 100s of Mg/dollar).

[20] The Elm International Database is a database of automotive supplier plant s. It includes their location, employees, assembler firms supplied, and parts made at a given point in time. The version used this paper is from 2008.

[21] This categorization was done largely on the basis of Klier and Rubenstein (2008).

[22] Both of these approaches seem to capture different dimensions of the data. For example, seats, which are frequently co-located with an assembly plant have a relatively low weight-by-value.

A.4 Firm Continent and Tying

I constructed variables for firms' continent of origin and historical ties using internet research and Klier and Rubenstein (2008). The continent of origin was determined on the basis of the parent company's country of origin.

The "historic ties" variable differs by the continent of the supplier. For North American owned firms, this variable is for suppliers and assemblers that were formerly vertically integrated. For Japanese firms, this is for firms that are in the same keiretsu (or in the case of Honda, a listed affiliate)

For some of the analysis, I look at whether firms have signed a previous contract. For these analysis, I run descriptive statistics and estimation on years after 2005 and use the data in 2004 and earlier to determine whether the firms had signed a contract. For supplier firms with no contracts in the dataset (for any assembler) prior to 2004, I interpolate this variable as the average share of other suppliers of their continent of origin who had contracts with this assembler.

A.5 Automotive Production

For assembler locations, I use information from Wards Automotive Yearbook about which car model was produced in which plant supplemented with internet research to obtain the location of the assembly plant.

A.6 Representativeness of Data

To compare the representativeness of the WSW data to the US automotive industry as a whole, I consider the relative frequency that each assembler appears in the data to their share of US automotive production. Table III shows these statistics, divided into 1999-2004 and 2005-2008 time period. The 1999-2004 period includes 3,509 contracts, of which 2,289 (65%) are won by a "Top 150" firm. The 2005-2009 time period includes 9,432 contracts, of which 5,543 (59%) were won by a "Top 150" firm.

Comparing the first column, share of US production, to the second column, share of contracts in the data, shows that nearly every firm producing in the United States has some reprsentation in the database. However, European assemblers (i.e., BMW, Daimler) are relatively overrepresented, while Asian assemblers (e.g., Honda, Toyota, Nissan) are underrepresented.

Comparing the second to the third column is also informative, since these compare all contracts to the contracts that were won by a "Top 150" supplier. These contracts look similar, which suggests that there is no obvious selection by assembler on which contracts were won by a "Top 150" firm. Contracts that are won by a non "Top 150" firm are considered the "outside option" in the estimation. Therefore, the identifying variation will come from differences in the characteristics of the 7,832 contracts that were won by a "Top 150" firm.

Assembler	Production Share	Contracts Share	Inside Contracts Share
BMW	1%	4.7%	3%
Chrysler	15.1%	16%	17.9%
Daimler	0.7%	0%	0%
Ford	28%	28.4%	30.4%
General Motors	33.6%	26.5%	26.1%
Honda	6.3%	3.7%	2.8%
Mazda	0.6%	0%	0%
Mitsubishi	1.2%	0%	0%
Nissan	4%	18.5%	17.5%
Subaru	1.3%	0%	0%
Toyota	8.2%	2.2%	2.3%

(a) 1999-2004

Assembler	Production Share	Contracts Share	Inside Contracts Share
BMW	1.3%	7.8%	7.1%
Chrysler	14.5%	21.9%	23.6%
Daimler	1.4%	7.6%	7.3%
Ford	21.9%	21.9%	22.3%
General Motors	28.1%	23.7%	23.1%
Honda	9.5%	5.6%	5%
Hyundai	2%	1.8%	1.8%
Mazda	0.7%	1.3%	1.3%
Mitsubishi	0.8%	0.7%	0.7%
Nissan	6.9%	2.4%	2.3%
Subaru	1%	0%	0%
Toyota	11.9%	5.4%	5.5%

(b) 2004-2008

Table III Production and Contracts in Data by Assembler

B Supplemental Tables and Figures

	1999-2004	2004-2009
Log Distance (in 100s of Miles)	-0.215	-0.143
	(0.015)	(0.01)
Asian Supplier and Assembler	1.423	1.722
	(0.176)	(0.115)
European Supplier and Assembler	0.85	1.028
	(0.285)	(0.105)
NorAm Supplier and Assembler	0.473	0.029
	(0.119)	(0.084)
Historical Connection	0.758	1.016
	(0.1)	(0.066)

Table IV Variable Cost Estimation Results By Year

Note: All regressions include supplier and assembler indicator variables and a linear time trend.

	All	No Michigan
Log Distance (in 100s of Miles)	-0.162	-0.152
	(0.008)	(0.01)
Asian Supplier and Assembler	1.619	1.611
	(0.096)	(0.109)
European Supplier and Assembler	0.883	0.865
	(0.093)	(0.094)
NorAm Supplier and Assembler	0.189	0.177
	(0.068)	(0.074)
Historical Connection	0.971	1.232
	(0.055)	(0.065)

Table V Variable Cost Estimation Results By Assembler Geography

Note: All regressions include supplier and assembler indicator variables and a linear time trend.

	Log	Piecewise Linear
Log Distance (in 100s of Miles)	-0.162	
	(0.008)	
PW Linear: Under 60 Miles		-0.969
		(0.072)
PW Linear: Between 60 and 400		-0.058
		(0.013)
PW Linear: Over 400		-0.021
		(0.008)
Asian Supplier and Assembler	1.619	1.599
	(0.096)	(0.096)
European Supplier and Assembler	0.883	0.867
	(0.093)	(0.093)
NorAm Supplier and Assembler	0.189	0.184
	(0.068)	(0.068)
Historical Connection	0.971	1.076
	(0.055)	(0.055)

Table VI Variable Cost Estimation Results By Functional Form of Transporation Costs

Note: All regressions include supplier and assembler indicator variables and a linear time trend. The piecewise linear terms are reported by line segment, with kinks at 60 and 400 miles.

Log Distance (in 100s of Miles)	-0.157
	(0.012)
Log Distance X Wgt By Value	-0.027
	(0.048)
Asian Supplier and Assembler	1.619
	(0.096)
European Supplier and Assembler	0.883
	(0.093)
NorAm Supplier and Assembler	0.189
	(0.068)
Historical Connection	0.971
	(0.055)

Table VII Variable Cost Estimation Results by Part Weight

Note: All regressions include supplier and assembler indicator variables and a linear time trend. Weight by value is measured in 10,000 Mg/dollar.

Log Distance (in 100s of Miles)	-0.35
	(0.027)
Asian Supplier and Assembler	0.911
	(0.29)
European Supplier and Assembler	-0.85
	(0.38)
NorAm Supplier and Assembler	0.92
	(0.203)
Historical Connection	-0.719
	(0.313)

Table VIII Variable Cost Estimation Results for JIT Parts

Note: All regressions include supplier and assembler indicator variables and a linear time trend.