Migration and Agglomeration Among Motor Vehicle Parts Suppliers*

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Abstract

Motor vehicle manufacturing in North America has been geographically clustered for most of its history, but the agglomeration forces that maintained such clustering have not prevented an industry migration in recent decades. As production migrates, states have offered large subsidies to new assembly plants in hopes of also attracting a cluster of suppliers. This paper uses supplier and assembly plant locations from 1986 to 2011 to estimate a dynamic structural model of suppliers' site selection and plant closure decisions. The model contains terms for various local costs and for agglomeration effects. It models future expectations of costs and assembler locations, which otherwise would bias static models. Finally, this paper estimates the locations of suppliers under counter-factual placement of assembly plants; this provides case-specific estimates for the additional employment gains a successful assembly plant subsidy bid generates.

1 Introduction

Motor vehicle manufacturing in North America has been migrating steadily for the past thirty years. Some policymakers have offered large subsidies to new assembly plants, hoping not only to lure the assembly plant but also to influence the migration of parts suppliers that supply the assembly plants. The effectiveness of such a strategy depends on how closely suppliers follow the assembly plants, how pronounced the agglomeration benefits of being near other suppliers are, and what the other factors determining supplier profitability are.

Because of their economic importance and policy relevance, industrial location decisions have inspired a sizable literature both in the motor vehicle parts industry and generally. Many studies have followed Carlton (1979) in applying a discrete choice framework to the

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site selection of new plants that had entered over a single set period. Early analysis of parts supplier location decisions, beginning with Smith and Florida (1994), followed such an approach. More recent work has included sophisticated variations of discrete choice modeling, but all have treated part supplier entry decisions as static decisions based only on conditions at the time of entry.[1] When plants are durable and require sunk construction costs, the profitability of a location will depend on how location characteristics evolve over the plant's life. Site selection decisions therefore must involve dynamic considerations.

If entrants expected local conditions to remain constant from period to period, static and dynamic models would give the same results. In motor vehicle manufacturing, conditions have been anything but constant. The sustained migration of assemblers forces suppliers to consider dynamics. An entrant valuing proximity to assemblers will evaluate regions with small but growing assembly clusters differently than regions without growth in assembly. Likewise, such a supplier would be more hesitant to enter a region where assembly plants are exiting or contracting. The steady growth of assembly in southern states like Alabama and the steady declines in Michigan over the last 25 years prevent suppliers from relying on conditions at the time as a proxy for the conditions they should expect over the life of a plant. While the migration complicates the problem for both suppliers and econometricians, it also provides the variation in the data needed to separate the effects of observed and unobserved location characteristics and produce unbiased estimates.

One reason dynamics have been omitted in previous analyses of location decisions is they are technically challenging to include. This analysis has several relevant variables in hundreds of locations, creating a state space that would have been intractably large before the development of new two-step techniques for estimating industry dynamics[2] allowed such models to be estimated. This paper adopts these techniques to estimate a dynamic entry and exit model where new parts supplier entrants choose between all locations. The first stage of estimations finds policy rules for entry and exit, as well as the transitions of location characteristics, directly from data. These recovered policy rules and transitions allow conditions in a location

[1] See also Woodward (1992) and Seim (2006). Static models of motor vehicle parts suppliers entry include Smith and Florida (1994), Klier and McMillen (2008), and Rosenbaum (2013). Head, Ries, and Swenson (1995) add state time trends to an otherwise static model.

[2] Bajari, Benkard, and Levin (2007),Aguirregabiria and Mira (2007), and Pakes, Ostrovsky, and Berry (2007); applications include Collard-Wexler (2014) and Ryan (2012)

and their associated payoffs to be simulated. The average discounted lifetime sums of these variables enter the value function. Using these simulated values, the second stage estimates structural value function parameters that rationalize the observed behavior, as estimated in the first stage. This generalizes the approach of earlier works, with their results corresponding to the first stage policy estimates. The structural parameters recovered in the second stage permit policy simulations that use expectations and replicate the suppliers' dynamic decision.

The model finds that proximity to assembly plants increases the profits of suppliers, but by a small enough amount that single assembly plants have a negligible effect on supplier location decisions. This finding is driven by the small response of observed entry to the enormous shift in assembly locations in the last 25 years. Entry persists in Michigan and the Great Lakes region despite sustained reductions in assembly output, and the quadrupling of assembly in the South has brought a much less pronounced migration of suppliers. This result is found in the first stage policy function estimates as well as the second stage dynamic estimates. The finding is present also in the static entry models similar to the first stage estimation (Klier and McMillen 2008). The most notable difference between the static and dynamic results are with the profitability from locating near other parts suppliers. Head, Ries, and Swenson (1995) first noted the presence of these agglomeration benefits, but static estimates underestimate their size. The relatively stable supplier base continues to attract new entrants to the North, even though assemblers are exiting the region.

The entry and exit model allows policy simulations that move assembly plants, which is effectively what state and local governments do with subsidy bids. The variables of interest, the number of suppliers in each location, are simulated by allowing entrants and exits to use their policy rules in a dynamic game. (See Benkard, Bodoh-Creed, and Lazarev (2010) for a methodologically similar counterfactual experiment.) The counterfactual experiment in section 8 predicts the evolution of supplier locations if the assembly plant recently opened in Tennessee had instead been placed in Michigan. For comparison, I also run model simulations with the actual placement of supplier plants. The supplier counts in the two simulations diverge from each other, responding both to different assembly plant locations and to the endogenous supplier counts themselves. But the two simulations do not diverge much. Since the effect of assembly plant proximity on supplier profits is so small, moving the assembly plants produces a cumulative effect of only one less supplier after four five-year periods. A separate experiment restricts the ability of a entrant to receive agglomeration benefits, and it finds such an entrant has a probability of entry into Michigan that is only a quarter of an entrant with using the actual profit function estimated.

The potential bias caused by unobserved location characteristics confounding the effects of variables of interest had not been directly addressed for part suppliers. Greenstone, Hornbeck, and Moretti (2010) in looking for productivity spillovers from large, new manufacturing plants were concerned that the unknown factors driving those plants to enter could also drive productivity or entry in other plants nearby. In this application, unobserved location characteristics that contribute to supplier entry may easily have influenced assembler or supplier entry in previous periods and therefore be correlated with assembler proximity and incumbent counts. While the approach here, using location fixed effects, differs from the regression discontinuity design of Greenstone, Hornbeck, and Moretti (2010), it addresses the same endogeneity concerns.

Location characteristics determine the profits that drive closure and site selection decisions in the model. The location characteristics considered here correspond to the reasons for clustering advanced by urban economic theory: proximity to customers is measured with proximity to assembly production, peer agglomeration effects are permitted with the number of other suppliers entering profit functions, and cost variables are included to account for the natural advantages of locations. The results contribute to the literature using industry migration to examine the causes of clustering, as in Holmes (1999) and Dumais, Ellison, and Glaeser (2002), and more generally to the literature testing which theorized causes of clustering are empirically important as in Ellison, Glaeser, and Kerr (2010).

The use of a dynamic entry and exit model to estimate agglomeration benefits is similar to Brinkman, Coen-Pirani, and Sieg (2012), but here entrants choose from a much wider set of locations. The two-step estimation techniques allows this paper to recover parameters without assuming an equilibrium selection rule or even calculating equilibrium. Unlike Brinkman, Coen-Pirani, and Sieg (2012), this paper does not estimate productivity or use firm age and size. This model is driven entirely by location characteristics, entry counts, and exit probabilities.

2 Industry Migration

Motor vehicle manufacturing in North America is geographically clustered and has been for nearly the entirety of the industry's history. Auto alley, defined here as Wisconsin, Michigan, Illinois, Indiana, Ohio, Kentucky, Tennessee, North Carolina, South Carolina, Georgia, Alabama, and Mississippi, hosts 82% of the motor vehicle final assembly and 76% of the employment at parts suppliers for the United States. Northern Auto Alley, the portion of auto alley north of 40.5° [3], alone contains 41% of national supplier employment and 36% of assembly production.

Suppliers locate near each other and near assemblers. Ellison and Glaeser (1997) found that clustering among suppliers (in SIC 3714) was far more concentrated than if plants were placed randomly according to the population distribution, and that the coagglomeration with assemblers (in SIC 3711) was one of the most pronounced among all upstream-downstream industry-pairs.

Northern Auto Alley traditionally had an even higher concentration of assemblers. In 1986 Northern Auto Alley produced 5.8 million vehicles, over half of the United States total. While the production totals fluctuated with the business cycle, the share of national production by Northern Auto Alley steadily declined. Ford and General Motors had established branch assembly plants near major markets throughout North America in the early 20th century. Starting in the 1980s, they gradually closed their outlying assembly plants, so production in the United States outside of auto alley declined even more than in Northern Auto Alley.

Meanwhile, automakers headquartered in Asia and Europe built "transplant" assembly plants in the Midwest and South. Honda opened an assembly plant in central Ohio in 1982, and Nissan entered in Tennessee in 1984. Toyota began joint operation of a California plant with General Motors in 1983 and built its own plant in Kentucky in 1987. In 2011, Asian and European firms operated 17 assembly plants in the United States,[4] of which 13 are in

[3] Michigan, Wisconsin, and the northern thirds of Illinois, Indiana, and Ohio are included by this definition. Figures 1 and 2 display the boundary used on a maps of Auto Alley. Southern Auto Alley is defined as the portion of auto alley south of 40.5°. This cutoff was chosen to group together all the assembly plants wholly owned by foreign carmakers. In estimation, latitude will be discretized in bins, with 40.5° as a divider, but this can be adjusted in robustness checks.

[4] The 2011 count includes Mazda's joint venture with Ford. Ontario, Canada also hosts 1 joint venture and 3 transplant assembly plants.

Table 1: Migration of motor vehicle manufacturing

	1986	1991	1996	2001	2006	2010
Assembly production (% of US total)						
Northern Auto Alley	51.6	48.8	45.3	41.2	36.7	36.3
Southern Auto Alley	12.1	21.9	26.5	31.4	40.5	45.3
US outside Auto Alley	36.2	29.3	28.3	27.4	22.8	18.4
Parts supplier employment (% of US total)						
Northern Auto Alley	50.3	48.7	46.1	42.6	43.1	41.3
Southern Auto Alley	27.0	26.5	29.1	32.7	32.7	35.1
US outside Auto Alley	22.7	24.8	24.8	24.6	24.2	23.6

Computed from production counts of cars and light trucks reported in various editions of Ward's Automotive Yearbook. Northern Auto Alley comprises Michigan, Wisconsin, and the portions of Illinois, Indiana, and Ohio north of 40.5° latitude. Southern Auto Alley comprises Alabama, Georgia, Kentucky, Mississippi, North Carolina, South Carolina, Tennessee and the portions of Illinois, Indiana, and Ohio south of 40.5° latitude.

the Southern Auto Alley. Because of transplant construction (and despite Ford and General Motors plant closures in Atlanta), the number of assembly plants in the Southern Auto Alley has more than doubled since the early 1980s. Southern Auto Alley eclipsed Northern Auto Alley production counts by 2006, reversing a gap of four million vehicles twenty years earlier. The top half of table 1 reports the percent of national assembly output by region and shows the steady migration throughout the 25 year period.

The migration of assemblers was identified while still underway(Rubenstein 1992). Books describing the advantages that transplants entering the south had over the incumbent assemblers concentrated in the north had even reached the popular press.[5] Suppliers of the period would have been aware of the migration and would have needed to consider it when making plans.

The changing landscape of motor vehicle assembly has provided states many opportunities to bid on new plants or compete to retain existing plants. State and local governments offer to pay training costs, build infrastructure, and provide other indirect subsidies for new assembly plants. Every winning bid in the past decade has had a reported value exceeding $100 million; the most recent assembly plant announced for North America, Volkswagen's Chattanooga assembly, followed a subsidy bid reportedly costing $588 million. While assembly plants

[5] James Womack, Daniel Jones, and Daniel Roos published *The Machine That Changed the World* in 1990. The first edition of David Halberstam's *The Reckoning* was printed in 1986.

are large employers, the subsidies governments pay exceed several years of plant payroll. Policymakers argue that a winning assembly plant bid will have a broader economic impact and that parts suppliers will follow the assembly plant. For example, following the Volkswagen announcement, the local press reported Tennessee's "Governor Bredesen said the 2,000 direct jobs at VW are 'the tip of the iceberg.'" Mississippi Governor Haley Barbour said: "We expect more suppliers to begin work and create jobs as the [Toyota Blue Springs] auto plant prepares to start production."[6]

The overall migration of suppliers has been less dramatic than the movement of assemblers, but still notable. Although assembly production between 1986 to 2011 decreased 58% in Northern Auto Alley, employment at supplier plants decreased only 12 % and plant counts increased by 15%. Assembly production during the same period increased in Southern Auto Alley 124%, but supplier employment grew by a more modest 40% and supplier plant counts increased by 73%. The bottom half of table 1 shows supplier plant employment in each region.

The more specific migration of suppliers into the area around new assembly plants varies. In the five years following Hyundai's 2005 opening of a new assembly plant in Montgomery, Alabama, the number of large[7] supplier plants within 100 kilometers rose from 9 to 17. Nissan's Canton, Mississippi two years earlier brought no such influx; the number of nearby supplier plant even decreased. Table 2 reports how the number of large supplier plants nearby changed after each assembly plant opening.

3 Data

I construct a panel of supplier plants and location characteristics for five five-year periods beginning in 1986 and ending in 2011. The data set is limited to 12 eastern states in Auto Alley. Part suppliers outside of auto alley may focus on the aftermarket or export market and have a wholly different set of location preferences from those operating in Auto Alley or considering entry into Auto Alley. The states within Auto Alley accounted for more than 75% of national employment in motor vehicle parts manufacturing in every data period.

[6] Pare, Mike. "Chattanooga 'best fit' for VW, CEO says" *Chattanooga Times Free Press*. 16 Jul 2008. and "Governor Barbour Announces Toyota Supplier Will Restart Operations in Baldwyn." Office of the Governor of Mississippi Press Release. 30 July 2010.

[7] Twenty of more employees.

Table 2: Supplier migration near new assembly plants

	Opening	Large Supplier Plants			
Assembly plant	Year	5 yrs prior	at opening	5 yrs after	10 yrs after
Roanoke, IN / GM	1986	57	52	71	85
Fairfax, KS / GM	1987	6	4	3	8
Georgetown, KY / Toyota	1987	11	15	22	35
Normal, IL / Mitsubishi	1988	5	9	11	7
Lafayette, IN / Subaru	1989	14	13	22	30
East Liberty, OH / Honda	1989	40	55	60	74
Spring Hill, TN / GM	1990	10	15	21	31
Greer, SC / BMW	1994	15	20	31	34
Princeton, IN / Toyota	1996	14	10	10	15
Vance, AL / Daimler AG	1997	5	5	5	9
Lincoln, AL / Honda	2001	8	6	9	13
Canton, MS / Nissan	2003	8	5	2	1
Montgomery, AL / Hyundai	2005	4	9	17	
San Antonio, TX / Toyota	2006	1	3	7	
Greensburg, IN / Honda	2008	51	50	21	
West Point, GA / Kia	2009	7	15		
Blue Springs, MS / Toyota	2011	7	5		
Chattanooga, TN / Volkswagen	2011	20	14		

Counts of motor vehicle part suppliers plants with 20 or more employees within 100 kilometers of the assembly plant site. Calculated from county counts reported in the US Census County Business Patterns.

Table 3: Summary Statistics for Location Characteristics

Variable	Mean	Std. Dev.	Min	Max
Interstate in county	0.80	0.40	0	1
Manufacturing wage (hundred $/wk)	5.55	1.30	2.37	8.53
Population density (hundred per sq km)	10.83	15.24	0.12	54.87
Incumbent suppliers in county	11.6	15.7	1.0	50.0
Private sector unionization rate	0.195	0.118	0.000	0.594
Assembly quantity within 100km (mil)	0.923	1.305	0	3.971
Assembly quantity within 700km (mil)	5.898	2.729	0	8.334
Locations	1106			

Data for 1986, weighted by incumbent suppliers.

For estimation, a county is a location. Location characteristics include local manufacturing unionization rates, interstate highway presence (reported as a binary), local manufacturing wage (reported as a weekly average in hundreds of 1986 dollars), and the production quantity of assembly plants within 100 and 700 kilometers (both reported in millions of vehicles per year). Appendix A1 lists specific sources for each variable. Table 2 displays summary statistics of these location variables.

Supplier plant locations are based on Dun & Bradstreet data. Supplier plants are establishments to which Dun & Bradstreet assigned the primary SIC classification of 3714 Motor Vehicle Parts and Accessories. This Standard Industrial Classification (SIC) code for parts includes steering wheels, transmissions, brake systems, some engine parts, and most other parts. It accounts for almost half of the inputs used by plants in the motor vehicle assembly classification. Separate classification codes were given to Carburetor, piston, piston ring, & valve mfg (3592), Vehicular lighting equipment (3647), and Engine electrical equipment (3694). Plants classified into these codes are not included in descriptive statistics, but have been used in robustness checks of the model. Other components, like seats and glass, were classified into general categories and will not be covered in this analysis.

A dynamic entry and exit model requires a panel data set. The Dun & Bradstreet data was selected because its cross sections can be linked. (For details of that procedure, see Appendix

A1.) Entry is defined as the appearance of a plant not open in any previous period, closure as a plant not present in any future period. The Dun & Bradstreet data for this period replicates patterns in plant counts found in County Business Patterns and is suited for entry and exit models. Appendix A2 discusses the quality checks on the Dun & Bradstreet data further.

Table 3 shows parts supplier plant counts. Note that in each cross section the plant count and employment totals (shown in table 4) are highly correlated, though average employment declines in all regions over time. For simplicity, the model will use plant counts.

New entrant counts are shown in table 5. Strikingly, the majority of new supplier entrants every period chose to locate in the north despite the dramatic exit of assemblers.

4 Model

The entry and exit model focuses on the location decisions of part suppliers. Incumbent supplier plants and potential entrants are players in a dynamic game of the class introduced by Ericson and Pakes (1995). Time is discrete in this model. In each period potential entrants choose if and where to enter. Incumbent supplier plants decide whether to exit the industry or remain in operation. New entrants and remaining incumbents earn profits based on their locations and the locations of other suppliers. After a new entrant selects its location and becomes an incumbent supplier, and its only remaining decision is when to exit.

Location characteristics drive supplier profits in the model. Locations are indexed by ℓ. At any time t, each location has a set of characteristics $X_{\ell t}$, which suppliers take as given. Assemblers are not players in this model, but assembler proximity is a component of $X_{\ell t}$. While supplier locations in the aggregate may influence assembly plant placement, as in Holmes (2004), the impact of any single supplier plant is negligible, so the suppliers modeled treat assembler proximity as exogenous. Modeling assembler and supplier location decisions jointly would increase the complexity, but would not greatly change estimation of the individual supplier decisions that are the focus of this work.

Every period each incumbent plant must decide whether to remain open or close permanently. Suppliers take all location characteristics and competitor locations as given. At the beginning of each period, each supplier draws a private, random scrap value ϵ_{it}^{exit} and a profit

Table 4: Supplier counts

	1986	1991	1996	2001	2006	2011
Northern Auto Alley	467	552	652	671	646	539
N Illinois	72	68	79	69	58	56
N Indiana	45	57	81	77	82	69
Michigan	228	282	324	360	377	297
N Ohio	93	108	124	120	92	77
Wisconsin	29	37	44	45	37	40
Southern Auto Alley	263	361	411	454	496	456
Alabama	18	20	20	23	31	37
Georgia	29	33	29	26	31	39
S Illinois	19	21	18	24	23	20
S Indiana	47	50	61	84	88	71
Kentucky	21	33	47	60	69	60
Mississippi	13	16	16	14	16	16
North Carolina	31	49	57	42	51	46
S Ohio	36	58	63	60	56	48
South Carolina	11	22	32	42	50	51
Tennessee	38	59	68	79	81	68

Table 5: Part supplier employment (thousands)

	1986	1991	1996	2001	2006	2011
Northern Auto Alley	171.3	203.4	199.0	231.1	186.7	151.6
N Illinois	13.7	11.7	13.0	14.2	8.1	8.8
N Indiana	10.0	11.8	17.7	16.0	15.2	15.3
Michigan	96.7	129.0	121.2	145.5	126.5	92.7
N Ohio	39.5	37.5	37.5	43.6	30.6	27.3
Wisconsin	11.3	13.4	9.7	11.7	6.4	7.5
Southern Auto Alley	91.9	110.8	125.3	177.6	141.6	128.9
Alabama	4.2	6.0	8.7	10.4	7.0	6.7
Georgia	3.5	4.0	3.4	6.1	5.4	5.2
S Illinois	4.5	5.9	6.5	8.1	8.7	7.0
S Indiana	33.1	27.1	35.7	55.9	34.5	36.6
Kentucky	4.0	8.2	11.0	16.2	17.1	16.0
Mississippi	3.4	4.2	4.3	4.7	2.5	2.7
North Carolina	6.3	12.7	12.4	12.9	11.3	10.2
S Ohio	17.4	25.8	19.3	31.8	21.7	16.0
South Carolina	2.2	4.0	7.5	11.3	13.3	11.4
Tennessee	13.2	13.1	16.6	20.1	20.1	17.1

Table 6: Supplier entry counts

	New entrant count for period beginning in				
	1986	1991	1996	2001	2006
Northern Auto Alley	299	287	258	163	115
Southern Auto Alley	212	174	182	141	100

shock ϵ_{it}^{stay}. After observing these draws the incumbent may either claim the scrap value by exiting permanently or remain and earn period profits $\pi(X_{\ell t}, n_{\ell t}, \xi_{\ell}) + \epsilon_{it}^{stay}$, where

$$\pi(X_{\ell t}, n_{\ell t}, \xi_{\ell t}) = \gamma_X X_{\ell t} + \gamma_n n_{\ell t} + \xi_{\ell t}$$

All production costs enter period profits linearly, that is as fixed costs, so that in estimation the parametric functional forms will be as simple and transparent as possible. Profits also depend on unobserved characteristics, $\xi_{\ell t}$ for each location. The unobserved characteristics may be correlated with $n_{\ell t}$ and $X_{\ell t}$, which would bias estimates that ignore $\xi_{\ell t}$. The correlation with the number of incumbents $n_{\ell t}$ arises because the unobserved characteristics suppliers find profitable would have prompted more suppliers to enter in previous periods. Assembler proximity is a component of $X_{\ell t}$ and the unobserved characteristics that benefit suppliers may also attract assembly plants. Greenstone, Hornbeck, and Moretti (2010) were concerned about bias caused from local unobservables enough to use a regression discontinuity design in their productivity estimation. This paper will offer several approaches to control for unobserved characteristics, most of them made possible by panel data and variation over time brought by the migration.

The scrap value is drawn from a Type I extreme value distribution. The profit shock is the sum of two random variables. The first is a private, idiosyncratic component drawn from a Type I extreme value distribution, the second a time-specific shock common to all suppliers. Motor vehicle production and profitability are highly cyclical, but the focus of this model is on supplier location choice and not the determinants of the macroeconomy. Some of the effects of recessions will come through in the wages and assembler production quantities contained in X_t, but all other macroeconomic conditions relevant to the closure decision of a supplier plant will enter into ϵ_{it}^{stay}.

Suppliers at the same location differ only in the idiosyncratic profit shocks and scrap values they draw. Since this model of location choice compares costs among locations without plants, plant-specific productivity measures are not estimated. (For production function estimation among motor vehicle assembly plants, see Van Biesebroeck (2003).)

A plant that remains open may operate or close and claim a scrap value in a future period, so its decision is a dynamic one. Each incumbent has expectations over the state variables $(X_{1t}, X_{2t}, \ldots, X_{Lt}, n_{1t}, n_{2t}, \ldots, n_{Lt})$. (For notational compactness, let $X_t = \times_{\ell=1}^{L} X_{\ell t}$, $n_t = \times_{\ell=1}^{L} n_{\ell t}$, and $xi_t = \times_{\ell=1}^{L} \xi_{\ell t}$). Let $a_{it} = 1$ denote closure for incumbent i in period t. Then the incumbent value function is

$$V_\ell(X_t, n_t, \xi, \epsilon_{it}^{inc}) = \max_{a_{it}} \begin{cases} \pi(X_{\ell t}, n_{\ell t}, \xi_{\ell t}) + \beta E_\ell[V_\ell(X_{t+1}, n_{t+1}, \xi_{t+1}, \epsilon_{it+1}) | X_t, n_t] + \epsilon_{it}^{stay} & : a_{it} = 0 \\ \epsilon_{it}^{exit} & : a_{it} = 1 \end{cases} \tag{1}$$

Expectations are indexed by ℓ as state variables can evolve according to different processes in different locations. The value function is indexed by ℓ only because expectations are also. Let χ_ℓ be the exit policy function that solves the value function in location ℓ.

Potential entrants select their location at the same time as incumbents make exit decisions. At the beginning of each period potential entrants draw location-specific entry costs for each location. They decide if and where to enter based on each location's incumbent value and the entry cost drawn for it.

Like the scrap value, the entry cost that potential entrant k draws for location ℓ has two components: $\epsilon_{k\ell t}^{entry} = \phi_t + \kappa_{k\ell t}$. The first component, ϕ_t, is a period-specific common cost drawn each period. As with exit, the relative attractiveness of entering or remaining outside the industry fluctuates with the macroeconomy. The second component, $\kappa_{k\ell t}$, is drawn from a Type I extreme value distribution and represents the entrant-specific considerations in the site selection problem.

All new entrants simultaneously choose a location in which to enter and become an incumbent or choose an outside option and remain outside the industry forever. The selection rule will be

$$\mu(X_t, n_t, \xi, \epsilon_t^{entry}) = \arg\max_l \begin{cases} \epsilon_{k0}^{entry} & : l = 0 \\ E[V_l(X_t, n_t, \xi, \epsilon_{kt})] - \epsilon_{kl}^{entry} & : l \in \{1, 2, \ldots, L\} \end{cases} \tag{2}$$

where $l = 0$ is the action for not entering and ϵ_{k0}^{entry} the random value of the outside opportunity. The entrants minimize their value minus entry costs through their site selection. Let $\mu(X_t, n_t, \xi, \epsilon_k^{entry})$ be the corresponding selection rule.

In this model an equilibrium is a policy function for potential entrants $\mu(X, n, \xi, \epsilon_k^{entry})$, a policy function for incumbent suppliers in each location $\chi_\ell(X_\ell, n_\ell, \xi, \epsilon_i^{inc})$, transition probabilities $g_\ell(X'_\ell, X_\ell)$, and a value function for each location $V_\ell(X, n, \xi, \epsilon_i^{inc})$ such that (1) given (X, n, ϵ, g), χ_l maximizes the value function in equation 1, (2) given $(X, n, \xi, \epsilon_k^{entry})$, $\mu(X, n, \xi, \epsilon_k^{entry})$ solves the entrants' maximization problem in equation 2, (3) supplier counts evolve according to $n'_\ell = n_\ell + \sum_k \mathbb{I}\left(\mu(X, n, \xi, \epsilon_i^{entry}) = \ell\right) - \sum_i^{n_\ell} \chi_\ell(X, n, \xi, \epsilon^{inc})$, (4) expectations on n_ℓ are rational, and (5) expected transition of exogenous state variables $g_\ell(X'_\ell, X_\ell)$ match those observed.

5 Estimation

5.1 Specification

For estimation, locations will be the 550 counties in auto alley that hosted a supplier plant sometime since 1986. The location characteristics, $X_{\ell t}$, include: interstate presence (interstate), local manufacturing wage (wage), state manufacturing unionization rate (union), and population density (popdenisty), quantity at assembly plants within 100 kilometers (qw100km), and quantity at assembly plants within 700 kilometers (qw700km). Interstate presence was largely constant throughout the 25 year data window and so is treated as a static variable. Unionization rates are a static variable, since the greater geographic detail needed would not have been available period by period. The supplier count n and all other components of X will be treated as dynamic state variables.

Only suppliers in the same county enter $n_{\ell t}$ and therefore period profits. The most widely proposed agglomeration mechanisms, such as labor pooling and knowledge spillovers, work on a very local level. Congestion costs related to overcrowded local infrastructure also are largely contained within a county. The influence of assembly plants is spread more widely, hence the assembler proximity measure in $X_{\ell t}$ account for plants far outside county boundaries. This unfortunately makes comparisons of assembly plant and supplier plant influence more difficult.

The unobserved characteristics $\xi_{\ell t}$ will be assumed to be permanent, and therefore location fixed effects can be used to recover the effects on entry and exit. Persistent characteristics are the ones most likely to be correlated with the entry decisions of assemblers and other suppliers that occurred in previous periods and therefore to the assembly proximity measures and supplier counts in the current period.

Periods will be five years and locations will be counties in auto alley. The number of potential entrants each period will be set at 700. The discount factor suppliers use will be $\beta = 0.90^5 \approx 0.59$, since periods are five years long. Robustness checks with different discount factors and potential entrant counts produce similar results.

5.2 Procedure

Estimation proceeds in two stages, following Bajari, Benkard, and Levin (2007). In the first stage, the entrants' location selection policy rule μ and incumbents' exit policy rule χ are taken directly from the data using flexible estimation. Transition functions for the exogenous state variables also are estimated. Using these estimates, forward simulations are run for each location and each period to find the discounted lifetime profits in terms of the model parameters. Finally, the second stage finds the model parameter values that best fit the observed behavior of potential entrants.

Locations are classified into two discrete bins by latitude, using the 40.5° latitude cutoff introduced in section 2. Each dynamic state variable in each latitude bin is assumed to follow first-degree autoregressive processes dependent only on itself. Separate regressions for each latitude bin are employed because different processes seem to be at work in the north and south during the migration.

The exit policy function $\chi(X_t, n_t, \epsilon_i)$ is estimated semiparametrically, with a flexible function of local state variables added to a logit error term. High order and interaction terms are included for the most important variables, while, for now, the characteristics of other locations are omitted from the regression.

To recover the entrants' selection rule, the expected incumbent value at each location is approximated by function of local state variables with higher order terms and interactions, but the estimation assumes the selection rule follows the multinomial discrete choice structure presented in the model. This multinomial logit accounts for the state variables for all locations, albeit in specific parametric form.

The existing static entry models for this industry follow a procedure similar to this policy function estimation. Indeed, one way to interpret the results of previous studies is as the policy function for far-sighted entrants.

Year fixed effects are included in the estimation of both the entry and exit policy functions to account for the common year-specific components in entry costs and profit shocks. Location fixed effects can control for the unobserved characteristic ξ_ℓ and prevent the endogenity bias that would otherwise occur.

Using the decision rule estimates and the observed transition frequency, the total expected lifetime discount profits of an incumbent are computed for each county-period observation. State variables and the exit decisions are forward simulated and the discounted sum for each variable recorded. The average of 500 simulations for each observation is used.

The second stage finds what parameters best fit the observed behavior of potential entrants. Instead of the minimum distance estimators originally proposed in Bajari, Benkard, and Levin (2007), estimation will again use the multinomial choice structure of entry decision. The Berry inversion allows for the difference in log shares of entrants in each location and the log shares of potential entrants remaining outside the industry to be regressed on the total lifetime discounted sum for each variable an incumbent expects in each location.

6 First Stage Results

First stage estimates of entry deliver the relative probabilities of entry in each location expected by incumbents. Table 6 reports five specifications. The first four columns contain only first order terms for ease of interpretation. They differ only by the type of location fixed effect used to control for the persistent unobserved location characteristics ξ. The unobservables are potentially correlated with assembly proximity and the number of incumbent suppliers, but the inclusion of location indicators affects coefficients on the variables of concern only minimally.

The coefficient signs largely match those found in established literature for this industry with suppliers seeking locations with interstates, lower population densities, and low union activity. The presence of additional assembly plants increases entry probability, something not clear in Klier and McMillen (2008).

Estimates for the autoregressive processes governing the exogenous state variables are reported in table 7. Separate processes are assumed to operate in each latitude bin, and indeed parameters for each group differ. The migration of assembly plants into the south means that a location in the south should expect more assembly within 100 kilometers next period than should a northern location with the same quantity this period.

Logit regressions describing the incumbent exit rule are reported in table 8. Again the simpler first specification is only to aid interpretation. The forward simulations use the second specification. Suppliers are more likely to exit if operating in a location with high wages, high union membership rates, and with little assembly within 100 kilometers. Note that the relative importance and even direction of some variables differ in the estimated entry and exit policy functions. Different plant turnover rates in the data drive these differences.

7 Second Stage Results

The second stage coefficient estimates for the full model are reported in table 9. Supplier profits are decreasing in local wages and unionization rates. The coefficient for suppliers, γ_n in the same county is positive, indicating that agglomeration benefits outweigh any costs of local competition. The model cannot distinguish between different sources for the agglomeration benefits, but benefits measured are in addition to the natural advantages of a location (measured with local characteristics in X_ℓ and ξ_ℓ) or the need to be near the final customers, the assembly plants. Since many parts suppliers have other parts suppliers as their customers in a multi-tiered network, some of the agglomeration may reflect the transportation costs

Table 7: First stage entry policy function estimation

	(1)	(2)	(3)	(4)	(5)
suppliers	0.0521***	0.0521***	0.0504***	0.0551***	0.115***
	(0.00220)	(0.00222)	(0.00231)	(0.00660)	(0.0110)
qw100km	0.0946***	0.0945***	0.0858**	0.336**	0.0210
	(0.0273)	(0.0273)	(0.0287)	(0.104)	(0.134)
qw700km	0.00423	0.00409	0.0237*	0.0453	0.00730
	(0.00492)	(0.00510)	(0.0115)	(0.0306)	(0.0192)
interstate	0.0630*	0.0630*	0.0576*	.	0.00137
	(0.0280)	(0.0280)	(0.0285)	.	(0.0265)
popdensity	0.0118***	0.0118***	0.0138***	-0.0506	0.0185***
	(0.00230)	(0.00231)	(0.00244)	(0.0315)	(0.00501)
union	-0.0597	-0.0650	0.00836	.	0.0533
	(0.135)	(0.145)	(0.167)	.	(0.311)
wage	0.0257	0.0257	0.0269*	-0.0167	0.0290
	(0.0132)	(0.0132)	(0.0136)	(0.0536)	(0.0574)
wage^2					-0.00269
					(0.00563)
union^2					0.491
					(0.634)
popdensity^2					-0.000453***
					(0.000116)
suppliers^2					-0.000920***
					(0.0000958)
qw100km^2					0.0290
					(0.0245)
qw700km^2					-0.000948
					(0.00159)
qw100km × qw700km					-0.00305
					(0.0154)
qw100km × suppliers					-0.00365
					(0.00260)
qw700km × suppliers					0.000386
					(0.00115)
Location indicators	none	latitude bin	state	county	latitude bin
Year indicators	yes	yes	yes	yes	yes

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Transition of local characteristics

	Southern Auto Alley			Northern Auto Alley		
	Lagged variable coeff	Constant	Mean Sq Error	Lagged variable coeff	Constant	Mean Sq Error
Population density	1.0336	0.0577	0.3669	0.9919	0.1489	0.5152
Wage	0.8925	0.5173	0.4692	0.8345	0.7897	0.5027
Assembly quantity with 100 km	0.8775	0.0322	0.1277	0.8646	0.0238	0.2584
Assembly quantity with 700 km	0.8649	0.5870	1.2381	0.6009	3.1980	1.3489

associated with receiving or sending intermediate goods. Nearby assembly plants increase profitability, but only slightly.

For comparison, dynamic results are compared to estimates of the static model. Suppliers in the dynamic model consider being in a region with high assembly quantity to be less important. The static model explains the persistence of suppliers in Northern Auto Alley by noting the high contemporaneous assembly production. In the dynamic model, suppliers see the transition of assembly quantity within 700 kilometers and know that high current assembly production is no guarantee of continued assembly production. Since suppliers persist in the north even though they suspect assemblers will leave, the dynamic model must find other, less transitory factors to explain the continued entry in the north. The dynamic model concludes that agglomeration effects must be bigger and that union costs must be smaller than static models would suggest.

Assembly quantity within 100 kilometers also is more important in the dynamic model than in the static estimates. Areas with the highest concentration of assembly plants also have the highest turnover rates and therefore the highest predicted exit rates and shortest expected plant lifetime. Yet entrants still select these areas. The model concludes that entrants must find the immediate proximity of assembly plants profitable enough to justify the higher hazard rate caused by other variables.

Table 10 reports the marginal effect of a unit increase of each variable on the expected number of new entrants in 2006 in a location with average state variables. The dynamic model differs from the static model not just in coefficient values, but in that future state variable

Table 9: First stage exit policy function

	(1)	(2)
suppliers	-0.00426	0.0504
	(0.00278)	(0.0303)
qw100km	0.0918	-0.0772
	(0.0533)	(0.408)
qw700km	-0.0681***	-0.292***
	(0.0150)	(0.0730)
wage	0.0831*	-0.114
	(0.0397)	(0.214)
union	0.460	1.531
	(0.356)	(0.934)
interstate	-0.0371	-0.0350
	(0.0886)	(0.0938)
popdensity	0.00480	0.0239*
	(0.00334)	(0.0118)
suppliers^2		-0.000101
		(0.000122)
qw100km^2		0.0655
		(0.0517)
qw700km^2		0.0183**
		(0.00565)
qw100km × qw700km		-0.00328
		(0.0424)
qw100km × suppliers		-0.00339
		(0.00341)
qw700km × suppliers		-0.00432
		(0.00288)
wage^2		0.0151
		(0.0203)
union^2		-1.565
		(1.765)
popdensity^2		-0.000441
		(0.000225)
northern auto alley	0.334***	0.319***
	(0.0852)	(0.0896)
Year indicators	yes	yes
N	4973	4973

Standard errors in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Dynamic and myopic results

	Static	Dynamic
	(1)	(2)
suppliers	0.0521***	0.192***
	(0.00222)	(0.00802)
qw100km	0.0945***	0.318***
	(0.0273)	(0.0831)
qw700km	0.00409	-0.0109
	(0.00510)	(0.0144)
wage	0.0257	0.00431
	(0.0132)	(0.0474)
union	-0.0650	-0.0744
	(0.145)	(0.397)
interstate	0.0630*	0.117
	(0.0280)	(0.0709)
popdensity	0.0118***	0.0351***
	(0.00231)	(0.00704)
Year indicators	Yes	Yes
Location indicators	latitude bin	latitude bin

Standard errors in parentheses. Standard errors currently account only for second stage and therefore are a lower bound.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

values are used to predict entry. The table calculates the effect of both a single period increase in each variable while holding the rest of a supplier's profit stream fixed and a permanent proportional increase in the variable in all future periods. A one million vehicle increase in nearby assembly production, the rough equivalent of three new assembly plants, brings up the number of supplier plants entering each county by only a small fraction.

8 Counterfactuals

8.1 Simulation with counterfactual placement of assembly plants

The dynamic model can simulate supplier entry and exit starting from actual or counterfactual conditions. The transition functions estimated in the first stage can be used to simulate

Table 11: Marginal effect on the number of new entrants

	Static model	Dynamic model single period change	Dynamic model permanent change
suppliers	0.022	0.054	0.093
qw100km	0.040	0.094	0.167
qw700km	0.002	-0.002	-0.005
wage	0.011	0.001	0.002
union	-0.025	-0.019	-0.031
interstate	0.026	0.033	0.054
popdensity	0.005	0.010	0.016

Marginal effects at the average values, measured by number of new entrants per period.

location characteristics in future periods, in much the same way that they were used in the forward simulations in the estimation routine. Because the policy functions estimated in the first stage are equilibrium objects, they too can be used in the forward simulation to simulate the site selection of new entrants and the closure decisions of incumbents.

The model can be used for the exact counterfactual experiments policymakers should consider. The additional number of suppliers brought to a jurisdiction by a successful bid can be estimated by comparing model simulations where assembler proximity variables are increased to reflect the new assembly plant locating in different sites.

The experiment here specifically moves the new Volkswagen assembly plant in Chattanooga, Tennessee to Grand Rapids, Michigan. The counterfactual location was motivated by press reports that before announcing their location decision, Volkswagen officials had considered three finalist sites in Alabama, Tennessee, and Michigan. Tennessee's efforts to become the host of the new plant included a subsidy bid reportedly costing $577 million.[8] If a smaller subsidy offer from Tennessee would have lead Volkswagen to place its plant in Michigan, this counterfactual experiment answers how many suppliers Tennessee's half billion dollar subsidy

[8]Pare, Mike. "VW Spends Most of $235 million in infrastructure aid." Chattanooga Times Free Press. 12 Oct 2011. The bid included $130 million in waived taxes that would not have existed without the plant anyway, but the rest of the subsidies represent real expenditures.

brought.

In the first model simulation all assembly plants are given their actual locations and actual production quantities for 2011. (Since the new Volkswagen plant opened near the end of 2011, I use an estimate of 150,000 units for its production count. This should form a better basis for supplier expectations than the actual count from the last few months of 2011.) From this, the assembly production within 100 kilometers and within 700 kilometers variables are calculated. All other location characteristics start with their 2011 values. Following Benkard, Bodoh-Creed, and Lazarev (2010), the first stage estimates of transitions and policy function simulate the evolution in each county of the number of suppliers and of all location characteristics, including assembly production nearby. The counterfactual simulation moves the coordinates for the Volkswagen plant to those for Grand Rapids, Michigan. This results in starting period values for assembly production within 100 kilometers and 700 kilometers that are lower for counties near Chattanooga and higher for counties near Grand Rapids. Otherwise, the procedure is identical to the model simulation. Both model and counterfactual simulation were run 10,000 times; the difference in average supplier counts for each county reflects the influence of the moved plant.

Table 12 reports the average supplier counts in the model and counterfactual simulations summed for all counties in Tennessee. Both simulations predict a continued increase in the Tennessee supplier base, though the growth is lower in the counterfactual that removes the Volkswagen assembly plant. The two models diverge only slightly, never by more the 0.5 suppliers (representing about 150 supplier jobs). The county with the largest difference between model and counterfactual simulation, was Hamilton County, the home of the assembly plant. Other nearby counties and counties throughout Tennessee with the largest existing supplier bases were also among the places that benefited the most. A few counties in Tennessee even had slightly more suppliers under the counterfactual, since the new assembly plant made them relatively less attractive than counties nearer Chattanooga, which are close substitutes to them. Nevertheless, almost all counties had fewer suppliers in the counterfactual in most periods, though the effect everywhere was small.

The model on which these simulations are built assumes all parts suppliers value the assembler proximity the same. In reality, different transportation costs for particular parts

Table 12: Supplier plant counts in the counterfactual simulation

	Supplier counts	
Period	Model	Counterfactual
Tennessee		
0 (2011)	68.00	68.00
1 (2016)	74.64	74.27
2 (2021)	78.52	78.02
3 (2026)	80.57	80.14

likely cause some heterogeneity. A subset of parts suppliers with a much higher affinity for nearby assembly plants would be more sensitive to the movement of assembly plants than averages would suggest, so a next step is to test the robustness of these results with different sub-classifications of the supplier parts industry.

8.2 Entry patterns without agglomeration

The second stage estimates emphasize the importance of a persistent supplier base to the profits of other part suppliers. To see how these agglomeration benefits are driving entry, suppose the profits of one new potential entrant do not depend on the number of suppliers in its prospective locations. That is, let $\gamma_n = 0$ for this one entrant, preventing it from benefiting from any spillovers or agglomeration benefits in excess of local competition or congestion costs. Such an entrant will not affect the overall equilibrium being played or any suppliers expectation of how the industry will evolve, so the first stage estimates will still represent the equilibrium policy functions for all other suppliers. The one new entrant, however, will have markedly different entry probabilities from the rest of its cohort.

Without net agglomeration benefits, a new potential entrant in 2006 would enter Michigan with 6.9% probabilities, while the dynamic model predicts the average probability of entry in Michigan at 28.2%. (Performing a similar experiment with a static model yields probabilities of 5.9% and 15.9% respectively.) Agglomeration benefits are therefore important to the maintenance of the persistent supplier base in Northern Auto Alley.

Probabilities and predictions under a counterfactual where no supplier can benefit from spillovers cannot be calculated, because such an experiment would change enough entry and exit policy functions. The Bajari, Benkard, and Levin (2007) methodology obtains its tractability by not solving for equilibrium and by using the data to implicitly solve for the equilibrium selection mechanism being used. Therefore, I am not able to calculate what the new equilibrium policy functions would be and so cannot find the evolutionary paths of location characteristics that suppliers expect. The experiment with one new entrant does hint that the impact would be large and that entirely different equilibria would emerge in the absence of peer agglomeration.

9 Conclusion

Durability and entry costs make selecting a site for plants a long term decision. An industry migration increases the importance of dynamic concerns, which static models may miss. In the case of motor vehicle parts suppliers, the static model underestimates the extent of peer agglomeration benefits.

A model that can estimate the entry and closure decisions of parts suppliers can be used to estimate the benefits of attracting assembly plants. It finds Tennessee's expensive subsidies of assembly plants have had little influence on the location decisions of parts suppliers.

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A Data Appendix

A.1 Data Sources

Supplier plant locations come from the Dun's Metalworking Directory for 1996 and before. For 2001 and latter, I use the Dun & Bradstreet Million Dollar Directory omitting plants with fewer than 20 employees to match the Metalworking Directory's inclusion criteria. Plants are matched through time mostly by DUNS number, a permanent identifier of each plant. Because the DUNS number sometimes changed without reason, plants that had no DUNS number match in the subsequent year were also linked by address. (Cases in which matching addresses lacked street numbers were linked only if the company name remained constant or a corporate merger could be verified.) The Dun & Bradstreet data sometimes contains separate records for divisions within the same plant, so exact address duplicates were merged together.

Wage data is from the Bureau of Labor Statistics's Quarterly Census of Employment and Wages (QCEW). The wages used are the county- and year-specific average weekly wage for manufacturing plants (SIC 31-33). In counties where the manufacturing wage is unavailable, the state average manufacturing wage is used.

Population estimates and county areas are from the US Census. Union membership rates are state level from the Union Membership and Coverage Database. The construction of that database from the Current Population Survey is described in Hirsch and MacPherson (2003).

Interstate highway indicators were constructed from map files published by the National Atlas. Because of the stability in the interstate system since 1986, highway presence is a static variable that uses current data. The location and production quantities for assembly plants are from Ward's Automotive Yearbook. (Pending the release of 2011 production figures, 2010 counts are used in their place.)

A.2 Quality of Plant Panel

Some early Dun & Bradstreet data are known to overreport employment, to overreport plant counts, and to detect new entrants belatedly. Neumark, Wall, and Zhang (2011) find that in a data set based on Dun & Bradstreet data from 1992 to 2006 employment measures are higher than in the QCEW or the Current Employment Statistics (CES), but by county-industry are

Table 13: Supplier counts (alternate data source: CBP plants with 20+ employees)

	1986	1991	1996	2001	2006	2009
Northern Auto Alley	418	486	535	602	619	496
N Illinois	57	65	61	69	65	58
N Indiana	45	67	80	99	97	64
Michigan	208	241	262	275	284	235
N Ohio	81	83	94	107	120	95
Wisconsin	27	30	38	52	53	44
Southern Auto Alley	253	343	419	525	575	504
Alabama	18	18	20	29	46	51
Georgia	19	25	29	36	44	31
S Illinois	11	17	15	18	22	20
S Indiana	34	49	57	77	80	72
Kentucky	15	34	47	69	77	73
Mississippi	16	25	24	30	23	18
North Carolina	36	41	59	66	66	59
S Ohio	47	60	65	69	72	55
South Carolina	9	18	33	50	54	52
Tennessee	48	56	70	81	91	73

highly correlated to both the QCEW and CES.

Table 3 shows the state-by-state count of plants with at least twenty employees and a primary SIC code of 3714 from the Dun & Bradstreet. Table 14 gives the same information, except using data from the County Business Patterns. The two data sets were produced with different methodologies and in different months, but their counts are broadly similar. In a few states and years counts differ by more than a third, but the pattern of plateauing plant counts in northern auto alley and dramatically increasing counts in southern auto alley is seen in both data sets.

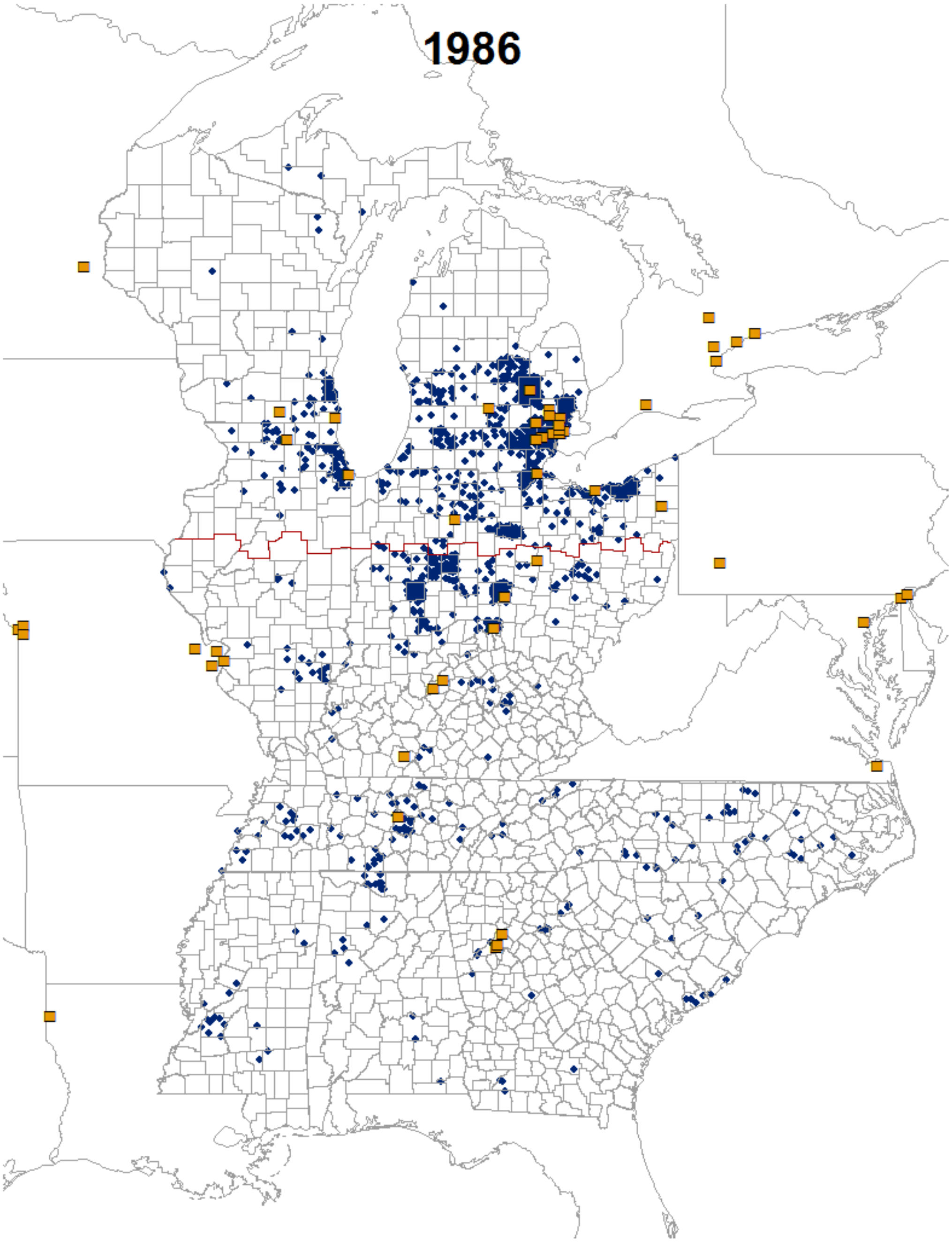

Figure 1: Supplier employment in auto alley and assembly plants in 1986. Squares indicate assembly plant locations. Each dot represents employment of 200 at supplier plants.

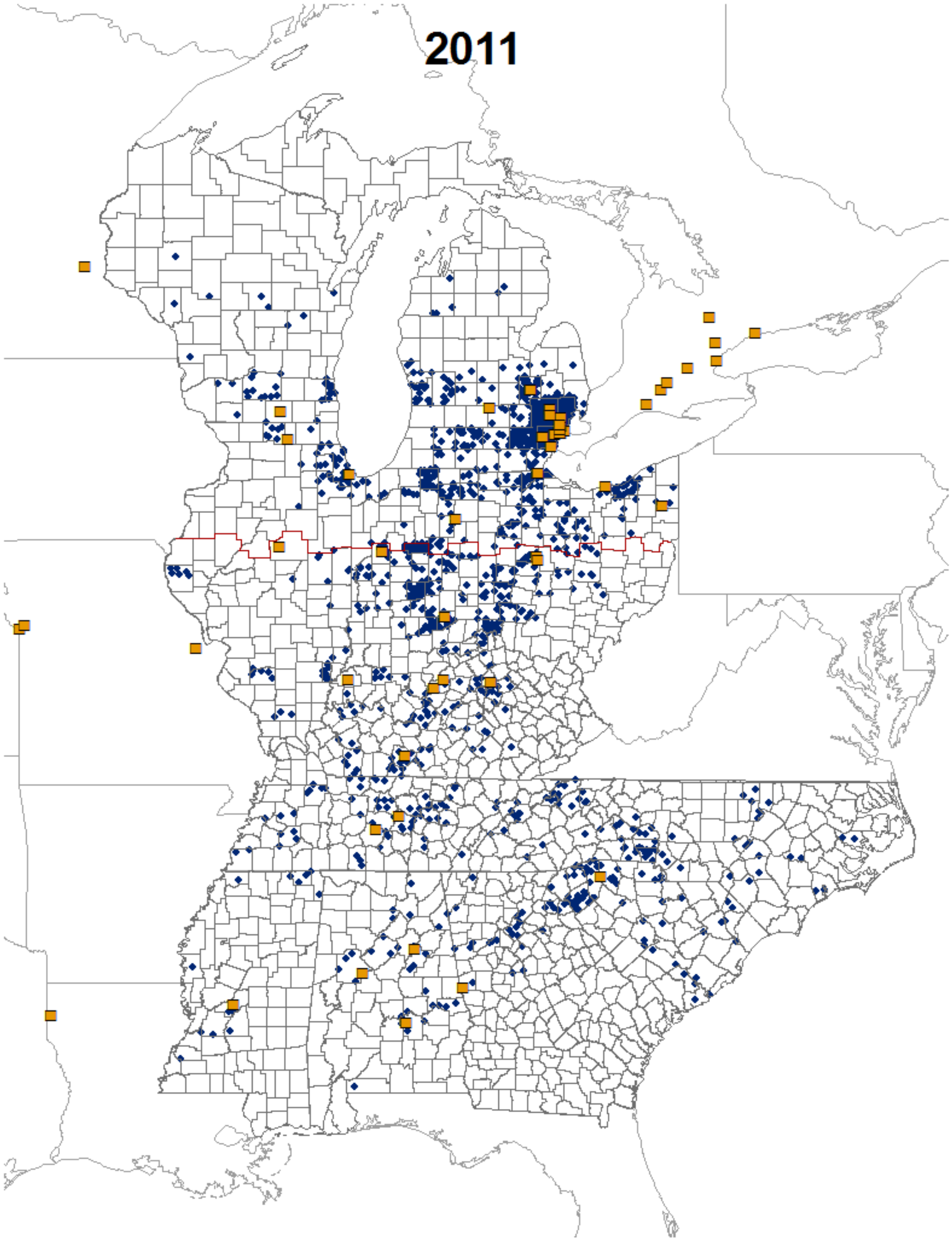

Figure 2: Supplier employment in auto alley and assembly plants in 2011. Squares indicate assembly plant locations. Each dot represents employment of 200 at supplier plants.