Federal Reserve Bank of Chicago

"Outsourcing Business Service and the Scope of Local Markets"

By: Yukako Ono

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Outsourcing Business Service and the Scope of Local Markets

Yukako ONO*
Federal Reserve Bank of Chicago

Abstract

This paper examines outsourcing to test whether productivity-enhancing specialization is facilitated in bigger cities. First, the paper provides a theoretical model which shows that greater local demand for a given input promotes the entry of suppliers into a city; the increased number of suppliers then results in lower outsourcing prices and a higher use of outsourcing by final producers, therefore reducing the final producers' production costs. I then test the predictions of the model by examining manufacturing plants' practices of outsourcing business services, by using plant-level data from the *1992 Annual Survey of Manufactures*. The empirical results show that an exogenous increase in local demand promotes the entry of service suppliers and increases a firm's probability of outsourcing for white-collar services. In particular, I found that doubling the intensity of the use of a service in a U.S. county, which can be attributed to the industrial composition of the county, results in a 7% to 25% increase in the probability of outsourcing.

Keywords: outsourcing, in-house production, business service, potential demand

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1 Introduction

Over the past few decades, many empirical studies have found evidence of a productivity advantage facilitated in larger cities.[1] The existing literature has explained the agglomeration economies by various factors such as knowledge spillovers, labor market economies for workers and firms searching, and greater opportunities for specialization in lager cities. However, only a few attempts have been made to test such microeconomic foundations through which agglomeration economies are produced.[2] In this paper, I provide empirical evidence that more specialization is made possible in larger cities, which supports the view that agglomeration economies are partially produced through greater opportunities for vertical specialization in larger cities. In particular, I examine a firm's decision between outsourcing (=purchasing) inputs and producing them in-house, which in turn determines a firm's degree of vertical specialization.

The benefit of outsourcing has been discussed by many economists (See Porter [25], Marshall [21], Romer [26]). For example, Porter [25] writes: "Outside specialists are often more cost effective and responsive than in-house units $\cdots$ Vertical integration [in-house production] consumes management attention that may be better spent elsewhere." [3] Addressing the cost-reducing feature of outsourcing, I first provide a theoretical model, which I then test empirically. Thus far, only a few empirical studies have examined the relationship between

[1] For empirical evidence of agglomeration economies, see Ciccone & Hall [6], Glaeser et al [8]., Henderson [12], and Moomaw [22].

[2] Abdel-Rahman and Fujita [2] provide a theoretical model in which greater variety of intermediate inputs in a larger city increases a final producer's efficiency. Jaffe, Trajtenberg, and Henderson [16] provide an empirical evidence that knowledge spillovers are geographically localized using patent citation data.

[3] As an example of works which consider both quality and costs of outsourced goods, see Hart et al. [11].

outsourcing and market size.[4] For example, using the *Business Contract-Out Survey* [4] of the Bureau of Labor Statistics, Abraham and Taylor [1] found that firms in metropolitan areas are more likely to outsource business services. However, their paper does not develop an explicit theoretical framework to examine what particular features in metropolitan areas increase a firm's probability of outsourcing. Holmes [13], on the other hand, provides a theoretical model within which the greater use of outsourcing in larger cities is obtained through monopolistic competition among suppliers. The empirical part of his paper uses industry-level data, and shows that there is a positive correlation between local demand for a specific input and local outsourcing of that input. Such an industry-level analysis, however, does not examine econometrically firm-level outsourcing decisions per se, nor does it account for the role that firm characteristics play.

The purpose of this paper is to look more closely at the mechanism by which a firm in a larger city enjoys greater opportunities for outsourcing. In the theoretical model, I consider a city in which service suppliers provide intermediate services to final producers located in the same city. Unlike material inputs, business service inputs are predominantly sourced locally (Kolko [18]), so in the model, I assume final producers buy all services locally.[5] Assuming that it is technologically feasible for final producers to produce a service in-house, some may choose to perform the service in-house, while others may outsource it. In thinking about an equilibrium allocation in local markets between outsourced and in-house productions, I

[4]Goodfriend and McDermott [9] and Stigler [27] provide theoretical models in which vertical disintegration becomes possible as the market size grows.

[5]While the advancement of communication technology seemingly integrates a local market with a national or the international market, statistically significant coefficients for a measure of a local market size presented in the empirical section support the view that local-level transaction is still important for the business services examined in this paper.

define *potential demand*. This is the demand which would result if, hypothetically, all final producers were to outsource all of their use of a service. In the model, this *potential demand* is the extent of a market for a service, and is determined by the number of final producers, and their technology which determines the intensity of use of a service. The model shows that greater local potential demand for a service induces more service suppliers to establish businesses in the city. This causes greater competition among the suppliers and lowers the market price of the service. As a result, a final producer in a bigger city is shown more likely to outsource the service. This is the main hypothesis tested in empirical sections.

I use plant-level data from the *1992 Annual Survey of Manufactures (ASM)* portion of the Logitudinal Research Database (LRD [30]) to test the validity of the model. I examine plants' outsourcing decisions for business services in relation to the local potential demand. In addition, the plant-level analysis allows us to directly relate the plant's decision between outsourcing and in-housing of a particular service to the local demand for the service, while controlling for the plant characteristics such as size, age, industry, etc.

I focus my analysis on white-collar services; outsourcing of such services is a big concern of many business firms [15]. The corresponding high growth of service industries is also one of important economic phenomena in recent decades. Part of this growth is related to increased outsourcing (Abraham & Taylor [1]). Reflecting these factors, in 1992, the U.S. Census Bureau started collecting the cost information of several white-collar services such as advertising, bookkeeping and accounting, legal services, and software and data-processing services. My analysis focuses on these four white-collar services. According to the *1997 Statistical Abstract of the United States* [32], of all manufacturing employees in the U.S. in 1992, as many as 32% are non-production workers who presumably engage in in-house performance of administrative and clerical tasks, some of which could have been provided through the market. The decision between outsourcing and performing services in-house should have a significant impact on the labor productivity of manufacturers.

Note that the *ASM* also provides the cost data of building repair, machinery repair, and refuse removal services. The market conditions of such blue-collar service sectors are subject to unionization and/or regulation, which are not considered in my theoretical model. Nevertheless I include these services for comparison.

For each of the above services, I test whether a plant's likelihood of outsourcing a given service is increased by the greater scale of a local market. Treating a county as a unit of local market, I begin the empirical analysis by measuring the potential demand in U.S. counties for each service. How this index is defined theoretically, how it is measured, and econometric reasons why the index is used to measure local market scale form a key part of the empirical sections. Having constructed the index, I test the hypothesis that greater potential demand for a service increases a firm's likelihood of outsourcing the service by performing probit analyses. I also perform fixed-effect logit analysis to take into account the possibility of biased estimation. For all white-collar services, the results are consistent with the hypothesis. For blue-collar services, however, the results are mixed; explanations for this will be provided.

As a whole, the empirical results suggest that my theoretical model is valid in the case of white-collar services and support the view that firms in a city with greater potential demand for services have more opportunities to specialize by outsourcing white-collar services, which in turn will provide a cost-reduction benefit and improve a firm's overall productivity.

2 Theoretical Model

This section presents a model that demonstrates why firms in larger cities have greater probabilities of outsourcing services. Let us consider a city with final producers, whose choice of city is exogenous to the model.[6] Final producers use services as inputs, either by producing them in-house or outsourcing to service suppliers.[7]

In Section 2.1, I analyze the behavior of final producers. Based on this, in Section 2.2 I analyze the price-setting behavior of service suppliers and solve for the market price of the service and the number of service suppliers. In Section 2.3, a comparative static analysis shows the effect of an exogenous increase in potential demand on the equilibrium values of the number of service suppliers, the price of the service, and the probability of outsourcing.

2.1 Final Producers

2.1.1 Final Producers' Probability of Outsourcing a Service

For simplicity, I assume that there is only one service input in the model. The model also assumes that a final producer's in-house production of a service does not require any fixed cost since it occurs in a facility which has already been set up for final production. The marginal cost is assumed to vary among final producers depending on their characteristics, such as age, size, and so forth. Let δ_i stand for the marginal cost of final producer i's in-house production of the service. Denoting the set of characteristics of final producer i by A_i,

[6] In the empirical section, I investigate manufacturers' outsourcing decisions. I assume that manufacturers' location decisions are determined by exogenous factors, such as proximity to the source of raw materials, ports, and so forth. My empirical analyses, however, also consider the case in which a final producer's choice of city is endogenous.

[7] As in Holmes [13], the model assumes that it is technologically feasible for a final producer to produce an intermediate service in-house, which would otherwise be outsourced.

I specify δ_i as

$$\delta_i = \delta(A_i) + u_i, \tag{1}$$

where u_i is a zero-mean random disturbance. Letting p stand for the market price of the service in a given city, a final producer i outsources the service if $p < \delta_i$. Let Y_i stand for an indicator variable which equals to 1 if final producer i outsources the service, and 0 otherwise. Then, from (1), denoting the cumulative distribution function for u_i by $F(\cdot)$, the probability that final producer i outsources the service $Prob(Y_i = 1)$ is written as:

$$Prob(Y_i = 1) = 1 - F(p - \delta(A_i)). \tag{2}$$

Controlling for the characteristics of a final producer, the probability of outsourcing a service is greater in a city where the market price of the service is lower.

2.1.2 Potential Demand and Outsourcing Demand for a Service

Here I derive the demand schedule that service suppliers face. Since final producers have the choice to produce a service in-house, the demand that service suppliers face is that from final producers who decide to outsource; I call this the *outsourcing demand.* However, for any market price, p, if all producers were hypothetically to outsource, there would be a resulting demand for local services which I call *potential demand.* This demand plays a key role in the estimation strategy.

For simplicity, I assume that final producers have an identical demand function for the service and specify it as $\tilde{q} = \theta a(p)$, where $\tilde{q}$ is the demand of a final producer, θ is a demand shifter,[8] and $a(p)$ is a downward sloping function of price. In a city with N final producers,

[8] θ can be seen as a share parameter of an underlying Cobb-Douglas production function in a special case (see Section 4.2).

the aggregate potential demand of the service, D^p is written as

$$D^p = \theta N a(p). \tag{3}$$

We can then derive the outsourcing demand by calculating the fraction of final producers who outsource the service. Again for simplicity, assuming that final producers share the same characteristics ($A_i = A, \forall i$), (1) is rewritten as $\delta_i = \delta + u_i$. Thus, from (2), a final producer's probability of outsourcing, $Prob(Y = 1)$, is $1 - F(p - \delta)$. Multiplying the potential demand D^p by this fraction, the city's outsourcing demand for the service is written as

$$D(p, \theta, N) = \theta N a(p)[1 - F(p - \delta)]. \tag{4}$$

For a given price, the potential demand $\theta N a(p)$ determines the upper bound of the outsourcing demand. The outsourcing demand D is decreasing in p and increasing in θ and N.[9] Facing the city's outsourcing demand schedule, service suppliers who enter local production maximize their profits with respect to (w.r.t.) production.

2.2 Service Suppliers

Here I describe how the market price of a service is determined as a result of service suppliers' profit maximization behavior. I assume that these specialized service suppliers require setup costs; since, for example, they have to construct a facility first. Assuming that setup costs are sunk, the model describes the entrance of suppliers into production by a standard two-stage entry process with Cournot oligopolistic competition. Thus I start with Stage 2.

[9] $\frac{\partial D}{\partial p}(p, \theta, N) = \underbrace{\theta N}_{\oplus}\{\underbrace{a'(p)}_{\ominus}\underbrace{[1 - F(p - \delta)]}_{\oplus} - \underbrace{a(p) f(p - \delta)}_{\oplus}\} < 0$. Since $0 \leq F(p - \delta) \leq 1$ and $0 \leq f(p - \delta)$, $\frac{\partial D}{\partial p} < 0$.

2.2.1 Stage 2

Let M stand for the number of service suppliers who have entered production in Stage 1, q_j service supplier j's output level, and Q an aggregate (city) market output level of the service ($Q = \sum_j q_j$). From (4), the inverse demand function is written as

$$p = P(\frac{Q}{N\theta}), \tag{5}$$

where N and θ enter symmetrically, and $P' = N\theta / \frac{\partial D}{\partial p} < 0$. Denoting the profit of supplier j in Stage 2 by π_j, and the marginal cost by w, we can write π_j as $\pi_j = P(\frac{Q}{N\theta})q_j - wq_j$. Supplier j maximizes π_j w.r.t. q_j. The first order condition (FOC) for this maximization is:

$$\frac{\partial \pi_j}{\partial q_j} = P(\frac{Q}{N\theta}) + P'(\frac{Q}{N\theta})\frac{q_j}{N\theta} - w = 0. \tag{6}$$

For simplicity, let us assume symmetry among the suppliers; $q_j = q = \frac{Q}{M}\ \forall j$. Substituting q for q_j in (6), p is solved as a function of M.[10]

$$p = \tilde{p}(M). \tag{7}$$

Let R stand for the second derivative of π_j w.r.t. q_j. From (6), the second order condition (SOC) is satisfied as long as $R = 2\frac{P'}{N\theta} + \frac{P''}{(N\theta)^2}q < 0$. To ensure well-behaved outsomes, I also assume that marginal revenue facing supplier j is steeper than the demand function (Long and Soubeyran [20]), which is satisfied by the following condition: $2\frac{P'}{N\theta} + \frac{P''}{(N\theta)^2}q < \frac{P'}{N\theta}$, that is simplified as

$$MP' + \frac{P''Q}{N\theta} < 0. \tag{8}$$

[10] In more general case where the price elasticity of the demand change with θ and N, p is solved as a function of M, θ and N.

2.2.2 Stage 1

The number of service suppliers M is determined in Stage 1, in which potential suppliers decide to enter production if their anticipated profits obtained in Stage 2 exceed the sunk cost of entry α.[11] Under the assumption of symmetry, M is determined by the zero-profit condition:

$$\pi = (p - w)\frac{Q}{M} = \alpha \tag{9}$$

From (5), (6), and (9), the equilibrium number of suppliers M^* is solved as a function of θ and N. Thus, using (7), the equilibrium price p^* is also written as a function of potential demand attributes, θ and N:

$$p^* = p^*(\theta, N). \tag{10}$$

2.3 Comparative Statics

This section shows how the equilibrium values for the number of suppliers, the price of the service, and a final producer's probability of outsourcing are changed by increases in potential demand attributes, θ and N. From the previous section, under the assumption of symmetry, we know that (5), (6), and (9) must be met in equilibrium.

In order to evaluate the impact of θ on the equilibrium price, I totally differentiate the system ((5), (6), (9)) w.r.t. p, q, M, and θ, and use Cramer's law, which yields the following expression:

$$\frac{dp^*}{d\theta} = \frac{\alpha^2}{\theta q^{*\,3} R} < 0, \tag{11}$$

where R is the second derivative of π and is negative so that S.O.C. holds. Thus (11) is negative and the equilibrium market price p^* is decreasing in θ. The increase in the demand

[11] For the purpose of exposition, I assume that entry occurs when $\pi = \alpha$.

shifter, which exogenously increases the local potential demand, decreases the equilibrium market price of the service. Because of symmetry between θ and N in (5), (11) implies also that $\frac{dp^*}{dN} < 0$.

Next, I examine the impact of an increase in θ on the equilibrium number of service suppliers. Again, using the method above, I obtain:

$$\frac{dM^*}{d\theta} = \frac{(M^* + 1)P' + \frac{QP''}{N\theta}}{N\theta^2 R}. \tag{12}$$

This is positive when condition (8) is met. An increase in θ has a positive impact on the equilibrium number of suppliers. For a given number of suppliers, a city with greater θ (or N) provides more profits per supplier. This induces the entry of more suppliers into the city, which will reduce the price.

Finally, I examine the effect of θ on the probability of outsourcing. From (2), we can write:

$$\frac{dProb(Y = 1)}{d\theta} = \frac{dProb(Y = 1)}{dp^*}\frac{dp^*}{d\theta},$$

where $\frac{dProb(Y=1)}{dp^*}$ is $\frac{dProb(Y=1)}{dp}$ evaluated at $p = p^*$. From (2), $\frac{dProb(Y=1)}{dp^*} < 0$, and from (11), $\frac{dp^*}{d\theta} < 0$. Therefore,

$$\frac{dProb(Y = 1)}{d\theta} > 0. \tag{13}$$

Again, replacing N for θ, $\frac{dProb(Y=1)}{dN} > 0$. Thus an increase in θ or N increases a final producer's probability of outsourcing.

3 Data

To test the above theoretical model, I use plant-level data from the *ASM* compiled in 1992, the first year when data on the outsourcing of white-collar services were collected. The addition resulted from the high growth of business service industries and the increasing trend of outsourcing. While the *1992 Census of Manufactures* canvased every manufacturing plant with a limited set of questions, the *ASM* is a sample survey from that plant population asking a longer set of questions. Out of the plants in the *ASM* sample, I choose those whose data are not known to be subject to imputation.[12] I also focus on plants in contiguous, continental U.S. states;[13] this leaves us 45,144 plants. Of these, 31,994 are in urban counties and 13,150 in rural counties;[14] I treat each county as a separate local market. I base most of the analyses on plants in urban counties, because the market boundary for rural counties is obscure, and therefore the analysis of rural plants is not suitable for the purposes of this paper. Of the 31,994 urban plants, 65.9% belong to multi-plant companies, and the average age of the plants is 12.9 years.[15]

In the *1992 ASM* questionnaire sent to the plants, the Census Bureau inquires about their expenditures for outsourced services. I focus my analysis on white-collar services: advertising; bookkeeping & accounting; legal services; software & data-processing. The *ASM* also collects the data on building repair, machinery repair, and refuse removal. While they are not main focus of my paper, I will include such services for instructive reasons.[16] For

[12]Most of plants excluded due to the imputation are small plants. Since plant sizes are controlled for in the empirical analyses presented in Section 5, the exclusion of such plants does not cause a qualitative change in the results.

[13]Some counties are merged to achieve consistent county definition over time. While this paper uses only one cross-sectional data set, the consistent county code will be useful for a possible extension of the work.

[14]urban county: county in primary metropolitan statistical area (PMSA)

[15]"Age" is defined as the years since a plant started the business classified in the same SIC-code as the plant's current business. The first year they started the current business is identified every 5 years by the Census of Manufactures.

[16]I exclude communication services from the analyses, since its definition given in the questionnaire does not suit an examination of the choice between outsourcing and in-housing; the definition includes "telephone service," and it is unlikely that some plants can produce telephone service in-house.

a given service, the observed expenditures on outsourcing tell us whether a plant outsources that service or not, the key decision variable. I will examine empirically a plant's decision to outsource *any* amount of a given service.[17]

Table 1: Percentage of Plants by Decision

Urban Plants (Sample Size: 31,994 plants)

	Outsource	In-House
White-Collar Services		
Advertising	53.5% (17,128)	46.5% (14,866)
Bookkeeping & Accounting	47.9% (15,314)	52.1% (16,680)
Legal Services	54.6% (17,472)	45.4% (14,522)
Software & Data-Processing	48.3% (15,456)	51.7% (16,538)
Blue-Collar Services		
Building Repair	61.3% (19,599)	38.7% (12,395)
Machinery Repair	82.7% (26,454)	17.3% (5,540)
Refuse Removal	72.0% (23,047)	28.0% (8,947)

Source: Author's calculations based on data from *LRD*

Table 1 summarizes the outsourcing decisions of the plants in the sample. For white-collar services, about half outsource and half performed the services in-house. Outsourcing tendencies also vary across counties. The percentage of plants that outsource each service calculated for each county roughly ranges from 0.3 to 0.7.[18] An issue for this paper is to what extent this spatial variation in outsourcing can be explained by differences in market conditions (i.e. potential demand) across space.

For blue-collar services, a greater proportion of plants outsource in general and the per-

[17]Note that when a plant outsources a service, it is possible that the plant also performs some amount of the service in-house. This does not qualitatively affect the main results of the estimation, under the assumption that the ratio of in-house production to outsourcing is exogenously determined. When a plant does not outsource any amount, it is possible that a plant did not require the service at all. Assuming that the probability of not requiring a service is exogenous to the model, this does not affect the qualitative results, as long as there is enough variation in actual decisions between outsourcing and producing in-house.

[18]In order to mitigate any possible appearance of the disclosure of confidential data, these numbers have been calculated based on an average of the top five and bottom five counties with at least 50 plants which appear in our sample before rounding.

centage of plants which outsource repair services could be consistent with all necessary repairs being outsourced. The problem is that building and machinery repairs are occasional events. Thus, the demand for these services in a particular year comes from the incidence of a breakdown or demolition, as well as any outsourcing decisions. It is possible that virtually all repairs are outsourced, so the relatively high percentage of outsourcing for repair services represents the proportion of plants that require repairs in the year that the data are collected. In that case, any results on outsourcing would be spurious. (Refuse removal may involve the public sector and strict regulation.) For these reasons, it is unlikely that blue-collar services are suitable for analysis, especially repair services.

4 Empirical Implementation

4.1 Empirical Strategy for Testing the Theoretical Model

This section describes the empirical strategy. Recall that the model incorporates four main factors: 1) the potential demand for a service, 2) the number of service suppliers, 3) the price of the service, and 4) the probability of outsourcing. As shown in Section 2.3, the exogenous increase in potential demand through the increase in θ or N promotes the entry of service suppliers, decreases the market price of the services, and increases the probability of outsourcing. (Below, the equilibrium price p^* and the number of suppliers M^* are denoted by p and M to simplify the notation.)

To test the theoretical model, it would be ideal to examine the relationships among all of the above factors. However, data on the market prices of services are not available. It is also not feasible to test the effect of M on the probability of outsourcing. Since M is jointly determined with the probability of outsourcing, M will be correlated with the error term with respect to a presence of county fixed effects. The state of the local transportation system is one example of such county fixed effects. A better local transportation system might enhance communication between demanders and suppliers and encourage outsourcing, which would attract more service suppliers. Therefore, I use the exogenous variables, θ and N, which determine the level of potential demand, and examine how the local potential demand influences a final producer's probability of outsourcing.[19] Note that it is important to distinguish the effect of θ from that of N. While N represents the county size in general, θ represents the intensity of the use of a given service, which more narrowly connects the local potential demand to a plant's decision regarding that specific service.

Let k stand for city k, and call plant i in city k, plant ki. I specify the net benefit of outsourcing $Y^{\star}_{ki}$ as:

$$Y^{\star}_{ki} = (\theta_k, N_k, \mathbf{A}'_{\mathbf{ki}})\boldsymbol{\beta} + u_{ki}, \tag{14}$$

where $\mathbf{A}_{\mathbf{ki}}$ represents the characteristics of plant ki. Plant ki outsources a service if $Y^{\star}_{ki} \geq 0$, and produces it in-house if $Y^{\star}_{ki} < 0$. By specifying some distribution for u_{ki}, we can estimate $\boldsymbol{\beta}$ by a maximum likelihood method. The coefficients for θ_k and N_k must be positive when my hypothesis holds.

4.2 Index for θ_k

In this section, I construct an index for θ_k by specifying the production function of manufacturing plants. Under the theoretical framework presented in Section 2, let us assume that final producers use both service and non-service inputs. Let x denote the output level of a

[19] Moreover, with more general demand function where price elasticity can change with θ and N, p is determined by θ and N which enters separately from M: $p = p(\theta, N, M(\theta, N))$. In this case, there is no obvious instrumental variable for M which allows us to distinguish the effect of M from that of θ and N.

final producer, $\tilde{q}$ the amount of the service, and z the amount of non-service input. Using the Cobb-Douglas specification, I write a final producer's production function as $x = \tilde{q}^{\gamma} z^{1-\gamma}$, where γ is a share parameter.

In contrast to the service input, which is assumed to be transacted within a local market, I assume the non-service input is transacted in international and/or national markets; its price is given to a city. Treating the non-service input as the numéraire, and solving the cost minimization problem taking the level of output as given at $\bar{x}$, we find that a final producer's demand for service outsourced is $\tilde{q} = (\frac{\gamma}{1-\gamma})^{1-\gamma}(\frac{1}{p})^{1-\gamma}\bar{x}$. I approximate this expression for $\tilde{q}$ using a Maclaurin series, and obtain

$$\tilde{q} \approx \frac{\gamma \bar{x}}{p}. \tag{15}$$

Note that share parameter γ is likely to be different between industries. Let us denote γ of industry l by γ_l, the share of industry l in the total output of final producers in county k by σ_{kl}, and the aggregate county output by $\bar{X}_k$. Then, using (15), we see the potential demand of industry l in city k is $\gamma_l \sigma_{kl} \frac{\bar{X}_k}{p_k}$. Thus, the aggregate potential demand for the service in city k, D_k^p is written as

$$D_k^p = \sum_l \gamma_l \sigma_{kl} \frac{\bar{X}_k}{p_k}. \tag{16}$$

Comparing this with (3), $\sum_l \gamma_l \sigma_{kl}$ corresponds to θ and $\frac{\bar{X}_k}{p_k}$ corresponds to $Na(p)$. I use $\sum_l \gamma_l \sigma_{kl}$ as the estimate for θ and call it the *potential demand shifter* ($\hat{\theta}$);

$$\hat{\theta}_k = \sum_l \gamma_l \sigma_{kl}. \tag{17}$$

$\hat{\theta}_k$ represents average intensity of the use of a service over local industries. Due to differences in industrial composition (represented by σ_{kl}) and the variation of cost share parameters among industries (γ_l), the potential demand shifter varies across counties.

For example, in terms of the number of business establishments, Washington, DC is about the same size as Denver County, Colorado (the *1997 County Business Pattern (CBP)* [29]). However, their industrial composition is quite different. The printing and publishing industry constitutes 80% of the manufacturing industry in Washington, while it represents only 30% in Denver. On the other hand, the fabricated metal industry constitutes only 2% of manufacturing in Washington, DC and 10% in Denver (the *1997 CBP* [29]). If the service's percentage of the total input is different between the printing and publishing industry and the fabricated metal industry, then the potential demand for that service is different in each county even though they are the same size in terms of their number of establishments.

4.3 Estimation of Potential Demand Shifter

Here I show how to estimate the potential demand shifter. Introducing multiple services and labelling each of them by s, we can rewrite (17) as

$$\hat{\theta}_k^s = \sum_l \gamma_l^s \sigma_{kl},$$

where $\hat{\theta}_k^s$ is the potential demand shifter of service s in county k,[20] and γ_l^s is the cost share parameter for service s of industry l.

First, I estimate the cost share parameter, γ_l^s, for each of the 3-digit SIC manufacturing industries for the seven services. For each plant, I calculate the share of the cost of service s in the total production cost.[21] I then take the average of such shares over plants in each industry in order to calculate γ_l^s. Note that this calculation is based on the data of plants

[20] s is a positive integer from 1 to 7 (the number of services examined).

[21] The total cost is calculated based on costs for labor, capital, materials, and other peripheral costs, which are provided in the *1992 ASM*. Note that if some services are produced in-house, it must be the case that the plant uses its employees to perform these services; since these costs are already accounted for in the labor costs, one would not underestimate the total cost in this case.

outsourcing the service; the data of the cost of a given service are not available for those producing the service in-house.[22] However, in my theoretical model, both outsourced and in-house services are assumed to be identical in terms of their productivity, and thus a service's cost share of a plant must be the same whether that plant outsources or produces the service in-house. Table 2 provides summary statistics for the estimated cost share parameters, which differ substantially across industries.

Table 2: Variation in Cost Share Parameters across Industries: γ_l^s

Estimated for each 3-digit Manufacturing Industry

	Mean	S.d.
White-Collar Services		
Advertising	.0127	.0126
Bookkeeping & Accounting	.0048	.0031
Legal Services	.0045	.0024
Software & Data-Processing	.0028	.0019
Blue-Collar Services		
Buildings Repair	.0042	.0014
Machinery Repair	.0144	.0095
Refuse Removal	.0031	.0022

Source: Author's calculations based on data from *LRD*

Next, I calculate σ_{kl}, the industries' shares in county production. Since the cost share parameters are calculated only for manufacturers, I calculate each manufacturing industry's share in county manufacturing production. Assuming that a service's cost share outside of the manufacturing sector is not systematically different from that of the manufacturers, the exclusion of other industries does not change the empirical results qualitatively.[23]

[22] When plant i produces service s in-house, the cost should be included in labor costs. However, the data provide neither the breakdown nor the number of employees engaged in the in-house production of a particular service.

[23] There might be attenuation because of possible noise in the measure of the potential demand shifter. However, this strengthens my empirical results, suggesting that coefficients could have been greater than estimated.

Table 3: Variation in Industrial Composition across Counties: Industries' shares in County Manufacturing $\{\sigma_{kl}\}$

Urban Counties (Total 731)

2-digit SIC Manufacturing Industries	Number of Counties w/ Ind.	σ_{kl} Mean	Min	Max	Inter-Quartile Distance*
20 : Food products	684	0.065	0.0071	0.531	0.050
21 : Tobacco products	52	0.011	0.0001	0.111	0.011
22 : Textiles	454	0.024	0.0008	0.333	0.017
23 : Apparel made from fabrics	660	0.052	0.0040	0.408	0.037
24 : Lumber & wood products, except furniture	714	0.104	0.0056	0.850	0.084
25 : Furniture & fixtures	626	0.035	0.0041	0.284	0.024
26 : Paper products	538	0.024	0.0013	0.200	0.018
27 : Printing and publishing	722	0.175	0.0183	0.807	0.103
28 : Chemicals	639	0.043	0.0049	0.333	0.030
29 : Petroleum refining	430	0.013	0.0002	0.079	0.010
30 : Rubber & plastic products	649	0.047	0.0040	0.217	0.030
31 : Leather products	315	0.011	0.0006	0.088	0.010
32 : Stone, clay, glass & concrete products	712	0.061	0.0037	0.500	0.038
33 : Primary metal products	563	0.025	0.0015	0.133	0.020
34 : Fabricated metal products	695	0.099	0.0104	0.400	0.052
35 : Industrial and commercial machinery & computer	717	0.153	0.0082	0.500	0.087
36 : Electronic & other electrical equipment	634	0.044	0.0045	0.221	0.033
37 : Transportation equipment	638	0.039	0.0014	0.238	0.029
38 : Measuring, analyzing, & controlling instruments	580	0.032	0.0029	0.176	0.024
39 : Miscellaneous manufacturing industries	654	0.048	0.0041	1.000	0.026

Source: *1992 CBP*

⋆: Distance between the 25th and 75th percentiles

Table 3 shows the variation of the industry's share across counties.[24] There are some counties where a particular industry does not exist, which suggests differences in the geographical diffusion across industries. In addition, the table shows that, among the counties which have a particular industry, the share of industry varies significantly. For example, the Stone, Clay, Glass & Concrete products industry (SIC 32) constitutes half of the manufacturing in Campbell County, SD, while it has a share of only .37% in New York City, where

[24]The plant counts from the *CBP* publication were used in Table 3 to ease the burden associated with reviewing this paper to make sure that no confidential data was revealed. Note that the potential demand shifter used in the estimations have share parameters based on the value of production from the *Census of Manufactures* in the *LRD* data set [30] for each of the 3-digit SIC manufacturing industries.

Table 4: Variation in Potential Demand Shifter across Counties: $\hat{\theta}_k^s$

Urban Counties (Total: 731)	Mean	S.d.
White-Collar Services		
Advertising	.0108	.0047
Bookkeeping & Accounting	.0042	.0010
Legal Services	.0042	.0010
Software & Data-Processing	.0025	.0008
Blue-Collar Services		
Buildings Repair	.0041	.0005
Machinery Repair	.0147	.0044
Refuse Removal	.0031	.0011

Source: Author's calculations based on data from *LRD*

the Apparel industry (SIC 23) dominates. More generally, I calculate the Inter-Quartile Distance.[25] Taking into consideration that the mean share is quite small, the Inter-Quartile Distance for all industries is relatively large and assures a variation in the industrial composition across counties.

Finally, by using the industries' shares in county manufacturing output $\{\sigma_{kl}\}$ as weights, I calculate $\hat{\theta}_k^s$ by taking the weighted average of cost share parameters $\{\gamma_l^s\}$, as presented in Table 4. Note that considerable variation in the index remains.

5 Empirical Tests

5.1 Probability of Outsourcing and Potential Demand

5.1.1 Probit Analyses

In this section, I examine whether or not greater potential demand actually increases the probability of outsourcing for each of the seven services. Assuming a normal distribution for the random disturbance, I perform probit analyses to estimate the coefficients in (14).

[25]The Inter-Quartile Distance shows the difference between the industry's share of a given county at the 25th and 75th percentiles.

Because it is difficult to identify final producers, I use the logarithm of county population as a proxy for N. The data on county population are obtained from the *1990 Census*. The controlled plant characteristics, obtained from the *1992 ASM*, are the following: plant size, age, industry, and its affiliation type (i.e. whether or not a plant belongs to a multi-plant company). While one might consider that plant size is endogenous to a plant's decision to outsource, I measure plant size by *Beginning-of-Year Asset*, which is determined before the decision is made and is therefore considered exogenous at least in the short run. Age is controlled by a set of dummy variables, where I know the first year a plant started the current business. Industry is controlled by 2-digit SIC industry dummies. Another dummy is used to control for affiliation type. (The summary statistics for continuous independent variables are found in Appendix C.)

First, I include plants in all counties in the probit analyses (Table 5). However, since the market boundary of rural counties may be rather obscure, I also perform the analyses by limiting the sample to the plants in the urban counties (Table 6).[26]

The Potential Demand Shifter $\hat{\boldsymbol{\theta}}^s$ As shown in Tables 5 and 6 for all white collar services, I obtained positive and significant coefficients for $\hat{\theta}^s$. The results suggest that, even when we control for county population, $\hat{\theta}^s$ has a significant net impact on a plant's probability of outsourcing. The results, from the construction of $\hat{\theta}^s$ (see Section 4.2), suggest that the

[26] In addition, I ran probits for urban plants without controlling for county population, since county population might be endogenous. The greater outsourcing propensity of a county induces greater entry of service suppliers, causing more service employees to move into the county. In a sense, the identification of the effects of the potential demand comes not from county population, but from the composition of local industries represented by θ. The results are presented in Ono [24] and are consistent with that of other probit analyses.

Table 5: Effect of Potential Demand on the Probability of Outsourcing

Probit 1: All Plants, controlling for County Population
Dependent Variable=1 if a plant outsources a service

	$\hat{\theta}^s$	County Population	Plant Size	Affiliation Type: Multi-plant Company Dummy
White-Collar Services				
Advertising	9.131**	.014***	.050***	-.483***
	(2.760)	(3.588)	(10.298)	(-22.649)
Bookkeeping & Accounting	50.92***	.014**	.007	-1.228***
	(5.194)	(2.445)	(1.492)	(-72.865)
Legal Services	75.652***	.015***	.146***	-.658***
	(8.744)	(3.134)	(29.119)	(-35.216)
Software & Data-Processing	85.086***	.016**	.212***	-.287***
	(8.082)	(2.895)	(47.615)	(-16.304)
Blue-Collar Services				
Building Repair	-107.253***	-.004	.150***	.272***
	(-5.328)	(-.834)	(30.802)	(16.543)
Machinery Repair	-13.791***	.001	.080***	.261***
	(-5.461)	(.232)	(14.372)	(15.850)
Refuse Removal	19.937	.020***	.142***	.282***
	(1.634)	(3.705)	(29.138)	(15.423)

Source: Author's calculations based on data from *LRD*
( ): Z-statistics calculated based on White-corrected s.d. with clustering over plants in the same county
⋆: Significant at 10 % Level
⋆⋆: Significant at 5 % Level
⋆ ⋆ ⋆: Significant at 1 % Level
Note: Plant age and industry (2-digit SIC) dummies are also included to control for these variables.

local industrial composition has a noticeable impact on a plant's probability of outsourcing.[27] In order to quantify the effect of industrial composition, based on the results in Table 6, I calculate the impact of a change in $\hat{\theta}^s$ on an average plant's probability of outsourcing. As shown in Table 7, for an average plant, the elasticities of the probability of outsourcing w.r.t. $\hat{\theta}^s$ range from .07 to .25.[28] I also calculate how the outsourcing probability of an average

[27] Note again that the potential demand shifter θ of a service is calculated based on the service's share parameters at the *national level*. Thus, outsourcing tendency in a county should not correlate with the potential demand shifter. If a manufacturing plant's location choice is endogenous, however, it is possible that its unobserved tendency of outsourcing correlates with the local potential demand shifter. Section 5.1.2 considers this issue by taking into account plant-fixed effects, which should subsume county-fixed effects.

[28] One could calculate the elasticities for every category based on age and industry dummies. However, there are over 100 age-industry categories. Thus I present the elasticities evaluated at overall mean plant characteristics.

Table 6: Effect of Potential Demand on the Probability of Outsourcing

Probit 2: Urban Plants, controlling for County Population
Dependent Variable=1 if a plant outsources a service

	$\hat{\theta}^s$	County Population	Plant Size	Affiliation Type: Multi-plant Company Dummy
White-Collar Services				
Advertising	8.292*	.002	.054***	-.434***
	(1.832)	(.345)	(9.335)	(-17.715)
Bookkeeping & Accounting	67.210***	-.004	.013**	-1.210***
	(4.399)	(-0.458)	(2.242)	(-61.844)
Legal Services	68.228***	-.001	.147***	-.643***
	(6.355)	(-.116)	(23.883)	(-27.703)
Software & Data-Processing	66.804***	.003	.207***	-.267***
	(4.931)	(.354)	(39.735)	(-12.947)
Blue-Collar Services				
Building Repair	-92.094**	-.020***	.161***	.266***
	(-2.884)	(-3.716)	(27.748)	(14.068)
Machinery Repair	-6.172	-.001	.088***	.254***
	(-1.214)	(-0.303)	(14.876)	(12.063)
Refuse Removal	20.615	-.002	.143***	.267***
	(1.243)	(-.257)	(24.593)	(12.633)

Source: Author's calculations based on data from *LRD*
( ): Z-statistics calculated based on White-corrected s.d. with clustering over plants in the same county
⋆: Significant at 10 % Level
⋆⋆: Significant at 5 % Level
⋆ ⋆ ⋆: Significant at 1 % Level
Note: Plant age and industry (2-digit SIC) dummies are also included to control for these variables.

plant changes when the potential demand shifter is a 2 s.d. deviation smaller or greater than the average. The differences in probabilities between each case are as much as 10% for bookkeeping & accounting and legal services. Earlier I noted that observed outsourcing propensities varies by about 40% across space. Thus, for the average plants, over one fourth of such variations in outsourcing propensities arises between areas with very high and very low potential demand.

For blue-collar services, however, the direction of the effect of $\hat{\theta}^s$ is mixed. Especially for repair services, the results contradict the prediction of the theoretical model.[29] However,

[29] I ran Probit 2 using the potential demand shifter calculated at PMSA-level and population in PMSAs. The results again show the negative and significant effects of $\hat{\theta}^s$ on outsourcing repair services.

Table 7: Net Effect of Potential Demand Shifter $\hat{\theta}$ on Probability of Outsourcing

Based on Probit 2

Service	$\hat{P}(Y=1)$ of Average Plant	Effect of +/- 2 s.d. change in $\hat{\theta}^s$ on $P(Y=1)$	Elasticity of P(Y=1) w.r.t $\hat{\theta}^s$ of Average Plant
White-Collar Services			
Advertising	.537	.059	.068
Bookkeeping & Accounting	.483	.102	.248
Legal Services	.550	.107	.212
Software & Data-Processing	.479	.084	.147

Source: Author's calculations based on data from *LRD*
Note: The blue-collar services are excluded from the table, since the coefficients obtained for these services in the probit analyses were not interpretable.

as noted earlier, the results may be viewed as spurious because they incorporate the determinants of the incidence of repairs, as well as reflecting how the contractual arrangements governing repairs might vary across markets.

County Population In Table 5, the results for all services indicate that county population has a positive and significant impact on the outsourcing probability; this is consistent with my hypothesis. However, in Table 6, which includes only urban plants, the impact of county population is insignificant. It might be the case that the effect of county population on the probability of outsourcing is greater when a county is relatively small (in terms of population); this effect becomes trivial once county population reaches a certain level.

Plant Size The results in Table 5 and 6 suggest that for every service, plant size has a positive and significant effect on the probability of outsourcing. The effect is quite large. For an average plant, the increase in plant size by one standard deviation point increases the outsourcing probability by 4.5% for advertising, 1.1% for bookkeeping & accounting, 11.7% for legal services, and 16.9% for software & data-processing. The result is counter-intuitive, since small and medium-size plants which do not have internal scale economies are usually considered to depend more on outsourcing. While the effect of plant characteristics is not a focus of this paper, the interpretation of the result is worth noticing. The result indicates the possible existence of scale economies in outsourcing services, which probably arise from fixed costs in service transactions and the searching process for matched suppliers. It also suggests that a larger plant purchasing a greater amount of a particular service might have more power in negotiating prices with suppliers.

Affiliation Type: Multi-Plant Company Dummy In Probits 5 and 6, all the coefficients for the multi-plant company dummies are statistically significant, and negative for white-collar services. The effect is quite large. A plant's outsourcing probability drops if the plant belongs to a multi-plant company, by 17% for advertising, 45% for bookkeeping & accounting, 25% for legal services, and 11% for software & data-processing services.

This result might reflect the fact that a Central Administrative Office (CAO) plays a role in providing administrative services to its manufacturing plants. CAOs also outsource services (See Griliches and Siegel [10]), but this is not reflected in the data for plant purchases. The effect of this inter-company transfer could offset a multi-plant company's possible negotiating power.

The plant size and affiliation variables suggest that there is considerable variation across individual plants in outsourcing propensities based on plant characteristics. More detailed analysis on this issue as well as the mechanism behind the intra-company sharing of performing services are conducted by supplementing the data with the *Survey of Auxiliary*

Establishments [31] and are presented in Ono [24].

5.1.2 Endogenous Location Choice: Fixed-Effect Logit

So far, I have taken a manufacturing plant's location choice as given. However, this choice could be endogenous. Consider a plant which has efficient technology for the in-house production of services and therefore does not actively consider outsourcing services or appreciate lower outsourcing prices in a larger city. It might prefer to locate in a small city where the land rent and wage costs are lower. In this scenario, county population influences a plant's location decision. On the other hand, a plant that has inefficient technology for the in-house production of services might prefer a city with greater potential demand for those services and therefore lower market prices. In this case, both $\hat{\theta}^s$ and county population influence a plant's location. Such endogenous location choices do not create a problem if we are able to control for all plant characteristics which determine the efficiency of in-house technology. However, some of these characteristics might be unobservable. Failure to control for these characteristics will cause biased estimation, causing a correlation between the disturbance term and θ and/or city size.

In order to overcome this problem, I first restrict the sample to plants whose location choices are considered exogenous. In particular, I restrict the sample to older plants that 1) started their business before the significant growth in the service industry during the 1970s and that 2) did not change their location since that time. The probit analyses based on such a sample obtain qualitatively the same results as ones with unrestricted samples. One can argue, however, that the location choices of the plants in such a restricted sample are still endogenous, by claiming that older plants which remained in the same location made their decision not to move even after changes occured in the geographical distribution of service suppliers.

Therefore, I conducted a different experiment. Here, using all plants, I directly control for unobservable plant characteristics by performing a fixed-effect logit analysis. Since I have only one year of data, I cannot use the variation in a plant's outsourcing decision over years. However, I can make use of the variation in a plant's outsourcing decisions for different services, in performing the fixed effect logit.

Let $Y_{ki}^{s\star}$ stand for the net benefit that plant ki obtains by outsourcing service s. Denoting plant specific effects by f_i, based on (14),

$$Y_{ki}^{s\star} = \mathbf{Z^s_{ki}}\boldsymbol{\beta^s} + f_i + u_{ki}^s, \tag{18}$$

where $\mathbf{Z^s_{ki}} = (\theta_k^s, N_k, \mathbf{A'_{ki}})$. With endogenous plants' location choices, f_i may be correlated with θ_k^s and/or N_k. To solve this problem, we work with a conditional likelihood function that is conditional on the number of services outsourced by a plant (see Chamberlain [5]). Notice that in the above specification (18), the effects of unobservable plant characteristics on a plant's in-house technologies, f_i, are common among different services. This assumption is necessary so that we can remove the potential effect of unobservable plant characteristics from the conditional likelihood function.

Let n_i stand for the number of services that plant i outsources, where n_i is a positive integer from 1 to 7. Following Chamberlain [5], I use the likelihood that a particular set of services are selected to be outsourced conditional on n_i services being outsourced, such that

$$L = \sum_k \sum_{i \in I_k} \ln \frac{\exp(\sum_s \mathbf{Z^s_i}\boldsymbol{\beta^s})}{\sum_{d \in B_{n_i}} \exp(\sum_s \mathbf{Z^s_i}\boldsymbol{\beta^s} d^s)}, \tag{19}$$

where I_k is a set of plants in county k.[30] $B_{n_i} \equiv \{(d^1, , , d^7) | d^s = 0 \text{ or } 1, \sum_s d^s = n_i\}$; B_{n_i} is the set of all possible combinations of outsourcing decisions made for the seven services where the total number of outsourced services is n_i. Maximizing the above likelihood function (19), we obtain the coefficients for $\hat{\theta}^s$ as shown in Table 8. Again, it is shown that the potential demand has a positive and significant effect on outsourcing for all white-collar services. This seems to indicate that the results of original probit analyses are robust, even when the location choice of the plants are endogenous.

Table 8: Fixed-Effect Logit

	$\hat{\theta}^s$	Z-stat.
White-Collar Services		
Advertising	7.330**	1.735
Bookkeeping & Accounting	104.140***	4.012
Legal Services	42.422**	2.298
Software & Data-Processing	44.488**	2.033
Blue-Collar Services		
Building Repair	-259.922***	-5.944
Machinery Repair	25.875**	2.866
Refuse Removal	49.038**	2.106

Source: Author's calculations based on data from *LRD*
$\star$: Significant at 10 % Level
$\star\star$: Significant at 5 % Level
$\star\star\star$: Significant at 1 % Level
Note: See (18) for other variables included in the estimation

For blue-collar services, the sign of the coefficient for building repair is again negative, while that for machinery repair is positive. Overall, the results for blue-collar services are mixed and therefore are not robust in the study.

[30] My specification takes into account the possibility that the effects of plant characteristics on outsourcing decisions are different among services.

5.2 The Relationship Between the Number of Service Suppliers and Potential Demand

The work presented above assumes that greater potential demand induces the entry of suppliers and hence a greater competition among suppliers. Regressing the number of suppliers on potential demand shifter and county population, here I test whether or not greater potential demand is associated with greater number of suppliers. The data on the number of service suppliers, $\{M^s\}$, are obtained from the *1992 CBP*. Since the definition of services given in the *1992 ASM* differs from the SIC definition in the *CBP*, I match the relevant categories as listed in Appendix A and B. Given that the matching for blue-collar services is less precise[31] and given that my model does not consider the nature of repair decisions, I only report results for white-collar services.

Table 9: Relationship between the Number of Service Suppliers and Potential Demand

Dependent Variable: Number of Service Suppliers in a County (M^s)

Service (s)	$\hat{\theta}^s$	County Population
Advertising	2335.94**	21.93***
	(2.007)	(4.743)
Bookkeeping & Accounting	17451.34***	72.339***
	(3.709)	(5.193)
Legal Services	48291.63***	147.10***
	(4.468)	(4.822)
Software & Data-Processing	57932.24***	51.55***
	(6.972)	(5.730)

Source: Author's calculations based on data from *LRD*
( ): T-statistics calculated with robust standard errors
⋆: Significant at 10 % Level
⋆⋆: Significant at 5 % Level
⋆ ⋆ ⋆: Significant at 1 % Level

As shown in Table 9, for all services, county population has positive and significant

[31] For example, repair service for a given machine can be provided by the manufacturers who sold that machine as well as machinery repair suppliers who are categorized in the machinery repair industry (SIC 7620).

Table 10: Net Effect of Potential Demand Shifter $\hat{\theta}^s$ on the Number of Service Suppliers M^s

Service	Average Number of Suppliers	Effect of one s.d. Increase in $\hat{\theta}^s$		Elasticity at Mean
		Level Effect	% Change from Average	
Advertising	24.1	10.9	45.2%	1.05
Bookkeeping & Accounting	83.9	17.4	20.7%	.88
Legal Services	168.5	49.6	29.4%	1.19
Software & Data-Processing	67.4	48.5	71.9%	2.18

Note: The results are for urban counties. Average numbers of suppliers are calculated based on the *1992 CBP*. Level effects of a 1 s.d. increase in the potential demand shifter on the number of suppliers are calculated by multiplying the coefficients of the potential demand shifter in the regression shown in Table 9 (column 2) by a 1 s.d. of the potential demand shifter shown in Table 4.

effects on the number of suppliers. In addition, the regressions reveal that the potential demand shifter $\hat{\theta}^s$ has positive and significant effects on the number of suppliers.[32] A county whose industries use a particular service more intensively will attract more suppliers for that service.

Based on the result, I also calculated the net impact of $\hat{\theta}^s$ on the number of suppliers in a county with averaged characteristics. As Table 10 shows, the predicted net impact of $\hat{\theta}^s$ on the number of suppliers is large. In a county with an average number of suppliers for each service, the increase in $\hat{\theta}^s$ by one standard deviation point results in a 20.7% to 71.9% increase in the number of suppliers of white-collar services, which is reflected in large elasticities.[33]

[32] There are some counties where suppliers of a particular service do not exist at all. Therefore, I also performed Tobit analyses, but the results remained qualitatively the same.

[33] As a robustness check, I also examined the effect of potential demand on a Hirschman-Herfindahl Index (HHI) of competition. Results are in Ono [24] and show a significant positive relationship for three of four services.

6 Conclusion

In this paper, I first provided a theoretical model which describes a mechanism by which firms in larger local markets achieve more opportunities for outsourcing services. The predictions of the model were then tested by using plant-level data from the *1992 ASM*. The empirical findings suggest that the industrial composition of a local market plays an important role in determining potential demand, and that firms, ceteris paribus, are more likely to outsource services in markets where there is greater potential demand for such services. Better outsourcing opportunities will improve manufacturing firms' overall productivity.

I also found that plant characteristics, such as size and whether or not a plant belongs to a multi-plant company, are important factors in outsourcing decisions. The empirical results suggest, in particular, the existence of scale economies in outsourcing services and the inter-company transfer of white-collar services.

Appendix

A Selected Services included in the *1992 ASM*

- Advertising: advertising services including printing, media coverage, and other services and materials
- Bookkeeping & Accounting Services
- Legal Services
- Software & Data Processing Services
- Communications Services: telephone, data transmission, telegraph, etc.
- Building Repair: all maintenance and repair work on the buildings
- Machinery Repair: all maintenance and repair work on equipment, Telex, photo transmission, facsimile (FAX), paging, cellular telephone, on-line access and related processing services
- Refuse Removal: refuse removal services including hazardous waste removal or treatment

B Attached SIC for Service Suppliers

	SIC
Advertising	7310
Bookkeeping & Accounting	8720
Legal Service	8100
Software & Data-Processing	7370
Building Repair	7340
Machinery Repair	7620
Refuse Removal	4950

Source: *Standard Industrial Classification Manual* [33]

C Summary Statistics

	mean	s.d.
ln (Beginning-of-year asset (thou.))	7.8	2.09
ln (County population)	12.5	1.9

These numbers are calculated for the urban sample of 31994 plants

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