Is Quality Certification Effective?
Evidence from the Childcare Market

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Abstract

The ineffectiveness of a quality certification mechanism can be attributed to consumers' low willingness to pay for what certifiers consider high quality. Alternatively, it can be attributed to the inability of certification status to provide consumers with information they do not already possess. I present a structural model of demand allowing consumers to infer quality from both certification status and firm reputation. I then estimate this model to assess the effectiveness and the impact of the national accreditation system for childcare centers on consumer welfare. My results suggest that consumers do value quality as gauged by the accreditation agency, but that on average they do not gain much information beyond what they infer from a firm's reputation. Overall, the accreditation system in the childcare market is only effective to a limited extent. Still, consumers gain some information about quality that otherwise would not be available. The estimates of structural parameters are then used to quantify the value of this information to consumers.

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1 Introduction

In a differentiated product market, product quality is often not readily observed by consumers. This potentially gives rise to under-provision of high-quality products (Akerlof, 1970) and may reduce social welfare in a variety of ways (Stiglitz, 1989). However, various information mechanisms could alleviate or eliminate the informational problem consumers face (Grossman, 1981; Milgrom, 1981). One of the mechanisms, quality certification, provides impartial but often inaccurate information. A wide range of professions, such as water and wastewater utilities, teacher education programs, health maintenance organizations, and ambulance services, are subject to this mechanism. Is certification an effective tool to provide information on quality to imperfectly informed consumers? If so, to what extent do consumers benefit from this type of formal assessment? This study examines these issues by empirically assessing the effectiveness and the welfare impact of the national accreditation system for childcare centers.

As consumers generally learn about product quality from multiple sources such as experience, brand name, and word-of-mouth, we need to conceptually distinguish two issues to assess the effectiveness of a certification mechanism. The first issue is the consumers' valuation of quality which certification status tries to gauge. If consumers do not value the specific attributes that the certification agency focuses on, then, whether a firm is certified or not will not matter to consumers. For example, parents' concerns regarding the convenient hours and the location of a childcare center may dominate their concerns regarding the developmental appropriateness of the provided programs. [1] The second issue is the information relayed through the certification status. If consumers have gained adequate information on product quality from the above-mentioned other sources, they might gain little additional value from the information

[1] Sonenstein (1991) finds that the best predictors of a mother's satisfaction with her child care arrangement are her rating of the convenience of the hours and the location and reliability of the arrangement. Blau and Hagy (1998) suggest that parents put little value on child care quality as defined by developmental psychologists such as group size, staff/child ratio, and staff training levels.

provided by the knowledge of a firm's certification status. Separating these two issues helps to identify different policy directions: Shall we first find out what consumers actually value? Shall we focus on how to improve the informational content of quality certification? Shall we reconsider the necessity of certification if market forces have already dealt well with the information problem?

Unique features of the childcare market offer a good platform for the investigation of the above issues. Parents mainly rely on a provider's reputation to gain information on unobserved quality attributes. Meanwhile, they collect additional information through providers' accreditation status, as evaluated by the National Association for the Education of Young Children (NAEYC).[2] Based on these features, I formulate a model of consumer demand in which consumers infer product quality from two unbiased but noisy signals----one is the firm's certification status, and the other is its reputation, which has been established over the years. Consumers' valuation of the certification status depends on how much consumers value the particular quality reflected by the status and how much consumers rely on the status relative to firm reputation for information. More specifically, consumers' reliance on certification status relative to firm reputation depends on the relative magnitudes of the variances of these two signals. I hypothesize that the longer a firm has operated in a market, the better consumers know about its true quality. As the noise of the reputation signal decreases over the years, consumers gradually shift reliance from the certification signal to the reputation signal.

Exploiting the panel nature of a random sample of childcare centers, I aggregate over individual consumer utility functions to derive product demand functions.[3] Then I estimate these demand functions using full information maximum likelihood estimation with fixed effects, accounting for the endogeneity of both accreditation status and prices. These demand functions

[2] NAEYC administers a national, voluntary, professionally sponsored accreditation system for all types of childcare centers. See www.naeyc.org for more information.
[3] For a comparison see Blau and Hagy (1998), in which they estimate a model of consumer demand for quality-related attributes of child care using consumer-level data as primary data and firm-level data I use for this study as supplement.

allow me to detect how product attributes, prices, and the accreditation status, as well as the reputation of a childcare center, enter consumers' utility functions. Using the number of years a center has been operating to proxy for the accuracy of the center's reputation, I am able to identify patterns on how consumers' valuation of the accreditation status varies with the accuracy of the center's reputation.

I find that consumers indeed gain less information from the accreditation status for a firm with a longer operating history. More importantly, consumers do value quality as gauged by the accreditation agency, but on average they do not gain much additional information from a firm's accreditation status relative to its reputation. However, consumers do gain some information from accreditation status that otherwise would not be available, and this will result in better consumer-product match. My counterfactuals show that the impact of the national accreditation system for the childcare market is positive, albeit small. I suggest that the low utilization rate of accreditation in the childcare market may be attributed to the lack of information conveyed by the accreditation signals, instead of the lack of parents' appreciation of quality as defined by childcare professionals.

A discrepancy arises when theory predicts complete voluntary disclosure with negligible disclosure costs while in the real world disclosure is barely complete. [4] A similar discrepancy exists in the literature on the effects of information on firm behavior and market operations. In contrast to the theoretical insight, many empirical studies detect small or negligible effects of increased information.[5] Researchers attribute these discrepancies either to firms' strategic

[4] For example, until 1998, less than half of operating health maintenance organizations voluntarily applied for accreditation by the National Committee of Quality Assurance (Jin, 2002). In the childcare market, the application rate is even lower----in 1997, around 20% of centers applied for NAEYC accreditation.

[5] Devine and Marion (1979) conducted an experiment in which they published comparative supermarket price information in local newspapers and found a small decrease in the mean and variances of prices. Milyo and Waldfogel (1999) analyze the effect of exogenous change in advertising on liquor prices and find that prices decrease insignificantly due to advertising. Chipty and Witte (1998) analyze the effects of location, availability, and quality information provided by local childcare resource and referral agencies (CCR&Rs) on prices, price dispersion and quality of local childcare markets. They find no significant difference in price dispersion for pre-school and school-age children care as well as in quality distributions for markets with CCR&Rs and for markets without.

consideration,[6] to econometric complications,[7] or to the competing roles of information supply. I probe the role of consumers for an alternative explanation for these discrepancies. My viewpoint offers a refreshing and perhaps more fundamental alternative explanation: consumers may not care about what is reflected in the increased information, or they may already know enough. In this sense, my work is closely related to a recent branch of empirical work on how and what consumers learn from a particular type of information supply.[8] These works, as a whole, highlight the different sources of information such as advertising, quality rating, and experiences, and more importantly, the different fashions by which consumers learn from information. My study adds to this line by emphasizing the context of multiple informational sources and the role of firm reputation. I find that this realistic setup plays a crucial role in shaping consumers' learning processes.

Methodologically, my study contributes in two dimensions to the firm-level empirical analysis. First, I combine the use of a random sample of firms and the Business Census to back up product-level demand, although the original methodology in Berry (1994) needs data on the universe of firms. This highlights the under-explored research potential for sample data and offers a straightforward and easy-to-implement formula for future researchers. Second, I combine the use of fixed-effects estimation with instrumental variables to solve the endogeneity

[6] These considerations include certain types of disclosure costs (Jovanovic, 1982), costs of information acquisition by sellers (Matthews and Postlewaite, 1985; Farrell, 1986, Shavell, 1994), alternative market structures (Jin, 2002), and consumers' multidimensional heterogeneity (Hotz and Xiao, 2002).

[7] Information supply such as advertising is usually a choice for firms, which complicates econometric analysis with endogeneity problem.

[8] Ackerberg (2001, 2003) finds that advertisements of a newly introduced brand of yogurt primarily affected inexperienced users of the brand, and suggests that the main role of these advertisements was to inform consumers. Chernew, Gowrisankaran and Scanlon (2002) exploit a natural experiment to estimate a Bayesian learning model allowing consumers to update their beliefs from health plan report cards. They find that the newly released information significantly affected consumers' choices of health plans. Crawford and Shum (2000) identify patients' incentives to experiment to gain information useful for future choices of pharmaceutical drugs. They find that patients, who have considerable uncertainty in the beginning of their treatment, quickly learn from their experiences. Relevant works about Bayesian learning models also include Erdem and Keane (1996), Erdem, Keane, and Strebel (2002), Ching (2002).

problem of both prices and accreditation status. My approach, though requiring panel data, should be useful to researchers who encounter the same problem.

The paper proceeds as follows. Section 2 introduces the childcare market and its accreditation system. Section 3 develops a model of consumer demand. Section 4 describes the data I employ and the construction of variables. Section 5 outlines my empirical strategy. Section 6 presents results and counterfactual welfare analysis. Section 7 concludes.

2 The Childcare Market and NAEYC Accreditation

2.1 A Sketch of the Childcare Market

Fueled mainly by the rise of female labor force participation,[9] the childcare market has been growing substantially, especially over the last two decades. The number of center-based programs (as contrasted to home-based programs) rose 26% from 40,631 in 1987 to 51,297 in 1992 and then rose 21% to 62,054 in 1997 (O'Neill & O'Connell, 2001).[10] Primarily small businesses, childcare centers compete in localized markets, as parents overwhelmingly prefer to have their children cared for in their own residential neighborhood (Chipty & Witte, 1994; Hofferth et al, 1991). Centers are subject to states' licensing requirements.[11] This study will

[9] According to the Bureau of Labor Statistics, in 1970 28.7 percent of mothers with children under age six worked; by 1990 this number had grown to 58.2 percent, and by 2000 64.4 percent. Correspondingly, non-parental childcare becomes increasingly a common choice. In 1995, according to the National Center for Education Statistics, there were approximately 21 million children under age six in the U.S. More than 12.9 million of these children were in non-parental childcare, and more than 6 million of these children were in center-based childcare. Nationwide, about half of all working families with children under age 13 paid for childcare in 1997. The monthly average of such expense was $286, about 9 percent of their earnings (Giannarelli and Barsimantov, 2000).

[10] Childcare establishments take two primary forms----center-based programs and home-based programs. Center-based programs care for relatively large numbers of children in institutional settings while home-based programs care only for three to four children in home settings. Centers usually group children according to age while home-based programs mix children of all ages in an informal atmosphere. They are very different entities and subject of different sets of state licensing requirements.

[11] Some may argue that the license status of a childcare center signals quality, as the accreditation status does. I agree that the license status can offer parents quality assurance. However, because licensing requirements are mostly about observable attributes (e.g., staff/child ratio, group size), I view the licensing status more as an observable quality measure instead of a quality signal.

focus on childcare centers because NAEYC accreditation only applies to center-based programs.[12] Furthermore, I will not incorporate into my study Head Start and public school sponsored programs (Pre-Ks), which are of a very different nature compared to the market-oriented centers.[13]

Childcare centers provide multiple types of services as children of different ages require different types of care.[14] The care services are both horizontally and vertically differentiated. On one hand, centers differ in horizontal attributes such as geographic location and operating hours. On the other hand, they differ in quality measures such as staff-child ratios, group sizes, square footage for children's activity, and staff training levels[15]. Besides these "hard" measures, there are also "soft" measures: Are children in the program generally comfortable, relaxed, and happy, and are they involved in play and other activities; are all areas of child development stressed equally, with time and attention being devoted to cognitive, social, emotional, and physical development? There is no absolute consensus on what exactly distinguishes low quality from high quality, but researchers seem to agree quality should be assessed comprehensively on all aspects of child care. Recent evidence suggests that the quality of child care in the United States is low and quite varied (Helburn, 1995).

There exists considerable asymmetric information between parents and providers: parents have difficulty ascertaining quality even when they incur substantial search costs to learn about

[12] Some may be concerned that the exclusion of informal family-based programs may seriously undermine my study since informal care providers constitute a major part of the childcare market. For example, in 1997, 488,734 out of 550,788 childcare establishments nationwide were non-employer businesses. I certainly agree with this view but think the undermining is at acceptance level. Although the number of non-employers greatly exceeds that of employers, it is to the contrary in terms of the number of enrolled children. In 1995, 31% of 21.4 million children under 6 were enrolled in center-based programs, while 18% were covered by home-base programs. So employer establishments are the main source of non-parental childcare supply.

[13] Head Starts and Pre-Ks are mainly concerned with the development of low-income children rather than the provision of child care. They generally operate on a part-year, part-day basis, and are more responsive to the availability of public funding than to market forces. They usually charge no or nominal fees.

[14] For example, infants need basic care such as changing diapers and feeding while older children need developmental activities and more indoor and outdoor space (Chipty & Witte, 1994).

[15] Research has investigated what certain quality factors are linked to positive outcomes for children. Characteristics as listed, especially group size, staff/child ratio and staff training levels, are associated with positive outcomes of children and hence with high quality (Peisner-Feiberg and Burchinal, 1995)

providers (Mocan, 2001). Parents may not be able to spend a significant amount of time at the center to observe various dimensions of the operation. Moreover, the multidimensional attributes of these services may be difficult to evaluate and/or monitor (Hotz and Kilburn, 1996). Parents receive most information about providers from informal sources: family, neighbors, friends, and coworkers. The 1990 National Childcare Survey Parents Study indicates that the majority (66%) responded that they learned of their providers from friends, neighbors or relatives, while 13% used advertisements and 9% turned to resource and referral agencies[16] (Hofferth et al, 1991).[17]

2.2 Accreditation as a Signal of Program Quality

NAEYC has been managing a national voluntary accreditation system for about two decades.[18] An applying childcare program needs to engage in an extensive self-study based on NAEYC's accreditation criteria. The accuracy of the program's self-study will be verified during a site visit to the program by a team of trained volunteer validators. The validated self-study, including the program director's responses to the validation visit, will be reviewed by a 3-member national committee composed of recognized experts in childcare and early childhood education. If it is judged to be in substantial compliance with the criteria, the program will be granted accreditation for a three-year period. Once a childcare center is accredited, parents can easily recognize it by noting the display of the Academy's insignia--a torch--on its stationery and promotional

[16] Community-based childcare resources and referrals agencies offer direct-to-consumers information about location, prices, availability and basic characteristics of local providers.
[17] A study on the behaviors of parents in south Chicago, Camden and Newark (Kisker et al, 1989) has similar findings: half of these parents who found non-relative care learned about the program or individual caregiver from family members or friends.
[18] NAEYC is the only national accreditation body for center-based childcare programs. National Association for Family Childcare (NAFCC) is a national accreditation body for family-based childcare programs. I do not incorporate NAFCC accreditation into this study because NAFCC did not start accreditation until 1988 and for various reasons very few family care providers were accredited for the first few years. Then NAFCC spent 3 years to build a new accreditation system from scratch in 1994, and started operating the new system national wide only in 1999. Meanwhile, NAEYC started accreditation in 1985, and by the year 1990(the year my data were collected) it has already been reasonably well adopted and recognized nationwide.

material.[19] NAEYC does not reveal the identities of centers with rejected applications.

The accreditation criteria cover broad issues such as interactions among teachers and children, curriculum, relationships among teachers and families, staff qualifications and professional development, administration, staffing, physical environment, health and safety, and nutrition and food service.[20] While the NAEYC accreditation process examines the total program, the greatest emphasis is placed on the quality of interactions between staff and children and the developmental appropriateness of the curriculum. The consensus by childcare professionals is that the accreditation status is an indicator of high quality. It is worth noting that though NAEYC accreditation has accumulated a critical mass, a low percentage of centers are actually accredited. Nationwide in 1997, the number of childcare establishments with payroll was 62,055, while the number of programs in self-study[21] for accreditation was 8,635 (Bredekamp and Glowacki, 1996). Around 7%, or 4,459, of childcare establishments with payroll were NAEYC accredited.

3 Model

To recapitulate, the childcare market is characterized by numerical local markets, multi-product firms, differentiated products, and asymmetric information between buyers and sellers. As is in the case of many personal services industries (cleaners, dentists, home care, etc.), in the childcare market informal information channels, like word-of-mouth, interact with formal ones, such as the national accreditation system. To accommodate these features, I formulate a model in which consumers infer unobserved product quality from two different types of signals: one is the firm's

[19] The current list of accredited programs is posted on-line and updated monthly. Also, NAEYC-accredited programs receive a large colorful poster depicting the characteristics of accredited programs along with a certificate of accreditation.
[20] For more on accreditation criteria, visit: http://www.naeyc.org/accreditation/naeyc_accred/info_general-components.htm.
[21] Self-study means that providers are in the process of applying for accreditation. Their application might be approved or rejected.

accreditation status, and the other is its reputation, which consumers learn gradually though the word-of-mouth effect among their family members, neighbors, friends and coworkers. My focus is not on characterizing the equilibrium outcomes with the accreditation mechanism. Instead, I restrict my attention only to the demand side----how consumers learn and value accreditation signals. Although the specifics of my model are tailored to the nature of data I have, the kernel----consumers gain information from two different signals---- is good for general use. A caveat of my model is that consumers disregard information on how firms' propensity for applying accreditation is determined. This eases my analysis but undermines consumers' inferring ability. For example, if well-reputed centers were less motivated to get accredited, rational consumers would value "accredited" less for centers with good reputation.

Let i index individual consumer, g the type of products/services offered by a firm, and j individual firm. At each local market, firm j produces multiple products indexed by g, and consumer i decides on which product to buy from which firm. In the context of the childcare market, a center offers different services and charges different prices for children of different ages. Parents purchase a certain type of services according to the age of their children.[22]

3.1 Product Quality, Quality Signals, and Consumer Perception

Each product g of firm j is differentiated along multiple dimensions, which can be captured by a vector of product and firm attributes $[X_{gj}, X_j, q_j]$. I define $[X_{gj}, X_j]$ to be observable attributes (by both consumers and econometricians), where X_{gj} is product-specific (for example, the staff-child ratio of an infant group), and X_j is firm-specific (for example, the license status of

[22] For example, if a consumer is looking for childcare services for a toddler, she will consider all the firms in the local market which offer toddler care.

a firm). I further define q_j to be a firm-specific[23] quality attribute that cannot be captured by $[X_{gj}, X_j]$. In other words, I define q_j to be the "residual" part of quality after the "correlated" part between X and q is effectively taken by X. By this definition, I have $X_{gj} \perp q_j, X_j \perp q_j$ holding. I use the following example to illustrate this point. The loving atmosphere of a childcare center is positively associated with, but cannot be fully captured by, its staff-child ratio. If consumers are aware of this positive connection, then when they evaluate the staff-child ratio, they actually evaluate the staff-child ratio and the likelihood that this staff-child ratio is associated with a loving atmosphere. By my definition q_j is the "residual" of the loving atmosphere, which is not captured and thus not correlated with the staff-child ratio. A firm perfectly observes its q_j while consumers, as well as its competitors, can only infer q_j by the firm's accreditation status and reputation. Consumers have diffuse (non-informative) priors about q_j.

Consumers receive an unbiased but noisy signal S_j^R on q_j, where S_j^R is the reputation of a firm, recognized by consumers through the local word-of-mouth effect. $S_j^R \sim N(q_j, \sigma_{jR}^2)$, where σ_{jR}^2, the variance of consumers' perception, depends on how long the firm has been operating in the local market. I hypothesize that the longer a firm has been operating, the smaller is the variance σ_{jR}^2, meaning, the better consumers know about the true quality of this firm by word-of-mouth. In the extreme case, if a firm just opens for business and has not established a reputation, the variance σ_{jR}^2 will be infinity and there is nothing for consumers to learn. I further assume that firms observe their own S_j^R and the S_j^R of other firms so that their accreditation and

[23] I define q_j to be firm-specific because: 1) the accreditation agency takes a child care center as a whole to measure quality; 2) reputation is also more likely to be firm-specific as parents tend to exchange their experiences in a general way. Conversations can easily go: "I know a really good daycare center in Santa Monica…"; 3) I think the unobserved quality of a services firm is more integrated in the firm level instead of in the product level; 4) I put product-specific unobserved quality into the idiosyncratic error terms.

pricing decisions will depend on their own reputation and that of their competitors.

Besides firm reputation S_j^R, I assume that an authoritative national accreditation agency administers a voluntary accreditation system for all the firms. The accreditation agency's rating of a firm is truthful but not accurate[24] so that consumers receive another unbiased but noisy signal S_j^A about q_j. $S_j^A \sim N(q_j, \sigma_{jA}^2)$, where σ_{jA}^2 is the variance of the accreditation signal, which is associated with the ability of the accreditation agency to measure quality accurately and other potential factors[25]. Therefore σ_{jA}^2 is a measure of informativeness of the accreditation signal.

Consumers infer q_j based on all information they could collect----the accreditation signal S_j^A and the reputation signal S_j^R. I denote $E(q_j \mid S_j^A, S_j^R)$ to be consumers' perceived q_j given S_j^A and S_j^R. $E(q_j \mid S_j^A, S_j^R)$ can be derived as a weighted average of S_j^A and S_j^R:

$$E(q_j \mid S_j^A, S_j^R) = \frac{\sigma_{jR}^2}{\sigma_{jR}^2 + \sigma_{jA}^2} S_j^A + \frac{\sigma_A^2}{\sigma_{jR}^2 + \sigma_{jA}^2} S_j^R$$

The above formula embodies the key feature of my model----what consumers learn from a particular signal depends on the value of this signal as well as the relative magnitude of the variance of this signal as compared to the variance of the other signal. For example, if a firm has good reputation, consumers will think positively about the inherent quality of the firm. However, if this reputation signal has a bigger variance than the accreditation signal, consumers will rely more on the firm's accreditation status for information. If the number of years in operation is positively correlated with the accuracy of a firm's reputation signal, as hypothesized, consumers will rely more on reputation and less on accreditation for firms with longer operating histories.

[24] Certification provides inaccurate information about product quality because of the possibility of classification error----certifiers make mistakes, and because of the discrete nature of certification status ---- binary or categorical status cannot fully reflect the continuous quality.

[25] Examples of these "other potential factors" are: the prominence of the window display of the accreditation status; the influence of accreditation awareness activities organized by local resource and referral agencies.

3.2 Consumer Choices and Firms' Demand Functions

I take a characteristics-based approach to view products as a bundle of all product- and firm-specific attributes. Consumers' utility depends on all the attributes as well as product prices and personal characteristics:

$$
\begin{aligned}
U_{igj} &= X_{gj}'\beta_1 + X_j'\beta_2 + D_j'\beta_3 + \gamma E(q_j \mid S_j^A, S_j^R) - \alpha \log P_{gj} + \varepsilon_{igj} \\
&= X_{gj}'\beta_1 + X_j'\beta_2 + D_j'\beta_3 + \gamma\left(\frac{\sigma_{jR}^2}{\sigma_{jR}^2 + \sigma_{jA}^2} S_j^A + \frac{\sigma_{jA}^2}{\sigma_{jR}^2 + \sigma_{jA}^2} S_j^R\right) - \alpha \log P_{gj} + \varepsilon_{igj}
\end{aligned} .
$$

In this utility function, ε_{igj} is consumer i's idiosyncratic preference of product g of firm j and is with a standard type I extreme value distribution. β_1 and β_2 are vectors of parameters respectively measuring consumer valuation of product-specific attributes X_{gj} and firm-specific attributes X_j, and β_3 is a vector of parameters measuring how demographics D_j shift consumers' overall tastes on child care services. I use γ as a measure of consumers' valuation for the perceived unobservable quality, and α as a measure of consumers' responsiveness to prices. $\log P_{gj}$ is the natural log of the price of product g of firm j. I normalize consumer i's utility from not buying any of the products (the outside product) to be zero: $U_{ig0} = 0$.

Consumers first decide which type of products to purchase based on their need then choose among firms which offer the products they request. At each local market, consumer i will buy product g of firm j if and only if $U_{igj} \geq U_{igk}, \forall k$. Following Berry (1994), I aggregate over individual consumer utility functions to derive the market shares for each product g of firm j. This is a simple Logit model and I can derive:

$$
\begin{aligned}
\delta_{gj} &= \ln ms_{gj} - \ln ms_{g0} \\
&= X_{gj}'\beta_1 + X_j'\beta_2 + D_j'\beta_3 + \gamma\left(\frac{\sigma_{jR}^2}{\sigma_{jR}^2 + \sigma_{jA}^2} S_j^A + \frac{\sigma_{jA}^2}{\sigma_{jR}^2 + \sigma_{jA}^2} S_j^R\right) - \alpha \log P_{gj}
\end{aligned} , \tag{1}
$$

where ms_{g0} is the market share of the outside product, and ms_{gj} is the market share of product

g of firm j. I call δ_{gj} mean utility level. As established by (1), δ_{gj} can be uniquely determined by $\ln ms_{gj} - \ln ms_{g0}$ and act as a dependent variable. By estimating (1), which is a tractable linear form, I will be able to back up all the parameters in consumers' utility functions.

4 Data

4.1 Primary Data: 1990 Profile of Childcare Settings: Center-Based Programs

I use the Profile of Childcare Settings (PCS)[26] as the primary data set, which consists of a nationally representative sample of childcare centers in 1990.[27] PCS collected extensive data on a number of topics including general characteristics, admission policies and vacancies, types of children served, subsidies, staff, curriculum and activities, meals, health and safety, and operating experiences (Lang & Card, 1992). The final sample includes 583 regulated home-based family providers and 2,089 center-based programs. For reasons I explained in section 2, I only study fee-charging center-based programs.[28] For non-price-charging centers, parents' willingness to pay is reflected in different ways such as queuing and parent involvement, which can be considered implicit prices. If the effects of accreditation status on non-price-charging firms are systematically different from the effects on price-charging ones, my results can be biased.[29] Out of 2089 centers, I drop 1013 out of analysis for their Head Start or public school sponsored

[26] PCS was made available by the American Family Data Archive (AFDA), Sociometrics Corporation. The study was conducted by Ellen E. Kisker and Valarie Piper, Mathematica Policy Research, Inc. The study was funded by the U.S. Department of Education, Office of Planning, Budget, and Evaluation. Funding support for preparing the revised documentation for public distribution was provided by a contract (N44-HD-0-2910) between the National Institute of Child Health and Human Development (NICHD) and Sociometrics Corporation. The original investigators, funding agency, and AFDA are not responsible for the analyses or interpretations presented here.

[27] Computer-aided telephone interviews were conducted with nationally representative samples of regulated home-based family day care providers and center-based early education and care programs between October 1989 and February 1990.

[28] Childcare centers and family providers, though both integrated parts of the childcare market, are of very different nature and usually do not compete directly with each other.

[29] Furthermore, poor markets tend to have more non-price-charging childcare centers than rich ones. When I keep only price-charging centers, I might over-select rich markets into my data.

status,[30] 129 because they focus on handicapped childcare instead of regular childcare, and 9 due to inconsistent data reporting or seriously incomplete data.[31] I am left with 938 firm-level observations.

4.2 Auxiliary Data

I use the following data sets to complement the primary data set.

- Zip code level demographics from the public 1990 Population Census. This data contains information on income level, education level, race composition, urbanization, and female labor participation for each zip code. I also use data on the number and percentage (over population) of children in different age profiles to construct market share variables. In addition, I construct a variable to measure the population mobility and use it as a control for the stock and flow of local information.
- Zip code level data on the childcare market from the public 1992 Business Census.[32] I use the number of childcare establishments at the zip code level and their approximate number of employees to construct the outside market share in each market. The number of childcare establishments also serves as an instrument for firms' accreditation decision.
- Childcare resource and referral agencies (CCR&Rs) special survey.[33] CCR&Rs are generally grass roots, non-profit local organizations whose primary function is to help parents find appropriate childcare for their children. They provide a centralized source of information on

[30] Head Starts and public school sponsored centers are of charity nature and charge no or nominal fees. Summary statistics indicate that compared to no-fee centers, fee-charging centers enroll significantly more children but fewer subsidized children, hire more employees but pay lower salaries, and are less likely to be accredited but more likely to be licensed and for-profit. They are located in neighborhoods that are wealthier, better educated, whiter, and more mobile. The have a higher female labor participation rate, more childcare centers, and are less likely to have a childcare resources and referral agencies. These differences are striking, however, I rely on pricing information to conduct estimation of my demand model so I have to put aside observations with no price information.

[31] For observations with occasional missing values, I supplement the data by plugging in the sample-medians for variables with missing values.

[32] 1992 Business Census is based on the 1990 Standard Statistical Establishment List. Therefore, the 1992 Business Census matches my 1990 data.

[33] I thank Chipty and Witte (1998) for making these data available. They conducted a survey reporting the existence of CCR&Rs in 1990 in the 100 county groups used in PCS.

location, price, and observable characteristics. I use the existence of a local CCR&R (county-level) to serve as a control for the stock and flow of local information.

I merge the primary data set with the first two auxiliary data sets by zip codes, [34] and with the last one (CCR&R survey) by county codes.

4.3 Variable Construction

I focus my attention on the following center attributes (see table 1 for variable construction):

- NAEYC accreditation status: a dummy variable, equal to one if the center is accredited, and equal to zero otherwise.
- Firm characteristics: enrollment, enrollment racial composition, years of operation, staff-child ratio, licensing status, organization status (for profit or non-profit), chain status, whether listed in a local CCR&R, subsidization status, distance to public transportation, and annual/hourly salary of a randomly-drawn teacher.[35]
- Product specific variables: prices, enrollment, staff-child ratios, and part-time/full-time status of each age group of a childcare center. Each center provides 1 to 4 types of services based on the age of the enrolled children----infants, toddlers, preschoolers, and school-age children.[36] Each age group could offer part-time services (0-20 hours per week), or full time services (20-40 hours per week). As required by state regulation and entailed by the nature of childcare, the number of staff for each age group usually increases as the age of children decreases----the younger the child, the more adult attention she needs.

4.4 Summary Statistics

I define product-firm as a unit of observation, yielding 2,196 observations across 938 centers.

[34] I thank Ellen Kisker for making the PCS zip code data available.
[35] As teacher salary usually increases with teacher qualification and experience, I use hourly salary of a randomly drawn teacher as a proxy for teacher qualification and experience.
[36] If a center offers multiple packages for the care of children of a particular age, I take average of staff-child ratios and prices across packages for this age.

Table 2 shows that an average center hires 9 employees and enrolls 66 children, of which the majority (78%) is white. The average center has operated for 11 years. Most of the centers are licensed (88%) and listed in a childcare resource and referral agency (70%), while only 38% are for-profit organizations and 6% are part of a chain. Around 30% receive subsidy from federal, state, and/or local governments, and 6% of their enrolled children are subsidized. A small proportion of the centers (15%) are NAEYC accredited. A randomly drawn teacher has an annual salary of $10k (in 1990 dollars). A center typically faces 4 competitors in a zip code.

Table 3 looks at variables of panel nature. The largest age group of children is the group of preschoolers (age 3 to 5). Staff-child ratios decrease with the age of children----infants require more labor-intensive care. The group of infants has the highest staff-child ratio. Full time childcare typically costs around $50 a week (in 1990 dollars).[37] Prices decrease with the age of children, and part-time services are more expensive than full time ones (see Table 4).[38]

As table 2 and table 3 indicate, the accredited centers are different, but not substantially different, from the non-accredited ones. The accredited centers are significantly more likely to be licensed, hire more employees, and have higher staff-child ratios, which is consistent with the NAEYC accreditation criteria. Accredited centers also seem to enroll more children and charge higher prices than non-accredited ones, but the differences are not significant. Interestingly, accredited centers operate for significantly more years than non-accredited ones. Is it because the accredited centers have better quality and hence last longer? Or is it because centers with longer operating histories have better quality and will pass accreditation criteria more easily?

4.5 Estimation of Outside Market Shares

To estimate mean utility level $\widehat{\delta_{gj}} = \ln ms_{gj} - \ln ms_{g0}$, I need to estimate market share of

[37] According to Consumer Price Indexes, $50 in 1990 is approximately equivalent to $70 in 2002.

[38] Table 3 does not show this pattern because table 3 summarizes statistics across different samples. The set of centers offering infant care is not the set of centers offering toddler care. If highly priced centers specialize in toddler care, table 3 does not necessarily show that infant care costs more than toddler care.

product g of firm j (ms_{gj}) and the share of consumers choosing not to buy services from any center (ms_{g0}). I directly observe the number of enrollment for every age group g of firm j and I can estimate the potential market size for product g, so estimating $ms_{gj} \equiv \dfrac{enrollment_{gj}}{market\_size_g}$ is relatively easy. For the childcare market, a natural proxy for the potential market size is the number of children in a certain age group. Estimating ms_{g0} is not this straightforward though. The ideal data has enrollment data for all childcare centers in the local market. However, my data is a random sample of firms instead of the universe, thus I have to find an alternative to estimate ms_{g0}. Here are the procedures I follow to deal with my data problem:

1. I use 1990 population census to estimate market size for each zip code (# of infants, toddlers, preschoolers, and school-age children).
2. I then use 1992 Business Census to get the number of child care centers for each zip code, and the approximate number of employees for each center in that zip code.
3. I assume the relationship between the number of employees and the number as well as age composition of enrollment follows what I observe in my random sample. I estimate the number of enrollment for each age group at each center, and then aggregate to get an estimate of enrollment of all centers in that zip code.
4. I define $\widehat{ms_{g0}} = 1 - \dfrac{enrollment\_of\_all\_centers_g}{market\_size_g}$.

I find the above method, though subject to measurement errors, a convenient and effective way to deal with the problem of estimating the outside share for studies using a random sample. My approach broadens the applicability of Berry (1994) and highlights the research potential for sample data.

5 Empirical Strategy

As the dependent variable, $\widehat{\delta_{gj}}$, is an estimate, we introduce a measurement error term into equation (1), which leads to:

$$\widehat{\delta_{gj}} = X_{gj}'\beta_1 + X_j'\beta_2 + D_j'\beta_3 + \gamma(\frac{\sigma_{jR}^2}{\sigma_{jR}^2+\sigma_{jA}^2}S_j^A + \frac{\sigma_{jA}^2}{\sigma_{jR}^2+\sigma_{jA}^2}S_j^R) - \alpha \log P_{gj} + \omega_{gj},$$

where $\omega_{gj} \sim N(0,\sigma_\omega^2)$. I cannot identify σ_{jR}^2 from σ_{jA}^2 because I will get the same results if I scale them proportionally, but I can identify their relative magnitudes. I normalize $\sigma_{jR}^2 + \sigma_{jA}^2 = 1$ and define $h_j = \sigma_{jR}^2$, which leads to: [39]

$$(2) \qquad \widehat{\delta_{gj}} = X_{gj}'\beta_1 + X_j'\beta_2 + D_j'\beta_3 + \gamma(h_j S_j^A + (1-h_j)S_j^R) - \alpha \log P_{gj} + \omega_{gj},$$

where h_j measures consumers' relative reliance on accreditation signals for information. The bigger h_j is, the more consumers rely on accreditation signals and the less on reputation signals. I define $h_j = \Phi(h_0 + h_1 R_j)$, where Φ is the cumulative density function of a normal distribution to ensure h_j between 0 and 1, as entailed by its construction, and R_j is the log of the years of operation of firm j. As I have discussed before, I hypothesize that a firm's longevity inversely influences the variance of its reputation. If my hypothesis holds, h_1 should be negative.

The estimation of equation (2) is to find a set of parameter values $[\beta_1, \beta_2, \beta_3, \gamma, h_0, h_1, \alpha]$ to map the model-predicted mean utility levels δ_{gj} to actually observed mean utility levels ($\widehat{\delta_{gj}} = \ln ms_{gj} - \ln ms_{g0}$). To complicate the identification, both the price variable and the accreditation variable are endogenous, as the econometrician does not observe reputation signals S_j^R. First, firms will certainly base their pricing decisions P_{gj} on reputation

[39] I use a different notation h_j here because by normalizing $\sigma_{jR}^2 + \sigma_A^2 = 1$, σ_{jR}^2 stands for the relative variance, not the absolute variance, of the reputation signal.

S_j^R. Second, as both accreditation signal S_j^A and firm reputation S_j^R are positively correlated with firms' unobserved quality q_j, S_j^A and S_j^R are also correlated (unconditional on q_j). Furthermore, firms may choose what accreditation signal S_j^A to send based on their reputation S_j^R. In this situation, ordinary least squares estimators will be biased. Therefore I develop a two-step estimation strategy, exploiting the panel nature of my data and instrumental variables to solve this technically challenging problem of double endogeneity. In the first step, I conduct fixed effects estimation to identify $[\beta_1, \alpha]$ using within-firm variation. In the second step, I conduct full information maximum likelihood estimation, using across-firm variation and instrumental variables for S_j^A to identify the remaining parameters $[\beta_2, \beta_3, \gamma, h_0, h_1]$.

5.1 Step 1: Fixed Effects Estimation

To deal with the endogeneity problem of the price variable P_{gj}, I explore the product-firm structure, or the panel structure, of my data. Viewing S_j^R as fixed effects, I use the across-group-within-firm variation of P_{gj}, δ_{gj} and X_{gj} to identify $[\beta_1, \alpha]$,

First, I take the mean of equation (2) across groups within firms:

$$(3) \qquad \overline{\delta_{.j}} = \overline{X_{.j}}'\beta_1 + X_j'\beta_2 + D_j'\beta_3 + \gamma(h_j S_j^A + (1-h_j)S_j^R) - \alpha\overline{\log P_{.j}} + \overline{\omega_{.j}}$$

Deducting equation (3) from (2), I get:

$$(4) \qquad \widehat{\delta_{gj}} - \overline{\delta_{.j}} = (X_{gj} - \overline{X_{.j}})'\beta_1 - \alpha(\log P_{gj} - \overline{\log P_{gj}}) + \omega_{gj} - \overline{\omega_{.j}}$$

The firm-specific term S_j^R goes away in equation (4), therefore OLS regression of $\widehat{\delta_{gj}} - \overline{\delta_{.j}}$ against $(X_{gj} - \overline{X_{.j}})$ and $(\log P_{gj} - \overline{\log P_{gj}})$ will yield consistent estimates of $[\beta_1, \alpha]$.

Then I plug the consistent estimates of $[\beta_1, \alpha]$ back into equation (3) and construct:

(5) $$\widehat{\lambda_j} = \overline{\delta_{.j}} - \overline{X_{.j}}'\beta_1 - \alpha\overline{P_{.j}} = X_j'\beta_2 + D_j'\beta_3 + h_j\gamma S_j^A + (1-h_j)\gamma S_j^R + \overline{\omega_{.j}}\ ,$$

in which $\widehat{\lambda_j}$ serves as the dependent variable in my second step estimation, and $(1-h_j)\gamma S_j^R + \overline{\omega_{.j}}$ is a composite error term with a heteroskedastic covariance matrix.[40]

5.2 Step 2: Full Information Maximum Likelihood Estimation

After the first step, I estimate the following equation in the second step:

(6) $$\widehat{\lambda_j} = X_j'\beta_2 + D_j'\beta_3 + \Phi(h_0 + h_1 R_j)\gamma S_j^A + (1-\Phi(h_0 + h_1 R_j))\gamma S_j^R + \overline{\omega_{.j}}$$

in which S_j^R, the econometrician-unobserved error term, causes the endogeneity of firms' accreditation signal S_j^A. A childcare center with good reputation may be more motivated to seek accreditation because it is more likely to be of a high quality and therefore be able to pass the criteria. Or it may be less motivated because its high quality is well embodied in its reputation. For this study I am content to acknowledge this endogeneity problem but leave a fully-specified model on firms' accreditation decisions for future research.

To further complicate the econometric analysis, instead of observing S_j^A I only observe the accreditation status A_j, a binary variable. My solution to this problem is to embed a stochastic threshold into firms' accreditation status. I view a firm's accreditation signal as a function of $[X_{gj}, X_j, D_j, T_j, S_j^R]$, where T_j are potential factors which affect firms' decisions on sending out accreditation signals but which are not contained in equation (6). I observe $A = 1$ if S_j^A>0, that is, $S_j^A = fn(X_{gj}, X_j, D_j, T_j, S_j^R) + \xi_j \geq 0$. I observe $A = 0$ otherwise. Assuming a

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[40] The variance of $\overline{\omega_{.j}}$ is $\dfrac{\sigma_\omega^2}{\kappa_j}$, where κ_j is the number of groups for firm j. I have an unbalanced panel and firms have different numbers of groups κ_j.

linear form for this threshold function, at the firm level the previous equation becomes: $A = 1$ if $S_j^A = Z_j'\pi + \xi_j \geq 0$, where $Z_j = [\overline{X_{.j}}, X_j, D_j, T_j, S_j^R]$; $A = 0$ otherwise.

The above solution brings me a system of simultaneous equations with mixed structures:

$$(7) \qquad \begin{aligned} \widehat{\lambda_j} &= X_j'\beta_2 + D_j'\beta_3 + \Phi(h_0 + h_1 R_j)\gamma S_j^A + v_j \\ S_j^A &= Z_j'\pi + \xi_j \end{aligned}$$

where $v_j = (1 - \Phi(h_0 + h_1 R_j))\gamma S_j^R + \overline{\omega_{.j}}$ and S_j^A is latent. ξ_j and v_j are allowed to be correlated to account for the relationship between S_j^A and S_j^R.

To deal with the endogeneity problem of S_j^A, the second equation in (7) contains instrumental variables T_j. Potential Instruments are variables influencing firms' accreditation decisions but not influencing firms' reputation, as detailed in the next section.

As equation (7) is a system of simultaneous nonlinear equations with heteroskedastic errors, I conduct full information maximum likelihood estimation (FIML) to estimate the set of structural parameters $\theta = [\beta_2, \beta_3, \gamma, h_0, h_1]$.

$$\widehat{\theta_{FMLE}} = \arg\max_{\theta} \sum_{1}^{J} \ln(prob(\widehat{\lambda_j}, A_j \mid X_j, D_j, R_j, Z_j, \theta)).$$[41]

To check the robustness of my estimates, I also conduct the two stage least square estimation and the Heckman-corrected model on equation (6) by assuming a linear form $h_j = h_0 + h_1 R_j$ and using A_j as a proxy for S_j^A.[42]

5.3 Choice of Instruments for Accreditation

Valid instruments for firms' accreditation signal S_j^A are variables correlated with S_j^A but not with the reputation signal S_j^R. Moreover, the instruments must be excluded from equation

[41] See appendix 1 for the derivation of the log likelihood function of my FIML model.
[42] See appendix 2 for details of how I conduct the 2SLS and Heckman-corrected model.

$\widehat{\lambda_j} = X_j'\beta_2 + D_j'\beta_3 + \Phi(h_0 + h_1 R_j)\gamma S_j^A + v_j$. I use the following instruments, the combination of which and $[X_j, D_j, R_j]$ constitute Z_j in the system of equations (7).[43]

- Administrative accreditation cost per enrollee: The administrative accreditation cost firms face inversely affect their accreditation propensity. Meanwhile, the accreditation cost is irrelevant with the formation of firm reputation. Furthermore, the accreditation cost does not influence consumers' valuation of childcare services. Therefore administrative accreditation cost per enrollee is a natural instrument for accreditation. NAEYC charges a categorical accreditation fee based on the number of enrollees.[44] I divide the total accreditation fee by the number of enrollment to get administrative accreditation costs per enrollee.[45]
- Market Structure: Market structure and competitive factors should affect firms' accreditation propensity for strategic considerations (Jin, 2002). However, firm reputation has more to do with the stock and flow of local information instead of the number of competitors. I use the number of childcare establishments per market to proxy for market structure.
- $\overline{X_{.j}}$ (firm-average of log of staff-child ratio): Sufficient staffing is an important criterion for a childcare center to become accredited. Therefore firm-average staff-child ratio should be positively correlated with a center's accreditation decision, while it is not correlated with S_j^R (see section 3: S_j^R is centered on the "residual" part of quality which can not be extracted

[43] I also put interaction terms between R_j and the instruments into Z_j, as there is interaction between R_j and A_j in my model.

[44] In 1990, NAEYC fee schedule was:

Enrollment	Application Fee	Validation Fee	Total
60 or fewer children	\$125	\$300	\$425
61 to 120 children	\$200	\$450	\$650
121 to 240 children	\$250	\$575	\$825
241 to 360 children	\$300	\$700	\$1000

For each additional 120 children above 360, the application fee and the validation fee are each increased accordingly. I thank Pat Mucci in NAEYC for providing this information.

[45] A drawback of this instrument is that I rely on variation of firms' size for variation of accreditation cost inside an enrollment category. I argue that the size of a childcare center is more related to its affordability and convenience than to its reputation and its inherent quality.

by X_{gj}). Moreover, $\overline{X_{.j}}$ are excluded in my step 2 estimation, as my fixed effects estimation of equation (5) puts a linear restriction on $\overline{X_{.j}}$. The idea and validity of using the firm-average of exogenous group-specific variables to serve as instruments for the endogenous firm-specific variable can be found in Hausman and Taylor (1981).

6 Results

6.1 Step 1: Fixed Effects Estimation Results

I present my results in tables 5, 6 and 7. Table 5 reports results from OLS, between-groups, and fixed effects estimation. Both OLS and between-groups estimates produce a significantly positive coefficient of the price variable $\log(price_{gj})$ due to the correlation between prices and firm-specific unobserved error term----firm reputation. In this case, within-groups estimators give consistent estimates for all variables with within-group variation. As column (3) of Table 5 shows, within-groups estimates produce a significantly negative price coefficient of -0.35.

For other factors affecting consumers' utility from consuming childcare services, I find that most results are consistent with my expectation. As Table 5 shows, a longer operating history, licensed status and better-paid employees contribute significantly and positively to consumers' valuation of childcare services, while part-time status, for-profit status and subsidized status have the reverse effects. Furthermore, markets with a better-educated and whiter population, higher female employment rate, and a CCR&R have higher willingness to pay, but more urban markets do not. Consumers also seem to have a higher valuation of centers located farther from public transportation, which are more likely to be located at quieter and safer residential areas. However, consumers living in richer markets have lower willingness to pay, which is against intuition and needs further investigation. For the significant negative coefficient for $\log(staff-child-ratio)_{gj}$, I suspect that it is due to the negative correlation between

δ_{gj} and $\log(staff - child - ratio)_{gj}$ because of the way they are constructed.[46]

6.2 Step 2 Reduced-Form Results

Table 6 reports reduced-form results from my step 2 estimation assuming that h_j (the informativeness of the accreditation signal) takes a specific functional form: $h_j = h_0 + h_1 R_j$, where R_j is the log of the number of the years in operation of firm j. I hypothesize that the reputation of a center with a longer operating history will reflect its true quality more accurately, as more word-of-mouth accumulated over years. If this hypothesis is true, for an older firm consumers will rely more on reputation for information, and as a result the accreditation signal will be less informative. I expect that the coefficient for the interaction term between accreditation status and log of the number of years will be negative.

The reduced-form evidence confirms my expectation. OLS, two stage least squares (2SLS), and Heckman-corrected estimation all report significant positive coefficients for accreditation status, but significant negative coefficients for the interaction term between accreditation status and log (years). Although I am not able to identify γ and h's from the reduced-form results, it is safe to say that there is strong and consistent evidence that consumers do value accreditation signals but value them less for older firms.

After controlling for the endogeneity of the accreditation status, the coefficients for the accreditation status A_j and interaction term are amplified. I attribute this change to the potential negative correlation between A_j and S_j^R, that is, firms with a better reputation have a lower propensity to seek accreditation. As for other firm-specific variables, their magnitude, signs and

[46] The number of enrollment in an age group enters the numerator of δ_{gj} as well as the denominator of $\log(staff - child - ratio)_{gj}$.

significance remain consistent across various specifications and estimation methods, and their signs and significance are close to what Table 5 OLS results report.[47]

6.3 Step 2: Maximum Likelihood Estimation Results

Now I discuss the estimation results of my structural parameters. Recall that γ measures consumers' valuation of the unobserved quality q_j----the higher γ is, the more consumers value the inherent quality reflected by firms' accreditation status and reputation. Meanwhile, h_j measures how much weight consumers assign to the accreditation signal relative to the reputation signal to gain information about the unobserved quality of firm j. The higher h_j is, the more consumers rely on the accreditation signal for information. Moreover, h_j depends on the operating history of a firm: the longer a firm has been operating in a market, the more consumers rely on its reputation and the less on its accreditation status for information

Table 7 reports results from maximum likelihood estimation. The first column reports limited information maximum likelihood estimation (LIML) results, in which I set $\rho = 0$ to restrict correlation between the two equations in (7). I find that γ is significantly positive (γ=1.473), that is, consumers do value the underlying quality reflected by the accreditation status and reputation. I find that h_0 is significantly positive (h_0=0.695), while h_1 is significantly negative (h_1= -0.556). Average h_j is around 0.352, which means that the information conveyed by a firm's accreditation status is not very revealing, and that consumers rely much more on a firm's reputation for information. On average, consumers assign a weight of around 35% on the accreditation signal and around 65% on firm reputation.

[47] There are several exceptions though. The coefficients for log of market median income and for female labor participation lose significance, while that for the measure of population mobility gains significance.

The second column reports the full information maximum likelihood estimation (FIML) results, in which I allow ρ to be estimated. All estimates are similar to the LIML results, with γ =1.478, h_0 =0.662, and h_1 =-0.539, and average h_j 0.351. ρ is significantly negative with a magnitude of 0.245, which confirm my conjecture in section 6.2: better-reputed firms are less motivated in pursuing accreditation.

Table 8 graphically shows how consumers' reliance on the accreditation signal relative to firm reputation varies with the operating history of a firm. Recall that consumers assign a weight of $\Phi(h_0 + h_1 * \log(years))$ to the accreditation signal for information. As h_1 is estimated to be negative, consumers' reliance on the accreditation signal will decline over a firm's operation history. In Table 8, consumers put 100% reliance on the accreditation signal for a newly opened childcare center. Consumers start to assign more weight on firm reputation for centers which have operated for more than 3 years. Consumers' reliance on the accreditation signal drops sharply over the first 5 years, continues to drop, and then stabilizes between 10% and 15% after fifteen years. For centers with eleven years of operating history, which is the sample average, consumers put approximately 20% reliance on accreditation.

6.4 Welfare Analysis

I now exploit the advantage of a structural model with an underlying consumer utility maximization framework to quantify the impact of the accreditation mechanism on consumer welfare. Accreditation improves consumer welfare through better consumer-product match. With the accreditation mechanism consumers rely on both accreditation signals and firm reputation for information. Otherwise consumers rely solely on firm reputation. The information gain from the accreditation mechanism comes from consumers' more accurate inference about unobserved product quality, which helps consumers to choose products they most desire. With estimates of the structural parameters, I use the equivalent variation[48] measure with discrete-choice models, developed by Small & Rosen (1981), to assess consumer welfare for regimes with and without the accreditation system. However, contrasted to a price or a quality change, information only provides value by changing consumers' purchase choices, because a consumer who does not switch gains (loses) no utility from learning their purchase has high (low) quality. I adapted Small and Rosen's methodology to reflect this particularity.

Another adaptation is to allow firms to adjust prices optimally under different regimes of information. I expect this adjustment to be trivial, because firms set prices based on their mean utility levels, which remain almost the same over the two regimes.[49] I combine the estimates of the structural parameters with firms' profit maximizing first order conditions to "back-out" the marginal cost of child care services. I assume that revenues and costs for each type of service a childcare center provide are additive. Center j maximizes its total profit over prices and accreditation decisions, holding other firms' accreditation status and pricing decisions constant:

$$\max_{P_{gj}, A_j} \Pi_j (P_{gj}, A_j) = \sum_{g}^{1,\ldots,G} P_{gj} * Q_{gj}(P_{gj}, A_j) - mc_{gj} * Q_{gj}(P_{gj}, A_j) - C_a * A_j$$

where Q_{gj} is the quantity for each product g of firm j (enrollment for each age group) and mc_{gj} is the marginal cost of product g of firm j. First order conditions with respect to P_{gj} yield:

$$mc_{gj} = \frac{\partial[P_{gj} * Q_{gj}(P_{gj}, A_j)] / \partial P_{gj}}{\partial Q_{gj}(P_{gj}, A_j) / \partial P_{gj}} = (1 - \frac{1}{\alpha(1 - ms_{gj})}) P_{gj} \ ,$$

where ms_{gj} is the market share of product g of firm j. With estimated marginal costs for care per hour (the average is $1.030), I can derive the optimal price level set under the non-accreditation regime and redo the welfare analysis with the adjusted prices.

Table 9 reports results of this welfare analysis. The first column evaluates consumer

[48] The equivalent variation is the change in consumer wealth (expressed in monetary terms) that would be equivalent to the change in consumer welfare due to the price or quality change.
[49] The presence of accreditation promotes the accuracy of information instead of the mean utility levels.

welfare with accreditation. The second column evaluates the non-accreditation regime without price adjustments, and the third column with price adjustments. As I expect, these two results are close. The welfare impact of the accreditation mechanism is herein estimated to be 3.48% (no price adjustments) and 3.41% (with price adjustments). We can see that consumers do benefit from the accreditation mechanism, although this benefit is small in magnitude. The result is consistent with my findings that consumers do gain, but do not gain much, information from the accreditation signal. This further suggests that, an uninformative accreditation system's welfare-improving role might be limited----policy makers shall either promote the informativeness of accreditation, or reconsider the necessity of accreditation if market forces are taking care of the information asymmetry problem adequately.

A restriction of my welfare analysis is that I take the accreditation status, and in turn the utility levels, of a firm's competitors constant over the two regimes, because I do not have detailed information on the competitors of the sampled firms in my data. However, the above analysis gives a lower bound of the welfare impact of accreditation because the information gain from non-accreditation to accreditation is even larger if I relax this assumption.

7 Conclusions

In this paper I formulate a model in which consumers gain information about product quality from two information channels----the accreditation status and reputation of a firm. I estimate this model to assess the effectiveness and welfare impact of the accreditation mechanism in the childcare market. My results are strong and consistent: first, consumers' reliance on the accreditation status is weaker for older firms; second, on average consumers rely less on the accreditation status for information than on firm reputation, although they do value the quality reflected by the accreditation status; third, consumers still gain information from the accreditation status that otherwise would not be available, and this information improves consumer welfare through better consumer-product match. Overall, I find that the accreditation mechanism in the childcare market is only effective to a limited extent.

This study offers an alternative and perhaps more fundamental explanation to account for the discrepancies between theory and reality. The theoretic literature predicts that the lack of information will distort firm behavior and market operation, potentially to a significant extent, while many empirical studies detect only small or negligible effects of a particular type of information supply. Moreover, the theoretic literature predicts that firms have sufficient incentives to voluntarily disclose verifiable quality information to consumers, while in reality voluntary disclosure is barely complete. I suggest that these discrepancies might be attributed to the lack of effectiveness of the information supply. Specifically in this study, I suggest that the lack of informativeness of a quality certification mechanism leads to a small welfare impact, and in turn, the low propensity for firms to use this mechanism.

Non-profit certification has been adopted in a wide range of professions such as health, personal services, safety and environmental industries. My perspective and findings shed new light on how certification works in markets where informal information prevails. My approach can also be applied to any market, from processed foods and used cars to financial services, where consumers cannot observe quality prior to purchase, and where certification or other types of formal information supply exist.

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Appendix 1: Deriving the Log Likelihood Function for FIML Estimation

I estimate a system of equations:
$$\widehat{\lambda_j} = X_j'\beta_2 + D_j'\beta_3 + \Phi(h_0 + h_1R_j)\gamma S_j^A + v_j$$
$$S_j^A = Z_j'\pi + \xi_j (A_j = 1 \Leftrightarrow S_j^A \geq 0; A_j = 0 \Leftrightarrow S_j^A < 0)$$

where $v_j = (1-\Phi(h_0 + h_1R_j))\gamma S_j^R + \overline{\omega_{.j}}$ and $\omega_j \sim N(0, \frac{\sigma_\omega^2}{\kappa_j})$. I assume that ξ_j is a mean zero error and normalize $\xi_j \sim N(0,1)$. I further assume that ξ_j and S_j^R are jointly normally distributed, with a correlation coefficient of ρ.

Plugging this second equation into the first one, I have:

$$\begin{aligned}
\widehat{\lambda_j} &= X_j'\beta_2 + D_j'\beta_3 + \Phi(h_0 + h_1R_j)\gamma(Z_j'\pi + \xi_j) + v_j \\
&= X_j'\beta_2 + D_j'\beta_3 + \Phi(h_0 + h_1R_j)\gamma(Z_j'\pi) + \tau_j, \\
&\mathit{where}\ \tau_j = \Phi(h_0 + h_1R_j)\gamma\xi_j + v_j \\
&\mathit{and}\ \mathrm{var}(\tau_j \mid M) = \Phi(h_0 + h_1R_j)^2\gamma^2 + (1-\Phi(h_0 + h_1R_j))^2\gamma^2 + \frac{\sigma_\omega^2}{\kappa_j}
\end{aligned}$$ [50]

Define $M = [X_j, D_j, R_j, Z_j, \theta, \sigma_\omega^2, \rho, \pi]$.

Define $\sigma_{jv} = \sqrt{\Phi(h_0 + h_1R_j)^2\gamma^2 + (1-\Phi(h_0 + h_1R_j))^2\gamma^2\sigma_{s^R}^2 + \frac{\sigma_\omega^2}{\kappa_j}}$ and $v_j^* = \frac{\tau_j}{\sigma_{jv}}$. Then $v_j^* \sim N(0,1)$. I can derive that ξ_j and v_j^* are jointly normally distributed, with a correlation coefficient of ρ_j^*. I can then derive:

$$f(v_j^*, \xi_j > -Z_j'\pi \mid M) = \int_{-Z_j'\eta}^{\infty} \frac{1}{2\Pi\sqrt{(1-\rho_j^{*2})}} e^{-\frac{(v_j^* + \xi_j{}^2 - 2\rho_j^* v_j^* \xi_j)}{2(1-\rho_j^{*2})}} d\xi_j$$

$$= \int_{-Z_j'\pi}^{\infty} \frac{1}{2\pi\sqrt{(1-\rho_j^{*2})}} e^{-\frac{(1-\rho_j^{*2})v_j^{*2} + (\xi_j - \rho_j^* v_j^*)^2}{2(1-\rho_j^{*2})}} d\xi_j = \phi(v_j^*)\Phi(\frac{Z_j'\pi + \rho_j^* v_j^*}{\sqrt{1-\rho_j^{*2}}})$$

$$f(v_j^*, \xi_j < -Z_j'\pi \mid M) = \phi(v_j^*)(1-\Phi(\frac{Z_j'\pi + \rho_j^* v_j^*}{\sqrt{1-\rho_j^{*2}}}))$$

and,

[50] $\mathrm{var}(\xi_j)$ is normalized to be one.

$$LogL = \log \prod_{1}^{J} [f(\lambda_j, A_j = 1 | M)]^{A_j} [f(\lambda_j, A_j = 0 | M)]^{1-A_j}$$

$$= \sum_{1}^{J} [A_j \ln(f(\lambda_j, \xi_j > -Z_j '\pi | M)) + (1 - A_j) \ln(f(\lambda_j, \xi_j < -Z_j '\pi | M))]$$

$$= \sum_{1}^{J} [A_j \ln(f(v_j^*, \xi_j > -Z_j '\pi | M) \frac{\partial v_j^*}{\partial \lambda_j}) + (1 - A_j) \ln(f(v_j^*, \xi_j < -Z_j '\pi | M) \frac{\partial v_j^*}{\partial \lambda_j})]$$

$$= \sum_{1}^{J} [\ln \phi(v_j^*) - \ln \sigma_{jv} + A_j \ln(\Phi(\frac{Z_j '\pi + \rho_j^* v_j^*}{\sqrt{1 - \rho_j^{*2}}})) + (1 - A_j) \ln(1 - \Phi(\frac{Z_j '\pi + \rho_j^* v_j^*}{\sqrt{1 - \rho_j^{*2}}}))]$$

Appendix 2: 2SLS and Heckman-corrected estimation

1) Two Stage Least Square Estimation:

- Step 1: conduct OLS regression of A_j on instruments Z_j; calculate $\widehat{A_j} = Z_j '\hat{\pi}$.
- Step 2: conduct OLS regression of $\widehat{\lambda_j}$ on $X_j, D_j, \widehat{A_j}$ and $R_j * \widehat{A_j}$.

2) Heckman-Corrected Estimation:

$$E(\lambda_j | A_j = 1) = X_j '\beta_2 + D_j '\beta_3 + h_j \gamma A_j + (1 - h_j) E(S_j^R | A_j = 1)$$

$$= X_j '\beta_2 + D_j '\beta_3 + (h_0 + h_1 R_j)\gamma A_j + (1 - h_0 - h_1 R_j)\rho\sigma_s \frac{\phi(Z_j '\pi)}{\Phi(Z_j '\pi)}$$

$$= X_j '\beta_2 + D_j '\beta_3 + h_0 \gamma A_j + h_1 \gamma R_j A_j + (1 - h_0)\rho\sigma_s \frac{\phi(Z_j '\pi)}{\Phi(Z_j '\pi)} - h_1 \rho\sigma_s R_j \frac{\phi(Z_j '\pi)}{\Phi(Z_j '\pi)}$$

$$E(\lambda_j | A_j = 0) = X_j '\beta_2 + D_j '\beta_3 + (1 - h_0)\rho\sigma_s \frac{-\phi(Z_j '\pi)}{1 - \Phi(Z_j '\pi)} - h_1 \rho\sigma_s R_j \frac{-\phi(Z_j '\pi)}{1 - \Phi(Z_j '\pi)}$$

The following 2-step estimation gives consistent estimates.

- Step 1: conduct Probit regression of A_j on instruments Z_j; calculate $mills_j = \frac{\phi(Z_j '\hat{\pi})}{\Phi(Z_j '\hat{\pi})}$ if A_j =1; $mills_j = \frac{-\phi(Z_j '\hat{\pi})}{1 - \Phi(Z_j '\hat{\pi})}$ if A_j =0.
- Step 2: conduct OLS regression of $\widehat{\lambda_j}$ on $X_j, D_j, A_j, R_j * A_j, mills_j$ and $R_j * mills_j$.

Table 1 Variable Definition

Variable Name	Description
Firm Attributes (data from 1990 Profile of Childcare Settings)	
accredit	NAEYC accreditation status (=1 if accredited; =0 otherwise)
enrollment*	# of enrolled children . This variable is also compiled for all 4 age groups: infant, toddler, pre-schooler, and school-age children.
# employees	# of employees
%_white	% children enrolled: white
staff-child ratio*	staff-child ratio (=# of staff/enrollment). This variable is also compiled for each age group.
years	# of years in operation
licensed	licensing status (=1 if licensed; =0 otherwise)
for-profit	for-profit status (=1 if for profit; =0 if non-profit)
chain	chain status (=1 if chain; =0 otherwise)
listed in R&R	listed in a resource and referral agency (=1 if listed; =0 otherwise)
subsidy	subsidization status (=1 if subsidized by a federal, state or local agency ; =0 otherwise)
%_subsidized	percent of children being subsidized (=# of children subsidized/enrollemnt
pub_trans	distance to public transportation (categorical)
r_salary	annual salary of a randomly drawn teacher
r_hour_wage	hourly wage of a randomly drawn teacher (as a measure of teacher qualification)
price_gj*	hourly price for age product g of firm j
part-time*	whether the age group offers only part-time (0-20 hours per week) services (=1 if yes; =0 otherwise)
Market Attributes (data from 1990 Census of Population unless otherwise noted)	
% college	zipcode: % of population over age 18 with a bachelor degree
% black	zipcode: % black
m_income	zipcode: median income
% female_work	zipcode: % of women in the labor force who are employed
% under13	zipcode: % of population under age 13
% urban	zipcode: % urban population
% mobile	zipcode: % population over age 5 who moved from other county/state/country in last 5 years
# centers	zipcode: # of childcare establishments with payroll (data from 1992 Census of Business)
CCR&R	county: whether there exists a childcare resource and referral agency (=1 if yes; =0 if no) (data from Chipty and Witte 1998 survey)

note: variables with a * are of panel nature, which have variation across age-groups within a firm.

Table 2 Summary Statistics

variable	all firms		accredited		non-accredited		
	mean	std. dev	mean	std. dev	mean	std.dev	t-test
Firm Attributes							
Accredit	0.151	0.359	1	-	0	-	-
enrollment	66.247	47.405	71.789	55.870	65.259	45.701	
# employees	8.595	7.185	9.796	7.491	8.381	7.112	**
% white	0.780	0.304	0.72	0.344	0.790	0.295	**
staff-child ratio	0.141	0.090	0.160	0.122	0.137	0.083	***
years	11.040	10.417	12.926	15.201	10.703	9.283	**
licensed	0.878	0.327	0.979	0.144	0.861	0.347	***
for-profit	0.381	0.486	0.458	0.500	0.367	0.482	**
chain	0.059	0.235	0.085	0.279	0.054	0.226	
listed in R&Rs	0.698	0.459	0.746	0.437	0.690	0.463	
subsidy	0.294	0.456	0.352	0.479	0.284	0.451	
%_subsidized	0.062	0.160	0.081	0.192	0.058	0.154	
pub_trans	2.824	2.005	2.739	2.075	2.839	1.993	
r_salary	10877.11	5180.482	11286.1	5111.922	10804.15	5192.407	
r_hour-wage	6.775	4.687	7.07664	4.167742	6.721	4.775	
Market Attributes							
% college	0.139	0.078	0.137	0.080	0.139	0.077	
% black	0.139	0.219	0.172	0.268	0.133	0.209	*
m_income	32915.55	12298.86	33789.93	14235.28	32759.57	11923.86	
% female_work	0.942	0.033	0.938	0.032	0.942	0.033	
% under13	0.193	0.040	0.195	0.041	0.192	0.040	
% urban	0.676	0.437	0.695	0.433	0.673	0.438	
% mobile	0.208	0.108	0.210	0.106	0.208	0.108	
# centers	5.188	3.731	5.423	3.920	5.146	3.697	
CCR&R	0.884	0.321	0.901	0.299	0.881	0.324	
# obs	938		142		796		

Two-sample t-test with equal variances
* significant at 10%; ** significant at 5%; *** significant at 1%. All the following tables use this notation

Table 3 Group Attributes

Variable	Obs	Mean	std.dev	Min	Max	A=1	A=0	ttest
						Mean	Mean	
# of infants (0-11 months)	273	7.004	7.154	1	75	7.5	6.903	
# of toddlers(12-35 months)	544	15.899	17.352	1	281	15.706	15.938	
# of preschoolers (36-59 months)	852	42.484	33.617	3	234	44.935	42.006	
# of school-age (60+ months)	527	27.066	28.261	1	271	25.481	27.338	
price: full-time, infants	258	1.300	0.509	0.5	4.2	1.338	1.292	
price: full-time, toddlers	464	1.300	0.567	0.46	5	1.284	1.303	
price: full-time, preschoolers	583	1.289	0.607	0.292	5.24	1.363	1.274	
price: full-time, school-age	256	1.277	0.537	0.38	5	1.232	1.285	
price: part-time, infants	28	2.262	1.013	0.67	4.5	2.633	2.217	
price: part-time, toddlers	163	2.539	1.344	0.46	8.89	2.797	2.476	
price: part-time, preschoolers	471	2.215	1.177	0.145	13.56	2.418	2.181	
price: part-time, school-age	426	1.836	0.708	0.10	5	1.907	1.826	
staff-child ratio: infants	273	0.324	0.215	0.067	2	0.341	0.321	
staff-child ratio: toddlers	544	0.212	0.127	0.042	1.430	0.220	0.210	
staff-child ratio: preschoolers	852	0.145	0.096	0.034	1.25	0.169	0.141	***
staff-child ratio: school-age	527	0.137	0.110	0.026	1	0.150	0.135	

Table 4 Group Attributes: Centers with All 4 Age Groups

Variable	Obs	Mean	std.dev.	Min	Max
price: full-time, infants	102	1.305	0.462	0.63	3
price: full-time, toddlers	102	1.201	0.396	0.63	3
price: full-time, preschoolers	102	1.099	0.296	0.59	2.11
price: full-time, school-age	102	1.187	0.377	0.38	2.5
price: part-time, infants	18	2.205	1.045	1	4.3
price: part-time, toddlers	18	2.140	0.928	1.15	4
price: part-time, preschoolers	18	2.002	0.754	1.15	3.5
price: part-time, school-age	18	1.856	0.672	0.97	3

Table 5 Step 1---Panel Analysis: Simple Logit model

Dependent: $\widehat{\delta_{gjm}}$	**(1) OLS**	**(2) Between Groups**	**(3) Within Groups**
log(price_gj)	0.127 (0.077)*	0.350 (0.105)***	-0.350 (0.111)***
group: log(staff-child ratio)	-0.272 (0.052)***	-0.325 (0.086)***	-0.224 (0.054)***
group: part-time	-0.233 (0.074)***	0.465 (0.102)***	-1.368 (0.095)***
accredit	0.373 (0.162)**	0.358 (0.219)	
accredit*log(years)	-0.145 (0.074)**	-0.119 (0.096)	
log(years)	0.123 (0.032)***	0.144 (0.043)***	
licensed	0.150 (0.121)	0.494 (0.125)***	
for-profit	-0.389 (0.065)***	-0.357 (0.087)***	
chain	-0.107 (0.113)	-0.110 (0.170)	
listed in R&R	-0.136 (0.075)*	-0.152 (0.092)	
subsidy	-0.144 (0.065)**	-0.127 (0.090)	
pub_trans	0.084 (0.017)***	0.103 (0.022)***	
log(r_hour_wage)	0.185 (0.050)***	0.137 (0.068)**	
% college	2.893 (0.613)***	2.107 (0.779)***	
% black	-0.519 (0.160)***	-0.393 (0.219)*	
log(m_income)	-0.432 (0.140)***	-0.344 (0.174)**	
female_work	3.435 (1.298)***	3.659 (1.629)**	
% urban	-0.787 (0.089)***	-0.813 (0.111)***	
% mobile	0.016 (0.299)	0.168 (0.393)	
CCR&R	0.571 (0.108)***	0.524 (0.139)***	
constant	-3.908 (1.459)***	-5.573 (1.906)***	-3.651 (0.109)***
obs	2196	2196	2196
R-squared	0.15	0.31	0.20
# of idcode		938	938

In parenthesis are standard errors.

Table 6 Step 2---Reduced-Form Firm Level Analysis

Dependent: $\widehat{\lambda_{gjm}}$	**(1) OLS**	**(2) 2SLS**	**(3) Heckman-corrected (a)**	**(4) Heckman-corrected (b)**
accredit	0.621 (0.272)**	4.672 (2.023)**	2.150 (1.090)**	4.559 (1.543)***
accredit*log(years)	-0.208 (0.118)*	-1.437 (0.731)**	-0.218 (0.113)*	-1.445 (0.543)***
inv_mills $E(S_j^R \mid A_j = 1)$			-0.844 (0.584)	-2.247 (0.857)***
inv_mills*log(years)				0.717 (0.308)**
log(years)	0.265 (0.053)***	0.454 (0.131)***	0.263 (0.056)***	0.462 (0.104)***
licensed	0.123 (0.151)	-0.076 (0.267)	-0.075 (0.211)	-0.057 (0.216)
for-profit	-0.650 (0.106)***	-0.686 (0.126)***	-0.688 (0.116)***	-0.678 (0.120)***
chain	-0.311 (0.210)	-0.361 (0.240)	-0.360 (0.225)	-0.374 (0.233)
listed in R&R	-0.243 (0.114)**	-0.302 (0.139)**	-0.296 (0.127)**	-0.290 (0.131)**
subsidy	-0.483 (0.109)***	-0.501 (0.123)***	-0.498 (0.116)***	-0.496 (0.121)***
pub_trans	0.099 (0.027)***	0.103 (0.031)***	0.101 (0.029)***	0.102 (0.030)***
log(r_hour_wage)	0.298 (0.084)***	0.274 (0.099)***	0.268 (0.091)***	0.274 (0.094)***
% college	4.073 (0.952)***	4.381 (1.112)***	4.373 (1.031)***	4.326 (1.068)***
% black	-1.220 (0.268)***	-1.349 (0.346)***	-1.377 (0.304)***	-1.306 (0.316)***
log(m_income)	-0.167 (0.212)	-0.330 (0.285)	-0.315 (0.247)	-0.292 (0.256)
female_work	2.300 (2.018)	3.537 (2.482)	3.286 (2.246)	3.389 (2.325)
% urban	-1.147 (0.136)***	-1.113 (0.153)***	-1.139 (0.145)***	-1.122 (0.150)***
% mobile	-1.273 (0.481)***	-1.491 (0.577)***	-1.477 (0.529)***	-1.484 (0.547)***
CCR&R	1.000 (0.170)***	0.996 (0.191)***	1.006 (0.181)***	0.997 (0.188)***
constant	-4.855 (2.342)**	-4.676 (2.762)*	-4.181 (2.526)*	-4.948 (2.637)*
obs	938	938	938	938
R-squared	0.32	0.32	0.32	0.32

Table 7 MLE Estimates of Structural Parameters

	(1) Limited Information MLE	(2) Full Information MLE
γ **(accredit)**	**1.473** **(0.129)*****	**1.478** **(0.060)** ***
h_0	0.695*** (0.246)	0.662*** (0.175)
h_1 (log_years)	-0.556 (0.156)***	-0.539 (0.059)***
mean $h_j = \Phi(h_0 + h_1 R_j)$	**0.352** **(0.078)*****	**0.351** **(0.212)***
ρ	0 (-)	-0.245** (0.105)
β log(years)	-0.082 (0.069)	-0.079** (0.039)
licensed	-0.367 (0.228)	-0.378* (0.222)
for-profit	-0.663 (0.103)***	-0.664 (0.097)***
chain	-0.329 (0.215)	-0.322 (0.205)
listed in R&R	-0.310 (0.107)***	-0.316 (0.111)***
subsidy	-0.438 (0.109)***	-0.438 (0.094)***
pub_trans	0.097 (0.024) ***	0.097 (0.022) ***
log(r_hour_wage)	0.264 (0.088) ***	0.263 (0.081) ***
% college	4.114 (0.887) ***	4.138 (0.841) ***
% black	-1.170 (0.278) ***	-1.177 (0.256) ***
log(m_income)	-0.304 (0.192)	-0.303* (0.163)
female_work	4.606 (1.002) ***	4.608 (1.026) ***
% urban	-1.070 (0.117) ***	-1.065 (0.119) ***
% mobile	-1.284 (0.382) ***	-1.361 (0.422) ***
CCR&R	0.948 (0.163) ***	0.948 (0.168) ***
constant	-3.865 (1.967) **	-3.852 (1.723) **
Log Likelihood	-2000.8	-2001.6

Table 8 Informativeness of Accreditation Signal

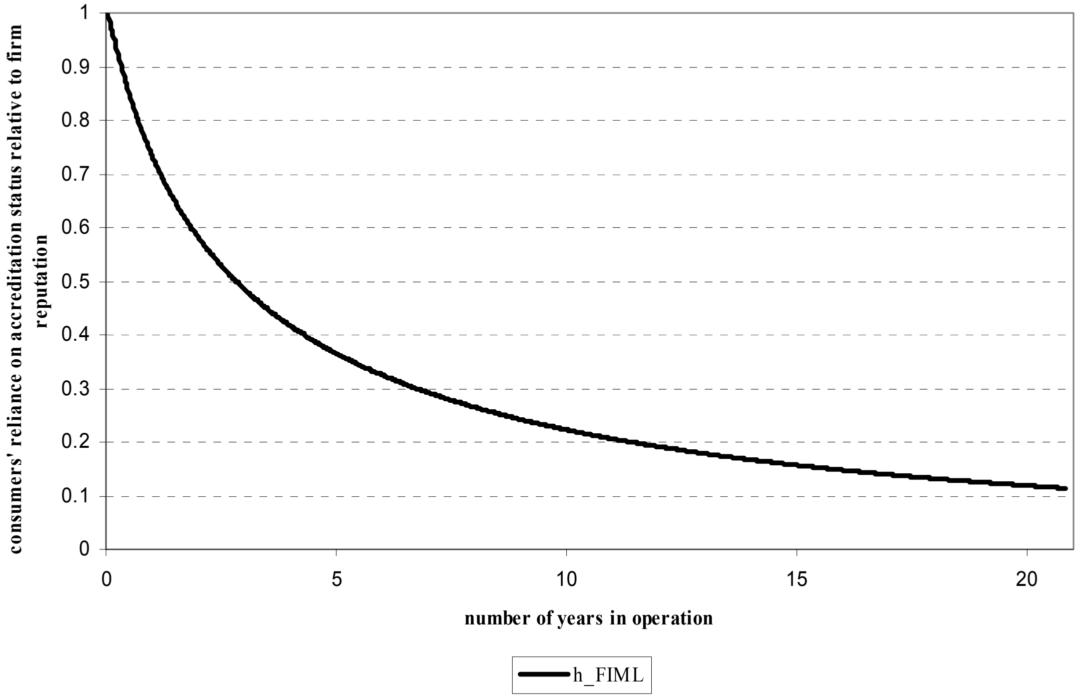

Table 9 Consumer Welfare Analysis

	(1) Estimated Equilibrium	(2) No Accreditation w/o Adjusting Price	(3) No Accreditation, Adjusting Price
Mean price	1.597	1.597	1.557
Equivalent Variation	45721	44184	44214

Welfare change from regime (2) to regime (1): 3.48%
Welfare change from regime (3) to regime (1): 3.41%