Who Benefits From Child Care Ratings? Evidence From Minnesota's ParentAware Program

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Abstract

Almost every state government intervenes in the market for child care services by providing quality ratings. This paper is about the effect of quality ratings children in Minnesota, with a particular focus on how the benefits from the ratings are distributed. Theory suggests an important reason why the impact of product quality ratings on consumers will be heterogeneous. Consumers benefit from quality information only to the extent that the information has a marginal impact on the choices made. The effect of quality ratings thus depends on what choices are available. Using geocoded panel data on Minnesota child care centers, paired with block group level demographics from the American Community Survey, I empirically investigate the effect of Minnesota's Parent Aware provider quality ratings on the number of children who use high quality providers. I estimate the treatment effect of the ratings separately from endogenous selection of the ratings by using a difference-in-differences style approach that relies on providers who switch ratings status during the data period. In order to minimize the effect of arbitrarily chosen market boundaries I treat all of Minnesota as a single market and include distance in the demand model, so that the extent of competition between particular providers depends in a realistic way on the geographic distribution of households and providers, replacing assumptions about market boundaries with assumptions about the structure of travel costs. I find that consumers respond to the ratings and are significantly more likely to choose a provider that receives the highest possible rating of Four Stars compared to an unrated provider. Estimates of welfare at the block group level suggest that density is the most important factor driving variation in the regional benefits of Parent Aware. Importantly, most low-income block groups are in dense areas with enough variation in locally available providers that the benefits of the ratings are high.

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1 Introduction

At least forty-two states have implemented child care Quality Rating and Improvement Systems, (QRIS) which give providers the opportunity to be evaluated by regulators and assigned a quality rating. (Herbst [2016].) Ratings are supported in part by the federal Child Care Development Fund, whose purposes include promoting parental choice over child care services, as well as increasing the fraction of low-income children using high quality child care. (42 U.S.C. §9857(b)) It is therefore of great interest whether the ratings are successful in helping households – especially low-income households – choose high quality care.

This paper estimates the effects of Minnesota's Parent Aware child care ratings on choice of child care center during the period when the ratings system was introduced statewide. I consider three closely linked research questions: What is the effect of Parent Aware ratings on the propensity of consumers to choose a rated provider? What is the value, in revealed preference terms, that consumers get from the ratings? How do the benefits of Parent Aware ratings vary depending on the location of the consumer?

I approach these questions using differentiated-products demand modeling techniques that are new to the literature on the child care market. I use geocoded data on household and provider locations and incorporate the preference for child care close to home into the estimated demand system. This is important because it allows me to estimate highly local variation in demand elasticity without relying on arbitrarily drawn market boundaries. I estimate the model using geographically detailed panel data on the location, enrollment, and characteristics of all Minnesota licensed child care centers, combined with data on the location of potential child care customers at the block group level from the American Community Survey. In order to estimate the model from provider-level enrollments, I adapt the classic Berry et al. [1995] ("BLP") method for using market shares data to estimate demand systems with latent heterogeneity. In my setting the key dimension of heterogeneity is household location, which affects which providers are attractive to each household and therefore governs patterns of substitution and competition between providers.

My estimate support that the ratings work. Consumers are significantly more likely to choose a provider that receives the highest possible rating of Four Stars compared to an unrated provider. Consumers appear to respond negatively to ratings of One, Two, or Three Stars (although the effect of a Three Star rating is not significantly different from zero). I also find that distance is quite important to center choice. A typical consumer is willing to pay about \$2.65 to avoid each mile of distance to the provider, but about \$12 to access a four star center instead of an unrated one. I estimate the welfare value of the ratings at the state, county, and block group levels. The statewide value grows over my sample period as the number of rated providers increases, and by the last year of my sample is more than \$3 million. Estimates of welfare at the county and block group levels suggest that density of available providers is the most important factor driving variation in the regional benefits of Parent Aware. Importantly, most low-income block groups are in dense areas with enough variation in locally available providers that they are in a position to receive high benefits from the ratings.

Quality ratings are a type of market intervention whose effects will inherently be heterogenous. One of the main contributions this paper makes to the literature on ratings and score cards is to consider this heterogeneity. I model one important reason why ratings may benefit differently situated consumers differently, which I will refer to as the "choice set effect".

Information can only help consumers if they have choices. Quality rating information can benefit consumers in two ways. Learning that a particular provider is high quality can benefit the consumer if they then choose that provider because of the new information. Conversely, learning that a provider is worse than expected benefits the consumer if it induces them to choose a different, more preferable provider. Either way, the benefit of the information depends on it being marginal for the consumers choice. The more varied choices a consumer has available, the more likely ratings are to influence that choice, and hence the more potential for the consumer to benefit from the ratings. Although this source of heterogeneity in the benefits of information is highly intuitive, it has not yet been fully explored in the literature on quality ratings.

This effect has important but theoretically ambiguous implications for understanding the effects of Parent Aware on low income consumers. The value of the ratings to households varies geographically and depends on the role of travel costs in household decision-making and the spatial distribution of providers of different types. On the one hand, the benefit from the ratings will thus be higher for consumers whose choice set includes many providers whose quality levels are varied and lower for consumers with few choices or whose choices have less variation in quality. On the other hand, less privileged households are more likely to live in denser urban areas where they can access a range of providers. Which effect is stronger is an empirical question that I address using estimates from my model. My results suggest that in practice, the density effect dominates: most low-income Minnesotans live in relatively dense areas with enough variety close enough to their locations, and sufficient access to highly rated providers, so that their benefit from the ratings is relatively high.

The local nature of child care choice poses a challenge for empirical work on child care demand, especially work focused on local heterogeneity. Due to the highly local nature of child care choice, child care "markets" tend to be overlapping rather than discrete. People tend to use child care that is close to their home, and the distances travelled to access child care tend to be small compared to urban areas. For example, estimates from the National Survey of Early Care and Education, conducted in 2016 by the federal Department of Health and Human Services, suggests the average distance between home and provider, among children using a center-based child care provider, is 4.6 miles for children 0-3 and 3.9 miles for children 4-5, a small distance compared to the size of most population centers. (National Survey of Early Care and Education Project Team [2016]). Previous work on child care demand has used ad-hoc market definitions by assumption, defining child care markets to be identical with statistical areas such as ZIP codes. Using statistical regions as a proxy for child care markets risks providing an inaccurate picture of child care access and variety in different locations. Moving beyond ad-hoc market definitions is particularly important for this paper, because market definition assumptions will directly effect estimates of local elasticity of demand, which is the key parameter driving the magnitude of both the choice set and quality gentrification effects.

My modeling strategy replaces assumptions about market boundaries with assumptions about the structure of travel costs. I allow for the fact that consumers prefer child care providers that are close to their home, and estimating the magnitude of this preference allows me to do away with the assumption that consumers must choose a provider within an arbitrarily defined market while still modeling the fact that close-together providers compete while far-away providers do not. The effective choice set that matters for any given consumer depends on a parameter that is estimated within the model. I propose that this approach provides a much more flexible and realistic picture of the child care market than would be possible with arbitrary market boundaries. In turn, this allows me to estimate heterogeneity effects that depend on local variation in demand elasticity with confidence that my results are not being distorted by the market boundary assumptions.

I use panel data on provider enrollments, prices, and characteristics, created by Davis et al. [2018] to study geographic variation in child care access. This data set uses information originally collected by Child Care Aware of Minnesota, a non-profit that surveys all Minnesota licensed child care providers in order to provide data to child care resource and referral agencies, supplemented with geospatially imputed values for some missing prices and quantities. I combine this with block-group level demographic data from the American Community Survey on the number of children 0-5 in each census block group in Minnesota.

There are two critical problems of endogeneity that must be resolved in order to use a structural model to measure the value of quality ratings, especially in a market as rich with product variation as the child care market.

First, as Jin and Sorensen [2006], Xiao [2010], and Dranove and Jin [2010] all emphasize, we must expect that quality ratings are endogenous. After all, they are an attempt to measure product quality, and it's reasonable to expect them to be correlated with other quality information that consumers may observe, for example through advertising or provider reputation. Any econometric specification that ignores this will systematically overestimate the impact of quality ratings. In their influential study of restaurant hygiene score cards, Jin and Leslie [2003] use an intuitive panel data strategy to address this, comparing the revenue of highly rated restaurants before and after their rating is disclosed. I use a similar strategy, controlling in the demand model for the time-invariant component of provider quality that is observed by households, but unobserved by the researcher and associated with the rating ultimately assigned.

Second, I expect that price will also be endogenous, as it will be in any model of a product market where consumers have access to information about product quality or characteristics that is not present in the data available to the researcher. I address this using an adaptation of the instruments strategy used by Berry et al. [1995]. For each provider, I construct price instruments based on a distance-weighted sum of the characteristics of nearby competing providers, capturing the expected inverse relationship between markup and local competition.

I use an approach designed by Jin and Sorensen [2006] to assign money values to the ratings. This approach adapts the computation of compensating variation to use the estimated utility function with the ratings to evaluate counterfactual choices for a counterfactual consumer without access to the ratings information. The question in the welfare counterfactual is "what would a consumer informed by the ratings need to be paid in order to have their decision made by a consumer with identical preferences, who did not have access to the ratings." I make an incremental addition to the Jin and Sorensen [2006] method by noting that it is a special case of the framework that Train [2015] derives for welfare calculations when a consumer makes choices based on incomplete information. This provides me with closed-form expressions for the welfare quantities, rather than needing to simulate choice draws. I construct estimates of the welfare value of ratings at each census block group location, allowing me to examine regional heterogeneity in the benefits from the ratings.

In section 2 of this paper, I survey the empirical literature on quality ratings and other informational interventions. In section 3, I describe the data that will be used to estimate the model. In section 4, I present the economic model. This section has two components. First is the model of choice of child care provider that will be estimated, which is a standard logit discrete choice model of demand, with allowance for household heterogeneity based on varying demographics and based on unobserved variation in tastes. Second is an exposition of the method for calculating welfare quantities, following Train [2015]. In section 5, I discuss the estimation methodology. I use the method of Berry et al. [1995] to estimate the demand model by the Generalized Method of Moments. The inversion of Berry [1994] is used to linearize the model and enable the use of instruments for price. A modified version of the Berry et al. [1995] instruments are used, where the instruments are weighted averages of the characteristics of nearby competitors. In section 6 I give a detailed presentation of the results from estimation, which show that the 4 star rating is positive, and other ratings are negative. Overall the ratings are valuable to consumers.

2 Literature Review

This paper contributes to the literature on the effects of quality ratings or “score cards”, much of which is reviewed in Dranove and Jin [2010]. The existing research suggests that disclosure of product attributes can have a big impact on consumer choice. Jin and Leslie [2003] consider Los Angeles County’s introduction of a rule requiring restaurants to post a letter grade that reflects their performance on a health inspection. They find substantial evidence that this requirement led to an improvement in the hygiene performance of affected restaurants. Bollinger et al. [2011] study the impact of New York City rules that require restaurants to post calorie values of menu items on sales in Starbucks stores, finding that these these rules led consumers to choose lower-calorie foods and increased the sales of food in Starbucks establishments that were close to competing Dunkin Donuts stores. Disclosure rules are thus an attractive intervention for policy-makers.

Evidence on the effectiveness of *voluntary* disclosure regimes is more mixed. In their study, Jin and Leslie [2003] compare the effectiveness of the mandatory letter grade regime to a transitional period when some municipalities in Los Angeles County required the letter grades to be posted, but others did not, characterizing the latter regime as voluntary disclosure. They find that the effects of the voluntary disclosure regime are much less. Similarly, Mathios [2000] studies the effect of the Nutrition Labeling and Education Act, which mandates disclosure of nutritional information, on the sales of different types of salad dressing. This paper compares the salad dressing market before the introduction of NLEA, when some products displayed nutritional information labels to a period after the introduction of NLEA, when such labeling became mandatory, and finds substantial differences in consumer behavior. Hotz and Xiao [2013] provide a theoretical treatment that illustrates conditions where firms choose not to participate in quality disclosure for strategic reasons related to the effect of quality disclosure on markups through changed competition patterns.

A close comparison can be made between the present study and Jin and Sorensen [2006]. That paper examines the National Center for Quality Assurance ratings, which are a voluntary ratings system for health plans. Consumers may be able, at least to some extent, to discern quality without the availability of the ratings, and in that paper, the authors use non-public ratings of health plans to separately identify the treatment effect of the ratings from the ratings' correlation with already-available information about quality. This study approaches the same problem by using data on the period before the ratings are available to control for the already-known information about quality that is likely to be correlated with the ratings.

A close comparison can also be made between the present study and Xiao [2010]. That paper examines the privately administered system of child care center accreditation managed by the National Association for the Education of Young Children (NAEYC). Like the present study, that paper estimates the value to consumers of the ratings in a discrete choice framework. The present study differs from Xiao's work in several ways. First, I am able to use true panel data, consisting of multiple observations over time of the child care providers, including data on the enrollment of rated centers before they were rated. My strategy for controlling for endogeneity in the ratings, using these pre-rating observations, is more direct than Xiao's instrumental variables strategy. Second, I model consumer heterogeneity.

Jin [2005] considers the strategic incentives to disclose quality information, concluding that HMOs use participation in National Center for Quality Assurance ratings to distinguish themselves from competitors, and in the ratings in highly competitive markets are less likely to participate in the ratings. My study provides a complementary perspective focused on consumers rather than firms. I consider the role of variation in what is locally available in determining the likelihood that the ratings will be marginal for a particular consumer's choice, arguing that the benefits of ratings will be greatest in markets with many varied providers.

3 Data

3.1 Provider Panel

I use a unique panel data set based on an annual census of Minnesota licensed child care providers.

Child Care Aware of Minnesota maintains a database of child care providers as part of NACCRAware, a national child care data system designed for use by child care referral agencies. Providers are surveyed annually by Child Care Aware of Minnesota, on a rolling basis, in order to keep this database up to date. Information is self-reported by the providers, and includes enrollment numbers by age group, price by age group, quality rating information, as well as several other provider characteristics such as accreditations and nonprofit status. Davis et al. [2018] have prepared panel data on Minnesota child care providers based on periodic pulls from this database, merged with additional information from state government sources and licensing records.

The NACCRAware data contains information on price and enrollment in four age groups: infant, toddler, pre-school, and school-age. To simplify the analysis, I treated the infant, toddler, and pre-school categories as a single market. I calculated enrollment as the sum of infant, toddler, and pre-school enrollment, and calculated a price for each provider as a weighted average, using the enrollment from each age group as the weights for each provider. I do not make any use of the school-age group in this paper, because it is likely that demand for school-age care behaves quite differently from demand in younger age groups.

The panel data covers fiscal years 2012-2015 and includes information about child care centers, family day cares, and certain public child care programs, such as Head Start and pre-K programs in schools. This paper focuses on licensed child care centers.

Parent Aware ratings reflect an attempt to measure provider characteristics that are related to preparing children for kindergarten. Regulators assess providers that volunteer to be rated on four tracks of criteria, relating to Physical Health and Well-being, Teaching and Relationships, Assessment of Child Progress, and Teacher Training and Education. The ratings are a hybrid block and point system. For One Star and Two Star ratings, the provider must fulfill all criteria for that level in each track. For Three and Four Star ratings providers must meet all the criteria up to Two Stars and then can earn points for fulfilling additional criteria, with the number of points determining the level of the rating. (Cleveland et al. [2015].)

3.1.1 Descriptive Statistics

Table 1 shows descriptive statistics for the subsample used in the estimation, which consists of licensed child care centers in fiscal years 2014-2016. Additionally, cross-sectional descriptive statistics for each of the years used in estimation are presented in Appendix A, below. The data show that there is substantial variety in firm size and price. The standard deviation

Table 1: Center Descriptive Statistics, Fiscal Years 2014-2016

	N	Mean	Std. Dev.	Min	25%	Med.	75%	Max
Enrollment	3426.0	57.25	35.87	2.00	34.50	52.50	69.23	392.67
Weekly Price	3426.0	219.03	58.53	12.08	182.07	224.52	253.51	517.00
Licensed Capacity	3426.0	82.21	55.42	0.00	46.00	73.00	109.00	1140.00
USDA Food Prog	3426.0	0.34	0.47	0.00	0.00	0.00	1.00	1.00
Non-Profit	3426.0	0.37	0.48	0.00	0.00	0.00	1.00	1.00
Accreditation	3426.0	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Rating Stars	3426.0	1.31	1.82	0.00	0.00	0.00	4.00	4.00

in weekly price is 27% of the mean weekly price of $219.03. The standard deviation in enrollment is 63% of the mean enrollment of 57.25.

3.1.2 Data on Child Care Ratings

The NACCRAware data contains data on participation in child care accreditation systems such as NAEYC, and data on ParentAware ratings from fiscal year 2014-2016.

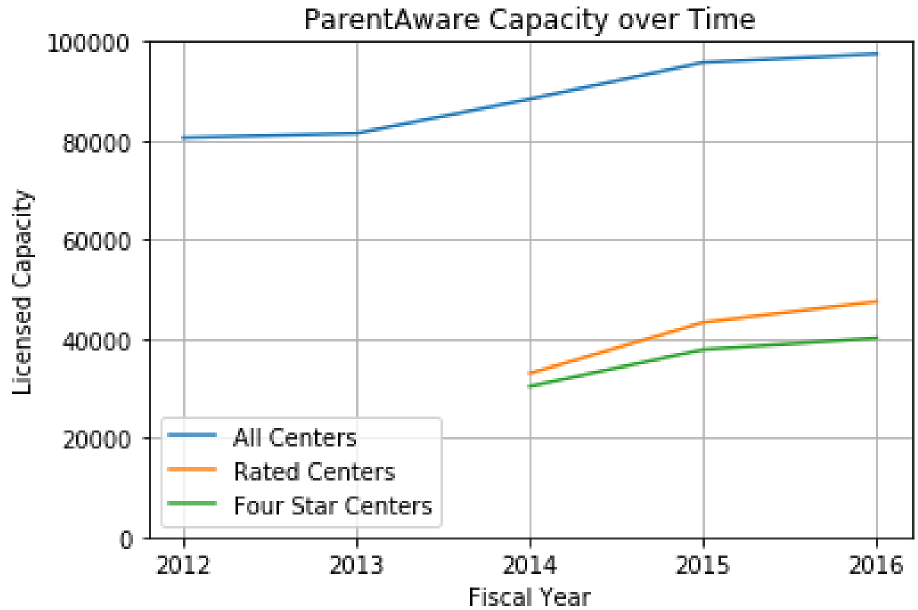
Table 2 shows the fraction of centers participating in different information systems for each year used in the estimation. The data show a steady increase in the fraction of centers participating in both Accreditation and in ParentAware.

Table 2: Fraction of Centers with Different Ratings

Year	N	Accreditation	4 Star Rating	Any Star Rating
2014	1063	0.317	0.262	0.298
2015	1194	0.315	0.304	0.363
2016	1169	0.349	0.326	0.409

Figure 1 shows the total licensed capacity in centers of various categories. Almost all of the rated capacity is in centers that have the highest 4-star rating.

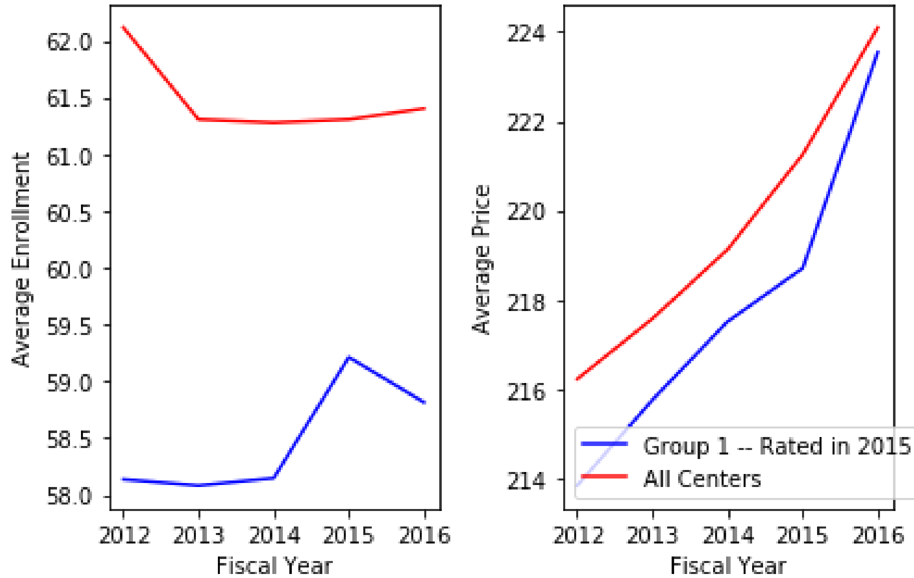
Figure 1:



3.2 Provider Locations and Supplementary Data

Provider location is geocoded based on provider address from the Child Care Aware data and licensing records. Provider data is supplemented by block group level household demographic data from the American Community Survey 2011-15 estimates, accessed through the NHGIS geocoded census data system. Household "locations" are actually the block group centroids. Each location is weighted by the ACS estimates of the number of children 0-5 in that block group. "Percent low income" is fraction of population in the block group under 200% of the poverty level. "Percent college" is fraction of adult population in the block group with bachelors degree or greater education. Household-provider distances are straight-line distance between the block group centroid and the provider address, calculated using Vincenty's formula.

Figure 2: Experience of Centers First Rated 4 Stars in FY 2015



4 Model

4.1 Demand

I represent choice of child care provider using a standard discrete choice model of product choice. Specifically, consider household i's decision over what child care arrangement to use. Suppose that i can choose any provider within R miles, where R is a distance radius around household i's location that is chosen to be large compared to child care travel distances, such as 50 miles. Then, the choice set for household i in period t is

$$J_{it} = \{j \in J_t | d_{ij} < R\} \cup \{0\}$$

where d_{ij} is distance between household i and provider j, and choice 0 is an outside option. The outside option represents any choice not explicitly represented in the choice set. Here, that would include parental care, care by friends and family, care in a licensed family day care, or care in a publicly provided center such as a Head Start program.

Following Berry, Levinsohn, and Pakes (1995) (hereinafter, "BLP",) I allow for a choice-specific utility that depends on both provider characteristics and characteristics (observed or postulated) of households.

$$u_{ijt} = X_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \gamma d_{ij} + \sum_h \sigma_h x_{jht}\nu_{ih} + \epsilon_{ijt}$$

Here, ξ_{jt} is a "structural" error term representing unobserved information about provider j in period t that is relevant to all households, and ϵ_{ijt} is error term that is "idiosyncratic" to the household. Choice-specific household utility depends on household "type" in two ways. First, random coefficients may be implemented through ν_{ih}, a random draw from a unit normal distribution, so that consumer i's "taste" for characteristic h is distributed $N(\beta_h, \sigma_h)$.[1] Second, through the effect of the household-provider distance term d_{ij}. Location is a dimension of household "type" because the household's location determines which providers are nearby, and hence comparatively attractive, versus far, and comparatively unattractive.

The purpose of allowing choice-specific utility to be different for different "types" of household is twofold. First, it allows for more patterns of substitutability between providers that are more complex than what could be represented in a non-mixed specification. Second, it allows for the model to incorporate important information about households that affects those substitution patterns.

Here it is worth saying a little bit about the role of household-provider distance in the model. Because provider market shares are observed only at the aggregate level, we do not directly observe the distance between households and the providers they choose. Households are assigned to providers endogenously through the demand model. However, the inclusion of household-provider distance allows the model to treat providers that are near to one another as closer substitutes than providers that are far away from one another, in a way that is shaped by specific information on where households live. In this way, the model's treatment of household-provider distance is analogous to the way BLP treat household income.

In the discrete choice model, each household chooses the provider in their choice set that

[1] This version of the paper, however, does not report the results of any random coefficients specifications.

provides the highest choice specific utility. Assuming that the idiosyncratic error term ϵ_{ijt} has the extreme value distribution, and is i.i.d., and normalizing the utility value of the outside option to be centered around zero, the probability that household i will choose provider j is given by the logit choice probability formula.

$$P_{ijt} = \frac{e^{X_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \gamma d_{ij} + \sum_h \sigma_h x_{jht} \nu_{ih}}}{1 + \sum_{k \in J_i} e^{X_{kt}\beta - \alpha p_{kt} + \xi_{kt} + \gamma d_{ik} + \sum_h \sigma_h x_{kht} \nu_{ih}}}$$

Demand, stated as market shares for each of the providers, has the form

$$s_{jt} = \int_i \frac{e^{X_{jt}\beta - \alpha p_{jt} + \xi_{jt} + \gamma d_{ij} + \sum_h \sigma_h x_{jht} \nu_{ih}}}{1 + \sum_{k \in J_i} e^{X_{kt}\beta - \alpha p_{kt} + \xi_{kt} + \gamma d_{ik} + \sum_h \sigma_h x_{kht} \nu_{ih}}} w_i di$$

where w_i is a weight function capturing the proportion of households of each type, based on the proportion of households at each location and the assumed distribution of the random taste parameter.

4.2 Calculation of Welfare Quantities

To measure the value of the ParentAware ratings to consumers, we wish to determine compensating variation. Compensating variation for quality ratings is the answer to the question "how much would consumers with the ratings information be willing to pay in order to avoid giving the information up?"

Jin and Sorensen [2006] point out an important subtlety about the calculation of welfare quantities for ratings systems and other informational interventions. When compensating variation is calculated for a price change, or the introduction of a new product, the change in market conditions affects the consumer's choice set but not their utility function. In contrast quality information has a direct effect on willingness to pay. To correctly value the counterfactual where consumers give up the ratings information, it is necessary to value the choices that would be made without the ratings information according to the utility function of the consumer who has the ratings information.

Let A and B be the information regimes without and with the ratings, respectively, and let $a(\varepsilon)$ and $b(\varepsilon)$ be the optimal choice functions corresponding to each regime. The compensating variation value of the ratings is:[2]

$$\frac{1}{\alpha}[V^B(b) - V^B(a)]$$

To illustrate why it is important to evaluate the choices according to the with-ratings utility function, it may be helpful to consider the hypothetical of the low-rated provider's loyal client. Suppose that there is a provider whose quality rating indicates a quality level lower than what consumers would have expected without the rating. Further suppose that there are some households who choose that provider despite the low rating. (Perhaps the cost is also low, or the household receives a good idiosyncratic utility draw for that provider.) We now ask how well that consumer would be if the quality information was not available. For this consumer, the quality information cannot have been marginal. If the chosen provider is the best choice even with the negative quality information, it will also be the best choice without the negative quality information. This consumer's choice is unaffected by the quality ratings, and their welfare should thus also be unaffected. However, if the welfare value of ratings to this were naively calculated as $V^B(b(\varepsilon)) - V^A(a(\varepsilon))$, then this consumer would be considered to have been *harmed* by the ratings. Using the with-ratings utility function to calculate the welfare value of the without-ratings choice function gives the desirable property that a consumer cannot be harmed by additional information.

Train [2015] considers the more general question of how to calculate welfare quantities when an agent bases their choice on inaccurate or incomplete estimates of value, and derives expressions for these welfare quantities. Jin and Sorensen [2006] calculate $V^B(a)$ by simulation, taking random draws from ϵ to simulate choices and then evaluating those choices

[2] More rigorously, compensating variation value of market conditions B over market conditions A is defined as the money transfer that would have to be paired with B in order to make the consumer indifferent between A and B-minus-transfer. Like Jin and Sorensen [2006], I am considering a model where the marginal utility of money is uniform across consumers, in which case compensating variation simplifies to the difference in consumer surplus divided by the marginal utility of money.

according to V^B. However the quantity they are calculating can also be as a special case of the framework explained by Train, who shows that $V^B(a)$ can be written as the sum of $V^A(a)$ and an adjustment term. In Appendix C, I use Train's framework to derived closed-form expressions for the compensating variation of quality ratings.

5 Estimation

5.1 Instruments

As is usual in a model of demand for differentiated products, we expect that price is likely to be endogenous. There are many inputs that we do not directly observe that would be expected to determine quality or other dimensions of desirability of child care providers to consumers, and it is reasonable to suppose that the "high-quality" providers should also be higher-priced.

Let x_j^x be a provider characteristics. A price instrument z_j^c is constructed by taking the distance-weighted sum of x_k^c across other providers in the market.

$$z_j^c = \sum_{j \in J_t, k \neq j} \frac{x_k^c}{d_{jk}}$$

Five instruments are constructed in this manner. Instruments are constructed from provider characteristics licensed capacity, nonprofit status, accreditation status, and ParentAware rating status. An instrument is also constructed using a constant for x_k^c, which provides a measure of the density of other nearby centers.

One test of instruments is to examine the results of the "first stage" regression of the endogenous variables on the instruments. If the instruments do not have explanatory power, they cannot be very satisfactory. Appendix B shows the results of the first stage regression. The specification uses year fixed effects to control for time trends in child care prices. Taken as a whole, the instruments provide substantial additional explanatory power. An F-test of the restriction dropping the five instruments from the model is rejected at the 1% significance level.

5.2 Berry Inversion and Estimation Strategy

I follow the strategy devised by Berry (1994) for how to use instruments to estimate a discrete choice model. The strategy involves inverting the market shares function in order to get a linear problem.

In order to explain how this works, it is helpful to re-write the choice-specific utility function as the sum of three terms

$$u_{ijt} = \delta_j + \mu_{ij} + \epsilon_{ij}$$

The first term, δ_j, captures the purely “vertical” dimension of differentiation between providers. That is, δ_j is everything about provider j that is valued the same by all households, including the unobserved quality term ξ_j, and the value placed on j’s observed characteristics by a consumer with average tastes. The second term, μ_{ij} captures the “horizontal” dimension of differentiation between providers; those parts of the household’s valuation that depend on the household’s type. This might include the effect on choice of the distance between household and provider. Even if all households place the same value on distance, the values of d_{ij} will be different for households at different locations. μ_{ij} will also include the effects of taste variation as expressed through random coefficients. Finally, ϵ_{ij} is the random idiosyncratic error term.

Given that μ_{ij} is a function of the data and some unknown parameters θ, and given a vector of values, $\delta = \{\delta_j\}$, fitted market shares can be computed, conditional on θ and $\{\delta_j\}$, using the formula

$$s_j(\delta;\theta) = \sum_i w_i \frac{e^{\delta_j + \mu_{ij}}}{1 + \sum_k e^{\delta_k + \mu_{ik}}}$$

The strategy for estimating the model has three parts. First, given a candidate value for θ, determine the vector of values $\delta(\theta)$ that matches the fitted market shares $s_j(\delta;\theta)$ to the observed market shares in the data. Second, considering the expression,

$$\delta_j = X_j\beta - \alpha p_j + \xi_j$$

estimate the vector of structural errors $\xi(\theta)$ as the residual of an instrumental variables regression with $\delta(\theta)$ as the left hand side. Third, using this vector of structural errors as an input into a GMM objective function, and re-computing δ and ξ for each candidate value of θ find the value of θ that minimizes that objective function. In the current version of the analysis, the only moment condition is the one from the demand equations, $E(\xi_j|Z_j) = 0$. The objective function I use to estimate θ is thus relatively simple.

$$\hat{\theta} = \arg\min_{\theta} \xi(\theta)^T \xi(\theta)$$

5.3 The BLP contraction

The foregoing discussion assumes that there is a method of determining the vector δ that matches the fitted market shares $s(\delta;\theta)$ to the observed market shares s^0. In order to do so I use the contraction described by BLP. This method uses a process of iterative adjustment. Define the operator $T\cdot$ by

$$T \cdot \delta_j = \delta_j + \ln s_j^0 - \ln s_j(\delta;\theta)$$

BLP show that this operator is a contraction and thus that it has a unique fixed point, which can be found by iteratively applying it to an initial "guess". Since the fixed point occurs when $s_j(\delta;\theta) = \ln s_j^0$, this provides a computational method for calculating $\delta(\theta)$. An initial value of δ is set, and then the contraction iteratively applied until the differences between δ and $T \cdot \delta$ are small compared to a specified tolerance.

5.4 Identifying a Treatment Effect

In specifying the model, the ParentAware star ratings are included in the provider characteristics matrix X_{jt}. We should, however, be concerned that the demand unobservable ξ_{jt} will be correlated with the ParentAware ratings variables. ξ_{jt} captures whatever information about providers that is unobserved by the researcher but that households know and incorporate into their choice decisions. If, as seems reasonable to expect, the providers that have high values of ξ_{jt} in the data generating process are more likely to be assigned a four star rating, then the coefficient on the four star rating parameter may be biased upwards.

In order to address this, I follow a difference-in-differences strategy. Implicit in this strategy is the assumption that the component of ξ_{jt} that is correlated with the eventual rating is stable over time. Each provider is assigned to a "group" based on the highest ParentAware rating they receive. Thus, a provider whose highest star rating is four stars is assigned to the four stars group. The providers that are never rated in the data are their own group. A dummy variable is assigned to each group and included in X_{jt}. These dummy variables account for the average differences between the providers that receive, for example, four stars, when they are rated, and those that receive three stars, or that never choose to become rated.

As part of this difference-in-differences strategy, I also include year fixed effects by incorporating year dummies into the characteristics matrix X_{jt}. Year fixed effects are equivalent to allowing the value of the outside option to be different in different years. This is necessary because the overall demand for child care, and for center-based care, is not constant over time, it is increasing. Since the likelihood of being rated is correlated with time – the ratings are only present in the later years – if we did not account for this overall demand trend it might bias the ratings coefficients upwards.

6 Results

6.1 Demand Estimates

In this subsection, I compare the estimates from the mixed logit demand model to logit models that do not account for the role of geography and travel costs in child care demand.

Table 3 shows these results. In all three specifications, the outcome variable can be understood as a score that captures the utility value to an average consumer of choosing product j. For models A and B the outcome variable is defined as $\ln s_j - \ln s_0$, the linearization of the logit model that Berry [1994] suggests in order to allow instrumental variables to be employed. Coefficients for models A and B are by ordinary (OLS) and instrumental variables (2SLS) least squares respectively. Model C is a mixed logit model where the household type varies with location, with a single household-product utility interaction term, a linear travel cost. Model C is estimated using nonlinear two stage least squares using the Berry et al. [1995] estimation algorithm.[3] The "outcome" variable in a mixed logit model is a mean utility score that is most intuitively understood by noting that if the utility specification contains no household-product interaction terms then the model specializes to the $\ln s_j - \ln s_0$ model of A and B. Thus if the model C estimation algorithm is run with the coefficient on travel distance dropped (or equivalently, fixed at zero), the results are the same as for model B. As a consequence of this, the coefficients in all three columns are on the same scale and can be compared directly.

All of these specifications include year fixed effects to control for population growth and statewide trends in the demand for child care.

Comparing the price coefficients in Table 3, we can see that price has a coefficient that is positive and statistically significant in model A, which was estimated with ordinary least squares. Taken at face value, the coefficient implies that consumers prefer to spend more rather than less on child care providers. This was to be expected given our presumption

[3] That is to say, I use BLP's nonlinear GMM estimation algorithm, but choose the weighting matrix that specializes the GMM estimator into 2SLS.

Table 3: Baseline Models

	OLS	2SLS	Nonlinear 2SLS /BLP
	(A)	(B)	(C)
Distance (Miles)	.	.	-0.093^{***}
			(0.002)
Price (Weekly)	0.001^{***}	-0.00004	-0.035^{***}
	(0.0002)	(0.0003)	(0.001)
Star Rating – 1	-0.182^{*}	-0.186^{*}	-0.425^{*}
	(0.096)	(0.096)	(0.249)
Star Rating – 2	-0.00001	-0.005	-0.440^{**}
	(0.075)	(0.075)	(0.194)
Star Rating – 3	0.107	0.094	-0.377
	(0.151)	(0.151)	(0.391)
Star Rating – 4	-0.007	-0.002	0.423^{***}
	(0.053)	(0.053)	(0.138)
Group – 1	0.079	0.067	-0.284
	(0.082)	(0.082)	(0.212)
Group – 2	0.059	0.049	-0.117
	(0.065)	(0.065)	(0.168)
Group – 3	0.058	0.052	-0.327
	(0.119)	(0.119)	(0.307)
Group – 4	0.037	0.033	0.131
	(0.052)	(0.052)	(0.134)
Capacity	0.006^{***}	0.006^{***}	0.011^{***}
	(0.0002)	(0.0002)	(0.0005)
USDA Food Program	-0.099^{***}	-0.103^{***}	0.035
	(0.021)	(0.021)	(0.055)
Nonprofit	0.014	0.002	-0.364^{***}
	(0.021)	(0.021)	(0.055)
Accreditation	0.070^{**}	0.099^{***}	0.671^{***}
	(0.030)	(0.033)	(0.085)
Constant	-9.345^{***}	-9.231^{***}	0.497^{***}
	(0.045)	(0.071)	(0.184)
Year F.E.	Yes	Yes	Yes
Observations	3,426	3,426	3,426

Note: *p<0.1; **p<0.05; ***p<0.01

that price is correlated with unobserved quality. Model B uses instrumental variables. Here, the price coefficient is small and its difference from zero is not statistically significant. In that model there is no accounting for travel costs, this model treats all providers as equally substitutable with one another regardless of distance. Model C includes travel costs, so the estimates are based on a demand structure where the degree of substitutability depends on geography. In the coefficient estimates for this model, distance and price are both statistically significant and have the expected sign. The relative size of the coefficients, $\theta_{Distance}/\beta_{Price} = 2.64$, multiplying by 52 to obtain a yearly quantity, suggests that a typical consumer is willing to pay about \$137 extra per year to avoid an additional mile of distance between home and the child care provider. This substantial distance penalty is consistent with our expectation that consumers prefer child care that is within a few miles of the home.

The key coefficients of interest are the ones associated with the star ratings. The omitted category is "unrated", and so the ratings coefficients can be understood as differences from the unrated category. In Model C, the coefficient on the highest rating, 4 Stars, is 0.423. Scaling this to the coefficient on price, $\beta_{4Star}/\beta_{Price} = \$12.09$, and multiplying this by 52 implies that a typical consumer is willing to pay about \$628 extra per year in order to use a 4 Star rated provider compared to an unrated provider. On the other hand, the coefficients on the lower rating, 1-3 stars are all negative, and all have values around -0.4. The results imply that providers that receive ratings lower than 4 Stars are perceived as worse than unrated providers. Scaling these coefficients in the same way as above suggests that, for example, a typical consumer would require about \$630 of compensation per year in order to accept a 1 Star rated provider rather than an unrated. All of the coefficients on the star ratings are statistically significant except the one on 3 Stars. The non-significant coefficient on the 3 Star rating may be attributed to the fact that there are comparatively few providers with this rating.

6.2 Welfare Calculations

6.2.1 By Year

Table 4: Welfare Quantities

FY	Actual	Counterfactual	Adjustment	Benefit
2014	\$100,975,800.42	\$93,104,316.91	-\$5,768,092.55	\$2,103,390.96
2015	\$115,533,611.15	\$106,222,502.29	-\$6,270,825.54	\$3,040,283.31
2016	\$115,804,854.12	\$107,021,278.21	-\$5,313,216.28	\$3,470,359.63

Table 4 shows the calculation of the total welfare benefit from the ParentAware ratings. The first column, "Actual" shows a money scaling of the total expected utility calculated from the model as follows. First, for each block group type i, I calculate $\frac{52}{\beta_{Price}} \log \sum_j e^{V_{ij}}$, the expected utility from the model to a consumer of that type evaluated over possible values of the idiosyncratic utility draw ε_i, scaled to a money value by dividing by the price coefficient, and translated into a yearly value by multiplying by 52. These per-person values are summed, weighted by the number of children 0-5 in that block group, to give the values shown in the table. To calculate the second column, "Counterfactual", I calculate counterfactual choice utilities by starting with the estimated model and setting the coefficients on the ratings to zero. I then calculate the same log sum calculation, scaling, and summing as for the previous quantity, yielding an estimate of the expected utility from the model to a consumer choosing without the ratings information. However, I wish to calculate the value of the without-ratings choices according to the with-ratings utility values. The third column, "Adjustment", is calculated at the consumer type level as $\sum_j P_{ij} D_{ij}$, where D_{ij} is the difference between choice utility with the ratings coefficients set to zero, and the choice utility with the estimated coefficients; and P_{ij} is the probability that i will choose j in the counterfactual with the ratings coefficients set to zero; scaled and summed in the same way. "Counterfactual" - "Adjustment" gives the total expected value to consumers of their choices without the ratings, evaluated using the with-ratings utilities. "Actual" - "Counterfactual" + "Benefit" gives the compensating variation of the ratings. That is, the amount of money that would compensate consumers who had the ratings for having their choices made by consumers with identical preferences except for the ratings.

The results show a rapid growth in the total value of the ParentAware ratings to consumers, up to a yearly total value of almost \$3.5 million in fiscal year 2016. This reflects the increase in the number of rated providers, and consequently in the number of consumers whose choice is influenced by the ratings.

6.2.2 By Location

The value of the ratings is inherently heterogenous. Consumers whose set of available choices includes a variety of different classifications of providers are more likely to have their choice affected by the ratings. Consumers with few choices, or whose choices had uniform ratings, would be unlikely to have the ratings affect their choice and would gain little from the ratings information.

Table 5 shows the per-child expected benefit per consumer, aggregated to the county level. The table includes sixteen Minnesota counties. The counties shown in the table are all the counties whose share of the children age 0-5 is at least 1%, according to the ACS. The column labeled "Benefit" is calculated by evaluating the yearly expected benefit at the block group level, and then averaging over the block groups in each county, weighted by the number of children age 0-5 in each block group. The column labeled "Benefit Share" is the total expected value of ParentAware to consumers in the county divided by the statewide total, and the column labeled "Child Share" is the number of children age 0-5 in the county divided by the statewide total.

Generally, the benefits of the ratings are greatest in the urban counties. The chart is topped by the counties containing Minnesota's three most populous cities: Minneapolis (Hennepin County), St. Paul (Ramsey County), and Rochester (Olmsted County). This is

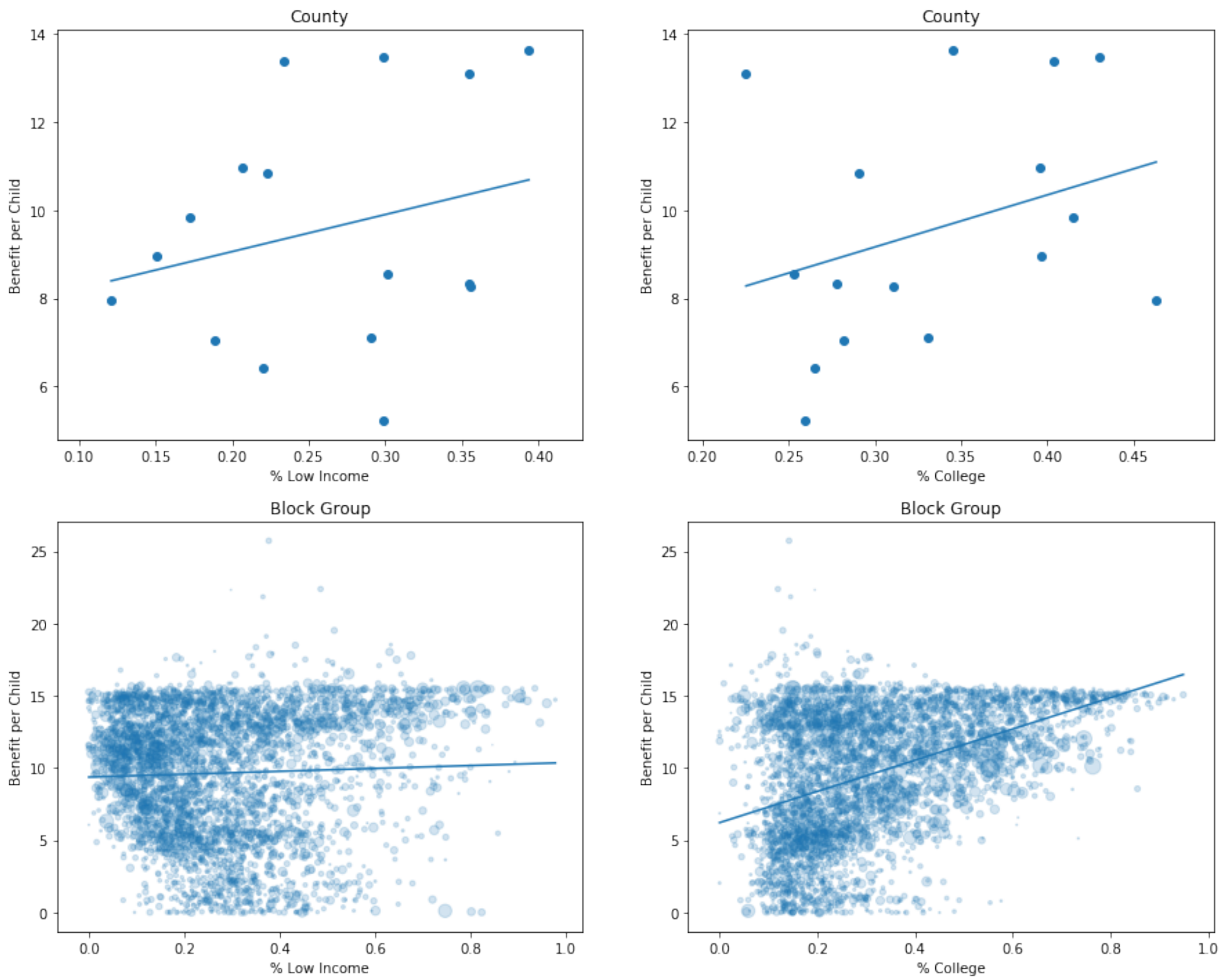
Table 5: Per-person Benefit by County (FY 2016)

County	MSA	Benefit ($)	Child Share (%)	Benefit Share (%)
Ramsey County	Twin Cities	13.64	10.67	14.64
Hennepin County	Twin Cities	13.48	22.65	30.74
Olmsted County	Rochester	13.39	3.06	4.12
Crow Wing County	(No MSA)	13.10	1.07	1.41
Dakota County	Twin Cities	10.96	7.76	8.56
Anoka County	Twin Cities	10.84	6.17	6.73
Washington County	Twin Cities	9.84	4.39	4.35
Scott County	Twin Cities	8.95	2.95	2.65
Stearns County	St. Cloud	8.55	2.75	2.36
St. Louis County	Duluth	8.34	2.99	2.51
Blue Earth County	Mankato	8.27	1.06	0.88
Carver County	Twin Cities	7.97	1.83	1.47
Clay County	Fargo-Moorhead	7.11	1.20	0.86
Wright County	Twin Cities	7.05	2.84	2.01
Sherburne County	Twin Cities	6.41	1.77	1.14
Rice County	(No MSA)	5.24	1.06	0.56

in line with our expectations that the benefits will be greater in dense cities where consumers have a wider variety of child care choices. The pattern is not absolute, however. Crow Wing, (a central Minnesota county whose principle city is Brainerd) has a larger than usual number of four star centers and consequently a high per-child expected benefit from ParentAware, exceeding that of suburban counties in the Minneapolis-St. Paul metropolitan area.

Figure 3 describes the relationship between the estimated benefits from ParentAware and some demographic characteristics. It should be noted that these estimates are based on the model that includes the distance cost but not any demographics in the choice utility specification, and therefore the variation in local benefits depicted in figure 3 arises wholly from differences in local child care choice sets and provider characteristics, rather than the direct effects of demographics. The top two subplots show county level aggregates, and the bottom two subplots show block group level estimates. In the left two subplots, the horizontal axis variable is the percent low income, defined as the proportion of households whose income is less than or equal to 200% of the federal poverty level. In the right two

Figure 3: Local Benefits of ParentAware, by Demographics



subplots, the horizontal axis variable is the percent college, defined as the proportion of individuals aged 25 and older whose highest education level is at least a bachelors degree. For each of these variables the county level quantity has been computed by taking a weighted average of the block group level variables, with the weight depending on the number of children in the block group (rather than the number of households or adults).

The left group of subplots of figure 3, describing the relationship between income and the benefits of ParentAware, are particularly interesting. At the county level, there is a loose positive relationship between the income variable and the estimated benefits from ParentAware. I interpret this as reflecting the effect of density. Many block-groups with a higher percentage of low-income people are urban block groups that are denser and where there is a greater variety of child care options. Consequently, there is a higher likelihood that the ratings will affect the choice of child care. At the block group level, however, the relationship between the income variable and the benefit variable is weaker. I interpret this as reflecting a balance of the effects of density against the fact that low-income neighbourhoods contain fewer highly rated centers.

The right group of subplots of figure 3 describe the relationship between education and the benefits of ParentAware. They show a positive relationship at both the county and block group level. This is in line with expectations. More college-educated people live in urban areas where the variety of child care options is greater and ratings are more likely to have an effect on choice. Furthermore, areas containing more college-educated people are also more likely to contain highly rated centers.

A Additional Descriptive Statistics

A.1 Provider Descriptive Statistics, Fiscal Year 2014

	N	Mean	St. Dev.	Min	25%	Med.	75%	Max
Enrollment	1063.0	56.67	34.55	2.00	34.00	50.50	70.40	302.17
Weekly Price	1063.0	216.76	59.13	12.68	178.29	221.37	253.97	517.00
Licensed Capacity	1063.0	83.14	47.23	0.00	48.00	74.00	110.00	372.00
USDA Food Prog	1063.0	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Non-Profit	1063.0	0.37	0.48	0.00	0.00	0.00	1.00	1.00
Accreditation	1063.0	0.32	0.47	0.00	0.00	0.00	1.00	1.00
Rating Stars	1063.0	1.11	1.75	0.00	0.00	0.00	4.00	4.00

A.2 Provider Descriptive Statistics, Fiscal Year 2015

	N	Mean	St. Dev.	Min	25%	Med.	75%	Max
Enrollment	1194.0	56.86	36.65	4.00	34.09	52.58	68.5	392.67
Weekly Price	1194.0	217.95	58.28	12.08	181.93	223.37	253.2	441.99
Licensed Capacity	1194.0	80.21	59.21	0.00	43.00	70.00	108.0	1140.00
USDA Food Prog	1194.0	0.33	0.47	0.00	0.00	0.00	1.0	1.00
Non-Profit	1194.0	0.37	0.48	0.00	0.00	0.00	1.0	1.00
Accreditation	1194.0	0.31	0.46	0.00	0.00	0.00	1.0	1.00
Rating Stars	1194.0	1.33	1.83	0.00	0.00	0.00	4.0	4.00

A.3 Provider Descriptive Statistics, Fiscal Year 2016

	N	Mean	St. Dev.	Min	25%	Med.	75%	Max
Enrollment	1169.0	58.17	36.24	2.38	35.33	54.00	69.23	371.65
Weekly Price	1169.0	222.21	58.13	12.53	186.01	228.76	253.48	475.68
Licensed Capacity	1169.0	83.39	58.23	0.00	46.00	73.00	110.00	1140.00
USDA Food Prog	1169.0	0.33	0.47	0.00	0.00	0.00	1.00	1.00
Non-Profit	1169.0	0.37	0.48	0.00	0.00	0.00	1.00	1.00
Accreditation	1169.0	0.35	0.48	0.00	0.00	0.00	1.00	1.00
Rating Stars	1169.0	1.46	1.85	0.00	0.00	0.00	4.00	4.00

B First Stage Regression of Price on Instruments

	Price
Capacity	0.191***
	(0.013)
USDA Food Prog.	−3.006*
	(1.570)
Nonprofit	−15.386***
	(1.494)
Accreditation	29.730***
	(2.123)
Rating – 1 Star	−7.494
	(7.085)
Rating – 2 Star	−5.379
	(5.513)
Rating – 3 Star	−12.214
	(11.129)
Rating – 4 Star	12.482***
	(3.915)
Group – 1 Star	−15.552***
	(6.034)
Group – 2 Star	−14.526***
	(4.767)
Group – 3 Star	−12.501
	(8.752)
Group – 4 Star	−4.313
	(3.826)
Z from Constant	−0.094***
	(0.032)
Z from Capacity	0.010***
	(0.001)
Z from Nonprofit	0.008
	(0.040)
Z from Accreditation	0.379***
	(0.146)
Z from Rated Status	−0.641***
	(0.130)
Constant	151.704***
	(2.190)
Year F.E.	Yes
Observations	3,426
R^2	0.536
Note:	*p<0.1; **p<0.05; ***p<0.01

C Closed Form Calculation of Welfare Quantities

Let A and B be the two different information regimes. A is without the ratings, and B is with the ratings. $a(\varepsilon)$ and $b(\varepsilon)$ are decision rules, that we will shortly associate with A and B. ζ_j^A and ζ_j^B are the mean utility values. Following Jin and Sorensen [2006], the value of the ratings is

$$\frac{1}{\alpha}\left(V^B(b) - V^B(a)\right).$$

This quantity can be calculated by simulating many draws of ε. However, another way is to derive closed form expressions. In order to do this it is helpful to write $\zeta_j^B = \zeta_j^A + D_j$. Then we can break down $V^B(a)$,

$$V^B(a) = E_\varepsilon\left[\zeta_j^B + \varepsilon_j | \zeta_j^A + \varepsilon_j = \max_k \zeta_k^A + \varepsilon_k\right].$$

Then, splitting up ζ^B,

$$V^B(a) = E_\varepsilon\left[\zeta_j^A + \varepsilon_j | \zeta_j^A + \varepsilon_j = \max_k \zeta_k^A + \varepsilon_k\right] + E_\varepsilon\left[D_j | \zeta_j^A + \varepsilon_j = \max_k \zeta_k^A + \varepsilon_k\right],$$

Substituting well-known expressions, (and writing out $D_j = \zeta_j^B - \zeta_j^A$)

$$V^B(a) = \log\left(\sum_k \exp\zeta_k^A\right) + \sum_j\left(\frac{\exp\zeta_j^A}{\sum_k \exp\zeta_k^A}\right)(\zeta_j^B - \zeta_j^A)$$

Then the value of the ratings is

$$\frac{1}{\alpha}\left[\log\left(\sum_k \exp\zeta_k^B\right) - \log\left(\sum_k \exp\zeta_k^A\right) - \sum_j\left(\frac{\exp\zeta_j^A}{\sum_k \exp\zeta_k^A}\right)(\zeta_j^B - \zeta_j^A)\right)$$

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