Distance Matters:
Proximity to Social Service Agencies and the Utilization of Child Care Subsidies[1]

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Abstract

This paper examines the impact of the spatial accessibility of social service agencies on the likelihood of receiving a child care subsidy among mothers with young children. In particular, we collect data on the location of virtually every social service agency in the U.S. and use this information to calculate the distance that families must travel from home in order to reach the nearest office that administers the subsidy application process. Using data from the Kindergarten cohort of the Early Childhood Longitudinal Study (ECLS-K), our results indicate that an increase in the distance to a social service agency reduces the likelihood that a family receives a child care subsidy. Specifically, we estimate an elasticity of subsidy receipt with respect to distance of -0.13.

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I. Introduction

Created alongside the passage of welfare reform in 1996, the Child Care and Development Fund (CCDF) is the primary funding stream devoted to child care assistance in the U.S. Indeed, child care subsidies play an increasingly important role in government efforts to reduce welfare caseloads and increase employment among economically disadvantaged families. Yet despite these goals, the take-up rate for child care subsidies—defined as the fraction of eligible families receiving assistance—remains considerably low. For example, recent studies estimate that approximately 15 percent to 30 percent of the eligible population is being served (Herbst, 2008a; U.S. DHHS, 1999). The low take-up rate is largely attributed to the CCDF's funding structure as a close-ended block grant, but subsidy participation rates continue to be low in states that devote relatively more resources to child care assistance (U.S. DHHS, 2000) and among families that are explicitly targeted by state administrators (Schumacher & Greenberg, 1999). This suggests that a combination of demand- and supply-side factors play an important role in influencing subsidy utilization.

In this paper, we examine one such factor that has been largely ignored by previous research: the spatial accessibility of social service agencies. Proximity to a local agency can impact participation during multiple stages of a family's interaction with the subsidy system. In particular, many parents are required to make one or more personal visits to an agency to conduct the initial in-take and eligibility screening. The number of office visits largely depends on state-specific rules governing the stringency of income and employment documentation and the extent to which families require assistance locating suitable child care providers. In addition, parents in many jurisdictions are required to report in-person all changes to employment and income. This can be particularly challenging for low-income parents, who tend to have less access to automobile transportation and are more likely to experience frequent job turnover, seasonal or irregular work hours, and highly volatile earnings. Finally, policies regarding eligibility recertification in some states require parents to make multiple trips to the local social service agency. In particular, the time-limited nature of

child care subsidies—usually lasting three to 12 months—implies that parents need to restart the eligibility process every few months or risk benefit termination. Again, the ease with which families are able to complete the recertification process depends on the number and types of documents required and whether parents are able to schedule appointments with caseworkers at convenient times.

At least two other factors interact with states' subsidy policies that make spatial accessibility a particularly important consideration for low-income families. First, it is plausible that families are more likely to apply for child care subsidies if they have sufficient information about the program's operation and requirements. Access to such knowledge is likely to be greater when the relevant social service agencies are located close to home. Indeed, previous studies find that information and awareness are important determinants of participation in other programs, including food stamps (Daponte et al., 1999) and Medicaid (Aizer, 2007). Second, social service agencies located close to home may increase families' trust in these institutions. If potential subsidy recipients view local agencies as invested in the success of surrounding neighborhoods, such individuals could be more likely to apply for assistance.

Economic models of program participation provide a structured approach to thinking about the impact of spatial accessibility on child care subsidy receipt (Moffitt, 1983). In particular, parents are predicted to apply for and receive assistance when the benefits of doing so exceed the costs. In this framework, the distance to a local agency represents real costs in terms of travel time, transportation expenditures, and foregone earnings. Therefore, parents in communities with less spatial accessibility to a social service agency face higher costs and thus greater constraints on subsidy participation. Many of these costs are compounded by the limitations of public transportation in high-poverty neighborhoods and low car ownership rates among low-income families (Allard, 2009; Berube & Raphael, 2005; Ong, 2002). With single mothers' commute times averaging 10 hours per week (Edin & Lein, 1997), greater distances to social service agencies make

it increasingly difficult to fulfill the program obligations discussed above. It is therefore expected that, all else equal, less spatial accessibility to a local agency would reduce the likelihood of receiving a child care subsidy.

II. Background

This study contributes to the large literature exploring demand- and supply-side determinants of child care subsidy receipt. Studies of demand-side explanations usually find that young, unmarried women with greater numbers of young children are more likely to receive child care assistance. Furthermore, subsidy recipients are simultaneously more likely to be employed and receive other means-tested benefits. Interestingly, the likelihood of subsidy receipt is greater among families with relatively high levels of education, possibly because of the skills necessary to navigate the complex application process (Durfee & Meyers, 2006; Herbst, 2008a; Tekin 2005; 2007).

As for supply-side factors, low program awareness is frequently cited as being prohibitive, even though most states conduct public awareness campaigns. For example, one study finds that 44 percent of eligible non-applicants are unaware of their eligibility (Schlay et al., 2004). High transaction costs also appear to be important factors. Recent interviews with parents and caseworkers in 12 states reveal substantial administrative barriers to subsidy participation (Adams, Synder, & Sandfort, 2002). In particular, the authors find that parents must communicate with a large number of administrative agencies to access and retain a subsidy. The frequency of eligibility recertification and the requirement that caseworkers be notified of all changes to income and employment are also cited by families as being extremely resource- and time-consuming.

A sizeable body of work finds that measures of geographic accessibility are strongly associated with work and welfare outcomes as well as participation in a variety of social services and means-tested programs. For example, Allard and Danziger (2003) find that job accessibility and proximity to employment opportunities increase the likelihood that low-income families find work and leave welfare. Allard, Tolman, and Rosen (2003) show that greater spatial proximity to social

service providers increases the probability that welfare recipients receive these services. Neidell and Waldfogel (2009) analyze the impact of local Head Start availability on immigrant children's participation. The authors find that having a Head Start center in a child's census tract significantly increases the likelihood of enrollment. It has also been shown that the distance to medical care facilities is positively correlated with health care utilization (e.g., Nemet and Bailey, 2000) and treatment intensity for acute myocardial infarction (McClellan et al., 1994). Geographic variation proximity to college campuses during childhood appears to be highly correlated with later college attendance (Card, 1995). Finally, Bertrand et al. (2000) show that social networks, as defined by proximity to use of services by others in the same language group, is a significant determinant of welfare participation.

There is considerable indirect evidence that decisions regarding child care subsidy receipt are likely to be sensitive to the geographic accessibility of agencies administering these programs. For example, one study finds that mothers' daily trip from home to the child care provider adds 28 percent more time to the total commute (Michelson, 1985). It is therefore not surprising that low-income working mothers, in particular, stress the importance of locating child care services close to home or work (Henly & Lyons, 2000). Another study finds that nearly 70 percent of low-income parents rate "conveniently located services" as very important to their child decisions, compared to 50 percent among high-income parents (U.S Department of Education, 1995). These preferences appear to translate in practice: a study of child care subsidy recipients in Cuyahoga County, Ohio finds that such families travel approximately two miles to center-based providers and 1.5 miles to family daycare homes (Bania et al., 2000). `

III. Conceptual Framework and Empirical Model

Following Moffitt (1983), we outline a simple model of program participation that serves as a guide for the empirical analysis. Let a mother's utility in the absence of a child care subsidy be expressed as U(Y; X, L), where Y is private income, X represents demographic preference shifters,

and L is a set of geographic characteristics that shape families' decision-making. If a mother receives a subsidy, her utility is expressed as U(Y + M; X, L) – D, where M captures the potential benefits of receiving child care assistance and D represents the disutility associated with program participation. The benefits of subsidy receipt include the growth in income that result from reductions in fixed work costs. The disutility of subsidy participation is related to the time, psychic, and transportation costs associated with trips to social service agencies.[2] It is further assumed that D is an increasing function of the distance between mothers' residential location and the nearest agency. A mother will therefore decide to receive a child care subsidy if U(Y + M; X, L) – U(Y; X, L) > D, that is, if the utility gain from receiving subsidized care exceeds the disutility. Based on this simple model, the decision to utilize child care subsidies can be expressed by the following equation:

$$S_i = X_i\beta_1 + \beta_2 d_i + L_i\beta_3 + \varepsilon_i \quad (1)$$

where S_i is an indicator of subsidy receipt for the i^{th} potentially eligible mother, L_i is a set of local characteristics such as the availability of other services that are potential substitutes for child care subsidies (e.g., church services, Head Start, etc.) that could affect participation; X is a set of maternal and family characteristics that could influence a mother's decision to take-up a child care subsidy, and ε_i is an idiosyncratic error term. The d_i is the measure of spatial accessibility, defined as the distance (in miles) between families' residential location and the nearest social service agency. The coefficient of interest is β_2, which captures the impact of distance to the on the probability of receiving a subsidy. Our main testable hypothesis is that the probability of subsidy receipt decreases with the distance to the local social welfare agency (i.e., $\beta_2 = \delta S/\delta d < 0$).

We estimate versions of equation (1) using a linear probability model.[3] A potential concern

[2] Another potential benefit of receiving a child care subsidy could be improved child well-being if a subsidy is used for a good quality child care arrangement. This would be formalized by including child quality as another argument in the mother's utility function. However, this is not necessary for the purposes of this paper. Another potential cost of receiving a child care subsidy could be stigma. However, we do not explicitly focus on stigma since it is largely unobservable and difficult to separate from transaction costs and information (Moffitt, 1983; Neidell & Waldfogel, 2009).

[3] The least squares estimates of coefficients in linear probability models are consistent estimates of average probability derivatives, but the standard errors are biased as a result of heteroskedasticity. We report standard errors that are robust to any form of heteroskedasticity.

with this estimation strategy is that our distance measure could be determined in part by the joint location preferences of families and social service agencies. For example, administrative offices might locate in low-income neighborhoods in order to be accessible to potentially eligible clients. In addition, given the low rates of car ownership among disadvantaged families, such individuals may prefer to reside near critical support services or employment and public transportation centers. If these unobserved neighborhood characteristics determine the relative location of families and agencies, the coefficient on the distance measure will be biased.

While endogenous location choices are plausible for entitlement programs or services with open-ended funding streams, we argue that it is highly unlikely that low-income parents move to a given neighborhood to be close to an agency administering child care subsidies. These benefits are heavily rationed by local agencies (because of the close-ended block grant funding structure), suggesting that the supply of subsidies is outstripped by demand. As a result, it is common for parents to experience frozen intake and long waiting lists (Herbst, 2008a). Children receiving subsidized care do so for only short periods before restarting the eligibility process, and all interim income and employment changes must be reported to caseworkers. Therefore, it seems fairly risky to choose a residential location based on the location of child care administrators. As pointed out by Allard (2009), the location choices of social service agencies are constrained in a number of ways. These constraints help to explain why one-fifth of the social service agencies in his three-city study had been operating in the same location for six to 10 years, and over half were in the same location for more than 10 years. As a result, social service agencies are unlikely to adjust rapidly to changes in the geographic distribution of low-income families.

Nevertheless, our preferred specification adds county fixed effects, which capture unobserved local determinants of the demand for child care subsidies that may bias the coefficient on d_i. In

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Since our distance measure is based, in part, on families' residential census tract, the standard errors are adjusted for clustering at the census tract-level. Our results are robust to clustering at the county-level.

addition to mitigating the influence of endogenous neighborhood characteristics, county fixed effects control for the availability of substitute forms of early care and education, which may affect the demand for a child care subsidy. The fixed effects also account for unobserved program and policy choices that are correlated with the spatial location and availability of social service agencies. For example, some jurisdictions allow families to request or apply for assistance via mail, telephone, or the web.[4] It is also plausible that some counties conduct outreach campaigns to raise awareness for subsidy programs as well as provide an array of support services to access local agencies.

IV. Data

Our data come from the Early Childhood Longitudinal Study – Kindergarten cohort (ECLS-K). The ECLS-K is a nationally representative sample of 21,260 children attending kindergarten in the fall of 1998.[5] Children in the ECLS-K are followed through the eighth grade, with detailed parent interviews and child assessments conducted in the fall and spring of kindergarten (1998 and 1999) and the spring of first (2000), third (2002), fifth (2004), and eighth (2007) grade. The analyses in this study are based on the fall of kindergarten wave of data collection, in which parents are asked about child care experiences, including subsidy participation, in the year prior to kindergarten entry.

Our analysis sample includes families potentially eligible for child care subsidies. To be eligible for CCDF funds, families must have at least one child ages 0 to 13; parents are required to participate in a state-defined acceptable work activity; and total income must fall below 85 percent of the state median income. In practice, however, the extraordinary amount of state variation in eligibility rules creates difficulties for precisely simulating eligibility (Giannarelli et al., 2001; Witte & Queralt, 2003). Therefore, we define the analysis sample to include families in the bottom three

[4] As of 1998, 14 states in our ECLS-K sample allowed families to request subsidy applications mail, telephone, or email (Alaska, Arizona, Arkansas, Kansas, Louisiana, Maine, Michigan, Missouri, Oregon, Pennsylvania, South Dakota, Tennessee, Texas, and Washington). Another five states (Maine, Michigan, Oregon, Texas, and Washington) allowed families to complete the subsidy application via mail or telephone.

[5] For more information on the ECLS-K, see Herbst and Tekin (in press a, b).

quintiles of the full sample socioeconomic status (SES) distribution.[6] Our final analysis sample includes 9,231 children.[7]

The outcome variable in our analysis is a binary indicator for whether a child received subsidized, non-parental child care in the year prior to kindergarten. Parents are asked a series of questions about child care use during the previous year, including the number of arrangements, the amount of time that each arrangement was used, whether there was a cost associated with each arrangement, and if so, the amount paid for care. Regarding subsidy receipt, parents were asked the following: "Did any of the following people or organizations help to pay for this … provider to care for {CHILD} the year before {he/she} started kindergarten?" Four possible choices were then presented to parents, and we coded those answering "a social service agency or welfare office" as receiving a child care subsidy.

An implication of limiting the sample to potentially eligible families is that the subsidy participation rate is likely to be an underestimate of the actual rate. Indeed, approximately seven percent of families in our sample receive a child care subsidy, whereas studies that carefully simulate eligibility find participation rates between 15 percent and 30 percent (e.g., Herbst, 2008a). Furthermore, consistent with the consensus in the child care literature, subsidy receipt leads to a significant increase in employment among mothers in our sample. It is important to note that we experiment with several alternative sample selection criteria, including explicit attempts to define a low-skilled sample (e.g, mothers with less than a B.A degree), a low-income sample (e.g., families below the poverty line), and those whose demographic characteristics are highly correlated with subsidy receipt (e.g., unmarried mothers). In no case do these alternatives materially change the results discussed below.

[6] Created by ECLS-K administrators, the SES index is based on parental education and occupation and total family income.

[7] To create the analysis sample, we dropped additional observations if there was missing information on the census tract identification number (2,256 observations), missing information on the entire parent interview (740 observations), missing information on the child care subsidy receipt question (35 observations), and mothers with nonsensical ages (6 observations).

The primary right-hand-side variable is a measure of the spatial accessibility of local social service agencies, defined as the distance (in miles) that families must travel from home in order to reach the nearest office that administers the subsidy application process. Appendix A provides a detailed description of the steps taken to generate the distance measure, so we include only a brief discussion here. The process began by creating a database containing the precise location (building number, street name, city, state, and zip code) of virtually every social service agency in the U.S. In doing so, we were careful to ensure that a given agency is involved in eligibility and benefit determination for child care subsidies. Our database contains location information on over 3,600 social service agencies. The next step in the process involved geocoding the location of administrative offices by assigning a latitude and longitude coordinate to each. In an overwhelming number of cases (95 percent), we were able to assign a geocode based on either the agency's exact location or its census block. Only five percent of offices were geocoded at the city- or zip code-level. In the final step, we calculated the Euclidean (or as-the-crow-flies) distance between the location of social service agencies and the centroid (or geographic center) of the census tract in which ECLS-K families reside. We generate the distance measure based on families' census tract because residential addresses are not available in the ECLS-K. In addition, given that states' child care subsidy programs are administered primarily at the county-level, we use families' county of residence as the geographic boundary for calculating the distances.

Following the literature on the determinants of child care subsidy receipt, we include a detailed vector of controls for child and family characteristics in the model. The child variables include gender, age, race/ethnicity, contemporaneous weight, premature birth, low birth weight, disability status, and first-time kindergartner. The set of family characteristics includes maternal age and educational attainment, family structure, number of other children in the household, whether English is the spoken language at home, and the log of household income. We also incorporate binary indicators to control for missing observations on each of our control variables.

Table 1 presents summary statistics for the analysis sample. Families are located, on average, 7.7 miles away from the closest social service agency. Seven percent of children in our sample received a child care subsidy in the year prior to kindergarten entry. As shown in columns two through five, the subsidy utilization rate decreases monotonically as the distance to an agency increases. A test of the null hypothesis of the equality of subsidy participation rates across the distance quartiles is strongly rejected ($F=11.04$; $p<0.000$), thereby providing initial evidence that greater distances to an agency are associated with lower participation rates. However, child and parent characteristics also exhibit several differences across the distance quartiles. For example, children living close to an agency are more likely to be black, less likely to live with two biological parents, and reside in households with substantially lower incomes.[8] Such differences imply that it is important to condition on child and family characteristics when examining the relationship between the distance measure and subsidy receipt.

V. Results

Results from estimating equation (1) are shown in Table 2. The top panel presents results from models using natural logarithm of the distance to the closest social service agency.[9] By employing the natural logarithm, we mitigate the influence of outliers in determining regression coefficients. In addition, we allow for non-linearities in the relationship between the distance measure and subsidy receipt by including binary indicators for the second, third, and fourth quartiles of the distance distribution (binary indicator for the first quartile is the omitted category). These results are presented in the bottom panel. In column (1), we display the basic results from models that only include the distance variable. In columns (2) and (3), we add child characteristics and

[8] The differences in child and family characteristics are driven in large part by differences in neighborhood characteristics across the distance distribution. For example, differences in urbanicity by distance quartile are highly statistically significant ($F=220.48$; $p<0.000$), as is household median income ($F=339.17$; $p<0.000$). In particular, families living near a social service agency tend to be located in densely populated and low-income neighborhoods. Accounting for these local factors removes most of the differences in child and family characteristics.

[9] Note that there are multiple agencies to choose from in some counties. In those cases, the distance measure represents the distance to the closest agency.

family characteristics, respectively. In column (4), we incorporate county fixed effects.

As shown in the top panel of Table 2, the coefficient on the distance measure is negative and statistically significant in all models, indicating that an increase in the distance to the nearest social service agency reduces the likelihood that a family receives a child care subsidy. Interestingly, the magnitude of the distance estimate in column (4), which is identified using only within-county variation, is similar to those in columns (2) and (3). The coefficient in column (4) implies that a one-percent increase in the mileage to the nearest agency decreases the probability of subsidy utilization by 0.9 percentage points. This estimate yields an elasticity of child care subsidy receipt with respect to distance of -0.13.

The results in the bottom panel of Table 2 suggest that, as one would expect, the probability of subsidy receipt decreases monotonically as families reside greater distances from the closest social service agency. Families located in the third and fourth quartiles of the distance distribution are 2.2 and 2.6 percentage points less likely to receive a subsidy than those in the first quartile, respectively. Those in the second quartile are about one percentage point less likely to receive a subsidy than those in the first quartile, although the coefficient is not precisely estimated.

Table 3 presents results from a number of robustness checks and sub-group analyses. In terms of robustness checks, we first add census tract controls to the model (in addition to county fixed effects) to further account for neighborhood-level unobservables that are correlated with the location preferences of families and social service agencies. The census tract controls include population density, percent females ages 16+ employed, percent ages 0 to17, percent ages 65+, percent employed in local government, percent employed in state government, percent ages 25+ with less than a high school degree, and percent foreign born. Adding these variables leaves the coefficient on the (log of) distance virtually unchanged. In the second row, we test a different distance measure. Recall that the results presented so far are based on the distance to the *closest* social service agency. Approximately one-third of families in our dataset live in jurisdictions that

contain multiple agencies administering CCDF subsidies. To account for the presence of multiple agencies, we create a distance variable based on the *average* distance across all potential agencies in the county of residence. The coefficient on this measure suggests that a one-percent increase in the mileage to the local administrative office reduces the likelihood of subsidy receipt by 1.3 percentage points. The implied elasticity is -0.18, which is somewhat larger than that generated by the minimum distance measure.

The bottom panel of Table 3 presents results from several sub-group analyses. When we estimate the models separately for families residing in urban and non-urban areas, the impact of distance is larger and more precisely estimated among those in non-urban areas.[10] This finding is plausible given that access to public transportation and major roadways is likely to be more restricted in non-urban areas. Furthermore, social service agencies are distributed over larger land areas in rural counties, resulting in longer travel distances for families residing in these jurisdictions.[11]

Next, we estimate models separately for states that do and do not allow families to request or complete subsidy applications through the mail, telephone, or web. It is important to reiterate that although some parents may not be required to visit an office for the initial application and eligibility screening, there are numerous factors subsequent to this that may necessitate in-person visits (Adams, Synder, & Sandfort, 2002). Therefore, it is plausible that distance continues to be costly for families that are allowed to submit subsidy applications through alternative means. Our results appear to corroborate this intuition: increases in the distance measure are associated with a statistically significant reduction in subsidy receipt irrespective of whether families must make personal visits to the local social service agency.

We also examine the extent to which access to reliable transportation differentially influences the role of distance in determining subsidy participation. It is possible, for example, that the impact

[10] We define urban as residence in a census-defined city (of any size) or another census-designated urban area.
[11] Indeed, the average distance to the closest agency in urban areas is 6.52 miles, compared to 12.37 miles in non-urban areas.

of distance is substantially greater among families facing high transportation costs because of low car ownership rates. In other words, if the distance to an agency influences subsidy participation by altering transportation costs, we might expect lower subsidy participation rates among families with low car ownership rates. To test this, we merge the ECLS-K data with household car ownership rates calculated at the census-tract-level, and use this information to divide neighborhoods into "high" and "low" car ownership neighborhoods.[12] We then estimate the full model separately for families in each of these neighborhood-types. Consistent with our expectation, the distance measure has a greater impact on subsidy participation among families with higher transportation costs (residing in "low" car ownership neighborhoods) than those with lower transportation costs (residing in "high" car ownership neighborhoods).

Finally, we estimate models separately by families' cash assistance status (receipt of AFDC/TANF or food stamps). Interestingly, the results indicate that distance serves as an obstacle to subsidy receipt only for those families not receiving other forms of cash assistance. To the extent that families receiving welfare and food stamps have already committed to traveling to social service agencies, distance should be less influential in the decision to apply for and receive other forms of assistance, including child care subsidies.

VI. Conclusion

This paper examines the relationship between the spatial accessibility of social service agencies and child care subsidy receipt. In particular, we calculate the distance that low-income families must travel from home in order to reach the nearest agency that administers the subsidy application process. We then use this variable to determine whether and to what extent the distance to the nearest agency influences the likelihood of subsidy receipt. Using data from the ECLS-K, our results indicate that the probability of child care subsidy utilization declines as the distance to social

[12] These data are drawn from the 2000 Decennial Census. Neighborhoods coded as having "high" car ownership rates are those in which the fraction of households owning zero cars is at or below the 25th percentile of the distribution or those in which the fraction of households owning two or more cars is at or above 75th percentile of the distribution. All other neighborhoods are coded as "low" car ownership neighborhoods.

service agencies increases. Specifically, we find a one-percent increase in the distance to the closest administrative office reduces subsidy participation rates by roughly one percentage point.

Aside from its policy significance, our results present researchers with a unique opportunity to more rigorously study the impact of subsidies on parent and child outcomes, including maternal employment and child development. Although there is a sizeable body of existing work examining these outcomes (e.g., Blau & Tekin, 2007; Tekin, 2005, 2007; Herbst, 2008b; Herbst & Tekin, in press a, b; Meyers, Heintze, & Wolf, 2002), scholars have struggled to development convincing empirical strategies to surmount the endogeneity of child care subsidy receipt. Our study has the potential to contribute to this literature by using the distance measure as an identifying instrument.

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Table 1: Select Summary Statistics by Distance Quartile

Variable	Full Sample	1st Quartile	2nd Quartile	3rd Quartile	4th Quartile
Distance to Social Service Agency (miles)	7.73	1.57	3.75	7.35	20.07
Child Care Subsidy Receipt (%)	0.070	0.088	0.077	0.062	0.048
Child Characteristics					
Boy (%)	0.507	0.508	0.506	0.515	0.500
Age (months, fall of K)	68.44	67.86	68.53	68.69	68.86
White (%)	0.457	0.288	0.418	0.545	0.633
Black (%)	0.199	0.226	0.217	0.205	0.142
Hispanic (%)	0.251	0.345	0.281	0.186	0.162
Asian (%)	0.059	0.099	0.048	0.042	0.036
Other Race/Ethnicity (%)	0.033	0.043	0.037	0.022	0.027
Premature Birth (%)	0.175	0.175	0.179	0.179	0.166
Disabled (%)	0.147	0.137	0.138	0.158	0.158
Maternal and Family Characteristics					
Maternal Age (years, fall of K)	31.60	31.22	31.40	31.93	31.97
Two Biological Parents (%)	0.554	0.516	0.529	0.569	0.614
One Biological Parent (%)	0.303	0.349	0.328	0.280	0.239
Blended Parents (%)	0.105	0.096	0.106	0.113	0.109
Adoptive/Foster Parents (%)	0.038	0.039	0.038	0.038	0.038
Less Than High School (%)	0.243	0.318	0.244	0.203	0.185
High School/GED (%)	0.467	0.428	0.464	0.478	0.513
Some College (%)	0.269	0.241	0.274	0.292	0.278
B.A.+ (%)	0.020	0.013	0.018	0.027	0.024
Total Family Income (annual, $)	31,297	26,225	31,171	34,112	35,272

Notes: Means are based on children and families with non-missing data.

Table 2: Estimates of the Relationship between Distance to Social Service Agencies and Child Care Subsidy Receipt

	(1)	(2)	(3)	(4)
Linear Specification				
ln(distance to social service agency)	-0.014***	-0.013***	-0.010***	-0.009**
	(0.003)	(0.003)	(0.003)	(0.004)
Non-Linear Specification				
Second Quartile of the Distance Distribution	-0.010	-0.010	-0.008	-0.009
	(0.008)	(0.008)	(0.008)	(0.008)
Third Quartile of the Distance Distribution	-0.026***	-0.025***	-0.019**	-0.022**
	(0.008)	(0.008)	(0.008)	(0.009)
Fourth Quartile of the Distance Distribution	-0.039***	-0.035***	-0.027***	-0.026***
	(0.008)	(0.008)	(0.008)	(0.010)
Child Characteristics	No	Yes	Yes	Yes
Maternal and Family Characteristics	No	No	Yes	Yes
County Fixed Effects	No	No	No	Yes
Number of Observations	9,231	9,231	9,231	9,231

Notes: Standard errors, displayed in parentheses, are adjusted for clustering at the census tract level. Distances are measured in miles. The linear specification takes the natural logarithm of the minimum distance to the nearest social service agency within a given county. The non-linear specification is expressed as a set of dummy variables denoting the quartiles of the minimum distance distribution. Column (2) adds controls for gender, child's age (in months), child's age squared, race/ethnicity (four dummy variables), child's weight, premature birth (one dummy variable), low birth weight (one dummy variable), disabled (one dummy variable), and first-time kindergartner (one dummy variable). Column (3) adds controls for mother's age, family structure (three dummy variables), mother's educational attainment (three dummy variables), number of other children in the family (two dummy variables), English as the primary spoken language in the household (one dummy variable), and the log of total household income. Column(3) adds county fixed effects. *, **, *** indicate that a given distance coefficient is statistically significant at the 0.10, 0.05, and 0.01 levels, respectively.

Table 3: Tests of Robustness and Sub-Group Analyses

Specification	Distance Coefficient (standard error)	Number of Observations
Robustness Checks		
Add census tract controls	-0.009**	9,231
	(0.004)	
Use the mean distance measure	-0.013***	9,231
	(0.005)	
Sub-Group Analyses		
Urban residence	-0.007*	7,320
	(0.004)	
Non-urban residence	-0.025**	1,911
	(0.011)	
Request or complete applications via mail/telephone/online	-0.010**	2,835
	(0.005)	
Cannot request or complete applications via mail/telephone/online	-0.013***	6,396
	(0.004)	
Families located in high car ownership neighborhoods	0.011	2,021
	(0.011)	
Families located in low car ownership neighborhoods	-0.008*	7,219
	(0.004)	
Families receiving AFDC/TANF or food stamps	0.003	2,894
	(0.009)	
Families not receiving AFDC/TANF or food stamps	-0.009**	6,251
	(0.004)	

Notes: Standard errors, displayed in parentheses, are adjusted for clustering at the census tract level. Unless noted otherwise, all specifications take the natural logarithm of the minimum distance to the nearest social service agency within a given county. The census tract controls include population density, percent females ages 16+ employed, percent ages 0-17, percent ages 65+, percent employed in local government, percent employed in state government, percent ages 25+ with less than a high school degree, and percent foreign born. The models run separately on the application policies do not include county fixed effects, but include a control for urban residence. Neighborhoods coded as having high car ownership rates are those in which the fraction of households owning zero cars is at or below the 25th percentile of the distribution or those in which the fraction of households owning two+ cars is at or above 75th percentile of the distribution. *, **, *** indicate that a given distance coefficient is statistically significant at the 0.10, 0.05, and 0.01 levels, respectively.

Appendix A: Construction of the Database on U.S. Social Service Agencies

The process for creating the distance measure began by collecting data on the precise location of every social service agency in the U.S. In most cases, address data were available on the website of the state agency responsible for administering the child care subsidy system. For example, the Department of Economic Security administers the subsidy program in Arizona, and the office locations can be found here: https://www.azdes.gov/main.aspx?menu=128&id=2724. In Maryland, the subsidy program is managed by the Office of Child Care in the Department of Education, and information on agency locations can be found here: http://www.dhr.state.md.us/county.php. For some states, we were not able to readily find the office locations on states' websites, so we relied on administrator contact lists provided by the National Child Care Information Center (NCCIC: http://nccic.acf.hhs.gov/statedata/dirs/display.cfm?title=ccdf#az) and the *Child Care and Development Fund Report of State Plans* (various years) for this information. We were careful to ensure that each agency is involved in eligibility and benefit determination for child care subsidies.

For each social service agency, we collected information on the state name, state FIPS code, county name and county FIPS code in which each office is located; the address (including building or suite number), city, and zip code; telephone and fax numbers; and the name of the agency that administers the subsidy program. Most states organize social service provision at the county-level, with one agency located in each county. However, in some urban counties and many cities, there are multiple agencies located in the jurisdiction. For example, La Paz county, located in Western Arizona, is a rural jurisdiction, and its residents have access to a single social service agency. Maricopa county, in contrast, is an urban area (containing the city of Phoenix), and its residents have access to eight offices. As for Maryland, every county contains one social service agency, except for Baltimore City, which has nine offices. In a small number of cases, a locale does not include a social service agency, so that its residents must travel to adjacent counties to apply for child care assistance. For example, Pend Orielle county in Washington State does not have a social service agency. Therefore, as stipulated by the Department of Social and Health Services, residents in this county must travel to a branch office in Spokane county (located south of Pend Orielle) to apply for assistance. Generally speaking, these agencies serve residents from multiple counties.

Our database attempts to account for these complications. Agencies located in multiple-agency-jurisdictions are each treated as separate entries in the database. Agencies that serve residents from multiple jurisdictions (because their county-of-residence does not have one) are repeated in the database, with each entry denoting the relevant county served by the office. In all, we collected data on approximately 3,600 unique social service agencies.

One concern is that our agency database captures the current address of each agency, while our child care subsidy data come from surveys the conducted in the late-1990s and early-2000s. To the extent that some of these agencies moved to their current address after these years, our distance measure contains measurement error. However, as previously stated, we recorded the telephone number of each agency in the database, and we asked two research assistants to make phone calls to more than 10 percent of (randomly chosen) offices to inquire about their location history since 1998.

Fortunately, an overwhelming majority of these agencies have been at the same location during this period, and we were able to identify the previous address in most cases for the small number of movers. Of the 405 phone calls made to social service agencies, we were able to speak to a representative in 228 cases. Of these cases, only 35 reported that they had moved at some point since 1997. The rest stated that they were either in the same location for sure or that they had "probably" been in the same location.

The next step in the process involved geocoding the location of social service offices by assigning a latitude and longitude coordinate to each. We worked in collaboration with Geocoder (www.geocoder.us) to generate the coordinates. Geocoder was able to provide these coordinates using its own application programming interface (API) as well as that from Google, now considered the gold standard for producing geocodes. Based on our discussions with Geocoder analysts, we concluded that the Google-based geocodes were of higher-quality, so we use these as the basis for making the distance calculations. Of the 3,659 social service agencies (unique or repeated) in our database, 2,887 (approximately 80 percent) were able to be geocoded to its exact location (i.e., typically to 30 feet or less). Another 543 agencies (15 percent) were goecoded to roughly block- or street-level accuracy. For 229 agencies (six percent), only the city or zip code was available to be geocoded, decreasing locational precision to as many as a few miles. In sum, approximately 95 percent of social service agencies were geocoded with a level of precision at the block-level or better.

A potential concern with the geocoding process is that the agency addresses would not match those found in Geocoder's database. For example, slight errors in spelling or formatting in a set of agency addresses could cause a different set of addresses to be geocoded. Fortunately, Geocoder provided us with a measure called the Levenshtein-Damerau, which calculates the "edit distance" (or level of textual discrepancy) between the addresses provided and the addresses actually assigned geocodes. We used this measure to double-check the accuracy of agency addresses that were assigned low scores, and we corrected any errors that were discovered. Generally speaking, we found this measure to be quite sensitive to small inconsistencies between the provided and geocoded addresses. Therefore, our data checks were extensive.

In the final step, we calculated the distance between the location of social service agencies and the residential location of each family in our analysis samples. Given that we plan to use this distance measure with a number of datasets (e.g., Early Childhood Longitudinal Study—Kindergarten cohort and Fragile Families and Child Well-Being Study), we utilized the following approach. Users of the ECLS-K and FFCW contract data are able to observe families' residential locations at the census tract-level. Since child care subsidies are distributed by agencies organized at the county-level, we use the county as the geographic boundary for calculating the distances. As a result, we calculated the Euclidean (or as-the-crow-flies) distance (in miles) between the location of social service agencies and *every* census tract centroid in the county in which each agency resides. For example, La Paz County in Arizona has one social service agency and six census tracts. Therefore, our database contains six sets of distances associated with this agency: one for each census tract. In Maryland, Montgomery County also has one social serve agency but 176 census tracts. Our database contains the distance from this agency to each census tract in the county.

Jurisdictions with multiple agencies have a set of distance calculations for each agency. For example, Baltimore City has nine agencies and nearly 200 census tracts, leading to approximately 1,800 separate agency-tract calculations. In addition to calculating the distance, we produced the census tract identification number associated with each agency-tract combination. We use the census tract code to merge the distance measure with families in our analysis samples. Although this process was extremely time-intensive, the results provide us with the flexibility to append the distance measure to virtually any dataset with census tract codes.