Generosity vs. Access: The Effects of Subsidy Policy on Price and Quality of Child Care

Serena Goldberg[*†]

November 11, 2026

Updated frequently. Click here for latest version.

Abstract

Quality child care can improve low-income children's long-run outcomes. To increase access to high-quality care, the largest child care program in the United States gives states $12.4 billion annually to fund child care subsidy programs. Given a fixed budget, states trade off serving more families against giving larger subsidies to fewer families. It is unclear which allocation is better for eligible families. I first show that market quality and prices change with the number of subsidized families and the maximum subsidy. To identify the effect of each, I use variation in application fixed costs across space and in the maximum subsidy across time, space, and provider type. I find that a higher maximum subsidy increases average out-of-pocket payments and subsidizing more local families increases the probability that a neighborhood has a higher-quality provider. Motivated by these findings, I estimate a model of the child care market with endogenous prices, quality, and number of subsidized families. I use the model to evaluate a reform Wisconsin adopted in 2022 after a federal budget increase. I compare the reform, which increased the maximum subsidy by 130% on average, against using the same budget to offer smaller subsidies to more families. Under the larger subsidy, 17% more low-income children enroll in either public care or high-quality private care relative to subsidizing more families. However, 19% more eligible children forgo formal care overall. Higher prices explain 61% of this decline. As a result, consumer surplus for low-income families is 17% lower and producer surplus is 2% lower.

[*]Yale University. Email: serena.goldberg@yale.edu.

[†]This research was supported with a grant from Washington Center for Equitable Growth. I am deeply grateful for my advisors Joseph Altonji, John Eric Humphries, Costas Meghir, and Christopher Neilson for their guidance and support. I also thank Jaime Arellano-Bover, Barbara Biasi, Jonathan Borowsky, Janet Currie, Matthew Famiglietti, Lorenzo Kaaks, Aaron Sojourner, Pamela Torola, Seth Zimmerman, and participants at the Yale Labor/Public Lunch for their helpful comments. I thank Wisconsin's Department of Children and Families for assisting me with multiple public records requests.

1 Introduction

High-quality child care can improve children's long-run outcomes, including their educational attainment and earnings (Almås, Drange, Meghir and Zachrisson, 2026; Bailey, Sun and Timpe, 2021; Garces, Thomas and Currie, 2002; Gray-Lobe, Pathak and Walters, 2023; Havnes and Mogstad, 2011), as well as their participation in risky or criminal behavior (Anders, Barr and Smith, 2023; Ando, Mori and Yamaguchi, 2025; Carneiro and Ginja, 2014; Garces et al., 2002; Gray-Lobe et al., 2023; Smith, 2015). Low-quality formal care can harm children's cognitive and socio-emotional skills in the short-run (Baker, Gruber and Milligan, 2008; Herbst and Tekin, 2016). Low-quality care may also harm children's long-run health and criminal behavior (Baker, Gruber and Milligan, 2019). Access to formal care of sufficient quality can particularly benefit low-income children because alternative care arrangements are more likely to be low-quality (Feller, Grindal, Miratrix and Page, 2016; Kline and Walters, 2016).

Child care subsidies are a common policy that governments use to enroll more children in high-quality care. The largest child care program in the United States, the Child Care and Development Fund (CCDF), gives states $12.4 billion annually to fund child care subsidy programs (Department of Health and Human Services, 2026). States can then choose how to allocate their funding. For example, states may trade off serving more families against giving larger subsidies to fewer families.[1] Quantifying this trade-off is difficult. Demand depends on both how many families receive subsidies and the maximum subsidy. In turn, the price and quality of local care may change in equilibrium. Additionally, it is unclear how many fewer families can be subsidized if the state offers a larger subsidy, given that families may choose different providers and providers may change their price or quality.

In this paper, I evaluate the effects of a larger maximum subsidy that Wisconsin adopted in 2022 after a federal funding increase. I focus on the effects of the reform on the child care

[1] Offering subsidies to more families does not require states to change eligibility criteria: states are not obligated to serve all eligible families and often do not have the resources to do so.

market and eligible families. I compare the reform to a counterfactual alternative: spending the same federal funding increase on serving more families under the prior maximum subsidy. I determine the extent to which changes in enrollment, as well as consumer and producer surplus, come predominantly from changes in family choices, prices, or quality. To answer these questions, I use novel administrative data from Wisconsin on prices, quality, subsidized enrollment, and other provider characteristics.

To motivate a model of the child care market, I show that child care providers change their price and quality in response to changes in the proportion of local families receiving a subsidy and the maximum subsidy. Both are endogenous, so I use two sources of variation to disentangle the effects of each. The first is variation in distance to offices where families can verify their eligibility for subsidies. Controlling for the proportion of families that are eligible, I show that a neighborhood that is one mile closer to an income-verification office subsidizes 0.9pp more families.[2] I argue that distance to income-verification offices is plausibly exogenous after controlling for the proportion of nearby families eligible for subsidies, the proportion of nearby families using the Supplemental Nutrition Assistance Program,[3] urbanicity, and other observables. Second, I leverage changes in the maximum subsidy over time, by county, and by provider type. The maximum subsidy is generally higher in counties with more expensive care. However, I control for these baseline differences and leverage variation in the timing and magnitude of a maximum subsidy increase.

At the average maximum subsidy, I find that subsidizing 1 percentage point (pp) more families increases the likelihood that a given census tract has a high-quality provider by 1.8pp.[4] I find no significant effect of the maximum subsidy on whether a census tract has a high-quality provider. However, I show that out-of-pocket payments increase significantly more when the maximum subsidy increases. Fixing the proportion of families subsidized at

[2]For a neighborhood with an average maximum subsidy.

[3]Income-verification offices often serve multiple programs. I argue that offices are more likely to be strategically located for larger programs like SNAP rather than in neighborhoods with higher unobserved demand for child care. Additionally, I control for potential income effects from participating in other safety-net programs by controlling for SNAP participation among young families.

[4]1.8pp is 5.9% of the sample mean.

the average, if the maximum subsidy is \$10 higher,[5] out-of-pocket payments are 18% higher. Additionally, 6.6pp more subsidized families must pay something out-of-pocket.[6] Sticker prices increase by 5.1%. Fixing the maximum subsidy at its average, subsidizing 1pp more families increases out-of-pocket payments by an insignificant 1.3% and sticker prices increase by 0.2%.[7]

While these quasi-experimental results are suggestive, it is unclear what the effect of a higher maximum subsidy is under a fixed budget. First, it is unclear how many fewer families would be subsidized if the state increases the maximum subsidy. Second, the quasi-experimental results focus on the effects of the maximum subsidy and the number of subsidized families on market prices and quality. It remains unclear how much these changes affect families' enrollment choices compared to the direct effects of receiving a larger subsidy or being unable to receive a subsidy because of state budget constraints.

With these questions in mind, I develop a model of the child care market with endogenous prices, quality, and number of subsidized families.[8] Given the number of subsidized families and the maximum subsidy offered, I determine the market equilibrium in three stages. First, providers invest in quality based on anticipated demand and local competition. Second, providers observe their quality and the quality of nearby providers and set prices to maximize expected profits. Third, families choose a private or public provider, or to forgo childcare altogether, based on provider characteristics. Family preferences vary by demographics.[9]

[5]The average maximum subsidy, weighted by capacity and averaged across age groups served, was \$216.82 per week in January 2020.

[6]67% of families pay something out-of-pocket. Average out-of-pocket payments paid by subsidized families, excluding co-pays and age-adjusted to the payment for three-year-olds, is \$34.52 per week (in 2020 dollars).

[7]As a robustness check, I show that similar patterns hold if I use a difference-in-differences approach comparing the effects of different policy changes in Wisconsin and Pennsylvania between high- and low-poverty neighborhoods.

[8]I assume that Head Start and public providers do not change their quality in response to these policies. I assume fee-based public providers also do not change their prices. I do not observe the non-profit status of private providers. I account for the possible presence of non-profit providers by incorporating unobserved cost shocks into the model. Providers who set lower prices, perhaps because of their non-profit status, are estimated to have lower unobserved costs.

[9]In estimation, I allow for preferences to depend on eligibility for subsidies and the age of the child. Because I have more limited data on children's ages, the age of the child only affects taste for formal care in general and whether the child is eligible to attend a given provider – utility is infinitely negative at providers

I also allow for unobserved variation in families' taste for high-quality care. Under an exogenous budget and maximum subsidy, the state offers subsidies to as many families as it can afford, pulling eligible families from a randomized queue.[10] Under this model, three channels affect the quality of care eligible families receive after a maximum subsidy increase.

First, holding price, quality, and other provider characteristics fixed, families may enroll at different providers (the *family choices* channel). Subsidized families pay lower out-of-pocket payments and pay a smaller difference in out-of-pocket payments across different providers than unsubsidized families. Accordingly, subsidizing fewer families reduces demand for desirable non-price characteristics, like quality. Increasing the maximum subsidy reduces the difference in out-of-pocket payments across providers, increasing demand for non-price characteristics. When both the maximum subsidy increases and fewer families receive subsidies, it is unclear how family choices, conditional on market offerings, will change.

Second, providers may change their prices (the *endogenous price* channel). Providers cannot price discriminate against subsidy recipients, so they set prices based on demand from both subsidized and unsubsidized families. Subsidized families are price insensitive up to the maximum subsidy. If fewer families are subsidized, providers with prices below the maximum subsidy have less incentive to set their price closer to the maximum subsidy. Additionally, subsidizing fewer families reduces demand for desirable non-price characteristics, so these providers may decrease their prices further. On the other hand, increasing the maximum subsidy increases demand for these characteristics. If high-quality providers obtain a greater market share, they can set higher prices.

Third, providers may change their quality (the *endogenous quality* channel). Providers are more likely to improve their quality if offering higher-quality care leads to higher expected

the child is ineligible to attend.

[10]Families are not obligated to use the subsidy if they are offered one. For tractability, the model assumes that receiving a subsidy, upon offer, has no additional fixed costs. This assumption may overestimate the take-up of subsidies. Alternatively, I could assume there is some fixed cost correlated with distance to the income-verification office that families must pay to obtain the subsidy. While this approach would incorporate frictions in reaching families, it would require estimating another stage of the model simultaneously with demand and additional structure to identify, since I only observe where families enroll, not where they live.

profits than offering lower-quality care. A provider's profit depends on their market shares and families' responsiveness to prices. Providers then have a greater incentive to improve their quality if demand for high-quality care increases and the cost of providing quality care remains fixed[11].

The trade-off between subsidizing more families versus giving larger subsidies to fewer families depends on how many fewer families are subsidized under the larger subsidy. To determine how many fewer families receive subsidies, I assume the state subsidizes as many families as it can afford, offering subsidies to eligible families from a randomized queue. If the state increases the maximum subsidy, the state may pay more per-family. Consider the case where families do not change their provider and providers do not change their price or quality. The state then pays more for providers with prices above the previous maximum subsidy. The state continues to pay the same sticker price for care that costs less than the previous maximum subsidy. However, subsidized families may enroll at more expensive providers if the maximum subsidy increases, as more desirable offerings become affordable. Additionally, providers may increase their prices to capture the larger maximum subsidy.

I use novel data from Wisconsin between 2022 and 2025 to estimate the model. During this period, I observe subsidized and total enrollment at almost all licensed providers in Wisconsin.[12] For 87% of providers, I observe state quality ratings, discrete values assigned annually by the state based on both structural and process quality.[13] I link data on providers' prices, quality ratings, Head Start status, other licensing characteristics, and addresses. By geolocating providers, I can account for variation in the kinds of families

[11]To be sure, it is possible that the cost of offering high-quality care may increase if more providers invest in quality. For example, as demand for child care workers increases, wages may also increase. This is not the focus of this paper, but may reduce the extent to which providers update their quality, and increase the price of care as quality improves. Given the counterfactual results, we may expect that even fewer families enroll in formal or high-quality private care if costs are also endogenous.

[12]I do not account for the nanny or informal care market. Using 2025 SIPP data, I find that 82% of families with children ages 0-14 paying for non-relative or formal care rely on center, family, or after-school care. In Wisconsin, any provider who supervises at least four children simultaneously outside of the family's own home, excluding schools or public recreational options, must be licensed DCF (n.d.).

[13]Structural quality relates to materials and physical space available for children. Process quality captures how teachers interact with children and other aspects of curriculum.

that live near each provider. Because I observe aggregate enrollment at each provider, I can estimate heterogeneous unobserved demand for each provider. As public care is a common alternative source of care, I also use geolocated enrollment data from all public 4-K programs in Wisconsin, including enrollment by Free and Reduced Price Lunch status.[14]

I estimate the parameters of demand and the marginal cost function using a two-step generalized method of moments (GMM) procedure (Berry, Levinsohn and Pakes, 1995; Conlon and Gortmaker, 2020; Petrin, 2002). First, I solve a fixed point problem to determine the average demand for each provider, matching predicted aggregate enrollment to actual enrollment. With average demand and the other parameters in hand, I back-out the expected mark-up. In the second stage, I estimate the remaining parameters using GMM. Because prices and quantities are endogenous, I use three sources of variation as instrumental variables: own and nearby exogenous provider characteristics, spillovers from a child care worker wage subsidy program that changed over time, and the distance to the nearest income-verification office.[15] I also match moments from survey and administrative data to discipline the estimates and identify variation in demand by eligibility status. I repeat the two stages until convergence. Given estimates of demand, I estimate the parameters for the returns to investing in quality by using nested pseudo-likelihood (Aguirregabiria and Mira, 2007; Bodéré, 2023; Sweeting, 2013). The expected profit under different quality ratings depends on the quality of nearby providers. To keep the problem tractable, I use a neural network to predict each provider's expected profit under a range of market outcomes. First, I determine the probability that other providers receive each quality rating. Given these probabilities, I update the estimated expected profit for each provider under each quality rating. Second, I choose the remaining parameters using maximum likelihood estimation (MLE). I then repeat the two steps until convergence.

[14]Wisconsin school districts use "4-K" to refer to their public preschools available for children under the age of five. In most school districts, preschool is only available to four year olds. For consistency I use the term "4-K" throughout to refer to these kinds of providers.

[15]To be sure, given that I do not directly observe where subsidized families live, distance to the nearest income-verification office is likely correlated with unobserved demand shocks. Instead, I use distance to the nearest income-verification office on the supply-side, as a quantity-shifter.

I find that families who are eligible for subsidies are more sensitive to price and distance from care. Families prefer high-quality care conditional on being quality-rated, but there is significant variation in taste for quality. Marginal and fixed costs for four- and five-star providers are higher than two- and three-star providers.

I then evaluate a reform Wisconsin adopted in 2022, which increased the maximum subsidy from the 35th percentile of prices to the 80th percentile of prices. Because the reform began at the same time as a federal budget increase, I compare the effects of the larger maximum subsidy against offering the prior maximum subsidy to more families. I endogenously determine the number of subsidized families so that the budget remains fixed. Under the larger maximum subsidy, I find that 8.4pp of eligible families receive the subsidy. If Wisconsin had instead maintained its previous maximum subsidy, 20.6pp of eligible families could have received the subsidy.

I find that 6.5pp more eligible children forgo formal care under the higher maximum subsidy relative to offering subsidies to more families, a 19% increase. I then decompose the effects on enrollment into three channels: changes in family choices (fixing price and quality), endogenous prices, and endogenous quality. 61% of the difference in formal care enrollment is explained by higher prices – prices are 9% higher under the larger maximum subsidy than the smaller maximum subsidy.

Under the larger subsidy, I show that 10.8pp fewer families enroll at middling-quality private providers[16] relative to when more families receive the subsidy, a 30% decrease. As discussed, most of these children instead do not enroll in any formal care. Some, however, substitute with other formal care. 1.4pp (11%) more low-income children enroll at low-quality private providers under the larger subsidy relative to subsidizing more families.[17] Most of the difference in enrollment at low-quality providers is explained by a larger number of low-

[16]Defined as three-star providers. These providers must meet standards for process quality (e.g., how to interact with children), structural quality (e.g., materials and space), and staff education and training. However, four- and five-stars have additional requirements and must meet a minimum score on the Environment Ratings Scale (ERS).

[17]Defined as providers with a rating of fewer than three stars. These are mostly providers who meet licensing standards, but do not commit to meet additional standards.

quality private providers under the higher maximum subsidy.[18] On the other hand, some unsubsidized families substitute with public care. 2.2pp (22%) more children enroll in public 4-K or Head Start as fewer families receive subsidies. Additionally, although enrollment at the highest-quality (five-star) private providers is lower under the larger subsidy, 1.2pp (54%) more children enroll at four-star providers. Among children who still receive the subsidy, 3.8pp (49%) more enroll at the highest-quality provider under the larger subsidy.

Consumer surplus for low-income families is 17% lower under the larger maximum subsidy relative to subsidizing more families. Higher prices explain 92% of the difference in consumer surplus. Producer surplus is 2% lower when fewer families are subsidized. Providers partially offset the effects of the larger maximum subsidy by increasing prices and changing their quality. If providers could not change their prices or quality, producer surplus would be 4% lower under the larger maximum subsidy than if more families are subsidized.

This paper builds on the literature evaluating child care subsidy policy on private markets,[19] especially those using structural methods.[20] Berlinski, Ferreyra, Flabbi and Martin (2024) and Borowsky, Brown, Davis, Gibbs, Herbst, Sojourner, Tekin and Wiswall (2022) treat child care as a choice between discrete types of care, including parental care. The cost of parental care is preventing mothers from working. Providers are price-takers in both models. Bodéré (2023) extends this work by allowing providers to set mark-ups. As in similar work by Allende (2021) and Neilson (2025) on education markets, providers set mark-ups based on which families live nearby. I extend this work by evaluating alternative cost-equivalent policies, in which the state may not subsidize all eligible families.[21] I also incorporate public

[18] 69% of the difference in enrollment at low-quality providers is explained by changes in quality. To be sure though, 57% of the difference in enrollment at low-quality providers is explained by sorting, as unsubsidized families switch to low-quality care. However, higher prices explain -26% of the difference in enrollment at low-quality providers: higher prices push families out of formal care altogether.

[19] Others have also considered the effect of public preschool on private markets (Bassok, Fitzpatrick and Loeb, 2014; Berne, 2024; Brown, 2018; Hoiting, Magnuson, Pilarz, Claessens, Yang and Awkward-Rich, 2025).

[20] A related paper using a structural approach to evaluate the child care market by Garcia-Vazquez (2026) evaluates the effect of child care regulations on private markets instead of subsidy policies.

[21] Other work evaluating the effects of expanding subsidy coverage have focused on changing eligibility requirements. However, because child care subsidies are not an entitlement program, even families who are eligible for subsidies may not be able to receive subsidies.

providers, so that I can determine the extent to which subsidies may crowd out public care. Additionally, my data covers the near-universe of licensed providers in Wisconsin, so I estimate heterogeneous unobserved demand shocks for each of these providers.

I also contribute to the literature evaluating how to improve the quality of child care, especially for low-income children. Many consider which interventions can improve children's outcomes, say by increasing per-child expenditures or teacher training (Currie and Neidell, 2007; Francis and Barnett, 2019; Joo, Magnuson, Duncan, Schindler, Yoshikawa and Ziol-Guest, 2020; Walters, 2015). I instead consider how subsidy policy design may "crowd in" quality investments from private providers. Others show that low-income families are more likely to enroll in low-quality care than high-income families, even when universal care is available (Drange and Telle, 2018) or after receiving more information (Herbst, 2018). Subsidized children are also more likely to enroll in low-quality care (Herbst and Tekin, 2016). I demonstrate that availability of quality care is relevant for subsidized families' choices.

Finally, I contribute to the broader literature on the effects of social safety net program design. Lee, Sojourner, Davis and Borowsky (2025) show the effects of higher maximum subsidies on child care prices in Minnesota. Others evaluate how subsidies may affect prices in other industries, such as health care (Cabral, Geruso and Mahoney, 2018; Duggan, Starc and Vabson, 2016; Finkelstein, 2007), housing (Collinson and Ganong, 2018; Eriksen and Ross, 2015; Fack, 2006; Susin, 2002), and groceries (Leung and Seo, 2023). Similarly, Rothstein (2010) considers how the Earned Income Tax Credit may lower wages by increasing labor supply. I extend this literature by accounting for the number of participating families. As discussed throughout, changes to the amount given to recipients may be correlated with changes to either program expenditures or the number of recipients. Furthermore, I demonstrate that program participation affects the quality of local care. My results suggest that reducing the costs to enroll in in-kind services may have positive spillovers, by "crowding in" higher-quality services. This is in contrast to other work suggesting that reducing the

cost to enroll leads the state to serve families less in need (Finkelstein and Notowidigdo, 2019; Rafkin, Solomon and Soltas, 2023).[22] Additionally, others evaluate the optimal design of tax and transfer programs (Beaudry, Blackorby and Szalay, 2009; Blundell and Shephard, 2012; Choné and Laroque, 2011; Saez, 2002), including for child care subsidies (Ho and Pavoni, 2020). These generally weigh the optimal tax and transfer policy across the income spectrum, accounting for labor supply responses. Instead of determining the optimal policy, I weigh cost-equivalent policies to quantify the trade-off between subsidizing more families or providing larger subsidies. I build on this literature by considering how prices of in-kind services may respond to subsidy policies.

The rest of the paper is organized as follows. In section 2, I review the institutional context and data. In section 3, I show the quasi-experimental evidence on the effect of the number of subsidized families and the maximum subsidy on price and quality of care. Motivated by these facts, in section 4, I introduce the model. I explain how the model is estimated in section 5. I present counterfactuals in section 6. In section 7, I conclude.

2 Institutional Context and Data

2.1 The Child Care Market in Wisconsin

Wisconsin has a diverse child care market, including both private and public options. The majority of enrollees in my sample enroll at private providers.

The majority of private providers are centers. Centers operate from commercial buildings and generally have higher capacities. Private providers that operate from residential facilities (including the provider's own home) are called family providers. Family providers have a licensed capacity of up to eight children. Because of their low capacity, while family providers

[22] To be sure, others have found that increasing the costs to enroll in social safety net programs can also reduce access for the neediest eligible individuals (Deshpande and Li, 2019). Public health care programs may also benefit from reducing costs of enrollment because less needy individuals are often lower cost (Shepard and Wagner, 2025).

represent 46.2% of all licensed providers, only 9% of private enrollees attend a family provider. Family providers are more popular for subsidized families, however, with 17.3% of subsidized children enrolled at family providers.

36.1% of enrollees in my sample attend public care. The largest public option in Wisconsin, public 4-K, is administered by local Wisconsin school districts. The program is free for all four-year-olds, but is optional. In 2023, 63% of Wisconsin four-year-olds enrolled in 4-K (NIEER, 2023). Similar to other grades, school districts are obligated to provide instruction to all children who live within the school district. 6.6% of public providers are charter schools and 6.7% also offer 3-K (e.g., preschool for three-year-olds). 32.4% have full school-day schedules. Of the remaining schools, 39.0% meet less than the full school week and 57.6% meet less than a full school-day. In addition, Head Start is available to families with incomes under the poverty line. My sample includes Head Start providers who are licensed to offer group care. I exclude, for example, Early Head Start providers which focus on in-home family support services.

2.2 Subsidy Use Across Wisconsin

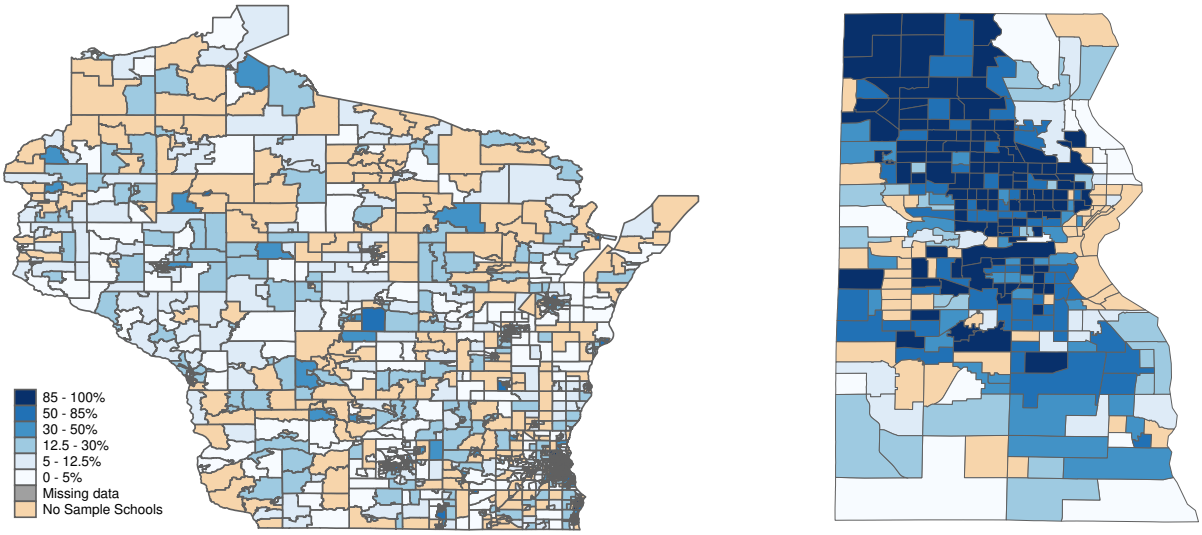
In Wisconsin, all families earning below 200% of the poverty line are eligible for subsidies. [23] Yet many eligible families fail to receive subsidies. About 17% of families with children in poverty receive child care subsidies. Subsidy use is higher for families with younger children: about 29% of children under age five in poverty are subsidized.[24] Despite the relatively small size of the program, subsidized children make up a large share of private enrollment. In my sample, 28% of full-time-equivalent enrollment at private providers is from subsidized families. The subsidized share of enrollment is highly heterogeneous over space though. In Figure 1, I map the share of private enrollment in each census tract from subsidized families.

[23] Prior to July 2024, families had to earn no more than 185% of the poverty line.

[24] Estimated using ACS 5-year estimated count of families with children under age 18 living in poverty (2024), Wisconsin Department of Children and Families counts of families served under the poverty line (July 2026), and Wisconsin Department of Children and Families counts of children under age five (2nd quarter, 2026). I assume in the estimate for children under age five that families with children under age five participating in the program are similarly likely to be under the poverty line.

In many census tracts, fewer than 5% of all enrollment comes from subsidized children. But in some neighborhoods of urban Milwaukee, over 85% of private enrollment comes from subsidized children.

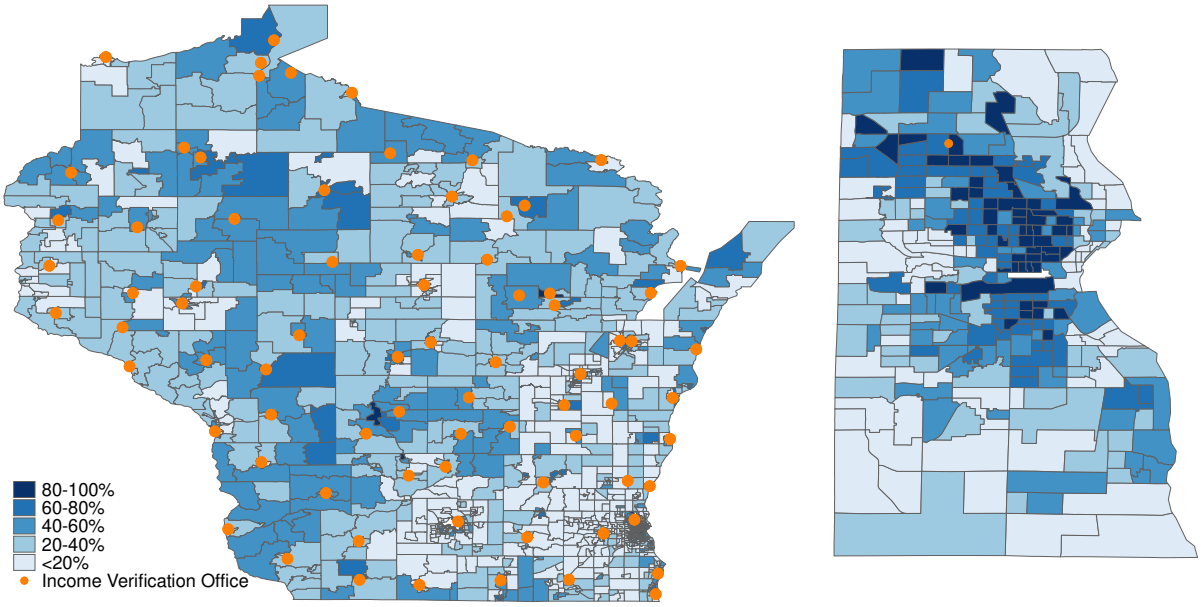
Figure 1: Proportion of Enrolled Children with Subsidies by Census Tract (2022-2025)



(a) Wisconsin (b) Milwaukee

Notes: Shows the proportion of enrolled children with subsidies in the census tract where the provider is located. Shown for sample providers only. Tracts with no sample providers are noted.

Comparing Figure 1 with Figure 2, neighborhoods where enrolled children are the most likely to be subsidized are often neighborhoods with more eligible children. Of course, families eligible for subsidies are more likely to be subsidized, but only a relatively small share of eligible families are subsidized. The high share of private enrollment that are subsidized in these neighborhoods suggests that low-income families who are unsubsidized are also less likely to enroll in private care.



(a) Wisconsin (b) Milwaukee

Figure 2: Proportion of Families Eligible for Subsidies (2025)

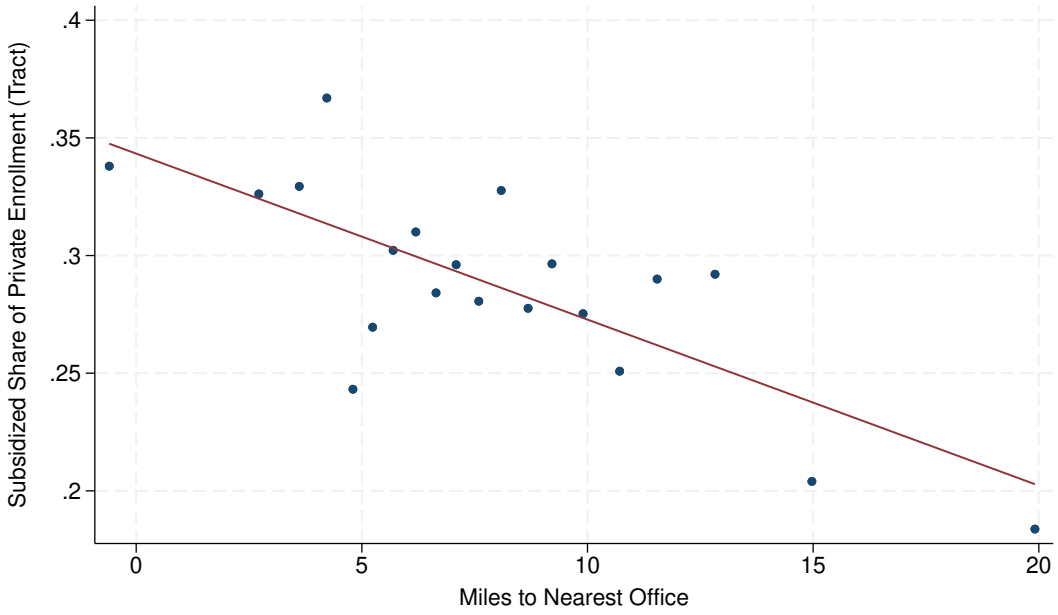
Notes: Shows the proportion of families with young children with incomes below 200% of the poverty line, the eligibility threshold in 2025. Orange dots represent the location of income-verification offices.

Even conditional on the share of families eligible for subsidies, it may be easier to obtain subsidies if you live in certain neighborhoods. Some neighborhoods are located closer to income-verification offices, where families can provide the paperwork to demonstrate they meet income requirements. Families must verify their income annually, increasing the costs of not only initially signing up, but also continuing to receive subsidies. Figure 2 shows where each of these offices is located across the state.[25] 56.5% of eligible families live at least 5 miles from the nearest income-verification office. In Figure 3, I show, conditional on the

[25]Families are not always able to go to the nearest office – families must go to offices within their "region." While these regions are often large enough that the nearest income-verification office is within the family's region, this requirement increases the average miles eligible families travel to their nearest office by 5%. While the state allows families to also apply online, low-income families in Wisconsin have historically been more likely to apply for other programs in-person. Families are also more likely to have a successful application if they apply in person (Voskuil, Friedsam and DeLeire, 2011). Others have leveraged office closings to causally identify the effect of living near income-verification offices. These studies have found persistent negative effects on participation in SSDI/DI (Deshpande and Li, 2019) and SNAP (Bitler, Cook, East, Porter and Tiehen, 2025).

proportion of families eligible for subsidies, the relationship between distance to the nearest income-verification office and the share of private enrollees who are subsidized. For every mile from the nearest income-verification office, the subsidized share of private enrollment falls by 3.5%, controlling for county, the share of families eligible for subsidies, and local urbanicity. Similarly, for every mile from the nearest income-verification office, the estimated share of eligible families receiving subsidies falls by 1.7%.

Figure 3: Providers Near Income-Verification Offices Have More Subsidized Enrollees



Notes: Outcome is the proportion of enrollment in the census tract from subsidized families (2022-2025). Controls for county, urbanicity, and the proportion of families eligible for subsidies.

2.3 Wisconsin Subsidy Policy from 2017-2025

Subsidized families can choose from any licensed private provider with a quality rating.[26] Say the family chooses a provider with price p. If the price is below a *maximum subsidy*[27], the state covers the cost of care. However, if p is greater than the maximum subsidy $MaxSub$,

[26] All providers which are quality rated must agree to accept subsidies.
[27] Also referred to as a maximum reimbursement rate.

the family pays the difference. Out-of-pocket payment can then be defined as:

$$OOP(p; MaxSub) = \begin{cases} p - MaxSub & \text{if } p > MaxSub \\ 0 & \text{if } p \leq MaxSub \end{cases} \tag{1}$$

Wisconsin sets the maximum subsidy separately by the age of children served, provider type (e.g., center or family provider), and county. Before 2017, the maximum subsidy had previously been set in 2014 to match local prices. Generally, maximum subsidies are higher for centers serving younger children. Maximum subsidies are higher in counties with higher local prices. In 2017, outside of Tribal Nations,[28] the maximum subsidy was as low as $99 a week for family providers caring for school-aged children in rural Jackson County and as high as $250 a week for centers caring for infants in Dane County (i.e., home to Madison).

In March 2018, Congress passed a 38% increase in CCDF funding (DHS, 2018). Thereafter, Wisconsin increased its maximum subsidy in a staggered fashion from October 2018-October 2019. The roll-out varied by ages served, provider type, and county. Averaging across county, the roll-out is summarized in Figure 4. In October 2018, Wisconsin increased the maximum subsidy for children ages zero to three by 5%. The maximum subsidy for children ages zero to one was also required to be at least $175 per week. Wisconsin then increased the maximum subsidy by an additional 5% in January 2019.[29] Finally, Wisconsin increased its maximum subsidy again in October 2019 to the 35th percentile of prices.[30] If the state determined the 35th percentile of prices was lower than the maximum subsidy, the maximum subsidy remained the same. The percent increase in the maximum subsidy from 2017 to October 2019 ranged from as low as 5% to as high as 77%.[31]

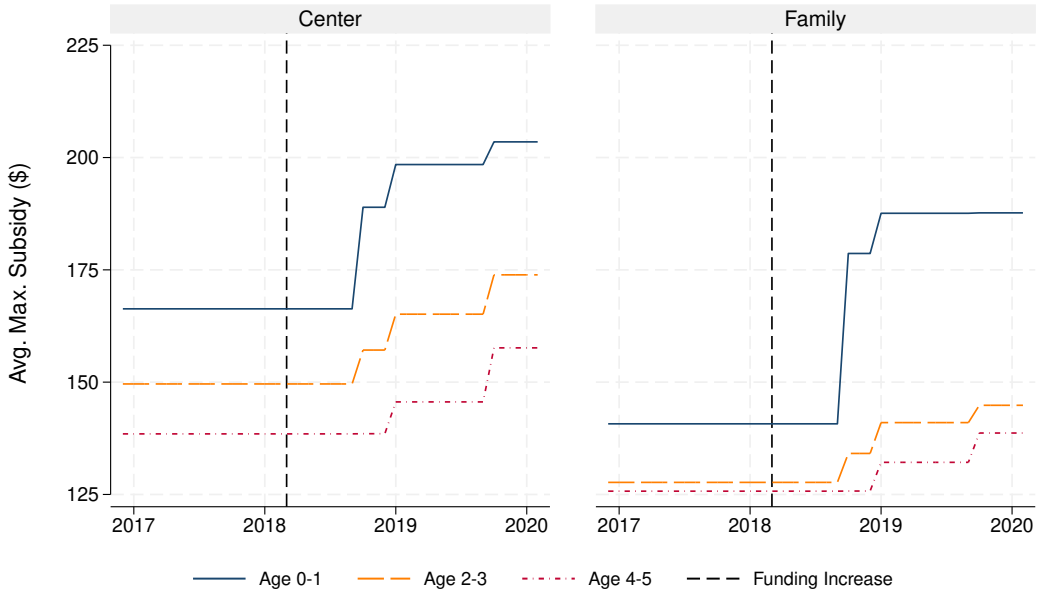
[28] Due to limited ACS data, I exclude Tribal Nations from the sample.

[29] In practice, because of the $175 a week floor, some providers had very large initial increases in their maximum subsidy, especially family providers. For family providers serving infants in Jackson County for example, the maximum subsidy increased by 49%.

[30] Based on prices submitted in a survey of providers. For counties or provider types with few providers, Wisconsin grouped similar counties together, based on the urban proportion of each county.

[31] Prior to 2022, Wisconsin also set its maximum subsidy differently by quality rating, offering an "add-on" to providers with higher quality ratings, proportional to the maximum subsidy. From October 2018 to January 2019, Wisconsin decreased its add-on for three-star providers by 3.8%, increased its add-on for

Figure 4: Maximum Subsidy Increases from October 2018 to October 2019



Notes: Nominal average maximum subsidy weighted by county population of eligible families. Funding increase shows the timing of passage of Congressional funding increase. Centers operate from commercial facilities. Family providers operate from residential facilities. Rates by age of participating child shown.

Despite the increase in federal funding, the number of subsidized families fell by 12% from 2017 to 2020. Eligibility cut-offs did not change over this period. However, the allocation of funds shifted over this period. The average subsidy paid per family increased, in real terms, from $845 per month in fiscal year 2016 to $1,217 per month in fiscal year 2019, a 44% increase. Funding for administration of the program, including for determining the eligibility of applicants, fell statewide by 2.1% over the same period (Gentry, 2017,1).

Excluding supplementary and one-time funding increases, Congress increased CCDF funding by 15% between the 2019 and 2021 fiscal years. Under the American Rescue Plan Act and the Coronavirus Response and Relief Supplemental Appropriations, Congress also

four-star providers by 0.9% and increased its add-on for five-star providers by 1.6%. While the changes to the add-ons are small relative to the increase in the maximum subsidy, because the add-ons are proportional to the maximum subsidy, the quasi-experimental results may conflate the role of these add-on changes and increases in the maximum subsidy. From 2022-2025, Wisconsin had no such add-on system, so I use the structural model to evaluate the effect of changes in the maximum subsidy on quality absent these add-ons.

allocated an additional $48.965 billion (83% of allocations for FY2021), which states were obligated to spend by 2024 (Lynch and Boyle, 2023). With this large funding increase, Wisconsin increased its maximum subsidy to the 80th percentile of prices. Providers in my sample faced an average increase in the maximum subsidy of 130% from 2021 to 2022.[32] The average subsidy paid per family[33] in fiscal year 2023 was $1,666 per month (Gentry, 2025), representing at least half of monthly income for 79% of participating families.

2.4 Data

Most of the data are from Wisconsin's Department of Children and Families (DCF). Additional data on public 4-K providers comes from Wisconsin's Department of Public Instruction (DPI).

Quasi-Experimental Sample The IV-DID approach I use in the following section requires I observe prices and quality prior to the maximum subsidy increase. The maximum subsidy increase in January 2022 is missing a reasonable pre-period: the COVID-19 pandemic greatly limited child care use from March 2020 to early 2021. For the IV-DID approach, I therefore evaluate the maximum subsidy increase from October 2018 to October 2019 using data from April 2017 until January 2020.[34] I limit the sample to licensed, year-round, full-time providers caring for at least some children younger than five. Because the quasi-experimental results focus on quality and price changes from private providers, I narrow the sample to private providers who accept subsidies (87% of all providers).[35]

[32] Details can be found at DCF (2026). Average increase is capacity-weighted and based on age-adjusted prices.

[33] Families may receive a subsidy for more than one child.

[34] April 2017 is when the state began its roll-out of Electronic Benefit Transfer cards for its child care subsidy program. I evaluate each year in January. I impute the results for January 2017 based on data from April 2017.

[35] Providers in Wisconsin sign an agreement with the state before accepting subsidies. All quality-rated providers must sign an agreement with the state to accept subsidies.

Structural Model Sample To estimate the structural model, I need data on total enrollment. I only observe total enrollment starting in fall 2020. To avoid estimating the model with data from the pandemic, I estimate the structural model using data from January 2022 to January 2025. I expand the sample to include Public 4-K, Head Start, and other public fee-based programs.[36] After dropping providers with missing data, the sample represents 84% of reported total enrollment and 88% of subsidized enrollment.[37]

Public 4-K Data From DPI, I observe for each school the total enrollment in public 4-K by eligibility for free or reduced-price lunch[38] each September.[39] I also observe school addresses, whether the school operates on a half or full school-day, and whether the school operates for part or all of the school-week.

Licensing Data As part of licensing, DCF tracks provider addresses, hours and months the provider is licensed to operate,[40] ages served, license start and end dates, the type of facility the provider operates from, and licensed capacity. Licensed capacity only reflects building size, rather than minimum student-teacher ratios, and should be treated as an upper-bound for true capacity.

Price and Subsidized Enrollment DCF collects provider-level prices and subsidized enrollment in the process of administering subsidies. Providers must submit prices so the state can allocate the correct amount each month. Monthly subsidized enrollment is tracked

[36] Public programs are less likely to be available year-round or for the full-day. I keep public providers operating in January and offering care to children younger than five.

[37] Some providers choose not to report any total enrollment. 13.6% of seats at otherwise in-sample licensed providers are unreported. Subsidized enrollment, however, is observed at every provider. Excluding public providers or Head Starts, sample providers represent 82% of reported total enrollment and 82% of subsidized enrollment. See Table A.1 and Table A.2 for a detailed comparison between sample providers and all licensed providers, as well as sample statistics.

[38] Families are eligible for free or reduced-price lunch if they earn no more than 185% of the poverty line

[39] I assume January enrollment is the same as September enrollment.

[40] Licensed hours are not necessarily the same as true operating hours, but rather when the provider can legally operate. I only use licensed hours to classify providers as full- or part-time.

in the same process.[41] Providers can update prices at any time, and prices may vary by the child's age.[42] For the structural model, only 2% of estimated enrollment is dropped from the sample because the provider never submits prices.[43]

Quality The state's quality rating system (YoungStar) gives licensed providers a discrete rating from one to five. The quality rating is updated annually. The vast majority of providers (87%) agree to be rated. Providers that apply but fail to meet licensing requirements receive one star, though this is rare.[44] Any provider that meets licensing standards and is willing to accept subsidies earns two stars. For 2022-2025, 41% of licensed providers have two stars. To earn three stars, providers must meet standards for process quality (e.g., how to interact with children), structural quality (e.g., materials and space), and staff education and training. Earning four or five stars requires meeting additional standards for process and structural quality, as well as staff education and training. Providers must also earn an average score of at least four or five, respectively, on the Environment Rating Scale (i.e., ITERS, ECERS or FCCERS), a long-standing standardized assessment (Blau and Currie, 2006). 28% of Wisconsin providers are at least four stars. We may worry that providers who are high-quality may not be quality-rated because of fixed costs of applying. Nevertheless, I find that unrated providers have higher average student-teacher ratios. Additionally, a validation study conducted in Wisconsin finds that lower-rated providers score lower, on average, on the Environment Rating Scale. Additionally, differences in quality between two to three stars are larger than the difference in quality from three to four stars (Magnuson and Lin, 2015).

[41] Wisconsin data comes from records obtained in the process of administering subsidies using Electronic Benefit Transfer cards, which Wisconsin began using in 2017 (DECE, 2018).

[42] I do not observe subsidized enrollment by age, so I use a fixed-effects model to estimate each provider's underlying price, differencing out age effects.

[43] For the structural model, I impute prices in earlier years based on later observations.

[44] In 2022, for example, only four providers in the sample received one star.

Total Enrollment Data I observe provider-level total enrollment collected as part of Wisconsin's administration of its Child Care Counts program. Wisconsin offered grants (Child Care Counts) to providers from 2020-2025 based on their total enrollment and employment. Participation was high: only 13.6% of seats at otherwise in-sample licensed providers are unreported. Any licensed provider in good standing could apply.

Additional Survey Data Neighborhood characteristics come from the American Community Survey. For the quasi-experimental results, I use tract-level data. For the structural model, I use block-level data. When necessary, I impute block-level variation from tract-level data. I also match moments on distance traveled and age of enrollment by income based on data from the National Survey of Early Care and Education (2024).

3 Quasi-Experimental Evidence

The model discussed in section 4 assumes providers respond to changes in the number of families subsidized and the changes in the maximum subsidy. In this section, I evaluate whether this assumption is reasonable. A challenge is that both the number of families subsidized and the maximum subsidy are endogenous. In subsection 3.1, I discuss the 2SLS-DiD approach[45] I employ to address these endogeneity concerns. I consider two outcomes. The first, discussed in subsection 3.2, is whether child care of a certain quality rating is available in a given census tract. I consider whether a tract has a provider of at least three, four, and five stars.[46] The second, discussed in subsection 3.3, is the out-of-pocket payment that subsidized families pay.[47] I find that neighborhoods with higher subsidy use are

[45] This is similar to the empirical strategy used by, for example, Johnson and Jackson (2019).

[46] Five stars is the highest possible rating. Validation studies have suggested that three star providers are more different from two star providers than four star providers. Four and five star providers must receive a certain average rating on the Environmental Rating Scale and three star providers must implement certain curricula and meet staffing standards.

[47] I observe the out-of-pocket payment and subsidized enrollment at the provider-level. In practice, I use the out-of-pocket payment as the outcome variable for a given provider and weight by subsidized enrollment. I weight all tract-level results by the number of children under age five living in the census tract.

more likely to have a high-quality provider. Neighborhoods with higher maximum subsidies have higher out-of-pocket payments. I conclude with a brief discussion of the findings and robustness checks.

3.1 Quasi-Experimental Methods

Both the proportion of families subsidized and the maximum subsidy are endogenous. I address each of these exogeneity concerns in turn in this section.

First, more families may be subsidized in neighborhoods with greater unobserved demand for child care. Neighborhoods with greater demand for child care will have higher prices. Neighborhoods with greater unobserved demand for high-quality care may have higher subsidy rates – because families wish to enroll at more expensive providers – and higher-quality providers. To address this endogeneity, I leverage variation in the location of income-verification offices.[48] Families can go to these offices to verify their eligibility for subsidies, as discussed in section 2. The fixed costs of applying for subsidies are lower in neighborhoods closer to these offices. We may still worry that these offices are strategically located. Offices are more likely to be located in poor, urban neighborhoods. Because these neighborhood characteristics are observable, I can condition on these characteristics. While the state may locate offices based on unobservables, these offices serve other, larger programs, and the state is more likely to locate offices based on these programs than the smaller child care subsidy program. With this in mind, I condition on participation in the Supplemental Nutrition Assistance Program (SNAP), which I observe in the ACS. I treat the location of these offices as exogenous conditional on these observables.

Consider, for example, if we were only interested in the effect of neighborhood subsidy use on the two outcomes of interest. Let Y_{it} be the relevant outcome observed in year t for

[48] Herbst and Tekin (2016) similarly use distance to income-verification offices as an instrument for a given family's participation in social safety net programs. (Deshpande and Li, 2019) alternatively treat the timing of income-verification office closures as exogenous in a difference-in-differences design.

either census tract i or provider i. The first and second stages can be described as

$$PrSub_{it} = \alpha_0 + \alpha_1 DistOffice_i + \alpha_2 X_{it} + \zeta_c + \zeta_t + \nu_{it} \quad (1)$$

$$Y_{it} = \beta_0 + \beta_1 PrSub_{it} + \beta_2 X'_{it} + \eta_c + \eta_t + \varepsilon_{it} \quad (2),$$

where $\zeta_c, \zeta_t, \eta_c, \eta_t$ are county and time fixed-effects, X_{it} are a set of demographic and provider controls, $DistOffice_i$ is the distance to the nearest income-verification office, and $PrSub_{it}$ is the proportion of families subsidized in the census tract (or the provider's census tract).[49]

Second, the state sets the maximum subsidy higher in counties with higher prices. The maximum subsidy is also higher for center-based care, which is more expensive than family care on average. To address this source of endogeneity, I leverage the roll-out of the maximum subsidy increase in 2018-2019.[50] I treat the maximum subsidy as exogenous *conditional* on baseline differences between different counties and provider types. I measure treatment as the maximum subsidy faced by the provider (or the average maximum subsidy faced by all providers within the tract[51]). I then condition on county and year differences η_c, η_t, as well as type differences in X_{it}:

$$Y_{it} = \beta_0 + \beta_1 MaxSub_{it} + \beta_2 X_{it} + \eta_t + \eta_c + \varepsilon_{it}. \quad (2)$$

[49] I do not observe the proportion of families subsidized in the census tract directly. Rather, I use the proportion of subsidies used at providers in the given tract relative to the number of young children who live in the census tract. In later model estimates, I demonstrate that families have a strong taste for providers located near where they live.

[50] For tract-level quality results, I use the average maximum subsidy faced by all providers in that tract. For provider-level out-of-pocket payment results, I use the baseline maximum subsidy faced by that provider.

[51] I use a tract-average of the maximum subsidy to evaluate the effects on quality of care available in the neighborhood. If there are no providers in the tract, I use the county-average. While all providers face the same *schedule* of maximum subsidies, the type of providers in the tract or county also affects the average maximum subsidy. For example, as discussed in section 2, family providers faced an earlier roll-out of the maximum subsidy increase, on average. Neighborhoods with more family providers will then have a different exposure to the maximum subsidy policy than neighborhoods with more centers. However, changes in the kind of providers in a neighborhood may be endogenous. To avoid the treatment incorporating changes in the composition of providers over time, I calculate the maximum subsidy average based on the composition of providers in the tract or county at baseline. The treatment then represents the average maximum subsidy if the composition of providers had remained fixed.

While I could test the effect of the maximum subsidy or the proportion of families subsidized, the proportion of families subsidized and the maximum subsidy are correlated. Families who can expect to receive a larger subsidy may be more willing to seek out the subsidy. Similarly, families who live in neighborhoods with more expensive child care options may seek out the subsidy. These neighborhoods also often have higher maximum subsidies. To address these concerns, I use 2SLS-DiD as my preferred specification, leveraging both sources of variation.

I once again instrument for the proportion of families receiving subsidies with distance to the nearest income-verification office. I also instrument for the interaction between the maximum subsidy and the proportion of families subsidized with the interaction between the maximum subsidy and distance to the nearest income-verification office. I again assume that the maximum subsidy is exogenous conditional on county, year, and provider type fixed-effects. In summary, with equations 1a and 1b as the first stage and equation 2 as the second stage, I perform the following:

$$\begin{aligned} PrSub_{it} =& \alpha_0 + \alpha_1 DistOffice_i + \alpha_2 DistOffice_i \times MaxSub_{it} \\ &+ \alpha_3 MaxSub + \alpha_4 X_{it} + \zeta_c + \zeta_t + \nu_{it} \end{aligned} \tag{1a}$$

$$\begin{aligned} (PrSub_{it} \times MaxSub_{it}) =& \gamma_0 + \gamma_1 DistOffice_i + \gamma_2 DistOffice_i \times MaxSub_{it} \\ &+ \gamma_3 MaxSub + \gamma_4 X_{it} + \zeta_c + \zeta_t + \nu_{it} \end{aligned} \tag{1b}$$

$$\begin{aligned} Y_{it} =& \beta_0 + \beta_1 PrSub_{it} + \beta_2 (PrSub_{it} \times MaxSub_{it}) \\ &+ \beta_3 MaxSub_{it} + \beta_4 X'_{it} + \eta_c + \eta_t + \varepsilon_{it}. \end{aligned} \tag{2}$$

Throughout, I control for local demographics, including measures of the income distribution, marital status for mothers of young children, birth rates by marital and educational status, Supplemental Nutrition Assistance Program (SNAP) receipt, the number of young children who live nearby, urbanicity, and provider types. For the out-of-pocket payment results, I further control for the provider's quality rating. Because I do not observe age, I use age-

adjusted out-of-pocket payments and sticker prices.[52]

3.2 Quality

Table 1 reports the 2SLS-DiD estimates. The instrument is strong, with F-statistics for the two instrumented variables of 36.0 and 34.7, respectively. The proportion of families subsidized has the largest effect on whether a census tract has a middling-quality provider, though this may reflect the fact that middling-quality providers are more common. A 1pp higher proportion of families subsidized increases the likelihood a tract has a provider of at least three stars by 4.4pp, or 6.9% of the sample mean. On the other hand, a 1pp higher proportion of families subsidized increases the likelihood a tract has a provider of at least four stars by 1.8pp (5.9% of the sample mean) and five stars by 1.3pp (6.3% of the sample mean).

On the other hand, a $10 higher weekly maximum subsidy has no significant positive effect on the quality of available providers. If anything, the effect of a higher maximum subsidy on having a provider of at least three stars is marginally negative.

3.3 Out-of-Pocket Payments

Table 2 reports the results on out-of-pocket payments from the 2SLS-DiD approach. Both instruments are relevant, with first-stage F-statistics of 34.4 and 42.0. I find that a $10/week higher maximum subsidy raises out-of-pocket payments by 18.1%, increases the likelihood a subsidized family pays anything out of pocket by 6.6pp, and raises sticker prices by 5.1%. A 1pp higher proportion of families subsidized increases sticker prices by a marginally significant 0.2%. These results suggest, conditional on provider quality, a higher maximum subsidy increases prices and out-of-pocket payments, while subsidizing more families has a

[52] I observe the price that the provider offers for each age group, as well as the maximum subsidy by age group. To age-adjust the prices, I use a fixed-effects model assuming that the difference in out-of-pocket payments by age are the same across providers. Prices and out-of-pocket payments are centered at the price and out-of-pocket payment for three-year-olds.

Table 1: Increasing Access to Subsidies Increases Access to High-Quality Providers

	(1) Any 3+ Star	(2) Any 4+ Star	(3) Any 5 Star
Proportion Families Subsidized (1pp)	0.044***	0.018***	0.013**
	(0.009)	(0.007)	(0.005)
Max. Sub. ($10/week)	-0.050*	-0.001	0.011
	(0.027)	(0.018)	(0.014)
Prop. Fam. Sub. × Max. Sub.	-0.007***	-0.002	-0.001
	(0.002)	(0.001)	(0.001)
N	5319	5319	5319
F (Prop. Fam. Sub.)	35.995	35.995	35.995
F (Prop. Fam. Sub. × Max. Sub.)	34.721	34.721	34.721

Notes: Outcome is an indicator for whether the census tract has at least one provider with a YoungStar rating of 3+ (column 1), 4+ (column 2), or 5 (column 3) stars. The sample is Wisconsin census tracts, 2017–2020. Result measured in January of each year. Proportion Families Subsidized is the proportion of families subsidized ($PrSub_{it}$, 1pp units, mean-centered). Max. Sub. is the year-varying maximum subsidy ($MaxSub_{it}$, $10/week units, mean-centered). The proportion of families subsidized and its interaction with the maximum subsidy are instrumented with the minimum distance from the tract to the nearest income-verification office and its interaction with the maximum subsidy. The maximum subsidy main effect is assumed to be exogenous conditional on county, year fixed effects. Controls include the number of young children, the proportion of young children's parents who are married, birth rate to married and college-educated women, coarse income distribution for families with young children (100%, 200%, 300%, 400%, 500+% of the federal poverty line), proportion of families with young children receiving SNAP, tract urbanicity, county and year fixed effects. Observations are weighted by the number of young children per tract. Standard errors are clustered at the county-year level and shown in parentheses. The F rows report the Angrist-Pischke conditional first-stage F-statistic for each endogenous regressor. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

relatively small effect.

Table 2: Out-of-Pocket Payments Increase with the Maximum Subsidy

	(1) ln(OOP)	(2) OOP>0	(3) ln(Price)
Proportion Families Subsidized (1pp)	0.013	0.006	0.002*
	(0.012)	(0.004)	(0.001)
Max. Sub. ($10/week)	0.181**	0.066**	0.051***
	(0.085)	(0.026)	(0.009)
Prop. Fam. Sub. × Max. Sub.	-0.003	-0.001*	-0.000
	(0.002)	(0.001)	(0.000)
N	7557	7557	7557
F (Prop. Fam. Sub.)	34.363	34.363	34.363
F (Prop. Fam. Sub. × Max. Sub.)	41.956	41.956	41.956

Notes: Outcomes are the log expected out-of-pocket payment (or $1 for providers with $0 out-of-pocket payment) for a subsidized family at the provider (ln(OOP), column 1), an indicator for a positive out-of-pocket payment (OOP>0, column 2), and the log sticker price (ln(Price), column 3), all measured at the provider-year level. The sample is Wisconsin licensed private providers with at least two stars, 2017–2020. Result measured in January of each year. Proportion Families Subsidized is the proportion of families subsidized ($PrSub_{it}$, 1pp units, mean-centered). Max. Sub. is the year-varying maximum subsidy ($MaxSub_{it}$, $10/week units, mean-centered). The proportion of families subsidized and its interaction with the maximum subsidy instrumented with the minimum distance from the tract to the nearest income-verification office and its interaction with the maximum subsidy. The maximum subsidy main effect is assumed to be exogenous conditional on county, year fixed effects. Controls include the number of young children in the provider's tract, the proportion of young children's parents who are married, birth rate to married and college-educated women, coarse income distribution for families with young children (100%, 200%, 300%, 400%, 500+% of the federal poverty line), proportion of families with young children receiving SNAP, tract urbanicity, and star, county, provider-type, and year fixed effects. Observations are weighted by subsidized enrollment. Standard errors are clustered at the county-year and shown in parentheses. The F rows report the Angrist-Pischke conditional first-stage F-statistic for each endogenous regressor. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Taken together, the evidence suggests that the proportion of families subsidized has a small effect on what subsidized families pay, conditional on the quality of care they receive. On the other hand, higher maximum subsidies raise both sticker prices and out-of-pocket payments.

3.4 Discussion and Additional Evidence

The quasi-experimental results establish that neighborhoods with more subsidized children have higher-quality providers and that higher maximum subsidies lead to higher out-of-

pocket payments.

In Appendix B, I report similar results when using an alternative difference-in-differences approach. I rely on Pennsylvania using the same federal funding increase to expand the number of children it served rather than increase its maximum subsidy. In each state, I compare the effects of living in high-poverty census tracts, where families are more likely to be eligible for the subsidy, before and after the federal funding increase. While Wisconsin saw no overall increase in quality in high-poverty tracts, out-of-pocket payments increased. In Pennsylvania, on the other hand, high-poverty tracts were more likely to have a high-quality provider after the policy change and were no more likely to have higher out-of-pocket payments, conditional on quality.

In Appendix C, I also consider an alternative approach that leverages variation in exposure to a statewide decline in subsidized families using triple-differences. Rather than rely on the instrument, I control for baseline differences in census-tracts exposed to larger declines in subsidy use. I confirm that increasing the number of families subsidized in a neighborhood increases the probability the neighborhood has a middling-quality provider and that a higher maximum subsidy leads to higher out-of-pocket payments. However, I also find that neighborhoods with higher maximum subsidies are more likely to have a higher-quality provider. I ultimately prefer the 2SLS-DiD approach because the changes in the proportion of families subsidized may be endogenous, reflecting either mean reversion or changes in neighborhood taste for child care.

But what drives these changes in quality and prices? How much do changes in price and quality affect where and whether families enroll in child care? How many fewer families can the state subsidize if the maximum subsidy increases? To answer these questions, in the next section I describe a model of the child care market.

4 Model

The market equilibrium is determined in three stages, given the maximum subsidy and the proportion of families subsidized. First, providers invest in quality, anticipating competition and demand. Second, providers observe their own quality and the quality of other providers in the market and set prices to maximize expected profit. Third, families choose a private or public provider, or no provider at all. Providers solve this game using backwards induction. Accordingly, in this section I first discuss demand, then price-setting behavior, and then quality-setting behavior. After establishing the demand and supply model, I discuss the state's problem. Based on the anticipated market equilibrium, the state offers subsidies to as many eligible families as it can afford, given an exogenously set budget and maximum subsidy. I conclude the section by discussing the implications of the model.

4.1 Demand

Family i consumes utility U_{ijt} if they enroll at provider j in market-year t. Utility depends on the characteristics of provider j (in market-year t) and family i's demographic-specific preferences. Provider j is associated with a quality rating $Qual_{jt}$, observable characteristics X_{jt}, and unobservable (to the econometrician) average demand shocks ξ_{jt}. Family i must travel a distance d_{ij} to attend provider j and pays an out-of-pocket payment ($OOP(sub_i, p_{jt}; MaxSub_t)$) that depends on family i's subsidy status, the price provider j charges and the maximum subsidy in market-year t. Family i also has an unobserved, idiosyncratic shock to demand for provider j (ϵ_{ijt}). Utility can be summarized as:

$$U_{ijt}(sub_i) = \beta_i^X X_{jt} + \beta_i^Q Qual_{jt} + \beta_i^{oop} OOP(sub_i, p_{jt}; MaxSub_t) + \beta_i^d d_{ijt} + \xi_{jt} + \epsilon_{ijt}.$$

As reflected in the i sub-scripts on the β terms, preferences may vary by i, either based on i's demographics or idiosyncratically.[53] Subsidies only affect utility through their effect on out-of-pocket payments.

Families choose the provider (or no provider) that maximizes their utility. The choice set family i can choose from depends on the market-year they live in, the age of their child, and income-based eligibility (in the case of Head Start). I define this choice set as J_{it}. The choice set includes private providers, public providers, and the outside option (or choosing to forgo formal care).[54] Market-years are discrete and non-overlapping.[55]

To simplify notation, we can divide $U_{ijt}(sub)$ into two components. First is the part of utility common to all families, δ_{jt}. For example, on average, families prefer higher-rated providers or providers with higher ξ_{jt}. Where $\bar{\beta}^X$ and $\bar{\beta}^Q$ are the average taste for provider characteristics and quality, then we can define δ_{jt} as

$$\delta_{jt} = \bar{\beta}^X X_{jt} + \bar{\beta}^Q Qual_{jt} + \xi_{jt}.$$

Second is the part of utility specific to family i, μ_{ijt}, excluding idiosyncratic taste. For example, eligible families may have a greater distaste for distance. Some families also need to travel longer distances to reach provider j or pay a smaller out-of-pocket payment because of a subsidy. μ_{ijt} can be defined as $U_{ijt} - \delta_{jt} - \epsilon_{ijt}$.

If we assume ϵ_{ijt} is extreme value type one, the probability that family i chooses provider

[53] During estimation, I will have twelve types, for four age groups (ages 0 to 2, age 3, age 4, and ages 5 to 12) and three eligibility types (subsidized, unsubsidized and eligible for subsidies, and ineligible for subsidies). Taste for most characteristics will vary only by whether the family is eligible for subsidies. Subsidy status does not change preferences, but does affect out-of-pocket payments. Age affects whether a child is eligible to attend a provider and taste for formal care. I also allow for idiosyncratic (random) preferences for the highest-quality private care.

[54] Utility for public providers is estimated the same as for private providers. I observe almost all characteristics for both public and private providers. The one exception are quality-ratings, which I do not observe for public 4-Ks. I treat public 4-Ks as if they have no quality-rating and include as a characteristic whether the provider is a public 4-K. Similarly, I only observe schedules for public 4-Ks, which I include as binary characteristics set to zero for private providers.

[55] In future work, the assumption of non-overlapping markets could be relaxed.

j is

$$Pr(i \text{ choose } j) = \frac{\exp(\delta_{jt} + \mu_{ijt}(sub_i, MaxSub_t))}{\sum_{j \in J_t} \exp(\delta_{jt} + \mu_{ijt}(sub_i, MaxSub_t))}.$$

Families are more likely to choose providers that are generally more desirable (e.g., have higher δ_{jt}) and where they prefer based on family-specific taste (e.g., have higher μ_{ijt}). Family i's demand for provider j further depends on which other providers there are, as summarized in the denominator. If there are other, better, providers, family i is less likely to choose provider j.

Total enrollment at provider j relative to the overall size of the market is called market share (sh_{jt}). Enrollment is the sum of all families who actually choose j. While the econometrician does not directly observe μ_{ijt}, we can assume its distribution.

$$sh_{jt} = \int \frac{\exp(\delta_{jt} + \mu_{ijt}(sub_i, MaxSub_t))}{\sum_{j \in J_t} \exp((\delta_{jt} + \mu_{ijt}(sub_i, MaxSub_t))} dF(\mu_{ijt})$$

Let's say we only observe aggregate enrollment.[56] We also do not observe where family i lives. However, we do observe the distribution of demographic types $\tau \in \mathcal{T}$ across census blocks in market t.[57] Call the set of census blocks $\mathcal{L}_t$. I approximate the distance family i travels to provider j as the distance from the population-weighted centroid to the provider's address.

Say μ_{ijt} varies only by observable characteristics of provider j, family type τ (which encompasses subsidy status), the census block the family lives at, and the maximum subsidy. Let w_{lt}^{τ} be the share of all families of type τ in the market t that live at block $l \in \mathcal{L}_t$. Let π_t^{τ} be the proportion of families in market t of type τ. We can then aggregate enrollment by summing over all types $\tau \in \mathcal{T}$ in each census block $l \in \mathcal{L}_t$ in the market, integrating out

[56] I observe aggregate enrollment at each private provider by subsidy status. I observe aggregate enrollment at each public provider by whether the child is eligible for Free or Reduced-Price Lunch.

[57] I observe the distribution of families eligible or ineligible for subsidies across space. However, I do not observe where subsidy recipients live. I impute the location of subsidized families using data on where eligible families live across space and the number of subsidy recipients choosing a provider within market t.

idiosyncratic taste for observables (e.g., random coefficients on observables):

$$sh_{jt} = \sum_{\tau \in \mathcal{T}} \sum_{l \in \mathcal{L}(t)} w_{lt}^{\tau} \pi_t^{\tau} \int \frac{\exp(\delta_{jt} + \mu_{ijt,l}(\tau, MaxSub))}{\sum_{k \in \mathcal{J}(t)} \exp(\delta_{kt} + \mu_{ikt,l}(\tau, MaxSub))} dF(\mu_{ijt,l}(\tau)) \tag{3}$$

4.2 Supply

Family choices depend on the price, quality, and availability of providers. Families may prefer high-quality care, but high-quality care may not be available nearby. In this section, I discuss how providers adjust their prices or quality in response to changes in underlying demand. Observed quality ratings are updated annually in Wisconsin. Accordingly, I model these choices as a two-stage game. In the first stage, providers observe private information about the fixed costs they would pay to earn each quality rating. Providers also know the *distribution* of fixed costs faced by all firms, but not their competitors' exact private fixed costs. With this information and their knowledge of demand, providers choose their quality rating. In the second stage, providers observe the quality rating of all providers in the market and their own cost and demand shocks.[58] Providers then set prices to maximize profit. In the remainder of this section, I provide greater detail on each stage.

In the first stage, providers choose their quality rating. Providers know their exogenous characteristics, the exogenous characteristics of other providers, the shape of demand, the maximum subsidy, and the proportion of families that are offered the subsidy. With this knowledge, providers can estimate their expected profits under each quality rating. Call this expected profit $\mathbb{E}\Pi(Qual_{jt} = q; X_{jt}^m, X_{jt})$, which depends on own characteristics X_{jt} and the characteristics of providers in the market X_{jt}^m. Nearby providers likely affect expected profits more than faraway providers, so X^m may differ by provider j in market-year jt, even within the same market. To fix ideas, say there are two quality ratings, "Lo" and "Hi."[59] I

[58] I assume that providers do not observe cost and demand shocks until after they select quality for two reasons. First, providers update their quality rating annually, while cost and demand shocks may change more frequently. Second, I can then treat quality as an exogenous characteristic – and therefore an instrumental variable – for the estimation of demand.

[59] The probability that a provider is quality q when there are five quality ratings is available at Appendix G.

normalize the fixed cost of being a "Lo" provider to zero. We can then say that the provider solves

$$\max_{q \in \{Lo,Hi\}} \mathbb{E}\Pi(Qual_{jt} = q; X^m_{jt}, X_{jt}) - c_q - \varepsilon_{qjt},$$

where c_q is the fixed cost the provider pays to be quality q and ε_{qjt} is the additional provider-specific fixed cost of becoming quality q. Assume that ε_{qjt} follows a Type 1 extreme value distribution with scale parameter θ^ε. We can say that the probability that a provider is "Hi" quality is:

$$Pr(Qual_{jt} = Hi) = \frac{\exp(\mathbb{E}\Pi(Qual_{jt} = Hi) - c_{Hi})}{\exp(\mathbb{E}\Pi(Qual_{jt} = Hi) - c_{Hi}) + \exp(\mathbb{E}\Pi(Qual_{jt} = Lo))},$$

where, for the sake of succinctness, I have dropped the notation for X_{jt} and set $\theta^\varepsilon = 1$. The provider is more likely to be high-quality as the returns to being high-quality relative to being low-quality increase. Additionally, if the fixed costs of being high-quality fall, the provider is more likely to be high-quality. In Wisconsin, providers must be quality-rated to receive subsidies and all quality-rated providers must accept subsidies. The difference in expected profits between offering high- and low-quality then also encompasses differences in profits between accepting and rejecting subsidies.[60]

After choosing the effort to expend, providers observe their own quality ratings, as well as the quality ratings of their competitors. Providers then set prices to maximize profits, given their knowledge of the shape of demand. Profit depends on enrollment sh_{jt}, the price the provider sets p_{jt}, and their marginal cost $mc_{jt}(Qual_{jt})$, which also depends on the provider's quality rating. Given the quality choice, we can say that profit represents the solution to

I also discuss the role of θ^ε.

[60] Throughout, I refer to unrated providers, and providers rated at only one or two stars, as low-quality. It is possible that unrated providers are not low-quality, but rather have a distaste for serving subsidized children. However, the set of unrated providers is relatively small: 87% of licensed in-sample providers are quality-rated. Additionally, unrated providers have higher student-teacher ratios on average (7.1 vs. 6.7 students per teacher). A validation study in Wisconsin also found evidence that lower-rated providers score lower, on average, on the Environment Rating Scale (Magnuson and Lin, 2015).

the following maximization problem:

$$\Pi_{jt} = \max_{p_{jt}>0} \; sh_{jt}(p_{jt} - mc_{jt}(Qual_{jt}))$$

Solving for first order conditions, the provider sets price to marginal cost plus a mark-up:

$$\implies p_{jt} = mc_{jt}(Qual_{jt}) + \underbrace{\left| \frac{sh_{jt}}{\frac{\partial sh_{jt}}{\partial p_{jt}}} \right|}_{\text{mark-up}}.$$

Providers set higher prices if they have higher marginal costs, higher enrollment (market share), or if demand for provider j is more inelastic to provider j's price.

The provider solves the first stage through backwards induction. The provider invests more in quality if the provider can charge a sufficiently higher mark-up compared to low-quality care.

4.3 Balanced Budget

The state must maintain a balanced budget: spending cannot exceed Y_t. Both the budget and the maximum subsidy are set exogenously. The state must then determine how many families to subsidize.

Some families are eligible for subsidies and others are not. Call the group of families eligible for subsidies $\mathcal{E}$. The state does not change eligibility criteria, so this group is fixed. Rather, the state subsidizes a certain proportion of families in $\mathcal{E}$, and places the remainder on a waitlist. In practice, the state solves for the equilibrium proportion of eligible families subsidized, $Pr(Sub)$, such that the budget balances. We can also write this problem as follows:

$$Y_t = Pr(Sub) \sum_{i \in \mathcal{I}(Elig)} \min\{MaxSub, p_{j(i,s=1),t}\},$$

where the state pays the minimum of the maximum subsidy $MaxSub$ and the counterfactual price $p_{j(i,s=1),t}$ of the provider that family i would choose if they were subsidized.

Increasing the maximum subsidy does not *necessarily* reduce the number of families subsidized. Fixing family choices and the price and quality of care, increasing the maximum subsidy reduces the number of families served if and only if there are some counterfactual prices $p_{j(i,s=1),t} > MaxSub$. These expensive providers would mechanically receive a larger subsidy if the state implemented a higher maximum subsidy.

4.4 Implications

Under what conditions can subsidy policy affect the quality of care families receive? First, I discuss why a family may be more likely to select a high-quality provider if they receive a subsidy. Second, I elaborate on the implications of subsidizing more families for the price and quality of care in the market. Third, I explain how, holding the proportion of families subsidized fixed, a higher maximum subsidy may affect a family's taste for quality and the resulting implications for the market equilibrium. Fourth, I consider the ambiguous effect of increasing the maximum subsidy under limited resources. Finally, I conclude by briefly discussing how public care may affect these results.

If a family is offered a subsidy,[61] their out-of-pocket payment falls by $\min\{p_{jt}, MaxSub\}$ for all formal providers accepting subsidies. The subsidy reduces the out-of-pocket payment more for providers with prices above the maximum subsidy. For all providers setting prices below the maximum subsidy, the family has an out-of-pocket payment of zero. Subsidized families then pay a smaller difference in out-of-pocket payment across providers. Providers are differentiated less by out-of-pocket payments and more by non-price characteristics, such as quality. If families are insensitive to the out-of-pocket payment, a subsidy will have a small effect on the family's choice. If families are sensitive to out-of-pocket payments, where families shift depends on their preferences for non-price characteristics and the available care

[61] Families are not obligated to accept a subsidy if they are offered one.

nearby.

If more families are subsidized, the portion of demand coming from subsidized families, $w_{lt}^{sub}\pi_t^{sub}$, increases and the portion of demand coming from eligible, but unsubsidized, families decreases. Prices increase for provider j in market-year t if families become less sensitive to the price provider j charges or enrollment sh_{jt} increases. Subsidized families are insensitive to marginal increases in the price below the maximum subsidy, since they pay nothing regardless. As more families are subsidized, providers can set prices closer to the maximum subsidy from below. Additionally, if more families are subsidized, demand for formal care increases, as does demand for providers with desirable non-price characteristics. So mark-ups may increase more for providers with these desirable non-price characteristics as more families are subsidized. If demand increases for high-quality care relative to demand for low-quality care, providers invest more in quality.

Let's now consider the case where the number of families subsidized is fixed, but the maximum subsidy increases from $MaxSub_1$ to $MaxSub_2$, where $MaxSub_1 < MaxSub_2$. The out-of-pocket payment to enroll at provider j falls by $\min\{\max\{0, p_{jt} - MaxSub_1\}, MaxSub_2 - MaxSub_1\}$, meaning that the out-of-pocket payment *only* falls for providers with $p_{jt} > MaxSub_1$ and falls the most for providers with $p_{jt} > MaxSub_2$. Increasing the maximum subsidy further limits the differences across providers, increasing demand for non-price characteristics.

If the maximum subsidy increases, only demand from subsidized families changes in response. If few families are subsidized, providers should not change their prices or quality in response. Subsidized families are indifferent to marginal price changes up to the new maximum subsidy. Providers with a large enough fraction of enrollees with subsidies will increase prices from below the old maximum subsidy to below the new maximum subsidy. If a higher maximum subsidy also increases demand for non-price characteristics among subsidized families, prices may increase more for providers with desirable non-price characteristics. Providers may invest in quality if demand sufficiently shifts from low-quality to high-quality

providers.

If resources are limited, increasing the maximum subsidy may reduce the number of families the state can serve. The extent to which the program contracts depends on three factors. First, payments to any provider with prices above the maximum subsidy are mechanically higher under the larger maximum subsidy. Second, subsidized families may choose more expensive providers if they have a larger maximum subsidy, holding the prices of providers fixed. Third, providers may change their price in response to the higher maximum subsidy. Each of these factors stretches the resources of the program. But if the maximum subsidy reduces the number of families subsidized, the aggregate effect on demand is ambiguous. While the maximum subsidy may increase demand for non-price characteristics among subsidized families, there are now fewer subsidized families.

Public care may alter these dynamics by offering a free alternative care arrangement for families who would otherwise be subsidized. Additionally, public care may lower provider mark-ups by offering a competitive alternative. However, public care is limited. In Wisconsin, the two most common public offerings are 4-K and Head Start. 4-K is only available to four-year-olds and, in a handful of school districts, three-year-olds. Head Start is only available to low-income children and may be located far away from some families. Subsidy policy changes may have a larger effect where public care is scarce.

5 Estimation and Results

The extent to which either offering a larger subsidy to more families or offering a smaller subsidy to fewer families leads to more eligible children enrolled in high-quality care depends on several parameters, including taste for price and quality, as well as how easy it is for a firm to obtain a higher quality rating. This section describes how I estimate the structural model and briefly discusses the estimates.

5.1 Demand

Demand estimation follows other work estimating spatial demand models of education markets (Bodéré, 2023; Neilson, 2025), which extend the method from Berry et al. (1995).

Markets combine nearby school districts.[62] Since I do not observe family locations, I divide each market into census blocks. Distance to a provider is taken as the distance from the centroid of the census block to the address of the provider.[63]

The algorithm iteratively estimates demand in three steps. First, given a starting guess of μ_{ijt}, I estimate δ_{jt} by matching aggregate shares through a fixed-point problem. With δ_{jt} in hand, I can estimate ξ_{jt} as the portion of average demand unexplained by observables.

Second, I back out unobserved cost shifters based on implied mark-ups. Rearranging the price-setting equation:

$$mc_{jt} = p_{jt} - \left| \frac{sh_{jt}}{\frac{\partial sh_{jt}}{\partial p_{jt}}} \right|$$

I directly observe market share, sh_{jt}, and prices. $\frac{\partial sh_{jt}}{\partial p_{jt}}$ can be determined using estimated δ_{jt}, μ_{ijt}, and the marginal dis-utility of out-of-pocket payments β_i^{OOP}.[64] While I have now determined marginal costs, for counterfactuals we need to know the relationship between marginal costs and quality. Providers near capacity may also charge higher prices, biasing

[62] I use school districts in part because public 4-K operates through the school district, creating a natural dividing line where providers compete. Wisconsin's geography also lends itself to splitting the state into several regional markets. Besides Milwaukee and Madison, cities are small and relatively far apart from other cities. Here, markets center around the largest school districts and are contiguous. They are generally at least 40 miles wide. There are 37 markets in Wisconsin each year (2022-2025). Descriptives on each market can be found at Appendix D

[63] I use Haversine distance throughout.

[64] Estimating price sensitivity requires an estimate of the marginal dis-utility of price rather than the marginal dis-utility of out-of-pocket payments. The marginal dis-utility of prices is the same as the dis-utility of out-of-pocket payments β_i^{OOP} for unsubsidized families. For subsidized families, the marginal dis-utility of price is zero below the maximum subsidy and equals β_i^{OOP} above the maximum subsidy. However, if all enrollees are subsidized and p_{jt} is strictly below the maximum subsidy, the implied mark-up may be infinite. To prevent the estimate from becoming negative, I cap estimated marginal costs below at zero. As with non-profits, which may set prices below the profit-maximizing optimum, I may underestimate marginal costs for these providers. Providers that do not profit-maximize are treated as having smaller (or negative) unobserved cost shocks.

our estimates of marginal costs. With this in mind, I parameterize marginal cost as

$$mc_{jt} = \theta^X X^S_{jt} + \theta^Q_t Qual_{jt} + \theta^C \exp(\frac{sh_{jt}N_t}{Capacity_{jt}}) + \omega_{jt},$$

where ω_{jt} is the part of marginal cost unexplained by observables, $sh_{jt}N_t$ is total enrollment at provider j in market-year t, and $Capacity_{jt}$ is provider j's capacity.

Although I now have an estimate of δ_{jt} and marginal cost, these estimates have relied on an initial guess of μ_{ijt}. In the final step, I estimate the i-specific parameters by Generalized Method of Moments. The GMM problem includes IV and micro-moments.

Prices and quantities are correlated with demand (ξ_{jt}) and supply (ω_{jt}) shocks. I therefore use as instrumental variables exogenous own-characteristics, spillovers from a child care worker wage subsidy program[65], distance to income-verification offices,[66] and BLP-style instruments that measure the availability of different kinds of providers in the market. Let Z^D be the set of demand-side instruments and Z^S the set of supply-side instruments.[67] These IV moments, where $\boldsymbol{\theta}$ is the full set of parameters, are:

$$g^{IV}(\boldsymbol{\theta}) = \frac{1}{N} \begin{bmatrix} Z^D & 0 \\ 0 & Z^S \end{bmatrix} \begin{bmatrix} \boldsymbol{\xi}(\boldsymbol{\theta}) \\ \boldsymbol{\omega}(\boldsymbol{\theta}) \end{bmatrix}$$

I stack micro-moments to the GMM problem. First, I match average quality, conditional on enrollment, by type τ[68] in market t. From the data, let N^{priv}_t be the number of families choosing a private provider in the data and $q_{j(i)}$ the observed quality rating of the provider that family i chooses. Let $\mathcal{I}(\tau, t)$ be the observed families of type τ in market t. The

[65]This program operated under Child Care Counts. Providers with higher quality ratings could earn a higher per-worker wage subsidy. Providers in markets with more high-quality providers or in years with higher wage subsidies are subject to higher average wage subsidies, conditional on their own quality.

[66]Because distance to income-verification offices are likely correlated with the demand shock, it is only included in Z^S.

[67]Because I allow for marginal costs to vary by how close a provider is to their capacity, I need an additional instrument. I use predicted enrollment relative to capacity, using the other instruments to first predict prices, then predicting enrollment based on starting values (using estimated demand parameters as in Salanié and Wolak (2019)).

[68]I observe enrollment by subsidy status, so τ here is either subsidized or unsubsidized

estimates of δ_j, μ_{ijt} then imply a share of families of type τ who choose a provider of quality rating q, conditional on the family choosing a private provider – excluding enrollment at public providers or the outside option, which by construction have no quality rating. The implied share depends on our current estimates of the parameters, which collectively I refer to here as $\boldsymbol{\theta}$. I call this predicted share $s^{priv}_{ljt,\tau}$. Letting w^τ_l be the proportion of families of type τ that live at census block l, I define the moment as

$$g^{MM,q}_{\tau,t} = \frac{1}{N^{priv}_{t,\tau}} \sum_{i \in \mathcal{I}_t(\tau)} q_{j(i)} - \frac{\sum_{l \in \mathcal{L}_t} w^\tau_l \sum_{j \in \mathcal{J}_t} s^{priv}_{ljt\tau}(\boldsymbol{\theta}) q_{jt}}{\sum_{l \in \mathcal{L}_t} w^\tau_l \sum_{j \in \mathcal{J}_t} s^{priv}_{ljt\tau}(\boldsymbol{\theta})}.$$

I also match similar moments for average out-of-pocket payment paid by type.

Additionally, I use micro-data on public 4-K enrollment to match the fraction of all public 4-K enrollment in a market (N^{pub}_t) from children eligible for Free or Reduced Price Lunch. Similarly to the private moments, s^{pub}_{jt} is the model-implied share of families enrolled in public 4-K:

$$g^{MM,Elig}_{\tau,t} = \frac{1}{N^{pub}_t} \sum_{i \in \mathcal{I}_t(\tau)} Elig_{\tau(i)} - \frac{\sum_{l \in \mathcal{L}_t} w^\tau_l \sum_{j \in \mathcal{J}_t} s^{pub}_{ljt\tau}(\boldsymbol{\theta}) Elig_{\tau(i)}}{\sum_{l \in \mathcal{L}_t} w^\tau_l \sum_{j \in \mathcal{J}_t} s^{pub}_{ljt\tau}(\boldsymbol{\theta})}$$

Lastly, I match moments from national survey data on distance traveled[69] and the share of private enrollment coming from children of different ages.

I then choose β_i to maximize the GMM objective function. With these updated parameters in hand, I repeat the algorithm until convergence. The GMM objective has a weighting matrix and it is unclear *ex ante* which weights to use, especially when moments may be correlated. I use a two-step process (Conlon and Gortmaker, 2020). First, I determine initial optimal weights using starting values as described in Salanié and Wolak (2019). Then, I update the weighting matrix based on the new estimates of demand and marginal cost.

[69]Specifically, the share of families, by urbanicity and subsidy eligibility, who travel zero to one mile, one to three miles, or three to eight miles to reach their primary care provider.

5.2 Quality Choice

After I estimate demand, I estimate the parameters in the quality-choice stage. To estimate the parameters, I use a nested pseudo-likelihood (NPL) approach (Aguirregabiria and Mira, 2007; Bodéré, 2023; Sweeting, 2013).

As in (Bodéré, 2023), I approximate expected profits, $\mathbb{E}\Pi$, using a neural network.[70] I also parameterize the average fixed cost of different quality levels to vary by whether the provider is a center or family provider.[71] I also allow for both the average fixed cost of each quality rating and the distribution of shocks to fixed cost to vary by whether the provider is in the Milwaukee market.

Given the assumed distribution of the private fixed cost shocks, I estimate the conditional choice probability that firm j selects quality q in market t as

$$Pr(Qual_{jt} = q) = \frac{\exp((\mathbb{E}\Pi(Qual_{jt} = q; X^m_{jt}, X_{jt}) - c_{tq})/\theta^{\varepsilon}_t)}{\sum_{q \in \mathcal{Q}} \exp((\mathbb{E}\Pi(Qual_{jt} = q; X^m_{jt}, X_{jt}) - c_{tq})/\theta^{\varepsilon}_t)},$$

where the average fixed cost of quality q, c_{tq}, and scale parameter, θ^{ε}_t, varies by whether the firm is in the Milwaukee market. Given a starting value for $c_{tq}, \theta^{\varepsilon}_t$, I start $Pr(Qual_{jt})^0$ using the estimates of a multinomial logit set to fit the observed quality distribution. However, expected profit, $\mathbb{E}\Pi$, depends on not only the quality provider j chooses, but also the expected choices of the other firms in the market. The goal of estimation is to set the choice probabilities to be consistent with the best response to the expected actions of other

[70] To estimate expected profits, I simulate profits across many quality perturbations. I then predict average profits given own quality choice and the quality of other providers in the market, based on observable features.

[71] The requirements to achieve a given quality rating are similar, but slightly different, between different types of providers. For example, family providers must achieve a minimum score on the Family Child Care Environment Rating Scale to be rated four to five stars. Centers must achieve the same minimum score on the Early Childhood Environment Rating Scale. While each are intended to represent similar levels of quality, testing may nevertheless vary. Additionally, it may be less costly to meet certain requirements in a commercial setting than a residential setting.

providers in the market. With $Pr(Qual_{jt})^0$ in hand, I update $\mathbb{E}\Pi$:

$$\mathbb{E}\Pi(Qual_{jt} = q)^0 = \int_{a_m, a_n} \Pi(a_m, a_n) * Pr(a_m, a_n) dF(a_m, a_n),$$

where a_m, a_n are measures of the endogenous quality of nearby (n) and market (m) providers.

Holding $\mathbb{E}\Pi(Qual_{jt} = q)^0$ fixed, $Pr(Qual_{jt} = q)$ depends only on parameters $c_{tq}, \theta_t^{\varepsilon}$. I then choose $c_{tq}, \theta_t^{\varepsilon}$ to maximize the likelihood of observing the observed quality in the data. The log-likelihood can be written as:

$$\mathcal{L}^0 = \sum_{t \in \mathcal{T}} \sum_{j \in \mathcal{J}_t} \log Pr(Qual_{jt} = q_{jt}^{obs}; \mathbb{E}\Pi^0, c_{tq}, \theta_t^{\varepsilon}),$$

where q_{jt}^{obs} is the observed quality of provider j at time t, $\mathbb{E}\Pi^0$ is the initial guess for expected profit for the given quality, and $c_{tq}, \theta_t^{\varepsilon}$ are the parameters for the distribution of provider-specific fixed costs. The log-likelihood sums over each market $t \in \mathcal{T}$ and each provider $j \in \mathcal{J}_t$.

With the estimates of $(c_{tq}, \theta_t^{\varepsilon})^1$, I then update my estimate of the choice probabilities:

$$Pr(Qual_{jt} = q)^k = (1 - \psi) Pr(Qual_{jt} = q)^{(k-1)} + \psi Pr(Qual_{jt} = q; \mathbb{E}\Pi^k, (c_{tq}, \theta_t^{\varepsilon})^k)$$

I repeat the steps until both $(c_{tq}, \theta_t^{\varepsilon})$ and the estimated choice probabilities update by less than 10^{-4}.

5.3 Estimates

5.3.1 Demand

Table A.7 reports the demand estimates. I allow for provider characteristics such as its type (e.g., center, family, public fee-based[72], public 4-K, or Head Start), the age of children

[72] These providers operate in public schools and require families to pay a fee. I treat these providers throughout as if they are not price-setters.

served, how many years the provider has operated for, and the quality rating. For public 4-Ks, I allow for demand for the public 4-K to vary by the operating schedule of the 4-K provider.

I also allow for demand to vary across families in five ways. First, I allow demand for a given provider to depend on the distance the family is from the provider. Because I do not observe family addresses but do know the distribution of families across space by income, I take distance traveled to be the Haversine distance from the centroid of the family's census block to the provider. I allow taste for distance to also vary by whether the family lives in Milwaukee, Wisconsin's densest city. Second, I allow the out-of-pocket payment to depend on the subsidy status of the family.[73] Receiving a subsidy affects demand only through its effect on the out-of-pocket payment. Third, families eligible for subsidies have different tastes for all provider characteristics than ineligible families, capturing variation in preferences due to income. Fourth, I allow individual variation in taste for the highest-quality rating. Fifth, I allow the age of the child to affect taste for formal care and the options available.[74]

I find that demand for formal care is highest for families with three-year-olds and for ineligible families. While all families have a significant distaste for the out-of-pocket payment they pay for care, I find that eligible families are more sensitive to their out-of-pocket payment. Eligible families and families living in Milwaukee are also significantly more sensitive to the distance they need to travel to their provider.

Conditional on a provider being rated, families generally prefer higher-rated providers. Eligible families prefer middling-quality providers, all else equal. Families prefer unrated providers to low-rated providers, perhaps reflecting beliefs that unrated providers may be higher quality, but have strategically chosen not to be rated, perhaps to avoid accepting subsidized children. I also find a high standard deviation on taste for high-quality, implying that quality is more important for some families regardless of demographics.

[73] I do not observe the exact address of subsidized families. For sake of estimating the model, I assume eligible families have an equal chance of being subsidized across a given market.

[74] If a provider does not accept an age group, I assume the provider gives families with children of that age infinitely negative utility, regardless of the provider's other characteristics.

The fit of the estimated model is described in Table A.10 and Table A.11. The model does best matching the quality of enrollment for unsubsidized families, the share of subsidized families choosing center-based care, the difference in the sticker price of care between subsidized and unsubsidized families, and the share of families at charter schools or full-day, full-week public 4-K programs who are eligible for Free- or Reduced-Price Lunch (FRPL). However, I underestimate the share of subsidized families choosing two-star and five-star providers.[75] I also over-estimate the share of families eligible for FRPL that enroll in public 4-K programs that cover less of the school-day or school-week.

5.3.2 Marginal Costs

Table A.8 describes the marginal cost estimates. Marginal cost varies with the provider's quality rating, ages served, years in operation, facility type, and average county wages. Providers may set higher prices as they approach capacity, biasing estimation of marginal costs, which are based on estimated mark-ups. To address this bias, I allow for marginal costs to increase as the provider approaches capacity.

Marginal costs are generally increasing in quality. In particular, the highest-quality providers have significantly higher marginal costs than other quality ratings. Marginal costs are falling for the first ten years in operation. Centers pay lower marginal costs than family providers. Provider costs are decreasing with the youngest age served after about 19 months and insignificantly decreasing with the oldest age served. I find evidence that providers set higher prices as they approach capacity.

[75] I may match the data better on the quality of enrollment for unsubsidized families because subsidized families are a selected group. I assume that subsidized families have the same preferences as other eligible families, but if there are fixed costs that eligible families need to pay to obtain a subsidy, subsidized families may be more price or quality-sensitive. One approach would be to add an additional estimation step to demand, where I determine the unobserved fixed costs of obtaining a subsidy to match actual subsidized enrollment. However, this would increase the computational demands of estimation.

5.3.3 Quality Stage

The estimates are presented in Table A.9. Family providers and centers are rated under similar, but slightly different methodologies, so I estimate the quality-transition stage separately by type. I also allow for fixed costs to vary by whether the provider is in the Milwaukee market, the largest city in Wisconsin. I find that providers pay higher fixed costs to be four or five stars. Centers pay lower fixed costs than family providers. Providers in Milwaukee generally pay higher fixed costs than providers outside Milwaukee. For centers, four-star providers pay a higher fixed cost than five-star providers.[76]

6 Counterfactuals

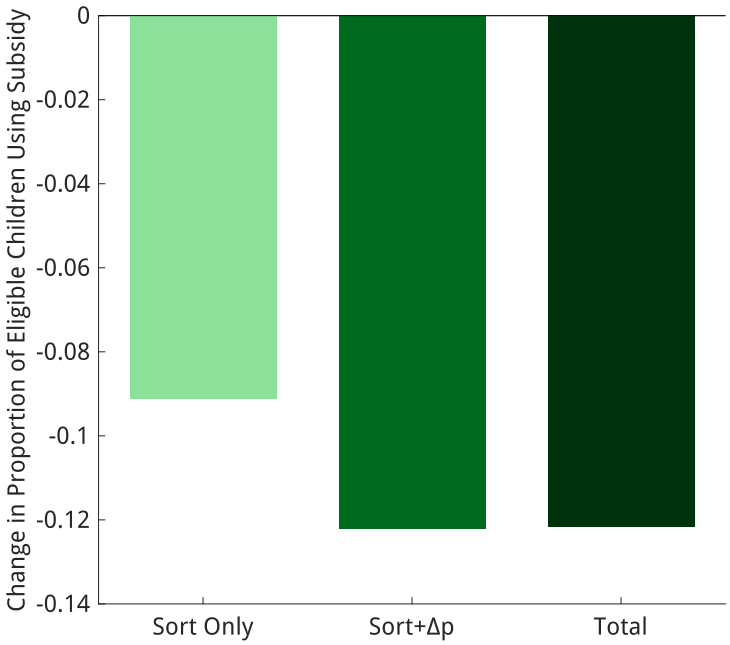
In this section, I evaluate a reform Wisconsin implemented in 2022, which raised the maximum subsidy from the 35th percentile of local prices to the 80th percentile. I compare the reform to a budget-neutral alternative: what would have happened if the state had not changed its maximum subsidy and instead used its federally-funded budget increase to serve more families? Using this approach, I can make a cost-equivalent comparison between the larger maximum subsidy versus serving more families. I decompose the relative effect of the reform into three channels: changes in family choices (holding prices and quality fixed), changes in prices, and changes in quality. I focus on the effects on children younger than five-years-old from families eligible for subsidies.

In Figure 5, I show how many fewer eligible children receive a subsidy under the larger maximum subsidy relative to the smaller maximum subsidy. I also show the effect decomposed into three counterfactuals: (1) holding prices and quality fixed; (2) holding quality fixed; and

[76]The larger fixed costs for four-star providers may reflect institutional features rather than the additional costs of earning four stars rather than five stars. In practice, providers can only earn four or five stars if they choose to be assessed by the state. Centers may be more likely than family providers to strategically submit themselves for assessment, only applying if they expect to qualify for five stars. Conditional on being quality rated, only 5.6% of centers have four stars, while 24.6% of centers have five stars. On the other hand, 5.2% of quality-rated family providers have four stars and 4.5% of quality-rated family providers have five stars. While centers do not pay higher fixed-costs to have five stars compared to four stars, I find that they pay higher *marginal* costs.

(3) allowing prices and quality to change. The third column can alternatively be interpreted as the total effect of the larger maximum subsidy relative to the smaller maximum subsidy. Holding the budget fixed, I find that the higher maximum subsidy serves 12.2pp fewer children than the smaller subsidy, a 59% decrease. In part, when the maximum subsidy increases, the number of subsidized children falls mechanically. However, providers may also increase their prices to capture more of the subsidy. If prices increase, each child is more expensive to subsidize. I find that the larger maximum subsidy would have served 36% more families if provider prices and quality were held fixed.

Figure 5: Subsidy Coverage Falls Under the Higher Maximum Subsidy

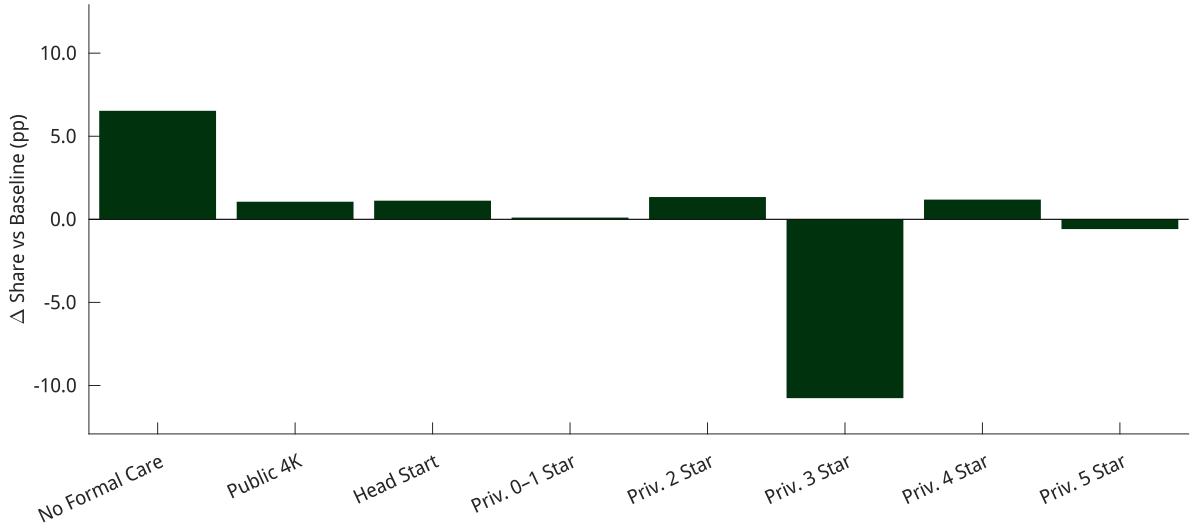


Notes: Shows changes in subsidy coverage among eligible children under age five. Changes compare enrollment under the maximum-subsidy reform relative to offering a smaller subsidy to more families.

Figure 6 shows the overall effect on type of enrollment under the higher maximum subsidy relative to the smaller subsidy offered to more families. Overall, 10.8pp fewer children from low-income families enroll at three-star private care under the larger subsidies relative to smaller subsidies given to more families, a 30% decline. Additionally, the larger subsidies enroll 0.6pp fewer children from low-income families at the highest-quality private providers

relative to smaller subsidies offered to more families. Where do these children go instead? Most switch out of formal care altogether: 6.5pp more children from low-income families forgo formal care under the larger subsidies, an 18.7% increase.[77] An additional 1.4pp more children from low-income families enroll at low-quality private care (e.g., zero to two-star providers), an 11% increase. On the other hand, the larger subsidies enroll 2.2pp more children in public care (22% more) and 1.2pp more children at four-star private providers (54% more) relative to offering smaller subsidies to more families.

Figure 6: Enrollment in Formal Care Falls Under the Larger Subsidy



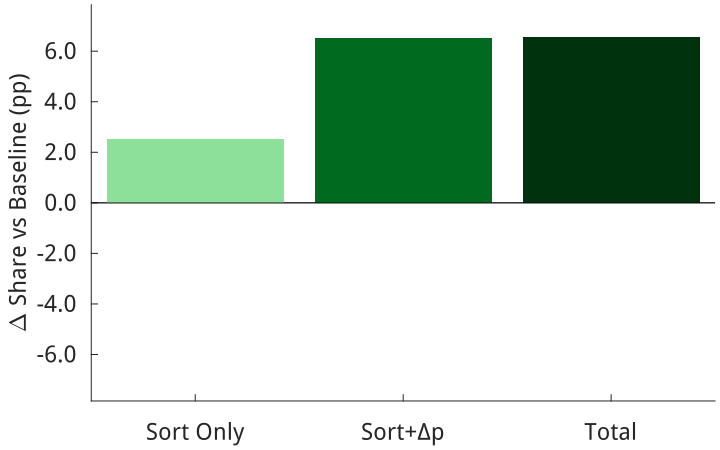
Notes: Shows changes in enrollment among eligible children under age five. Changes compare enrollment under the maximum-subsidy reform relative to offering a smaller subsidy to more families. Columns sum to zero.

Figure 7 shows that higher prices explain the decline in formal care under the larger subsidies. The left-most column shows the relative change in low-income families choosing to not enroll in formal care under the larger subsidy if prices and quality are fixed. The middle column shows the relative change if quality is fixed. The right-most column shows

[77] While I refer to this category as not formal care, it also encompasses providers that are out of my sample. For example, providers that operate part-time are not included in the sample.

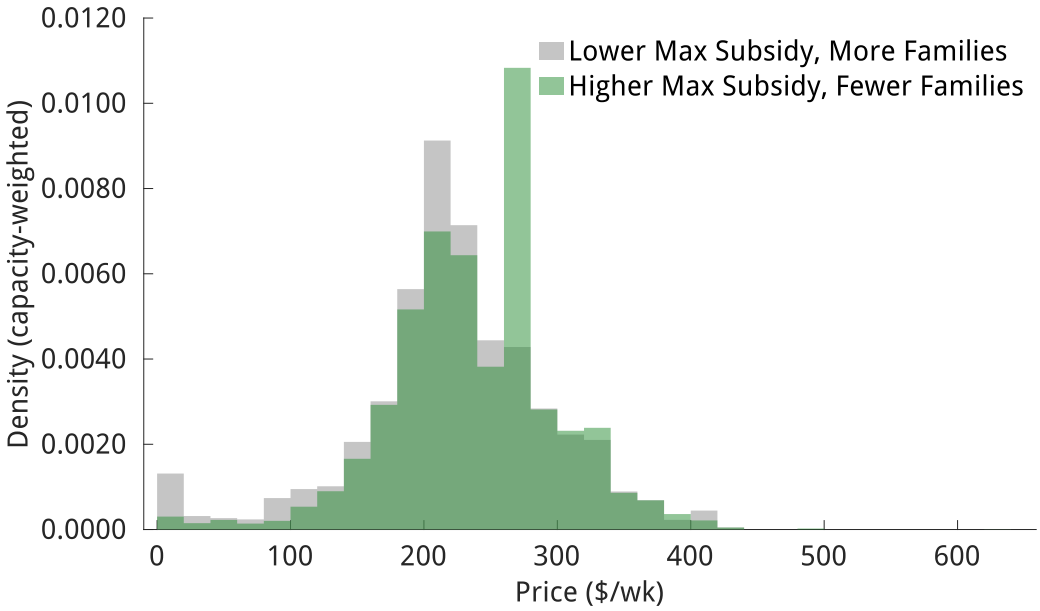
the total relative change when prices and quality can change. Subsidizing fewer families explains 38.6% of the decline in formal care enrollment. 61.3% is explained by providers increasing prices. As shown in Figure 8, the distribution of prices is shifted to the right under the larger maximum subsidy. The mean difference in sticker prices is 8.5%.

Figure 7: Prices Explain Most of Increase in Families Opting Out of Formal Care



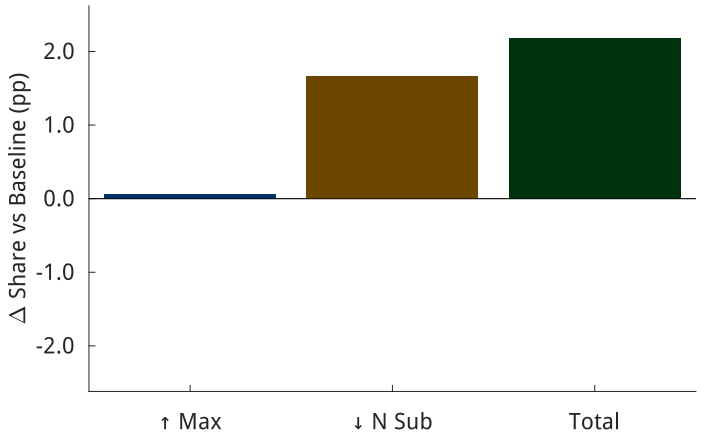
Notes: Change in formal-care enrollment by eligible families, decomposed into family choices, price changes, and quality changes.

Figure 8: Sticker Prices Increase Under Larger Subsidy



Notes: Distribution of provider sticker prices under the maximum-subsidy reform relative to subsidizing more families.

Figure 9: Public Enrollment Increases Under Maximum Subsidy Because of Reduced Crowd-Out



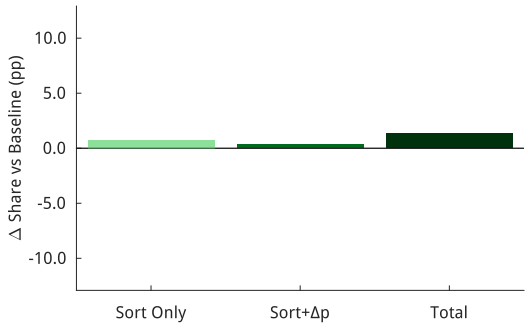
Notes: The effects of (1) offering a higher maximum subsidy to more families, (2) offering the smaller subsidy to fewer families, and (3) offering the larger subsidy to fewer families, relative to offering a smaller subsidy to more families

Public alternatives absorb some children who would otherwise have been subsidized. Public 4-K and Head Start enrollment increases by 21.9% under the reform. Figure 9 decomposes this total effect into the effects from a higher maximum subsidy or from subsidizing fewer families.[78] The effect is predominantly from families losing the subsidy rather than the maximum subsidy itself, suggesting that the subsidy crowds out public enrollment in part.

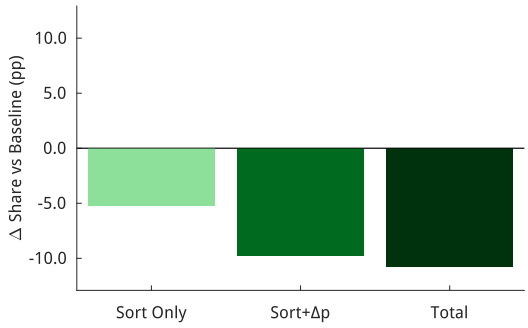
Enrollment in private care is 8.7pp lower under the larger maximum subsidy relative to offering smaller subsidies to more families, a 15.8% decrease. The largest decrease is among middling-quality providers (see Figure 10b). 48.7% of the decrease in enrollment at three-star providers is because of changes in family choices. In part, the decrease in middling-quality care is because subsidized families are more likely to choose higher-quality care. For example, 48.6% more subsidized families choose the highest-quality provider under the larger maximum subsidy relative to the smaller subsidy (see Figure 11d). However, the decrease in formal care overall is also an important contributor.

[78] Specifically, the effect of the higher maximum subsidy alone does not reduce the number of subsidized families to pay for the maximum subsidy increase. The effect of reducing the number of subsidized families compares offering the smaller subsidy to more families to offering the smaller subsidy to fewer families.

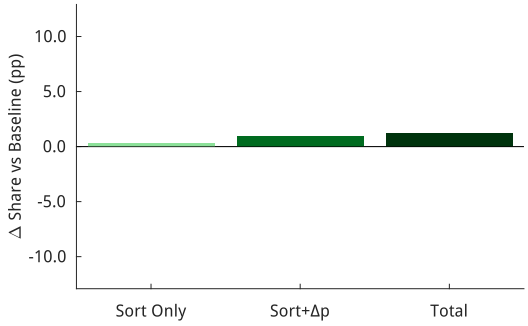
Figure 10: Fewer Families Use Middling-Quality Private Care Under Larger Subsidy



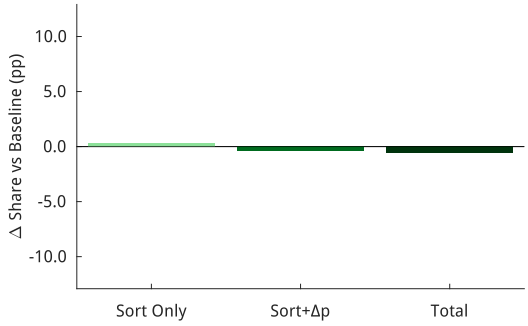
(a) Private 2 Star



(b) Private 3 Star



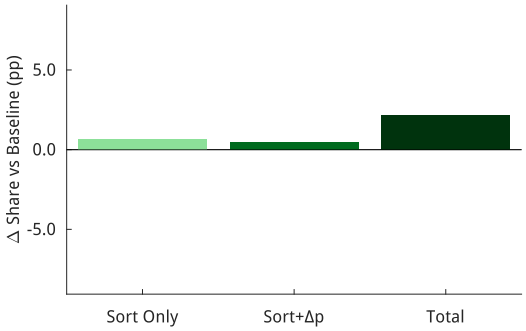
(c) Private 4 Star



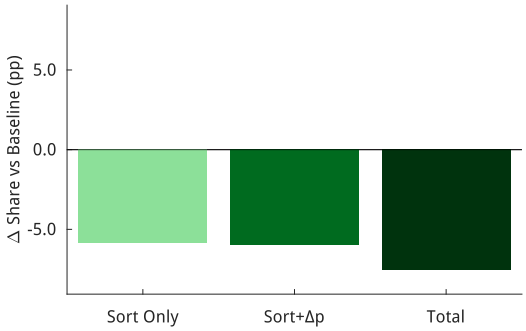
(d) Private 5 Star

Notes: Change in the share of eligible families enrolling at each private star rating (percentage points) from a larger maximum subsidy, relative to offering smaller subsidies to more families, if (1) provider prices and quality are held fixed, (2) provider quality is held fixed, and (3) prices and quality can both change.

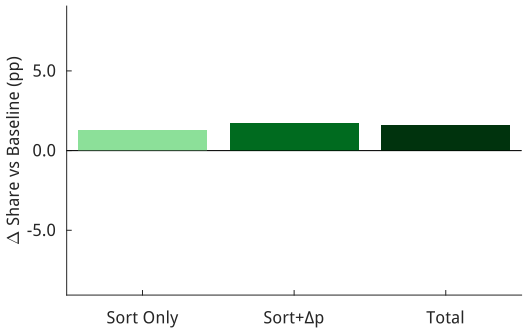
Figure 11: Subsidized Families Move to Highest-Quality Care Under the Larger Subsidy



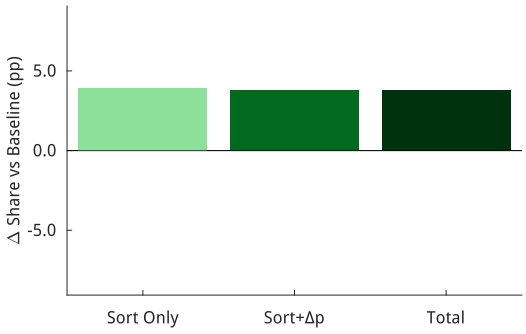
(a) Private 2 Star



(b) Private 3 Star



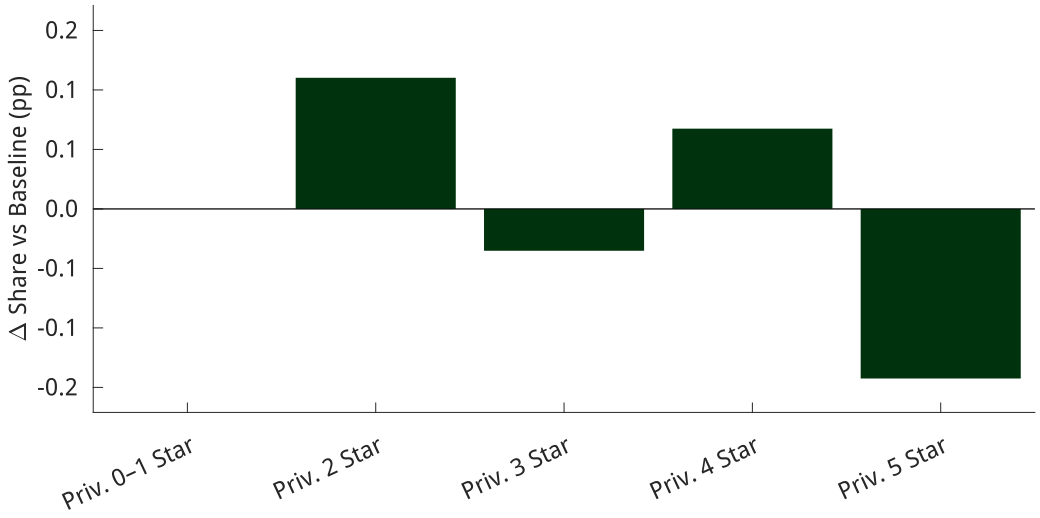
(c) Private 4 Star



(d) Private 5 Star

Notes: Change in the share of subsidized families enrolling at each private star rating (percentage points) from moving from a smaller maximum subsidy to a larger maximum subsidy if (1) provider prices and quality are held fixed, (2) provider quality is held fixed, and (3) prices and quality can both change.

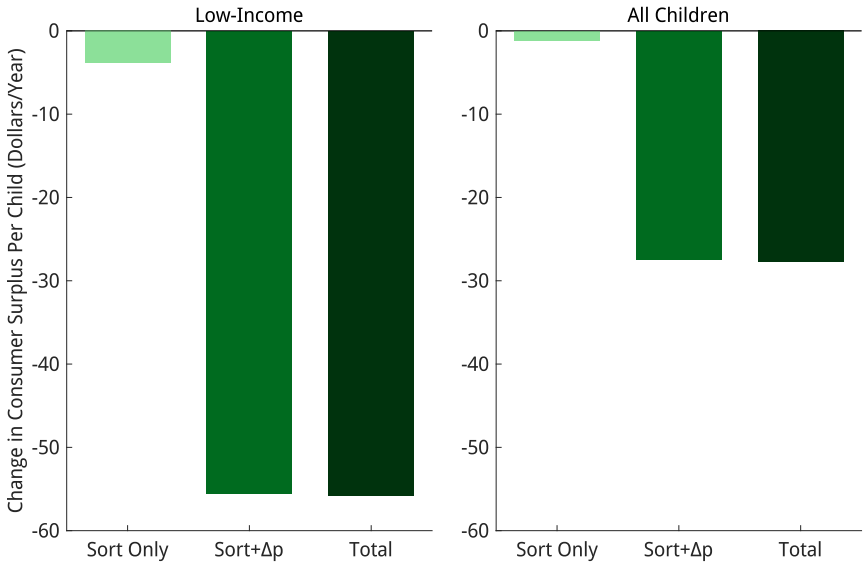
Figure 12: Quality is Higher Under Larger Maximum Subsidy



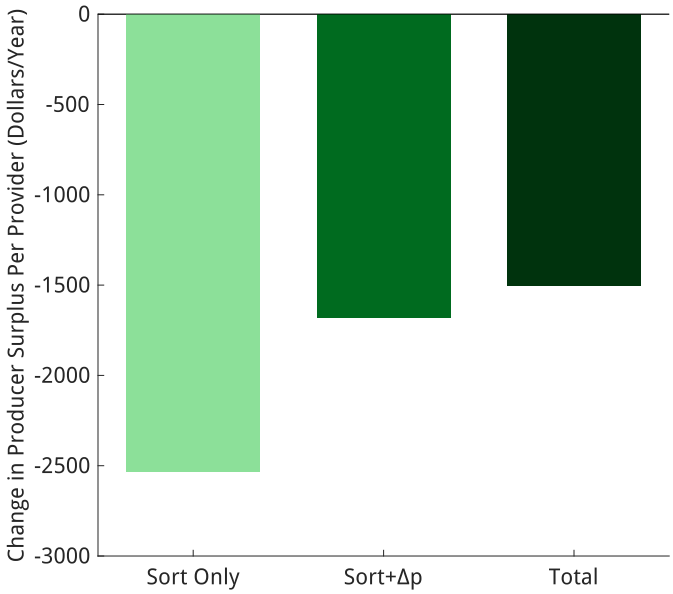
Notes: Overall change in the distribution of provider quality from the smaller maximum subsidy to the larger maximum subsidy.

An additional 42.1% of the decrease in enrollment at three-star providers is explained by higher prices. The change in prices has little effect on where subsidized families enroll, so much of this additional decrease in enrollment is explained by unsubsidized families being priced out of middling-quality care. The remaining 9.2% of the decrease in enrollment at three-star providers is explained by changes to private quality. As shown in Figure 12, there are 0.1% (37) fewer seats at three-star providers under the larger maximum subsidy relative to subsidizing more families. There are also 0.6% (150) fewer seats at five-star providers. On the other hand, there are 1.0% (71) more seats at four-star providers and 0.3% (116) more seats at providers with two or fewer stars. Weighted by capacity, 0.3% of providers lower their quality rating under the larger maximum subsidy relative to subsidizing more families.

Figure 13: Consumer and Producer Surplus Fall Under the Larger Maximum Subsidy



(a) Consumer Surplus



(b) Producer Surplus

Notes: Change in the consumer and producer surplus from a larger maximum subsidy, relative to offering smaller subsidies to more families, if (1) provider prices and quality are held fixed, (2) provider quality is held fixed, and (3) prices and quality can both change. Consumer surplus is reported per-child, per-year. Producer surplus is reported per-provider, per-year

To weigh these policies, I finally consider changes to consumer and producer surplus.

Details on the calculation of consumer and producer surplus can be found in Appendix H. To be sure, consumer surplus captures the effect of each policy on *parental* welfare, which partially incorporates altruistic taste for quality of care. Figure 13a shows the change in consumer surplus for low-income families and for all families under the higher maximum subsidy relative to the smaller maximum subsidy offered to more families. I find that consumer surplus per low-income child is $55.80 lower per year under the larger maximum subsidy relative to offering a smaller subsidy to more families. Looking across all children, regardless of eligibility, consumer surplus falls by $27.76 per year. 92.5% of the decrease in consumer surplus for low-income families is explained by higher prices. Turning to producer surplus, Figure 13b shows that providers are also better off when the state serves more families. Producers earn, on average, $1,502 less per year under the larger maximum subsidy. Increases in prices and quality offset the losses in part: the loss in provider surplus would be 69% larger if providers could not change their price or quality.

7 Conclusion

In this paper, I have demonstrated that offering a larger maximum subsidy may push low-income families out of formal care by increasing prices and by requiring the state to further ration access. Using quasi-experimental variation, I first showed that neighborhoods with 1pp more subsidized families are 1.8pp more likely to have a high-quality provider. On the other hand, a $10 higher maximum subsidy per week leads to subsidized families being 6.6pp more likely to have to pay anything out-of-pocket and 5% higher sticker prices. Motivated by these findings, I estimated a model of the child care market with endogenous prices, quality, and number of families subsidized to determine how many fewer families would need to be subsidized to maintain a balanced budget if the maximum subsidy increased. I found that, although the maximum subsidy increases the number of subsidized families choosing high-quality care and pushes some families to instead take-up public care options, the maximum

subsidy also leads to higher prices. As a result, 19% more eligible children forgo formal care. Consumer surplus for eligible families is 17% lower under the larger maximum subsidy compared to offering a smaller subsidy to more families. Producer surplus is 2% lower. These results suggest that welfare would be improved if the state instead offered a smaller subsidy to more families.

Would the increase in enrollment at public providers and four-star providers lead to sufficiently large development gains to outweigh lower enrollment in formal care? I do not have data on children's outcomes and cannot evaluate this question directly. However, research on Head Start from Feller et al. (2016); Kline and Walters (2016) suggests that the gains from Head Start are largest for children whose counterfactual care option was no formal care rather than center care. Suggestively, low-income children may benefit more from receiving middling-quality formal care than receiving no formal care at all. Caution is encouraged, however, given that center providers are highly heterogeneous – greater research is needed on the effect of pushing children to higher-quality formal care on their long-run development.

A higher maximum subsidy to fewer families may have other costs. If families cannot afford formal care, they may turn to parental care. Mothers, in particular, may not be able to work as a result. Lower maternal employment comes with other fiscal costs, whether in lower tax revenue or higher take-up of other benefits. Additionally, I find that more children turn to public care if fewer families are subsidized. Since Public 4-K is not free, subsidizing fewer families may transfer the cost of providing care to public 4-K programs.

This paper has a few limitations. First, I do not allow for the costs of providing care to endogenously respond to policy changes. As providers improve their quality, demand for key inputs like labor may increase, increasing wages. As the marginal cost of providing quality rises, fewer firms may improve their quality than suggested by the model here. As marginal costs rise overall, prices may increase too. We may then expect an even larger decrease in formal care under the higher maximum subsidy than suggested here. Second, I

do not explicitly model entry, exit or capacity constraints. Instead, I proxy for free entry by allowing providers to enroll more children than their capacity would otherwise allow. However, I may overestimate entry, since entry may be costly. Capacity constraints may also lead to providers charging higher prices – providers may set prices to attract only as many students as they have the capacity to serve. The current approach also does not allow entry in new locations without an existing provider. Both the role of an endogenous child care labor market and capacity constraints are the subject of ongoing work.

Looking beyond child care markets, I have demonstrated here that the density of subsidy participation may affect the price and quality of privately-provided, publicly-funded services. These kinds of subsidies are common in the United States: consider similar, large programs like Section 8 housing vouchers or Medicaid. Additionally, many programs operate under limited budgets, whether because of reliance on federal grants or political limitations. I have demonstrated here that expanding the per-person generosity of assistance may harm the individuals the program seeks to help by increasing rationing and raising prices. More work is needed to understand the extent to which these findings apply to other programs.

References

Aguirregabiria, Victor and Pedro Mira, "Sequential Estimation of Dynamic Discrete Games," *Econometrica*, January 2007, *75* (1), 1–53.

Allende, Claudia, "Competition Under Social Interactions and the Design of Education Policies," 2021.

Almås, Ingvild, Nina Drange, Costas Meghir, and Henrik D. Zachrisson, "Early Childcare Attendance and Cognitive skills in Adolescence," April 2026, (35109). DOI: 10.3386/w35109.

Anders, John, Andrew C. Barr, and Alexander A. Smith, "The Effect of Early Childhood Education on Adult Criminality: Evidence from the 1960s through 1990s," *American Economic Journal: Economic Policy*, February 2023, *15* (1), 37–69.

Ando, Michihito, Hiroaki Mori, and Shintaro Yamaguchi, "Universal early childhood education and adolescent risky behavior," *Journal of Public Economics*, May 2025, *245*, 105353.

Bailey, Martha J., Shuqiao Sun, and Brenden Timpe, "Prep School for Poor Kids: The Long-Run Impacts of Head Start on Human Capital and Economic Self-Sufficiency," *American Economic Review*, December 2021, *111* (12), 3963–4001.

Baker, Michael, Jonathan Gruber, and Kevin Milligan, "Universal Child Care, Maternal Labor Supply, and Family Well-Being," *Journal of Political Economy*, August 2008, *116* (4), 709–745.

____ , ____ , and ____ , "The Long-Run Impacts of a Universal Child Care Program," *American Economic Journal: Economic Policy*, August 2019, *11* (3), 1–26.

Bassok, Daphna, Maria Fitzpatrick, and Susanna Loeb, "Does state preschool crowd-out private provision? The impact of universal preschool on the childcare sector in Oklahoma and Georgia," *Journal of Urban Economics*, 2014, *83*, 18–33.

Beaudry, Paul, Charles Blackorby, and Dezsö Szalay, "Taxes and Employment Subsidies in Optimal Redistribution Programs," *American Economic Review*, February 2009, *99* (1), 216–242.

Berlinski, Samuel, Maria Marta Ferreyra, Luca Flabbi, and Juan David Martin, "Childcare Markets, Parental Labor Supply, and Child Development," *Journal of Political Economy*, None 2024, *132* (6), 2113–2177.

Berne, Jordan, "The Long-Run Impacts of Universal Pre-K: Evidence from the First Statewide Program," 2024.

Berry, Steven, James Levinsohn, and Ariel Pakes, "Automobile Prices in Market Equilibrium," *Econometrica*, 1995, *63* (4), 841.

Bitler, Marianne, Jason B. Cook, Chloe N. East, Sonya R. Porter, and Laura Tiehen, *The Intersection of Place and Need: How Lack of Enrollment Offices Deters Participation in the Safety Net*, University of Chicago Press, November

Blau, David and Janet Currie, *Pre-School, Day Care, and After-School Care: Who's Minding the Kids?*, Vol. 2, Elsevier,

Blundell, R. and A. Shephard, "Employment, Hours of Work and the Optimal Taxation of Low-Income Families," *The Review of Economic Studies*, April 2012, *79* (2), 481–510.

Bodéré, Pierre, "Dynamic Spatial Competition in Early Education: an Equilibrium Analysis of the Preschool Market in Pennsylvania," Job Market Paper November 2023.

Borowsky, Jonathan, Jessica H. Brown, Elizabeth E. Davis, Chloe Gibbs, Chris M. Herbst, Aaron Sojourner, Erdal Tekin, and Matthew J. Wiswall, "An Equilibrium Model of the Impact of Increased Public Investment in Early Childhood Education," 2022, (30140). DOI: 10.3386/w30140.

Brown, Jessica, "Does Public Pre-K Have Unintended Consequences on the Child Care Market for Infants and Toddlers?," Job Market Paper December 2018.

Cabral, Marika, Michael Geruso, and Neale Mahoney, "Do Larger Health Insurance Subsidies Benefit Patients or Producers? Evidence from Medicare Advantage," *American Economic Review*, August 2018, *108* (8), 2048–2087.

Campanini, Tracey, "Increase to Child Care Works Base Payment Rates," February 2021.

Carneiro, Pedro and Rita Ginja, "Long-Term Impacts of Compensatory Preschool on Health and Behavior: Evidence from Head Start," *American Economic Journal: Economic Policy*, November 2014, *6* (4), 135–173.

Choné, Philippe and Guy Laroque, "Optimal taxation in the extensive model," *Journal of Economic Theory*, 2011, *146* (2), 425–453.

Collinson, Robert and Peter Ganong, "How Do Changes in Housing Voucher Design Affect Rent and Neighborhood Quality?," *American Economic Journal: Economic Policy*, May 2018, *10* (2), 62–89.

Conlon, Christopher and Jeff Gortmaker, "Best practices for differentiated products demand estimation with PyBLP," *The RAND Journal of Economics*, December 2020, *51* (4), 1108–1161.

Currie, Janet and Matthew Neidell, "Getting inside the "Black Box" of Head Start quality: What matters and what doesn't," *Economics of Education Review*, February 2007, *26* (1), 83–99.

DCF, "Wisconsin Division of Early Care and Education Administrator's Memos," 2026.

____ , "Frequently Asked Questions Regulated Child Care and YoungStar Child Care Finder Website."

DECE, *2017 Annual Report Early Care and Education in Wisconsin* March 2018.

Department of Health and Human Services, "Restoring Flexibility in the Child Care and Development Fund (CCDF)," May 2026.

Deshpande, Manasi and Yue Li, "Who Is Screened Out? Application Costs and the Targeting of Disability Programs," *American Economic Journal: Economic Policy*, November 2019, *11* (4), 213–248.

DHS, "Increase in Child Care and Development Fund (CCDF) Discretionary Funds in the Consolidated Appropriations Act of 2018 (Public Law 115-141)," August 2018.

Drange, Nina and Kjetil Telle, "Universal child care and inequality of opportunity. Descriptive findings from Norway," Discussion Papers, Statistics Norway, Research Department 2018.

Duggan, Mark, Amanda Starc, and Boris Vabson, "Who benefits when the government pays more? Pass-through in the Medicare Advantage program," *Journal of Public Economics*, 2016, *141*, 50–67.

Eriksen, Michael D. and Amanda Ross, "Housing Vouchers and the Price of Rental Housing," *American Economic Journal: Economic Policy*, August 2015, *7*(3), 154–176.

Fack, Gabrielle, "Are housing benefit an effective way to redistribute income? Evidence from a natural experiment in France," *Labour Economics*, December 2006, *13* (6), 747–771.

Feller, Avi, Todd Grindal, Luke Miratrix, and Lindsay C. Page, "Compared to what? Variation in the impacts of early childhood education by alternative care type," *The Annals of Applied Statistics*, 2016, *10* (3).

Finkelstein, A., "The Aggregate Effects of Health Insurance: Evidence from the Introduction of Medicare," *The Quarterly Journal of Economics*, February 2007, *122* (1), 1–37.

Finkelstein, Amy and Matthew J Notowidigdo, "Take-Up and Targeting: Experimental Evidence from SNAP," *The Quarterly Journal of Economics*, August 2019, *134* (3), 1505–1556.

Francis, Jessica and William Steven Barnett, "Relating preschool class size to classroom quality and student achievement," *Early Childhood Research Quarterly*, 2019, *49*, 49–58.

Garces, Eliana, Duncan Thomas, and Janet Currie, "Longer-Term Effects of Head Start," *American Economic Review*, 2002, *92* (4), 999–1012.

Garcia-Vazquez, Martin, "The equilibrium effects of state-mandated minimum staff-to-child ratios," Job Market Paper February 2026.

Gentry, John D., *Wisconsin Works (W-2) and Other Economic Support Programs* number 43 January 2017.

____ , *Wisconsin Works (W-2), Child Care, and Other Economic Support Programs* number 43 January 2019.

____ , *Economic Support Programs* number 48 January 2025.

Gray-Lobe, Guthrie, Parag A Pathak, and Christopher R Walters, "The Long-Term Effects of Universal Preschool in Boston," *The Quarterly Journal of Economics*, 02 2023, *138* (1), 363–411.

Havnes, Tarjei and Magne Mogstad, "No Child Left Behind: Subsidized Child Care and Children's Long-Run Outcomes," *American Economic Journal: Economic Policy*, May 2011, *3* (2), 97–129.

Herbst, Chris M., "The impact of quality rating and improvement systems on families' child care choices and the supply of child care labor," *Labour Economics*, October 2018, *54*, 172–190.

____ **and Erdal Tekin**, "The Impact of Child-Care Subsidies on Child Development: Evidence from Geographic Variation in the Distance to Social Service Agencies," *Journal of Policy Analysis and Management*, January 2016, *35* (1), 94–116.

Ho, Christine and Nicola Pavoni, "Efficient Child Care Subsidies," *American Economic Review*, January 2020, *110* (1), 162–199.

Hoiting, Jill, Katherine Magnuson, Alejandra Ros Pilarz, Amy Claessens, Hyunwoo Yang, and Leah Awkward-Rich, "Examining the Role of Public Pre-K Expansions in the Changing Supply of Child Care in Wisconsin," *Social Service Review*, March 2025, *99* (1), 172–196.

Johnson, Rucker C. and C. Kirabo Jackson, "Reducing Inequality through Dynamic Complementarity: Evidence from Head Start and Public School Spending," *American Economic Journal: Economic Policy*, November 2019, *11* (4), 310–349.

Joo, Young Sun, Katherine Magnuson, Greg J. Duncan, Holly S. Schindler, Hirokazu Yoshikawa, and Kathleen M. Ziol-Guest, "What Works in Early Childhood Education Programs?: A Meta–Analysis of Preschool Enhancement Programs," *Early Education and Development*, January 2020, *31* (1), 1–26.

Kline, Patrick and Christopher R. Walters, "Evaluating Public Programs with Close Substitutes: The Case of Head Start*," *The Quarterly Journal of Economics*, November 2016, *131* (4), 1795–1848.

Lee, Won Fy, Aaron Sojourner, Elizabeth E. Davis, and Jonathan Borowsky, "Effects of Child-Care Vouchers on Price, Quantity, and Provider Turnover in Private-Care Markets," *Journal of Human Capital*, March 2025, *19* (1), 1–30.

Leung, Justin H. and Hee Kwon Seo, "How do government transfer payments affect retail prices and welfare? Evidence from SNAP," *Journal of Public Economics*, January 2023, *217*, 104760.

Lynch, Karen E. and Conor F. Boyle, *What Is the Child Care Funding Cliff?* number IN12243. In 'Congressional Research Service Insight.' 2023.

Magnuson, Katherine and YingChun Lin, *Validation of the QRIS YoungStar Rating Scale* Wisconsin Early Child Care Study 2015.

Neilson, Christopher A., "Targeted Vouchers, Competition Among Schools and the Academic Achievement of Poor Students," *Econometrica (Conditionally Accepted)*, 2025.

NIEER, "Wisconsin," 2023.

Petrin, Amil, "Quantifying the Benefits of New Products: The Case of the Minivan," *Journal of Political Economy*, August 2002, *110* (4), 705–729.

Rafkin, Charlie, Adam Solomon, and Evan Soltas, "Self-Targeting in U.S. Transfer Programs," 2023.

Rothstein, Jesse, "Is the EITC as Good as an NIT? Conditional Cash Transfers and Tax Incidence," *American Economic Journal: Economic Policy*, February 2010, *2* (1), 177–208.

Saez, E., "Optimal Income Transfer Programs: Intensive versus Extensive Labor Supply Responses," *The Quarterly Journal of Economics*, August 2002, *117* (3), 1039–1073.

Salanié, Bernard and Frank A. Wolak, "Fast, "Robust", and Approximately Correct: Estimating Mixed Demand Systems," April 2019, (25726).

Shepard, Mark and Myles Wagner, "Do Ordeals Work for Selection Markets? Evidence from Health Insurance Auto-Enrollment," *American Economic Review*, March 2025, *115* (3), 772–822.

Smith, Alexander A., "The Long-Run Effects of Universal Pre-K on Criminal Activity," *SSRN*, 2015.

Susin, Scott, "Rent vouchers and the price of low-income housing," *Journal of Public Economics*, 2002, *83* (1), 109–152.

Sweeting, Andrew, "Dynamic Product Positioning in Differentiated Product Markets: The Effect of Fees for Musical Performance Rights on the Commercial Radio Industry,"

Econometrica, 2013, *81* (5), 1763–1803.

Voskuil, Kristen, Donna Friedsam, and Thomas DeLeire, *The Target Efficiency of Online Medicaid/CHIP Enrollment: An Evaluation of Wisconsin's ACCESS Internet Portal* State Health Access Reform Evaluation February 2011.

Walters, Christopher R., "Inputs in the Production of Early Childhood Human Capital: Evidence from Head Start," *American Economic Journal: Applied Economics*, October 2015, *7* (4), 76–102.

A Sample Descriptives

Table A.1: Model-Estimation Sample vs. All Licensed Providers

	(1) WI Model (2022-2025)	(2) WI Lic. + Publics (2022-2025)	(3) Inc. Missing Data (2022-2025)
Panel A: Full Sample (Enrollment-Weighted)			
Family provider	0.056	0.056	0.060
Public: Fee-Based	0.030	0.029	0.029
Public 4K	0.306	0.271	0.304
Head Start	0.061	0.055	0.060
Panel B: Private Sample (Enrollment-Weighted)			
Quality rating	3.10	2.89	3.03
Sticker price, mo. (2017$)	849.40	815.90	849.40
OOP, subsidized, mo. (2017$)	70.83	70.35	71.42
Cap.-constrained (lic. only)	0.348	0.383	0.352
Min. age accepted (months)	5.5	11.5	5.5
Max. age accepted (months)	144.1	143.6	143.8
Serves school-age only (5+)	0.000	0.068	0.000
Years of operation	15.2	15.2	15.0
Total est. subsidized enrollment	98,686	120,780	107,420
Total est. enrollment	346,874	423,500	355,737
Panel C: Public 4K Only (Raw Means)			
Full day, full week	0.324	0.324	0.324
Half day, full week	0.287	0.287	0.287
Full day, half week	0.100	0.100	0.100
Half day, 4 days/week	0.289	0.289	0.289
Charter school	0.052	0.066	0.066
Offers K3	0.068	0.067	0.067
Share FRPL-eligible	0.376	0.377	0.377

Notes: Column (1), the WI Model sample, includes Wisconsin licensed child care providers that are year-round and full-time and Public 4Ks; not a licensed camp or certified family provider; accept children under age five; report enrollment; linked to an address; and report prices Column (2), WI Lic. + Pub., includes all Wisconsin licensed providers plus all Public 4K schools, without any additional filters. Column (3) includes providers that are otherwise in-sample but are dropped for missing enrollment, address, or price. Panels A and B weight by each provider's reported enrollment. Providers with missing enrollment do not contribute to those panels. Panel B is restricted to the private sample, which excludes Public 4Ks, Head Start, and public fee-based providers. Panel C is restricted to Public 4Ks and reports unweighted means across those schools. "Public: Fee-Based" is a licensed provider operating from a public school. These providers charge fees, unlike public 4Ks. 'Quality Rating' is the provider's YoungStar quality rating on a 1-5 scale (0 = not rated). "Sticker Price" is the monthly price an unsubsidized family would pay to attend. "OOP, subsidized" is the estimated monthly out-of-pocket payment for subsidized children, weighted by subsidized enrollment. Monthly prices and OOPs are for three-year-olds, expressed in 2017 dollars "Cap.-constrained" is the share of licensed providers whose estimated enrollment meets their licensed capacity. Panel C describes Public 4K program schedules. Full-day is generally a full school-day, rather than a full work-day.

Table A.2: Model-Estimation Sample vs. Quasi-Experimental Sample: Private Providers

	(1) WI Model Sample (2022-2025)	(2) WI Licensed (2022-2025)	(3) WI Sample (2017-2020)	(4) PA Sample (2017-2020)
Family provider	0.064	0.069	0.102	0.050
Public: Fee-Based	0.082	0.105	0.000	0.000
Head Start	0.112	0.109	0.000	0.000
High-quality	0.315	0.259	0.280	0.335
Sticker price, mo. ($2017)	760.15	718.00	909.37	823.55
Avg sticker price if > 0	856.45	811.92	909.37	823.55
No subsidized enrollees	0.135	0.225	0.180	0.023
Serves school-age only (5+)	0.000	0.068	0.000	0.000
Total licensed seats	524,150	715,882	494,491	1,272,832
Number of providers	10,672	17,874	13,025	22,077

This table compares private child care providers across four sub-samples: the Wisconsin sample used in the structural model; all licensed WI private providers from 2022-2025; and the Wisconsin and Pennsylvania sub-samples used for the additional quasi-experimental results. All four columns exclude Public 4Ks. All main-body rows report capacity-weighted means "Total seats" is the unweighted sum of licensed capacity across all providers in the column, and "Total providers (N)" is the unweighted provider count. "Family providers" offer child care services from a residential facility. "Public: Fee-Based" is a licensed provider operating from a public school. These providers charge fees for participation, unlike public 4Ks. "High quality" uses state-specific thresholds on the quality rating that require scoring an average of four on the Environment Rating Scale. "Sticker price, mo." is the monthly price for a three-year-old in 2017 dollars; "Avg sticker price if > 0" restricts the mean to providers charging a positive price. "No subsidized enrollees" is the share of providers with zero subsidized enrollees, where such data was available.

B Robustness Check: Alternative Difference-in-Differences

To evaluate how subsidy policy affects local quality, I compare the effects of policy changes in Wisconsin and Pennsylvania after the same federal funding increase. As discussed in section 2, Wisconsin raised its maximum subsidy between October 2018 and October 2019, but also served 12% fewer children from 2017 to 2020. Over the same period, Pennsylvania raised its maximum subsidy by 2.5% and served 5% more children. Notably, Pennsylvania increased its maximum subsidy to the 40th percentile of prices in 2021 (Campanini, 2021), so the differences in the maximum subsidy between the states reflect differences in *timing*. Nevertheless, Pennsylvania and Wisconsin may have had other state-specific changes over this period unrelated to changes to subsidy policy. To better isolate the effect of subsidy changes, I rely on means-testing causing the policy to have a larger effect in poorer census tracts than richer census tracts.[79] I use a difference-in-differences design, with high poverty census tracts as the treated group and January 2019 to January 2020 as the treatment period. I estimate the treatment effect separately by state for each census tract l in time t:

$$Y_{lt} = \beta_0 + \beta_1^{state} HighPov_l + \beta_2^{state} Post_t + \beta_3^{state} HighPov_l * Post_t + \beta_4 X_{lt} + \eta_{county(l)} + \epsilon_{lt} \quad (2)$$

I evaluate the effect of the policy on (1) whether a census tract has any high-quality provider and (2) the out-of-pocket payment paid by subsidized families. Helpfully for making a cross-state comparison, both Wisconsin and Pennsylvania rely on the Environmental Rating Scale to evaluate child care providers. Each requires an average score of at least four to earn a rating of four stars in Wisconsin and three stars in Pennsylvania. I therefore use this cut-off to define "high-quality" across both states. I first find that treated census tracts in Pennsylvania are 2.2pp more likely to have a high quality provider after the policy change, while Wisconsin tracts show no change. Next, I show that out-of-pocket payments increased in Wisconsin's high poverty tracts, conditional on quality, but did not change in Pennsylvania.

[79] "High poverty" is defined at the 75th percentile of the poverty rate in 2018, measured separately by state. In Wisconsin, this is any tract with at least 35% of young children under the poverty line and in Pennsylvania this is any tract with at least 40% of young children under the poverty line.

Table A.3: PA Policy is More Effective at Increasing Quality

	P(Any HQ Provider)
WI × Post × High Pov	0.000
	(0.014)
PA × Post × High Pov	0.022**
	(0.010)
Dep. Mean WI (High Pov. + 2018)	0.289
Dep. Mean PA (High Pov. + 2018)	0.285
County FE	✓
Local Controls	✓
Observations	17093

Standard errors clustered by county-year. Control for demographics, such as number of local children, age distribution of women, marriage rates for mothers of young children, birth rate, birth rate for married and college-educated women, income distribution of families with young children, SNAP coverage rate, and pre-period care availability. High quality defined as provider rated in top two ratings available by state. Results weighted by number of children under age five.
* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

C Robustness Check: Alternative Triple Differences

I take advantage of the fact that caseloads fell statewide from 2017 to 2020, but did not fall evenly across the state. Let $\Delta lnPrSub_i$ denote the change in the log proportion of families subsidized in tract i[80] between 2017–2018 and 2019–2020. I treat $\Delta lnPrSub_i$ as exogenous conditional on baseline differences and county fixed effects. I also once again treat $MaxSub_{i,1920}$ as exogenous conditional on baseline differences and county fixed effects. The triple-differences approach can be summarized as follows:

$$\begin{aligned} Y_{it} = \beta_0 &+ \beta_1 \Delta lnPrSub_i + \beta_2 MaxSub_{i,19-20} + \beta_3 \text{Post}_t \\ &+ \beta_4(\Delta lnPrSub_i \times MaxSub_{i,1920}) + \beta_5(\Delta lnPrSub_i \times \text{Post}_t) + \beta_6(MaxSub_{i,1920} \times \text{Post}_t) \\ &+ \beta_7(\Delta lnPrSub_i \times MaxSub_{i,1920} \times \text{Post}_t) + \beta_8 X_{it} + \eta_c + \varepsilon_{it}, \end{aligned} \tag{4}$$

where the relevant coefficients of interest are β_5, β_6, and β_7.

Table A.4 reports the results from the triple-differences approach on quality. A 10% higher proportion of families subsidized increases the probability that a census tract has a provider with at least three stars by 1pp. The proportion of families subsidized has no significant effect on whether there are providers with higher quality-ratings. Offering a $10 higher maximum subsidy increases the probability that a census tract has a provider with at least three stars by 0.4pp ($p < 0.05$) and at least four stars by 0.5pp ($p < 0.01$). There is no significant interaction effect between the two policies.

Table A.5 shows the triple-differences approach evaluated on out-of-pocket payments.

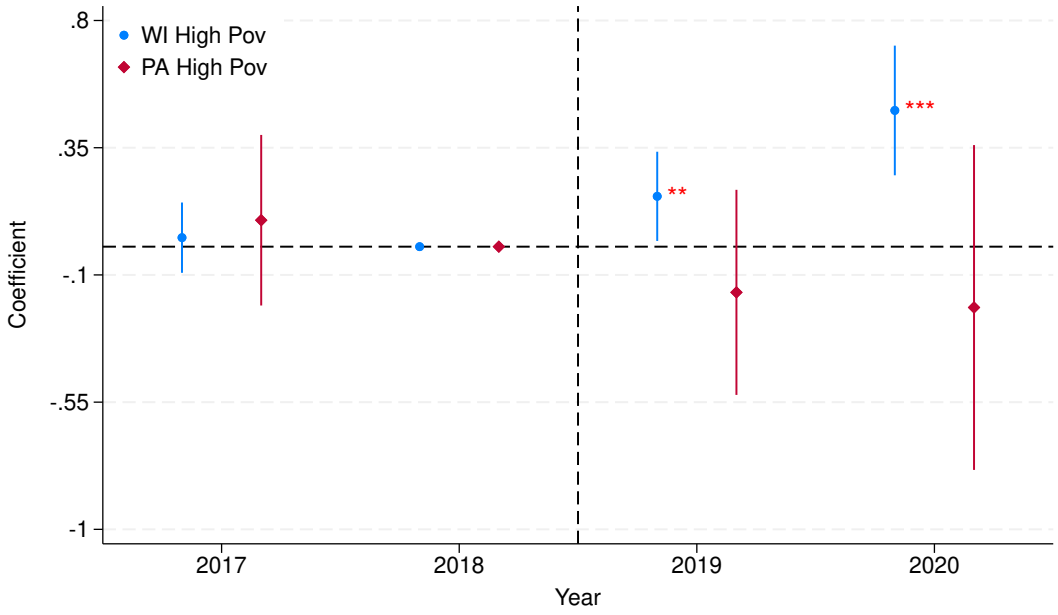
[80] Or the tract that provider i is located in, in the case of out-of-pocket payment outcomes.

Table A.4: Increasing the Maximum Subsidy or Proportion of Families Subsidized Increases Access to Middling-Quality Providers

	(1) Any 3+ Star	(2) Any 4+ Star	(3) Any 5 Star
Change in Log Prop. Fam. Sub. × Post	0.099***	0.025	0.014
	(0.030)	(0.015)	(0.013)
Max. Sub. ($10/week) × Post	0.004**	0.005***	0.002
	(0.002)	(0.002)	(0.003)
Change in Sub. × Max. Sub. × Post	0.007	-0.005	0.003
	(0.008)	(0.004)	(0.005)
N	5324	5324	5324

Notes: Outcome is an indicator for whether the census tract has at least one provider with a YoungStar rating of 3+ (column 1), 4+ (column 2), or 5 (column 3) stars. The sample is Wisconsin census tracts, 2017–2020. Result measured in January of each year. Change in Log Prop. Fam. Sub. is the log change in the proportion of families subsidized between 2017–2018 and 2019–2020 ($\Delta lnPrSub_i$). If the number of subsidized children in a tract is smaller than 1% of the number of young children in the neighborhood, the log proportion of families subsidized is set to ln(0.01). Max. Sub. is the 2019–2020 average maximum subsidy ($MaxSub_{i,19-20}$, $10/week units, mean-centered). Post is an indicator for years $\geq$ 2019 ($Post_t$). The regression includes all main effects and two- and three-way interactions of Log Change, Max. Sub., and Post; only the interactions with Post are shown. Controls include the number of young children, the proportion of young children's parents who are married, birth rate to married and college-educated women, coarse income distribution for families with young children (100%, 200%, 300%, 400%, 500+% of the federal poverty line), proportion of families with young children receiving SNAP, tract urbanicity, and county fixed effects. Observations are weighted by the number of young children per tract. Standard errors are clustered at the county-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure A.1: Out of Pocket Payments Increased in Wisconsin



Notes: Outcome is the estimated log out of pocket payment at the provider, weighted by subsidized enrollment. Each year's result is shown for January as the representative month. Controls for county FE, provider type, capacity, provider quality, demographics, such as number of local children, age distribution of women, marriage rates for mothers of young children, birth rate, birth rate for married and college-educated women, income distribution of families with young children, SNAP coverage rate. Cluster SEs by county-year.

The maximum-subsidy pass-through survives essentially unchanged in magnitude, though the effect on prices (0.1% increase for every $10 higher maximum subsidy) is measured more precisely. The change in the local proportion of families subsidized has no significant effect on out-of-pocket payments.

Table A.5: Out-of-Pocket Payments Increase with the Maximum Subsidy

	(1) ln(OOP)	(2) OOP>0	(3) ln(Price)
Log Change in Prop. Fam. Sub. × Post	-0.107	-0.013	-0.001
	(0.130)	(0.045)	(0.008)
Max. Sub. ($10/week) × Post	0.038***	0.011***	0.001**
	(0.012)	(0.004)	(0.001)
Log Change × Max. Sub. × Post	-0.029	-0.015**	-0.002
	(0.020)	(0.007)	(0.002)
N	7556	7556	7556

Notes: Outcomes are the log expected out-of-pocket payment (or $1 for providers with $0 out-of-pocket payment) for a subsidized family at the provider (ln(OOP), column 1), an indicator for a positive out-of-pocket payment (OOP>0, column 2), and the log sticker price (ln(Price), column 3), all measured at the provider-year level. The sample is Wisconsin licensed private providers with at least two stars, 2017–2020. Result measured in January of each year. Log Change in Prop. Fam. Sub. is the log change in the proportion of families subsidized in the provider's tract between 2017–2018 and 2019–2020 ($\Delta lnPrSub_i$). If the number of subsidized children in a tract is smaller than 1% of the number of young children in the neighborhood, the log proportion of families subsidized is set to ln(0.01). Max. Sub. is the 2019–2020 average maximum subsidy ($MaxSub_{i,19-20}$, $10/week units, mean-centered). Post is an indicator for years $\geq$ 2019 ($Post_t$). The regression includes all main effects and two- and three-way interactions of Log Change, Max. Sub., and Post; only the interactions with Post are shown. Controls include the number of young children in the provider's tract, the proportion of young children's parents who are married, birth rate to married and college-educated women, coarse income distribution for families with young children (100%, 200%, 300%, 400%, 500+% of the federal poverty line), proportion of families with young children receiving SNAP, tract urbanicity, and star, county, and provider-type fixed effects. Observations are weighted by subsidized enrollment. Standard errors are clustered at the county-year level and shown in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

D Market Descriptives

Table A.6: Market descriptives (2022)

	Demographics		Providers						
Market	Elig.	Urban	N Priv.	Ctr.	N HS	N Pub. 4K	Sub. Enr.	Avg. Stars	Avg. Price
Milwaukee	0.42	0.97	934	0.89	42	195	0.54	3.06	264
Madison	0.23	0.89	232	0.96	12	39	0.13	3.28	284
Kenosha, Racine	0.36	0.85	119	0.97	8	62	0.42	2.97	216
Appleton	0.26	0.76	81	0.95	5	26	0.15	3.38	231
Green Bay	0.33	0.75	80	0.97	4	44	0.20	3.23	216
Rock, Walworth County	0.33	0.71	66	0.95	10	44	0.20	3.40	202
Wausau	0.35	0.65	41	0.91	1	9	0.15	3.40	202
La Crosse, Vernon County	0.33	0.65	67	0.92	6	31	0.12	2.68	190
Oshkosh	0.35	0.64	57	0.94	2	22	0.20	2.88	200
Sheboygan	0.35	0.62	52	0.97	12	24	0.16	3.01	198
Lake Superior, North Douglas County	0.26	0.62	15	0.89	3	11	0.21	2.66	174
Oconomowoc, Jefferson County	0.19	0.61	39	0.98	5	24	0.11	3.48	243
Stevens Point	0.37	0.55	55	0.89	4	17	0.15	3.03	189
Eau Claire	0.32	0.53	92	0.92	10	21	0.16	3.56	208
Prairie du Chien	0.50	0.51	7	0.74	0	3	0.12	2.29	141
West Bend	0.25	0.47	30	0.99	2	15	0.14	3.37	191
Beaver Dam	0.37	0.46	24	0.94	2	11	0.17	3.11	175
Monroe	0.26	0.44	15	0.89	1	8	0.08	2.22	191
Ashland, Bayfield, Bad River	0.42	0.35	17	0.58	3	6	0.27	1.76	157
Baraboo, Portage, Adams, Marquette	0.29	0.32	44	0.88	8	22	0.15	2.44	174
West Dane, Iowa County	0.18	0.32	19	0.75	1	5	0.03	3.32	200
Menominee, Shawano	0.40	0.30	18	0.88	3	16	0.22	3.00	164
Door County	0.38	0.28	6	0.95	1	4	0.20	2.81	199
Marshfield, Clark County	0.40	0.28	28	0.89	1	9	0.14	3.03	189
St. Croix, Pierce, Polk County	0.28	0.26	64	0.91	2	19	0.09	2.85	206
Juneau, Tomah	0.45	0.24	11	0.91	1	10	0.22	2.45	173
Oconto, Marinette, Peshtigo	0.40	0.23	12	0.92	5	6	0.13	2.74	144
Florence County	0.35	0.20	2	0.86	2	4	0.09	2.00	134
Platteville, Lancaster, SW Wisc	0.39	0.18	27	0.87	6	14	0.13	2.44	167
Buffalo, Trempealeau, Jackson County	0.47	0.13	11	0.77	6	7	0.27	2.05	152
Oneida, Vilas, Forest County	0.38	0.12	18	0.95	7	20	0.14	3.25	189
Richland	0.52	0.12	5	0.71	4	8	0.30	1.82	177
Barron, Rusk, Washburn	0.42	0.11	28	0.81	4	17	0.16	2.55	148
Medford	0.42	0.11	14	0.72	3	6	0.18	2.74	161
Price County	0.56	0.00	6	0.56	1	6	0.26	2.26	130
Burnett County	0.43	0.00	3	0.00	2	4	0.00	3.00	127
Hayward, Lac Courte Oreilles	0.49	0.00	6	0.77	3	4	0.11	2.68	165

Notes: Eligible share (Elig.): fraction of children ages 0–4 in households with income at or below 200% of the federal poverty level. Urban share: fraction of tract population in a Census-designated urban area. Private providers: count of private centers and family providers, excluding Head Start. Center share (Ctr.): fraction of total private, licensed capacity at centers. Head Start: count of Head Start locations. Public pre-K: count of public 4K providers. Subsidized enrollment share (Sub. Enr.): subsidized enrollment as a fraction of total enrollment at private providers. Avg. Stars: enrollment-weighted average quality rating. Avg. Price: enrollment-weighted average age-adjusted, weekly price at private providers (2022 dollars).

E Model Estimates

Table A.7: Demand-Side Parameter Estimates

	Est.		Est.
2 Stars	−6.2114	4 Stars × Elig	−0.5501
	(2.5969)		(0.1874)
3 Stars	−10.9830	5 Stars × Elig	−7.6373
	(2.5846)		(0.2770)
4 Stars	−2.4627	Out-of-Pocket × Elig	−4.5385
	(3.0677)		(0.0974)
5 Stars	3.4796	Out-of-Pocket × Inelig	−2.2864
	(2.8199)		(0.0513)
Center-Based	−0.5531	Center × Elig	14.9996
	(1.1664)		(0.3372)
Capacity	0.1022	Elig × Public 4K	−10.4724
	(0.0118)		(0.4129)
Youngest Age	0.2263	Elig × Pub 4K, FDHW	−2.7503
	(0.0412)		(2.0321)
Oldest Age	−0.1254	Elig × Pub 4K, HDFW	−6.3655
	(0.0191)		(0.5355)
Years in Op.	−0.7484	Elig × Pub 4K, HD4D	−6.5367
	(0.0481)		(0.4403)
Inside Option	125.8478	Elig × Pub 4K Fee	6.6290
	(4.7205)		(0.2354)
Head Start	−68.4632	Distance × Elig	−14.9992
	(3.2737)		(0.3695)
Public 4K	−35.6361	Distance × Inelig	−0.2213
	(4.3703)		(0.2091)
Pub 4K, FDHW	77.5105	Distance Squared	−10.1714
	(6.3138)		(0.2370)
Pub 4K, HDFW	5.0965	Dist × Milw × Elig	−0.0648
	(2.9320)		(1.1175)
Pub 4K, HD4D	8.7906	Dist × Milw × Inelig	−2.4916
	(3.2249)		(0.6755)
Public Fee-Based	−26.0161	Age 0–2 × Inside	8.3895
	(2.6787)		(0.2930)
Eligible	−3.4020	Age 3 × Inside	18.2254
	(0.2327)		(0.5050)
2 Stars × Elig	2.1306	Age 4 × Inside	0.7797
	(0.1822)		(0.1912)
3 Stars × Elig	10.9624	σ (High-Quality)	9.3260
	(0.2687)		(0.2312)

Star coefficients are relative to an unrated/one-star baseline. One star providers make up less than 0.1% of the sample and so are combined with unrated providers. Inside Option applies to any formal provider. Public 4K variants FDHW, HDFW, and HD4D denote the full-day/half-week, half-day/full-week, and half-day/four-day schedules. Public Fee-Based refer to public fee-based providers, not limited to 4-K. Out-of-Pocket is the family's out-of-pocket price. Distance is Haversine distance from the centroid of the family's tract to the provider. Milw denotes Milwaukee County. Age 0–2, 3, and 4 reflect differences in taste for the inside good for difference age groups. σ is the standard deviation of the random coefficient on high-quality (5 star) providers. Standard errors in parentheses.

Table A.8: Marginal Cost Parameter Estimates

	Est.		Est.
2 Stars	0.3910	Oldest Age Served	−0.0022
	(0.1754)		(0.0113)
3 Stars	0.2588	Oldest Age Squared	0.0000
	(0.1840)		(0.0000)
4 Stars	0.4551	Years in Op.	−0.0214
	(0.2261)		(0.0114)
5 Stars	1.9998	Years in Op. Squared	0.0011
	(0.1741)		(0.0003)
Local Wages	−0.0093	Center-Based	−0.7606
	(0.0026)		(0.1038)
Youngest Age	0.0347	exp(Utilization)	0.1880
	(0.0152)		(0.0643)
Youngest Age Sq.	−0.0009		
	(0.0004)		

Star coefficients are relative to a 1-star baseline. Local Wages is the county-level average child-care worker wage. Years in Op. is the number of years the provider has had their license. Utilization is the effect of operating near capacity on marginal costs. Standard errors in parentheses.

Table A.9: Quality-Stage Parameter Estimates

	Family Non-Milw.	Family Milwaukee	Center Non-Milw.	Center Milwaukee
θ^{ε}	14.97	–	–	–
c_2	0.00	0.00	0.00	0.00
c_3	4.05	0.00	0.00	0.00
c_4	20.86	29.13	23.65	18.66
c_5	23.88	38.78	5.32	7.34

θ^{ε} is the scale parameter for the distribution of private fixed costs. c_k is the additional cost of being a k star provider compared to being unrated. θ^{ε} does not vary by provider type or whether the provider is in Milwaukee. I assume that fixed costs to be quality-rated are at least zero, but otherwise am agnostic on the distribution of fixed costs.

F Model Fit

Table A.10: Model Fit: Conditional on Choosing Private Care

	Sub.		Unsub.		
Moment	Data	Model	Data	Model	Matched
Prop. 0/1 Stars	0.00	0.00	0.06	0.00	
Prop. 2 Stars	0.38	0.28	0.25	0.28	✓
Prop. 3 Stars	0.36	0.53	0.35	0.39	✓
Prop. 4 Stars	0.06	0.05	0.07	0.05	✓
Prop. 5 Stars	0.20	0.12	0.28	0.20	✓
Prop. Center-based	0.82	0.85	0.90	0.74	
Avg. Provider Age	12	17	17	17	
Avg. Weekly Sticker Price	240	200	210	170	
Avg. Weekly OOP	18	7.8	210	170	✓

Statistics are computed over families who chose a private provider, separately for subsidized (Sub.) and unsubsidized (Unsub.) families. Stars refers to the provider's YoungStar quality tier, where 0 is unrated. Capacity is the provider's licensed enrollment capacity. Provider Age is years since licensure began. Sticker Price is the provider's age-adjusted weekly price. OOP is the family's weekly out-of-pocket cost. For subsidized families, this accounts for the value of the subsidy. Checkmarks indicate moments targeted in GMM estimation.

Table A.11: Proportion of Children Eligible for Free or Reduced Price Lunch, by Public 4K Characteristics

Public 4K Subset	Data	Model	Matched
All Public 4K	0.38	0.54	✓
Charter	0.51	0.52	
Full Day, Full Week	0.54	0.59	
Full Day, Half Week	0.42	0.57	
Half Day, Full Week	0.31	0.49	
Half Day, 4 Days/Week	0.36	0.52	

Each row reports the share of children attending the given type of Public 4K program who are eligible for free or reduced-price lunch. The first row is overall for all Public 4Ks. The Charter row covers programs operated by charter schools. Checkmarks indicate moments targeted in GMM estimation.

G Optimal Quality Choice Under Multiple Discrete Quality Types

In my setting, there are five quality ratings: unrated, two, three, four, or five stars. We can then say that the probability the provider is quality q is:

$$Pr(Qual_{jt} = q) = \frac{\exp((\mathbb{E}\Pi(Qual_{jt} = q) - c_q)/\theta^{\varepsilon})}{\sum_{q \in \mathcal{Q}} \exp((\mathbb{E}\Pi(Qual_{jt} = q) - c_q)/\theta^{\varepsilon})},$$

where $\mathcal{Q} = \{0, 2, 3, 4, 5\}$ stars. As θ^{ε} increases, expected profit explains less of the variation in the quality distribution.

H Welfare Estimation

To evaluate welfare under different maximum subsidies, I compute consumer and producer surplus.

H.1 Consumer Surplus

Family i's utility from enrolling at provider j in market-year t is defined as

$$U_{ijt} = \delta_{jt} + \mu_{ijt} + \epsilon_{ijt},$$

where δ_{jt} is the component of utility common to all families – some providers j are better than other providers j' – and μ_{ijt} is the component of utility specific to family i based on observables – some providers are more appealing to family i, say because the provider is located nearby. ϵ_{ijt} captures idiosyncratic taste from family i for provider j. Define $V_{ijt} \equiv U_{ijt} - \epsilon_{ijt}$.

I use the same consumer surplus definition as used in Conlon and Gortmaker (2020). For family i in market-year t, CS_{it} is defined as:

$$CS_{it} = \frac{1}{|\beta_{\tau}^{OOP}|} \log \sum_{j \in \mathcal{J}_t} \exp\big(V_{ijt}\big),$$

where I divide by β_{τ}^{OOP} so I can interpret the result in dollars. I then sum consumer surplus across all individuals across the state. In practice, I estimate:

$$CS_{2022} = \sum_{t \in \mathcal{T}_{2022}} N_t \sum_{\tau \in \Theta} \pi_t^{\tau} \sum_{l \in \mathcal{L}_t} w_{lt}^{\tau} \int \frac{1}{|\beta_{\tau}^{OOP}|} \log \sum_{j \in \mathcal{J}_t} \exp\big(V_{ijt}(\mu_{ijt})\big)\, dF(\mu_{ijt}^{\tau}).$$

Within the integral is CS_{it}, but summed across the values of the random coefficient. I estimate the integral using Gaussian quadrature. I then weight CS_{it} within each market by the share of individuals of type τ that live at node l (w_{lt}^{τ}) and the share of families in market t of type τ (π_t^{τ}). To calculate the statewide consumer surplus, I weigh the market-level consumer surplus by the number of families living in market t (N_t).

I report in the main results the average consumer surplus per eligible child and per any child, respectively.

H.2 Producer Surplus

I calculate producer surplus only for in-sample, private providers. Producer surplus is defined as profit:

$$PS_{jt} = sh_{jt} N_t (p_{jt} - mc_{jt}),$$

where $sh_{jt} N_t$ is total enrollment at provider j, p_{jt} is the price charged by provider j in market-year t, and mc_{jt} is marginal cost. Total producer surplus is calculated by summing PS_{jt} over each provider in the state. I report average producer surplus in dollars per year per provider.