NET WORK LISER

Discussion Paper Series

IZA DP No. 18597

April 2026

Undersupply or Lack of Demand? Evaluating Measures of Child Care Access

Jessica H. Brown
University of South Carolina and
IZA@LISER

IZA@LISER NETWORK
ISSN: 2365-9793

IZA DP No. 18597 April 2026

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Abstract

The most widely used measure of child care access is "child care deserts," defined as areas with three or more young children per licensed child care slot. However, a high child-to-slot ratio may reflect low demand for formal care rather than a shortage. In the canonical model, equilibrium quantities perfectly reflect local demand and costs, implying that the ease of finding care should not vary systematically. In this paper, I use center-based provider vacancy rates as a proxy for families' ability to access care. I test whether these vacancy rates are negatively correlated with child care desert status and with two alternative measures that adjust for community characteristics. The first alternative measure captures deviations between actual and predicted supply, where predicted supply is based on supply in areas with similar demographic characteristics. The second alternative measure is based on a more recent measure of child care access, the "child care gap." It compares the number of licensed slots to the number of young children with all parents working, a proxy for demand. Desert status is only weakly predictive of low center-based vacancy rates, while the alternative measures are strongly predictive of low infant and toddler vacancy rates. These findings suggest that child care is more challenging to find in some areas, providing suggestive evidence of market frictions and a potential role for policy. However, identifying such areas requires adjusting low supply thresholds for local population characteristics.

JEL classification

J13, H75, H54

Keywords

child care market, child care deserts, targeting

Corresponding author

Jessica H. Brown
Jessica.Brown@moore.sc.edu

* The author gratefully acknowledges helpful comments from Chloe Gibbs, Chris Herbst, Sandy Black, Jesse Rothstein, seminar participants at the University of South Carolina, and conference attendees at APPAM 2025 and SEA 2025.

Access to child care plays a key role in parental labor supply, and quality of care affects children's long-term outcomes. Thus, measuring access to high-quality child care is important for policy. An ideal measure would take into account both supply and demand. However, demand is difficult to measure, so access measures are typically based on licensed supply per capita and not adjusted for differences in demand across geographies.

The most common access metric defines areas where there are more than three children per licensed slot as "child care deserts" (Center for American Progress, 2018). This metric has been used to target investments in child care: when allocating American Rescue Plan Act grants for opening, expanding, or updating private child care facilities, more than 40% of states prioritized centers located in areas designated as "child care deserts" (First Children's Finance, 2024). However, it is unclear whether purely supply-based measures accurately identify the areas with the greatest need for infrastructure investments or whether they simply capture areas with low demand for formal care.

Thus, when using a measure of child care access for targeting investment, it is important to validate the measure to ensure it is truly identifying areas where parents have the greatest difficulty accessing care. One promising metric for validation is provider vacancy rates, which provide a key indicator of parents' ability to enroll their children in child care. Although access has many dimensions (prices, hours, quality, etc.), the most fundamental is whether a provider has an available slot. Parents in markets with particularly low vacancy rates are likely to face more difficulty securing care when they need it. Vacancy rates are impractical to use as a primary access metric due to the difficulty of data collection. However, they are useful for validating measures that are more feasible to calculate at scale.

In this paper, I first validate the child care desert measure using center-based provider vacancy rates. To measure these vacancy rates, I use restricted nationally representative data from the 2019 National Survey of Early Care and Education (NSECE), which includes county identifiers. I merge this data with county-level counts of licensed slots from the 2018 Center for American Progress child care desert map (Center for American Progress, 2018), along with county-level characteristics from the American Community Survey (ACS).[1] I use OLS regression to estimate the extent to which child care desert status is predictive of vacancy rates. I use both the typical desert threshold of three or more children per licensed slot (abbreviated as CCD3) and a more stringent threshold of four or more children (CCD4) per licensed slot.

In addition, I construct two alternative measures that adjust for demand. For the first measure, I identify counties with especially large gaps between observed and predicted supply of licensed care, where predicted supply is based on exogenous county demographic characteristics. Specifically, I regress the county-level number of licensed slots per child under age 5 on county-level demographic characteristics and use the estimated coefficients to generate predicted supply for each county. I classify the 20% of counties with the largest gaps between actual and predicted supply as having demographic-adjusted low supply (DALS). These

[1] While child care desert status is typically determined at the Census tract level, the smallest geographic unit available to researchers in the NSECE is the county.

are counties that have substantially fewer slots than would be predicted by their demographic profiles. The second measure relaxes the restriction that demand predictors should be exogenous to child care supply and is based on the newly released "child care gap" measure (Buffett Early Childhood Institute, 2025). I calculate the number of licensed slots per child under 5 with all parents in the labor force and classify the 20% of counties with the lowest ratios as having a child care gap (CCG). This measure is appealing for its straightforward way of adjusting for demand, though it may miss differences in demand for formal care and relies on a measure (parental labor force participation) that may be endogenous to child care supply.

Overall, I find that child care desert status is only weakly correlated with low vacancy rates. Across 15 relationships (five single-year age bands by three vacancy measures), only four are statistically significant for CCD3 and one for CCD4, often only marginally. In contrast, both DALS and CCG are robustly predictive of reduced availability, particularly for infants and toddlers, with point estimates often double those of the CCD measures and highly statistically significant. For example, providers located in DALS (CCG) counties are 22 (19) percentage points less likely to have an opening in their infant room, 40% lower than the baseline mean of 48%. These findings show that it is possible to identify areas with tighter child care markets by using measures that account for local demand. However, failing to account for differences in demand across geographies likely leads to misidentification of areas most in need of additional capacity.

Under perfect competition, we would not have expected these measures to be correlated with vacancy rates. In any area where demand exceeds supply, prices would rise and/or new providers would enter to clear the market. However, there may be frictions in the market that prevent those adjustments from happening. For example, a combination of high fixed costs and market power may lead to anti-competitive pricing behavior (Bitler and Haider (2011); Sutton 2007; Ellickson 2007). The goal of this paper is to determine whether it is possible to identify areas where it is more difficult for a parent to find a provider with an open slot. If so, an important avenue for future work is determining why they exist.

This paper contributes to a broader literature on the existence and measurement of "deserts." Bitler and Haider (2011) provide a thorough economic analysis of the potential theoretical foundations for food deserts, which, like child care deserts, may be driven by a lack of demand or by market failures. Allcott et al. (2019) addresses the question empirically and finds that food deserts are driven by a lack of demand: equalizing access only closes 10% of the gap in nutritional inequality, with the rest due to differences in demand. I contribute to this literature by assessing whether deserts are driven by a lack of demand in the context of child care. The literature on child care deserts has primarily focused on supply-side measurement and identifying community characteristics associated with lower per-capita supply (Bassok et al. 2011; Gordon and Chase-Lansdale 2001; Fuller and Liang 1996; Davis et al. (2019)). I contribute to this literature by studying whether supply-per-capita measures of deserts meaningfully capture the difficulty parents face in finding center-based care. I also provide evidence that taking into account indicators of demand may provide a better prediction of (lack of) access to child care, with implications for the targeting of public funds.

More broadly, this paper contributes to the literature on how governments target scarce public resources

when they must rely on observable proxies for underlying need. In some settings, targeting is based on individual characteristics, and previous research studies how well observable proxies or screening rules identify high-need beneficiaries or generate improved return on investment in contexts such as cash or in-kind benefits, homelessness prevention programs, and retrofitting buildings to improve energy efficiency (Alatas et al., 2012; Brown et al., 2018; Basurto et al., 2020; Phillips and Sullivan, 2025; Christensen et al., 2024). In other settings, funds are allocated using geographic indicators of local distress, as in the case of child care deserts. Previous research evaluates the effectiveness of different geographic targeting rules (Kochar et al., 2009; Corinth et al., 2025). I contribute to this literature by comparing alternative geographic targeting measures in child care policy, showing that the standard child care desert measure is only weakly related to an indicator of market tightness, while demand-adjusted alternatives perform substantially better.

The remainder of the paper proceeds as follows. Section 1 provides background on the child care market and current measures of child care supply. Section 2 describes the data used for the analysis, and Section 3 describes the DALS metric and the empirical strategy used to assess the relationship between access measures and vacancies. Results are presented in Section 4, and Section 5 concludes.

1 The Child Care Market and Current Access Measures

1.1 The Child Care Market

The market for non-parental care is comprised of three primary sectors: center-based, home-based, and informal. Center-based care takes place in non-residential buildings and is highly regulated by state licensing agencies. Home-based care occurs in the provider's home and may be licensed or unlicensed. Informal care includes care by family, friends, and neighbors and care in the child's own home by a nanny or babysitter. Access to center-based care provides a good proxy for access to high-quality care as center-based care is on average the highest quality form of non-parental (Bassok et al., 2016).

1.2 Measuring Child Care Access

The most common measure of care access is "child care deserts," identified as areas where the number of young children per licensed child care slot is greater than three (Malik and Hamm 2017; Malik et al. 2018)). The Center for American Progress periodically collects child care capacity from licensing agencies on a state-by-state basis to calculate these ratios, with maps published online for years 2018 and 2020.

The child care desert metric uses the same threshold for low supply in all geographic areas. If demand per capita is similar across geographies, then it will provide a good approximation of areas in the greatest need of child care infrastructure investment. However, if demand varies across geographies (for example, if demand is higher in cities), then measures that rely only on the number of children per slot will be less informative. However, determining how demand for care varies across geographies is theoretically and empirically challenging, and so this measure is appealing for its parsimony. Thus, if purely supply-based

measures provide a sufficiently good signal of insufficient supply, they may be more practical than more complicated measures that take into account differences in demand across space.

A newer measure, the Buffett Institute's Child Care Gap, accounts for demand by comparing the number of licensed slots to the number of children with all parents working. The measure also uses methods similar to Davis et al. (2019) to provide a measure that is more continuous across space. This measure is appealing for its parsimonious way of adjusting for demand. One downside of the measure is the potential endogeneity of labor force participation to child care availability, which could lead to an understatement of the true care gap. For the purposes of targeting infrastructure investments, this understatement would only be problematic to the extent that the elasticity of parental labor supply with respect to the availability of care differs across regions, which could lead to a misordering of areas most in need. The CCG may also fail to capture variation in demand for formal care (relative to informal care) among working parent households and differences in the use of care for households in which at least one parent is not employed. The extent to which these concerns affects interpretation is an empirical question.

One additional practical challenge with these measures for policy targeting is that as ratio-based measures, CCD and CCG do not distinguish well among areas with zero licensed supply. When slots are zero, both measures mechanically categorize the area in the most extreme category of low access. This issue is particularly limiting at finer geographic scales, where zeros are more common.

2 Data Sources

This section describes the data used in the paper. Data on the number of licensed child care slots was scraped from the Center for American Progress's published map for 2018. Provider-level vacancy rate data is from the National Survey of Early Care and Education (NSECE) 2019. Finally, I use county-level demographic data from the 2019 5-year American Community Survey (ACS) estimates and the 2020 U.S. Census of Religion.

2.1 Child Care Desert Data: Center for American Progress

The Center for American Progress periodically publishes detailed maps of child care supply in order to map child care deserts. For this paper, I use data from the 2018 map, which closely aligns with the NSECE data collected in the first half of 2019. I scrape tract-level data from the Center for American Progress's child care desert website (`https://childcaredeserts.org/2018/index.html`). This data provides the number of licensed child care slots (combining both home-based and center-based providers) for each Census tract in the country as of 2018. For the analysis, I aggregate the number of licensed slots to the county level, the finest geography provided in the NSECE restricted data.

2.2 Vacancy Rate Data: National Survey of Early Care and Education

The primary data source for the analysis is the 2019 NSECE (National Survey of Early Care and Education Project Team, 2022). The NSECE provides a nationally representative survey of center-based providers. I use the 2019 survey, which was in the field from January to July 2019, for this analysis as the timing lines up well the 2018 CAP Child Care Desert map. All analyses use NSECE sample weights to create nationally representative estimates.

The NSECE asks detailed questions about provider prices, enrollment, and other topics. In particular, the NSECE provides information about the number of children currently enrolled and the number of vacancies by single year age band.[2] I use the vacancy and enrollment numbers to construct vacancy rates for each single year age band.

2.3 Demographic Data: American Community Survey and the U.S. Religion Census

I compile county-level demographic characteristics from the 5-year 2019 ACS estimates provided by the U.S. Census Bureau (U.S. Census Bureau, 2019). The ACS is a nationally representative annual household survey of 1% of the population of the United States. In order to provide estimates of demographic characteristics at finer geographic levels, the Census Bureau combines responses from five years of survey data to create the 5-year estimates. The 2019 estimates are based on survey years 2015 to 2019. From these demographic estimates, I use information on total population, race and ethnicity, education levels, and household structure.

To calculate urbanicity, I combine the 5-year tract-level population estimates with land area in square miles from the Census Gazetteer to calculate population density. Population density is then translated into Rural-Urban Continuum Codes (RUCC). A tract is considered urban if the RUCC is less than four. I then aggregate these tract-level measures of urbanicity to the county level to calculate the population-weighted fraction of the county living in an urban area.

I use data from the United States Religion Census, which is conducted every ten years by the Association of Statisticians of American Religious Bodies (ASARB) (Association of Statisticians of American Religious Bodies, 2020), to calculate religiosity. The ASARB collects county-level data from formal denominations, capturing 372 religious bodies with 356,739 congregations. As a proxy for the religiosity in an area, I use the fraction of the population who are religious adherents, where adherents are defined as the number of people affiliated with a congregation.

[2]The survey asks providers for enrollment using the age cutoffs that they use to group children. The NSECE then converts these to single-year age bands assuming a uniform distribution of ages within classroom.

3 Methodology

This section first describes the estimation approaches for the methodologies used to designate counties as having demographic-adjusted low supply (DALS) or a significant child care gap (CCG). Like CCD, DALS is based on exogenous demographic characteristics, while CCG relaxes this assumption and uses parental labor force participation as a proxy for demand. I then describe how I estimate how predictive the access measures are of vacancy rates.

3.1 Demographic-Adjusted Low Supply

The goal of this first exercise is to allow different counties to have different thresholds for determining low access to care. These thresholds are determined by the demographic characteristics of the county, under the assumption that individuals with similar demographic characteristics but located in different parts of the country may have similar demand for licensed child care.

I first run a county-level regression of number of licensed slots per child under 5 on demographic characteristics to estimate a relationship between these characteristics and child care supply:

$$SlotsPerKid_{rc} = \alpha + \beta_1 Religiosity_c + \beta_2 Religiosity_c^2 + \beta_3 BA_c + \beta_4 BA_c^2 + \beta_5 Urban_c + \beta_6 Urban_c^2 + \beta_7 Hispanic_c + \beta_8 Hispanic_c^2 + \beta_9 Black_c + \beta_{10} Black_c^2 + \beta_{11} TwoParents_c + \beta_{12} TwoParents_c^2 + \psi_r + \epsilon_{rc} \quad (1)$$

where $SlotsPerKid_{rc}$ is the number of licensed child care slots per child under the age of 5 in county c located in Census region r.[3] $Religiosity_c$ is the fraction of the population who are adherents to a religious congregation, BA_c is the fraction of the adult population with at least a bachelor's degree, $Hispanic_c$ and $Black_c$ are the fractions of the population who are Hispanic and non-Hispanic Black, respectively, and $TwoParents_c$ is the fraction of children living with two parents. $Urban_c$ is the population-weighted fraction of the county that is urban, and ψ_r are fixed effects for Census regions (South, Midwest, and West, with Northeast as the reference group). Note that this model only includes exogenous characteristics that are not directly impacted by the availability of child care. For example, I do not include mother's labor force participation or income as these could be endogenous to the availability of care, leading to bias in the predicted number of slots per kid.

I then use the estimated coefficients from this model to create a predicted number of licensed slots per

[3] I use "slots per kid" rather than the typical "kids per slot" because the former is defined everywhere there are children under 5, while the latter is undefined in areas with no licensed care.

child under 5 for each county:

$$\widehat{SlotsPerKid}_{rc} = \hat{\alpha} + \hat{\beta}_1 Religiosity_c + \hat{\beta}_2 Religiosity_c^2 + \hat{\beta}_3 BA_c + \hat{\beta}_4 BA_c^2 + \hat{\beta}_5 Urban_c + \hat{\beta}_6 Urban_c^2$$
$$+\hat{\beta}_7 Hispanic_c + \hat{\beta}_8 Hispanic_c^2 + \hat{\beta}_9 Black_c + \hat{\beta}_{10} Black_c^2 + \hat{\beta}_{11} TwoParents_c + \hat{\beta}_{12} TwoParents_c^2 + +\hat{\psi}_{rc} \tag{2}$$

I bound this prediction below by zero so that no counties have negative predicted slots, affecting eight counties.[4] The predicted slots per child for each county are shown in Figure 1. The darkest color represents counties that are predicted to have relatively high levels of predicted supply, with at least 0.5 slots per child. These areas are prevalent in the mid-Atlantic and South along with the upper Midwest. The lightest color represents counties with relatively low levels of predicted supply, with 0.2 slots or less per child. These areas are most prevalent in the West, particularly in Utah.

I then compute the residuals from this regression:

$$\widehat{SupplyResidual}_{rc} = ActualSlotsPerKid_c - \widehat{SlotsPerKid}_{rc} \tag{3}$$

These residuals represent the difference between actual supply and predicted supply, with negative values indicating actual supply is lower than predicted. One advantage of this approach, in addition to potentially better accounting for demand for care, is that, unlike ratio-based measures, it can distinguish among areas with zero licensed supply. Incorporating predicted supply allows zero-slot areas to differ in access severity depending on whether zero supply is close to or far below what would be expected given local demographic characteristics, a useful feature for policymakers targeting aid.

I designate the 20% of counties with the most negative residuals as areas with "demographic-adjusted low supply" (DALS). The threshold for this designation is -0.14, or areas where we would have predicted there would be at least one more slot for every seven children. Figure 2 shows counties that are designated as DALS along with the approximately 20% of counties where there are least four children per licensed child care slot (CCD4). About 60% of the counties with a given designation also have the other designation. All three types of areas are scattered across the country, but areas that are only CCD4 are more likely to be in the West, while areas that are only DALS are more likely to be in the eastern part of the country.

3.2 Child Care Gap

For the second alternative access measure, I calculate a simplified version of the Buffett Institute's Child Care Gap (Buffett Early Childhood Institute, 2025), relaxing the restriction that the access measure be based only on exogenous demographic characteristics. For each county, I calculate the difference between the number of children under the age of five with all parents in the labor force and the number of licensed

[4] I exclude Kalawao County, Hawaii from the analysis as ACS 5-year estimates indicate only one young child in the county and thus some demographic variables are missing due to insufficient sample size.

slots, then normalize this gap by the number of children. Specifically, I calculate:

$$ChildCareGap_c = \frac{NKids_c - NLicensedSlots_c}{NKids_c}$$

where $NKids_c$ is the number of children under five in the county with all parents in the labor force. All parents in the labor force means that both parents are employed in two-parent families or the only parent is employed in single parent families. I designate the 20% of counties with the largest gaps as having a substantial child care gap (CCG). CCG relies on the assumption that the number of children without a stay-at-home parent is a sufficient statistic for child care demand. This assumption could fail if either working parents or non-working parents in different regions vary substantially in their demand for formal care.

3.3 Comparison of Low Access Designations

Table 1 compares the characteristics of all counties and counties designated as CCD4, DALS, and/or CCG. Column (1) provides the mean of the given county characteristic for all counties. Columns (2) through (4) provide means of the county characteristics for CCD4, DALS, and CCG counties, respectively, with stars indicating whether the means are statistically different from counties without the given designation. Overall, counties designated as low access look significantly different from other counties. CCD4 and CCG counties look more similar to each other than to DALS counties, attributable to the substantial overlap between counties with these designations: among CCD4 counties, 85% are also CCG counties compared to 63% also having the DALS designation. A key distinction between these counties is that DALS counties would be predicted to have slightly higher than average licensed slots per child (based on demographic characteristics), while CCD4 and CCG counties are predicted to have lower than average licensed slots per child. In other words, CCD4 and CCG counties are on average areas where we would have expected to see lower than average supply.

All three measures identify counties that are much less urban than the full sample, though DALS counties are considerably more urban than CCD4 and CCG counties. Consistent with DALS identifying larger counties than the other measures, although all three contain about 20% of counties, CCD4 and CCG counties contain only 6-7% of the national under 5 population, while DALS captures 14%.

3.4 Estimating the Relationship between Vacancy Rates and Access Measures

I use univariate regression to determine how predictive the access measures are of vacancy rates:

$$VacRate_{iac} = \alpha + \beta Access_c + \nu_{iac} \tag{4}$$

where $VacRate_{iac}$ is the vacancy rate for center i in age group a located in county c. Age groups are single-year age bands for each age from 0 to 4. I also consider binary outcome variables $AnyVacancy_{iac}$, an indicator for whether there are any openings, and $HighVacancy_{iac}$, an indicator for whether the vacancy

rate is particularly high (over 15%). Although the access measures are based on the total licensed slots across center- and home-based care, I focus on center-based vacancy rates as the validation outcome because center-based care is, on average, higher quality and thus a better proxy for access to higher-quality formal care. I use total licensed slots in constructing CCD3, CCD4, CCG, and DALS both to maintain consistency with existing access measures and because the CAP data report only total licensed slots and do not separate center-based and home-based slot counts.

$Access_c$ represents one of the access measures for county c: $CCD3_c$, $CCD4_c$, $DALS_c$, or CCG_c. $CCD3_c$ is an indicator that equals one if the county has three or more children per licensed child care slot, the predominant measure of low access to care. $CCD4_c$ is an indicator that equals one if the county has four or more children per licensed slot, applying a more stringent threshold than the standard measure. $DALS_c$ is an indicator that equals one if the area is designated as having demographic-adjusted low supply, as defined in Section 3.1. CCG_c is an indicator that equals one if the area is designated as having a significant child care gap, as defined in Section 3.2. All regressions include sample weights to provide nationally representative estimates. Standard errors are clustered at the county level.

The coefficient of interest in this regression is β, which estimates the difference in vacancy rates (or probability of having any vacancies or a high vacancy rate) between areas designated as having low access to care and those that are not. If β is statistically different from zero, then we can reject the null hypothesis that the access to care measure is not predictive of vacancy rates. A negative β would suggest it is more difficult for parents to find a provider with a vacancy in an area designated as having low access to care.

Policies that provide grants, tax credits, or other incentives for making investments in child care infrastructure typically support standalone, private pay centers. Therefore, for the main analysis, I restrict the sample to providers that are not co-located with an elementary school and where at least some families pay for care. Results including all providers are in the Appendix. I also consider heterogeneity by for-profit status as vacancy rates at non-profits and for-profits may have a different relationship with the access measures, though it is an empirical question whether low access will be more or less predictive of vacancy rates at non-profits. On the one hand, non-profit providers may be more willing to locate in areas with low demand even if it means higher vacancy rates. On the other hand, non-profit providers may have lower prices due to not being pure profit maximizers, and this may lead to lower vacancy rates.

4 Results

Table 2 presents results estimating the relationship between child care access measures and vacancy rate measures, following equation 4.[5] Overall, Table 2 shows few statistically significant relationships between the two child care desert measures (CCD3 in Panel A and CCD4 in Panel B) and the three vacancy rate

[5]This analysis is restricted to private-pay center-based providers who are not co-located with an elementary school as these are the most relevant providers when considering infrastructure investments. Table A1 in the Appendix provides the same set of analyses including all center-based providers, and conclusions are similar.

measures. The only relationship that is relatively robust is that CCD3 is predictive of lower vacancy rates for one-year-olds. Providers in counties where there are three or more children per licensed slot (compared to areas with less than three children per slot) have a 9.1 percentage point lower probability of having any slot (Panel A, column 2), 3.9 percentage point lower vacancy rates (Panel A, column 7), and a 9.2 percentage point lower probability of having a high vacancy rate (Panel A, column 12) for one-year-olds, statistically significant at the 10%, 5%, and 10% levels respectively. A few other relationships are statistically significant but are not robust across the different vacancy measures.

On the other hand, Panels C and D show robust evidence that the two alternative measures, DALS and CCG, respectively, are predictive of greater difficulty finding an open slot, particularly for infants and toddlers. Providers in DALS (CCG) counties are 22 (19) percentage points less likely to have a vacancy in their infant room, compared to providers in other counties. In DALS counties, infant vacancy rates are on average 7.8 percentage points (60%) lower and providers are 19 percentage points (61%) less likely to have a high infant vacancy rate, with both estimates statistically significant at the 1% level.[6] Similarly, for 1-year-old classrooms, DALS and CCG status are strongly predictive of low vacancy rates, with coefficients that are large in magnitude (both absolutely and relative to the CCD measures) and highly statistically significant. Center-based providers in DALS (CCD3) counties are 16.5 (14.4) percentage points less likely than providers in other counties to have an opening in their one-year-old classroom, statistically significant at the 1% level, and over 50% larger than the analogous estimate for CCD3 counties. For two-year-olds, the relationship is slightly weaker, with only two of the three vacancy measures correlated with DALS or CCG status: providers in DALS (CCG) counties are 12 (12) percentage points less likely to have a vacancy for two-year-olds and have vacancy rates that are 3.3 (4.4) percentage points lower. Neither measure is particularly predictive of vacancy rates for three- or four-year-olds.[7]

For-profit and non-profit providers may be located in different types of markets and may behave differently even if they are located in the same markets. Table 3 presents estimates of the relationship between vacancy rates and the access measures split by non-profit status. Note that some estimates are missing due to NSECE restricted data disclosure requirements.[8] For brevity, this table only includes the vacancy rate outcome variable. Overall, the access measures are more predictive of vacancy rates at for-profit providers (columns 1 to 5) than they are for non-profit providers (columns 6 to 10). Both the CCD3 and DALS measures are predictive of for-profit provider vacancy rates for infants, one-year-olds, and four-year-olds (with higher point estimates for DALS), and CCD4 and DALS are predictive of for-profit provider vacancy rates for two-year-olds. For the non-profit providers, the DALS measure remains predictive of lower vacancy rates for infants and toddlers, with smaller point estimates but also smaller baseline means so that the reduction is of

[6] The analogous results for CCG counties were suppressed due to restricted data disclosure requirements.

[7] Another measure of child care accessibility is prices. If areas designated as child care deserts have higher prices, that could also indicate a lack of accessible care. Table A2 in the Appendix provides the same set of estimates with measures of price as the dependent variable. There is no consistent evidence that care is more expensive in child care deserts.

[8] None of the CCG estimates could be disclosed, so CCG is excluded from the table.

a similar magnitude compared to for-profit providers. However, CCD3 is no longer predictive of vacancies at these ages, with very small and statistically insignificant point estimates. Interestingly, vacancy rates for 3- and 4-year-olds at non-profit providers in CCD3 counties are actually 5 to 6 percentage points *higher* compared to providers not located in CCD3 counties. This finding suggests that non-profit providers may be willing to locate in areas with low demand even if it means higher vacancy rates, while for-profit providers are not. The positive correlation also suggests that some CCD3 counties may already have greater supply relative to demand than an average county (despite their low supply absolutely), and thus infrastructure investments to these areas would be mistargeted. Table A3 in the Appendix provides the same analysis for the outcome of having any vacancies, while Table A4 does the same for the outcome of having a high vacancy rate, both with similar conclusions.

5 Conclusion

In this paper, I investigate the relationship between measures of child care access and private center-based provider vacancy rates, which provide a proxy for parents' ability to access care when they need it. Understanding whether low access measures are predictive of greater difficulty finding care has important policy implications given a desire to target child care infrastructure investment funds to areas in greatest need. If an access measure is predictive of difficulty finding care, it can be useful for identifying areas most in need of investment.

I find that the most prevalent measure of low access, child care deserts, defined as areas with three or more children per licensed child care slot, are at best weakly predictive of center-based provider vacancy rates. Thus, targeting funds based on this measure (as some states did with American Rescue Plan Act dollars) could lead to misallocation. On the other hand, I find that two alternative measures that adjust for demand are very predictive of infant and toddler vacancy rates. Areas with low supply by these metrics (DALS and CCG) have vacancy rates that are 30 to 60% lower than areas that are not. In addition, I find that both the CCD and DALS measures are more predictive of vacancy rates at for-profit providers than at non-profit providers.

These findings suggest that current measures of low access to care, which use the same threshold per capita for adequate care in all geographic areas, are not especially predictive of parents' ability to find private center-based care. However, I demonstrate that adjusting the threshold based on measures of demand for care does yield measures of low access that are predictive of vacancy rates, suggesting that it is possible to create a measure that can be used at scale to identify areas where parents may have more difficulty finding an open center-based slot for their child. Parents differ in their demand for care, and what may be an inadequate level of care in one area may be sufficient to meet demand in another area. Thus, using the same threshold for inadequate care nationwide leads to both Type I and Type II errors: some areas are misidentified as having insufficient supply when they actually have low demand, while other areas are identified as having adequate supply when there may actually be insufficient care due to particularly high demand. Policymakers

interested in targeting funds for infrastructure investment to areas in greatest need should therefore consider measures that account for local demand for care. An additional practical advantage of the DALS measure specifically is that unlike ratio-based measures such as CCD and CCG, it may better distinguish the degree of shortage among zero-slot geographic areas, allowing policymakers to prioritize areas where the absence of licensed care appears most severe. The finding that child care access measures are more predictive of vacancies at for-profit providers also suggests that, among areas identified as having low supply, those served by only for-profit providers may be more likely to have particularly tight markets.

There are several limitations to using vacancy rates to validate child care access measures. First, vacancy rates are only one measure of the ability to access care. They do not capture, for example, the affordability or quality of the available care, both of which are important for families seeking care. Vacancy rates are therefore best for validating whether access measures are predictive of the ability to find care at existing market rates and quality. Second, vacancy rates are only available when an area actually has a center-based provider. If a measure is good at predicting vacancy rates for existing providers, that provides suggestive evidence that it may also be good at determining which areas with zero providers represent true insufficient access to care, but they do not provide a direct test for such areas.

Finally, this work suggests several useful avenues for future research. First, policymakers would benefit from future work that further refines the estimation of adequate supply to provide a metric that is most useful for policy while retaining parsimony. Second, future research could propose alternative approaches for validating measures to access to care. In particular, access measures may be used for different purposes (information, to target investments in public care, to target investments in market rate care), and different measures and validation methods may make sense for different purposes. Third, future research should investigate why there are lower vacancy rates in some areas than others. In other words, future research could shed light on why the market does not appear to be adjusting to demand in some areas.

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Table 1: Characteristics of Counties Designated as Low Access

	(1) All Counties	(2) CCD4	(3) DALS	(4) CCG
Fraction Non-Hispanic Black	0.089	0.050***	0.084	0.052***
	[0.144]	[0.113]	[0.141]	[0.115]
Fraction Hispanic	0.094	0.099	0.077***	0.089
	[0.139]	[0.159]	[0.133]	[0.142]
Fraction of Children Living with Two Parents	0.646	0.667***	0.612***	0.660***
	[0.141]	[0.159]	[0.168]	[0.161]
Fraction in Poverty	0.155	0.162***	0.168***	0.158
	[0.065]	[0.071]	[0.078]	[0.071]
Fraction with a BA	0.220	0.180***	0.216	0.184***
	[0.096]	[0.066]	[0.091]	[0.066]
Fraction Religious Adherents	0.496	0.496	0.463***	0.495
	[0.191]	[0.270]	[0.170]	[0.219]
Fraction Urban	0.359	0.175***	0.291***	0.175***
	[0.336]	[0.269]	[0.320]	[0.264]
Mothers' Labor Force Participation	0.679	0.627***	0.664***	0.652***
	[0.108]	[0.133]	[0.111]	[0.128]
County <50 Licensed Slots	0.077	0.315***	0.254***	0.320***
	[0.267]	[0.465]	[0.436]	[0.467]
Licensed Slots per Child Under 5	0.428	0.151***	0.199***	0.156***
	[0.230]	[0.077]	[0.119]	[0.084]
Predicted Slots per Child	0.412	0.343***	0.437***	0.354***
	[0.109]	[0.107]	[0.103]	[0.104]
CCD4	0.207	1.000***	0.653***	0.877***
	[0.405]	[0.000]	[0.476]	[0.328]
DALS	0.200	0.632***	1.000***	0.658***
	[0.400]	[0.483]	[0.000]	[0.475]
CCG	0.200	0.846***	0.657***	1.000***
	[0.400]	[0.361]	[0.475]	[0.000]
Number of Counties	3,142	651	629	628
Share of Counties	1.000	0.207	0.200	0.200
Share of Population under 5	1.000	0.070	0.136	0.055

Notes: Table displays the average characteristics of all counties as well as the counties that are designated as CCD4 (four or more children per licensed slot), DALS (demographic-adjusted low supply, based on the deviation between actual and predicted supply), and CCG (child care gap, based on the gap between licensed slots and the number of children with all parents in the labor force). DALS is discussed in more detail in Section 3.1, and CCG is discussed in more detail in Section 3.2. Standard deviations are located in brackets below the means. Stars in Columns (2) through (4) indicate whether the mean is statistically different from the mean of counties without the given designation. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 2: Relationship between Child Care Access Measures and Vacancy Rates by Child Age

	Any Vacancy					Vacancy Rate					High Vacancy Rate (>15%)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Age 0	Age 1	Age 2	Age 3	Age 4	Age 0	Age 1	Age 2	Age 3	Age 4	Age 0	Age 1	Age 2	Age 3	Age 4
Panel A: Child Care Desert (3:1)															
CCD3	-0.049	-0.091*	-0.064	-0.023	-0.023	-0.037*	-0.039**	-0.017	0.011	0.005	-0.061	-0.092*	-0.026	0.006	0.018
	(0.076)	(0.054)	(0.044)	(0.044)	(0.046)	(0.021)	(0.015)	(0.013)	(0.015)	(0.016)	(0.062)	(0.055)	(0.043)	(0.041)	(0.037)
N CCD3	260	320	420	480	460	220	280	380	420	400	220	280	380	420	400
Panel B: Child Care Desert (4:1)															
CCD4	-0.082	-0.094	-0.090	-0.063	-0.036	-0.018	-0.023	-0.027**	0.000	0.028	-0.089	-0.100	-0.018	-0.021	0.034
	(0.117)	(0.057)	(0.056)	(0.054)	(0.057)	(0.036)	(0.019)	(0.013)	(0.016)	(0.026)	(0.081)	(0.067)	(0.063)	(0.057)	(0.053)
N CCD4	80	100	100	120	120	80	100	100	100	100	80	100	100	100	100
Panel C: Demographic-Adjusted Low Supply (DALS)															
DALS	-0.222***	-0.165***	-0.120**	-0.101*	-0.074	-0.078***	-0.063***	-0.033**	-0.021	-0.010	-0.190***	-0.189***	-0.062	-0.066	-0.030
	(0.064)	(0.061)	(0.059)	(0.060)	(0.064)	(0.017)	(0.015)	(0.016)	(0.017)	(0.021)	(0.043)	(0.042)	(0.048)	(0.042)	(0.045)
N DALS	260	280	400	440	420	240	260	380	400	400	240	260	380	400	400
Panel D: Child Care Gap (CCG)															
CCG	-0.194*	-0.144**	-0.121**	-0.080	-0.031	.	-0.061***	-0.044***	-0.014	0.029	.	-0.224***	-0.074	-0.057	0.024
	(0.107)	(0.058)	(0.057)	(0.052)	(0.055)	(.)	(0.016)	(0.016)	(0.018)	(0.033)	(.)	(0.047)	(0.083)	(0.075)	(0.069)
N CCG	60	60	60	80	80	.	60	60	80	60	.	60	60	80	60
N	2,420	2,900	3,540	3,840	3,620	2,280	2,700	3,280	3,540	3,360	2,280	2,700	3,280	3,540	3,360
Dep. Var. Mean	0.478	0.544	0.557	0.572	0.579	0.127	0.129	0.124	0.124	0.131	0.313	0.317	0.317	0.310	0.316

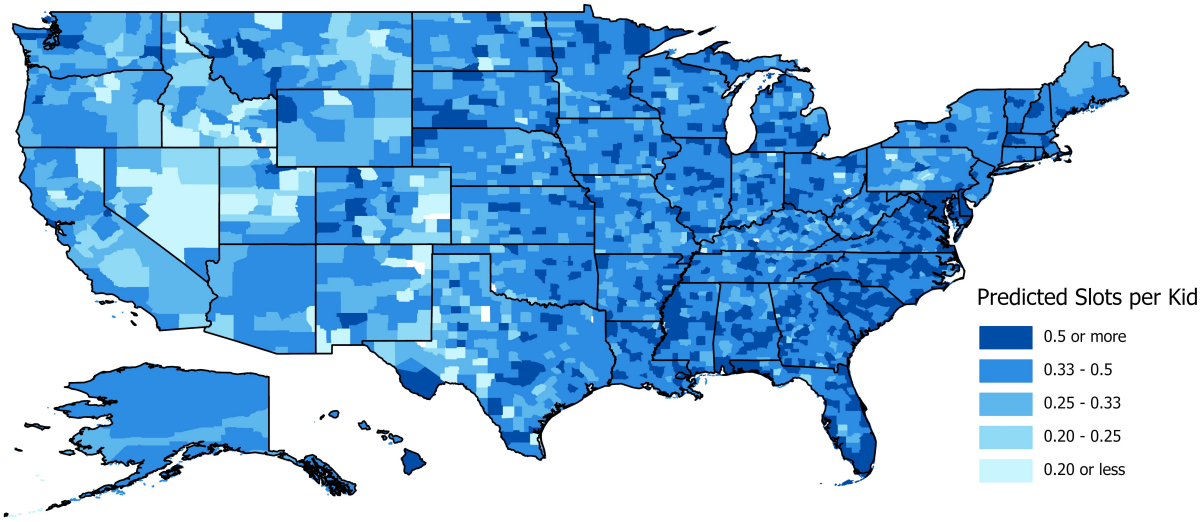
Notes: Table shows OLS estimates of the relationship between vacancy rates (by single year age band) and the child care access measures. The analysis is restricted to providers where at least some families pay for care and that are not co-located in elementary schools. Each column also only includes providers who serve that age group. The outcome of interest in columns (1) to (5) is a binary variable that equals one if the provider has any openings in that age group and equals zero otherwise, the outcome of interest in columns (6) to (10) is the provider's vacancy rate for that age group, and in columns (11) to (14), the outcome of interest is a binary variable that equals one if the providers vacancy rate for the age group is 15% or more and equals zero otherwise. In Panel A, the independent variable is a dummy variable that equals one if there are three or more children per licensed child care slot in the county. In Panel B, the independent variable is a dummy variable that equals one if there are four or more children per licensed child care slot in the county. In Panel C, the independent variable is a dummy variable that equals one if the area is designated as having demographic-adjusted low supply, where this designation is defined in Section 3.1. In Panel D, the independent variable is a dummy variable that is equal to one of the county is designated as having a significant care gap (the gap between the number of slots and number of children with all parents in the labor force, expressed as a percent) as defined in Section 3.2. In each panel, "N CCD3," "N CCD4," "N DALS," or "N CCG" provides the raw number of providers for whom the independent variable is equal to one. Note that all counts are rounded to the nearest 20 due to NSECE restricted data disclosure requirements and some coefficients are missing from the table due to disclosure requirements. All regressions include survey weights designed to create nationally representative estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Relationship between Child Care Access Measures and Vacancy Rates by Non-Profit Status

	For-Profit Providers					Non-Profit Providers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Age 0	Age 1	Age 2	Age 3	Age 4	Age 0	Age 1	Age 2	Age 3	Age 4
Panel A: Child Care Desert Measure										
Desert (3:1)	-0.055**	-0.050**	-0.025	-0.020	-0.041**	-0.005	-0.019	0.000	0.053**	0.060*
	(0.028)	(0.022)	(0.017)	(0.021)	(0.016)	(0.026)	(0.019)	(0.019)	(0.024)	(0.032)
N CCD3	140	160	200	220	200	80	100	160	200	200
Panel B: Child Care Desert (4:1)										
Desert (4:1)	.	-0.018	-0.039*	-0.027	-0.038	.	.	.	.	.
	(.)	(0.030)	(0.023)	(0.026)	(0.026)	(.)	(.)	(.)	(.)	(.)
N CCD4	.	60	60	60	60	.	.	.	.	.
Panel C: Demographic-Adjusted Low Supply (DALS)										
DALS	-0.091***	-0.070***	-0.045**	-0.030	-0.049**	-0.053**	-0.052***	-0.013	-0.004	0.034
	(0.020)	(0.022)	(0.018)	(0.025)	(0.019)	(0.024)	(0.020)	(0.026)	(0.027)	(0.043)
N DALS	160	160	200	200	180	80	100	180	200	200
N	1,520	1,720	1,940	1,980	1,840	700	900	1,260	1,440	1,400
Dep. Var. Mean	0.141	0.143	0.135	0.132	0.136	0.102	0.105	0.105	0.108	0.121

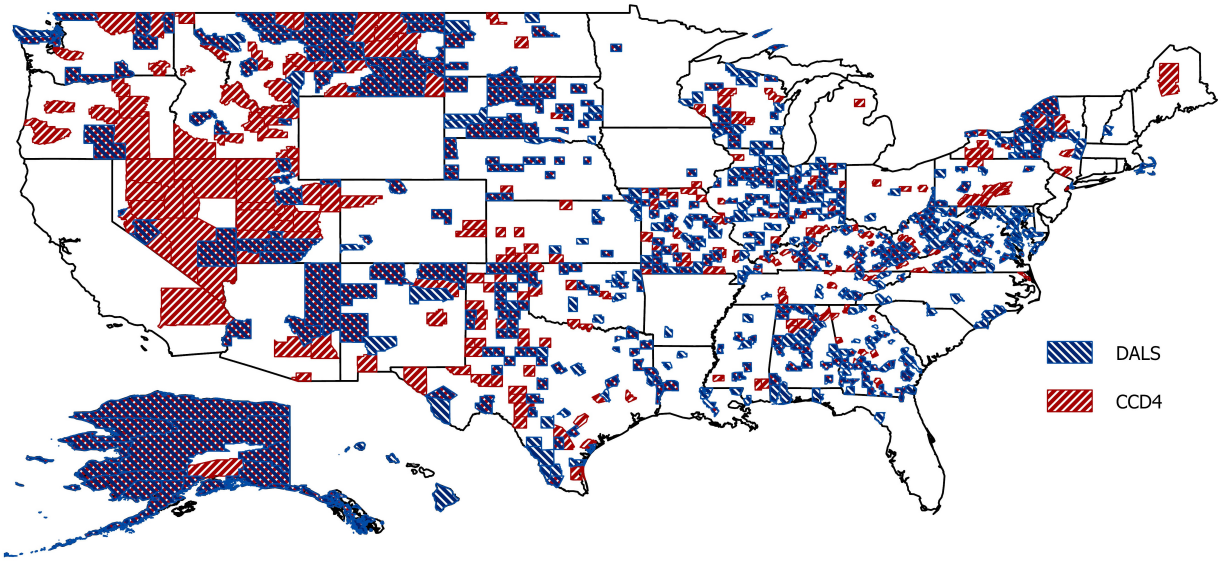
Notes: Table shows OLS estimates of the relationship between vacancy rates (by single year age band) and the child care access measures. The analysis is restricted to providers where at least some families pay for care and that are not co-located in elementary schools. Each column also only includes providers who serve that age group. The outcome of interest in all columns is the provider's vacancy rate for the given age group. Columns (1) to (5) include only for-profit providers, while columns (6) to (10) include only non-profit providers. In Panel A, the independent variable is a dummy variable that equals one if there are three or more children per licensed child care slot in the county. In Panel B, the independent variable is a dummy variable that equals one if there are four or more children per licensed child care slot in the county. In Panel C, the independent variable is a dummy variable that equals one if the area is designated as having demographic-adjusted low supply, where this designation is defined in Section 3.1. Note that some values are missing from the table due to disclosure requirements, and the Care Gap measure is not included because all results were suppressed. In each panel, "N CCD3," "N CCD4," or "N DALS" provides the raw number of providers for whom the independent variable is equal to one. Note that all counts are rounded to the nearest 20 due to NSECE restricted data disclosure requirements. All regressions include survey weights designed to create nationally representative estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1: Predicted Licensed Child Care Slots per Child Under Age 5



Notes: Figure shows the predicted number of slots per child based on equation 2, which predicts the number of slots per child in the county based on the demographic characteristics of that county.

Figure 2: Counties Identified under Standard and Adjusted Metrics



Notes: Figure shows counties where there are more than four children under 5 per licensed child care slot (CCD4) in red and counties with demographic-adjusted low supply (DALS) in blue. Demographic-adjusted low supply is defined as the 20% of counties with the largest (negative) gaps between actual supply and predicted supply based on county demographic characteristics. Counties that fit both definitions have both red and blue stripes.

A Additional Tables and Figures

Table A1: Relationship between Child Care Access Measures and Vacancy Rates by Child Age (All Providers)

	Any Vacancy					Vacancy Rate					High Vacancy Rate (>15%)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	Age 0	Age 1	Age 2	Age 3	Age 4	Age 0	Age 1	Age 2	Age 3	Age 4	Age 0	Age 1	Age 2	Age 3	Age 4
Panel A: Child Care Desert (3:1)															
CCD3	-0.055	-0.088	-0.059	-0.045	-0.028	-0.040**	-0.038**	-0.017	-0.009	-0.008	-0.070	-0.081	-0.023	-0.022	0.006
	(0.064)	(0.055)	(0.045)	(0.036)	(0.036)	(0.018)	(0.015)	(0.014)	(0.012)	(0.010)	(0.050)	(0.058)	(0.049)	(0.035)	(0.029)
N CCD3	300	360	540	800	960	260	320	480	700	760	260	320	480	700	760
Panel B: Child Care Desert (4:1)															
CCD4	-0.056	-0.108	-0.075	-0.052	-0.037	-0.015	-0.029	-0.017	-0.015	-0.006	-0.075	-0.109*	0.012	-0.021	0.022
	(0.101)	(0.066)	(0.075)	(0.054)	(0.049)	(0.030)	(0.021)	(0.024)	(0.014)	(0.012)	(0.067)	(0.061)	(0.095)	(0.051)	(0.044)
N CCD4	100	120	140	220	240	100	120	120	200	220	100	120	120	200	220
Panel C: Demographic-Adjusted Low Supply (DALS)															
DALS	-0.204***	-0.167***	-0.114**	-0.020	0.009	-0.074***	-0.063***	-0.031*	-0.015	-0.013	-0.183***	-0.187***	-0.055	-0.032	-0.014
	(0.058)	(0.058)	(0.058)	(0.049)	(0.045)	(0.016)	(0.015)	(0.017)	(0.013)	(0.011)	(0.038)	(0.039)	(0.058)	(0.037)	(0.034)
N DALS	300	340	500	820	960	280	300	460	640	700	280	300	460	640	700
Panel D: Child Care Gap (CCG)															
CCG	-0.147	-0.163**	-0.094	-0.042	-0.027	-0.051*	-0.062***	-0.027	-0.023	-0.011	-0.146**	-0.213***	-0.028	-0.029	0.015
	(0.099)	(0.075)	(0.091)	(0.061)	(0.053)	(0.027)	(0.020)	(0.031)	(0.016)	(0.014)	(0.064)	(0.048)	(0.123)	(0.062)	(0.051)
N CCG	80	80	100	160	160	60	80	80	140	140	60	80	80	140	140
N	2,800	3,400	4,260	5,820	6,060	2,620	3,140	3,920	5,140	5,240	2,620	3,140	3,920	5,140	5,240
Dep. Var. Mean	0.472	0.527	0.539	0.543	0.551	0.125	0.124	0.120	0.108	0.108	0.306	0.303	0.299	0.274	0.267

Notes: Table shows OLS estimates of the relationship between vacancy rates (by single year age band) and the child care access measures. The analagous table in the main paper (Table 2) restricts to providers where at least some families are private pay and that are not co-located in elementary schools, while this table includes all center-based providers. Each column also only includes providers who serve that age group. The outcome of interest in columns (1) to (5) is a binary variable that equals one if the provider has any openings in that age group and equals zero otherwise, the outcome of interest in columns (6) to (10) is the provider's vacancy rate for that age group, and in columns (11) to (14), the outcome of interest is a binary variable that equals one if the providers vacancy rate for the age group is 15% or more and equals zero otherwise. In Panel A, the independent variable is a dummy variable that equals one if there are three or more children per licensed child care slot in the county. In Panel B, the independent variable is a dummy variable that equals one if there are four or more children per licensed child care slot in the county. In Panel C, the independent variable is a dummy variable that equals one if the area is designated as having demographic-adjusted low supply, where this designation is defined in Section 3.1. In Panel D, the independent variable is a dummy variable that is equal to one of the county is designated as having a significant care gap (the gap between the number of slots and number of children with all parents in the labor force, expressed as a percent) as defined in Section 3.2. In each panel, "N CCD3," "N CCD4," "N DALS," or "N CCG" provides the raw number of providers for whom the independent variable is equal to one. Note that all counts are rounded to the nearest 20 due to NSECE restricted data disclosure requirements. All regressions include survey weights designed to create nationally representative estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2: Relationship between Child Care Access Measures and Price Measures by Child Age

	Annual Price				Log(Price)				Annual Price, Normalized by Income			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Age 0	Age 2	Age 3	Age 4	Age 0	Age 2	Age 3	Age 4	Age 0	Age 2	Age 3	Age 4
Panel A: Child Care Desert (3:1)												
CCD3	934	-7,290	-10,400	-9,320	0.118	0.044	0.022	0.035	0.030	-0.237	-0.350	-0.326
	(997)	(6,970)	(6,780)	(6,780)	(0.075)	(0.069)	(0.074)	(0.080)	(0.033)	(0.246)	(0.239)	(0.240)
N CCD3	240	360	400	380	240	360	400	380	240	360	380	360
Panel B: Child Care Desert (4:1)												
CCD4	-1,360*	-7,890	-10,900*	-8,840	0.011	-0.038	-0.122	-0.054	0.019	-0.185	-0.291	-0.238
	(808)	(6,450)	(6,270)	(6,360)	(0.068)	(0.094)	(0.119)	(0.108)	(0.034)	(0.233)	(0.227)	(0.229)
N CCD4	80	100	100	100	80	100	100	100	80	100	100	100
Panel C: Demographic-Adjusted Low Supply (DALS)												
DALS	1,500	-6,650	-9,610	-6,740	0.151**	0.078	0.070	0.076	0.036	-0.225	-0.333	-0.290
	(1,100)	(6,880)	(6,690)	(6,970)	(0.064)	(0.064)	(0.075)	(0.080)	(0.043)	(0.241)	(0.234)	(0.236)
N DALS	240	340	360	360	240	340	360	360	240	320	360	340
Panel D: Child Care Gap (CCG)												
CCG	-1,990**	-7,440	-10,500*	-9,250	-0.044	0.024	-0.084	-0.070	.	-0.104	-0.223	-0.208
	(838)	(6,390)	(6,240)	(6,340)	(0.074)	(0.069)	(0.099)	(0.106)	(.)	(0.240)	(0.234)	(0.233)
N CCG	60	60	60	60	60	60	60	60	.	60	60	60
N	2,360	3,080	3,320	3,280	2,360	3,080	3,320	3,280	2,300	3,020	3,260	3,200
Dep. Var. Mean	12,600	18,200	20,100	19,300	9.270	9.180	9.090	9.060	0.420	0.605	0.670	0.652

Notes: Table shows OLS estimates of the relationship between prices and the child care access measures. Note that the NSECE does not ask about 1-year-old prices, so those are excluded from the table. The outcome of interest in columns (1) to (4) is the annual price of care, the outcome of interest in columns (5) to (8) is log of annual price, and in columns (9) to (12), the outcome of interest is annual price normalized by the local median income for women. In Panel A, the independent variable is a dummy variable that equals one if there are three or more children per licensed child care slot in the county. In Panel B, the independent variable is a dummy variable that equals one if there are four or more children per licensed child care slot in the county. In Panel C, the independent variable is a dummy variable that equals one if the area is designated as having demographic-adjusted low supply, where this designation is defined in Section 3.1. In Panel D, the independent variable is a dummy variable that is equal to one of the county is designated as having a significant care gap (the gap between the number of slots and number of children with all parents in the labor force, expressed as a percent) as defined in Section 3.2. In each panel, "N CCD3," "N CCD4," "N DALS," or "N CCG" provides the raw number of providers for whom the independent variable is equal to one. Note that all counts are rounded to the nearest 20 due to NSECE restricted data disclosure requirements. All regressions include survey weights designed to create nationally representative estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A3: Relationship between Child Care Access Measures and Having Any Vacancy by Non-Profit Status

	For-Profit Providers					Non-Profit Providers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Age 0	Age 1	Age 2	Age 3	Age 4	Age 0	Age 1	Age 2	Age 3	Age 4
Panel A: Child Care Desert Measure										
Desert (3:1)	-0.099	-0.148*	-0.085	-0.133**	-0.117*	0.036	0.001	-0.020	0.118**	0.092*
	(0.090)	(0.078)	(0.064)	(0.064)	(0.070)	(0.104)	(0.086)	(0.067)	(0.058)	(0.055)
N CCD3	160	180	220	240	220	100	120	200	220	220
Panel B: Child Care Desert (4:1)										
Desert (4:1)	.	-0.158	-0.171**	-0.142	-0.106	.	.	.	0.050	0.064
	(.)	(0.098)	(0.085)	(0.090)	(0.101)	(.)	(.)	(.)	(0.102)	(0.096)
N CCD4	.	60	60	60	60	.	.	.	60	60
Panel C: Demographic-Adjusted Low Supply (DALS)										
DALS	-0.239***	-0.203**	-0.132*	-0.158*	-0.126	-0.205**	-0.110	-0.093	-0.026	-0.008
	(0.075)	(0.090)	(0.076)	(0.088)	(0.089)	(0.081)	(0.110)	(0.086)	(0.093)	(0.100)
N DALS	160	180	200	200	200	100	120	200	220	220
N	1,620	1,860	2,080	2,140	2,000	760	980	1,360	1,560	1,520
Dep. Var. Mean	0.507	0.579	0.577	0.579	0.577	0.423	0.483	0.517	0.544	0.566

Notes: Table shows OLS estimates of the relationship between a binary variable indicating whether the provider has any open slots in that single year age band and the child care access measures. The analysis is restricted to providers where at least some families pay for care and that are not co-located in elementary schools. Each column also only includes providers who serve that age group. The outcome of interest in all columns is the provider's vacancy rate for the given age group. Columns (1) to (5) include only for-profit providers, while columns (6) to (10) include only non-profit providers. In Panel A, the independent variable is a dummy variable that equals one if there are three or more children per licensed child care slot in the county. In Panel B, the independent variable is a dummy variable that equals one if there are four or more children per licensed child care slot in the county. In Panel C, the independent variable is a dummy variable that equals one if the area is designated as having demographic-adjusted low supply, where this designation is defined in Section 3.1. Note that some values are missing from the table due to disclosure requirements. In each panel, "N CCD3," "N CCD4," or "N DALS" provides the raw number of providers for whom the independent variable is equal to one. Note that all counts are rounded to the nearest 20 due to NSECE restricted data disclosure requirements. All regressions include survey weights designed to create nationally representative estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A4: Relationship between Child Care Access Measures and High Vacancy Rates by Non-Profit Status

	For-Profit Providers					Non-Profit Providers				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
	Age 0	Age 1	Age 2	Age 3	Age 4	Age 0	Age 1	Age 2	Age 3	Age 4
Panel A: Child Care Desert Measure										
Desert (3:1)	-0.125*	-0.124**	-0.092*	-0.087*	-0.106**	0.050	-0.039	0.071	0.130*	0.166**
	(0.069)	(0.058)	(0.049)	(0.045)	(0.042)	(0.110)	(0.079)	(0.077)	(0.076)	(0.070)
N CCD3	140	160	200	220	200	80	100	160	200	200
Panel B: Child Care Desert (4:1)										
Desert (4:1)	.	-0.042	-0.087	-0.078	-0.081	.	.	.	.	.
	(.)	(0.085)	(0.074)	(0.072)	(0.074)	(.)	(.)	(.)	(.)	(.)
N CCD4	.	60	60	60	60	.	.	.	.	.
Panel C: Demographic-Adjusted Low Supply (DALS)										
DALS	-0.210***	-0.186***	-0.133***	-0.103**	-0.131***	-0.151***	-0.197***	0.035	-0.007	0.087
	(0.052)	(0.056)	(0.051)	(0.051)	(0.046)	(0.058)	(0.040)	(0.089)	(0.079)	(0.092)
N DALS	160	160	200	200	180	80	100	180	200	200
N	1,520	1,720	1,940	1,980	1,840	700	900	1,260	1,440	1,400
Dep. Var. Mean	0.343	0.355	0.352	0.327	0.330	0.257	0.253	0.266	0.272	0.291

Notes: Table shows OLS estimates of the relationship between a binary variable indicating whether the provider has a high vacancy rate (>15%) in that single year age band and the child care access measures. The analysis is restricted to providers where at least some families pay for care and that are not co-located in elementary schools. Each column also only includes providers who serve that age group. The outcome of interest in all columns is the provider's vacancy rate for the given age group. Columns (1) to (5) include only for-profit providers, while columns (6) to (10) include only non-profit providers. In Panel A, the independent variable is a dummy variable that equals one if there are three or more children per licensed child care slot in the county. In Panel B, the independent variable is a dummy variable that equals one if there are four or more children per licensed child care slot in the county. In Panel C, the independent variable is a dummy variable that equals one if the area is designated as having demographic-adjusted low supply, where this designation is defined in Section 3.1. Note that some values are missing from the table due to disclosure requirements. In each panel, "N CCD3," "N CCD4," or "N DALS" provides the raw number of providers for whom the independent variable is equal to one. Note that all counts are rounded to the nearest 20 due to NSECE restricted data disclosure requirements. All regressions include survey weights designed to create nationally representative estimates. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.