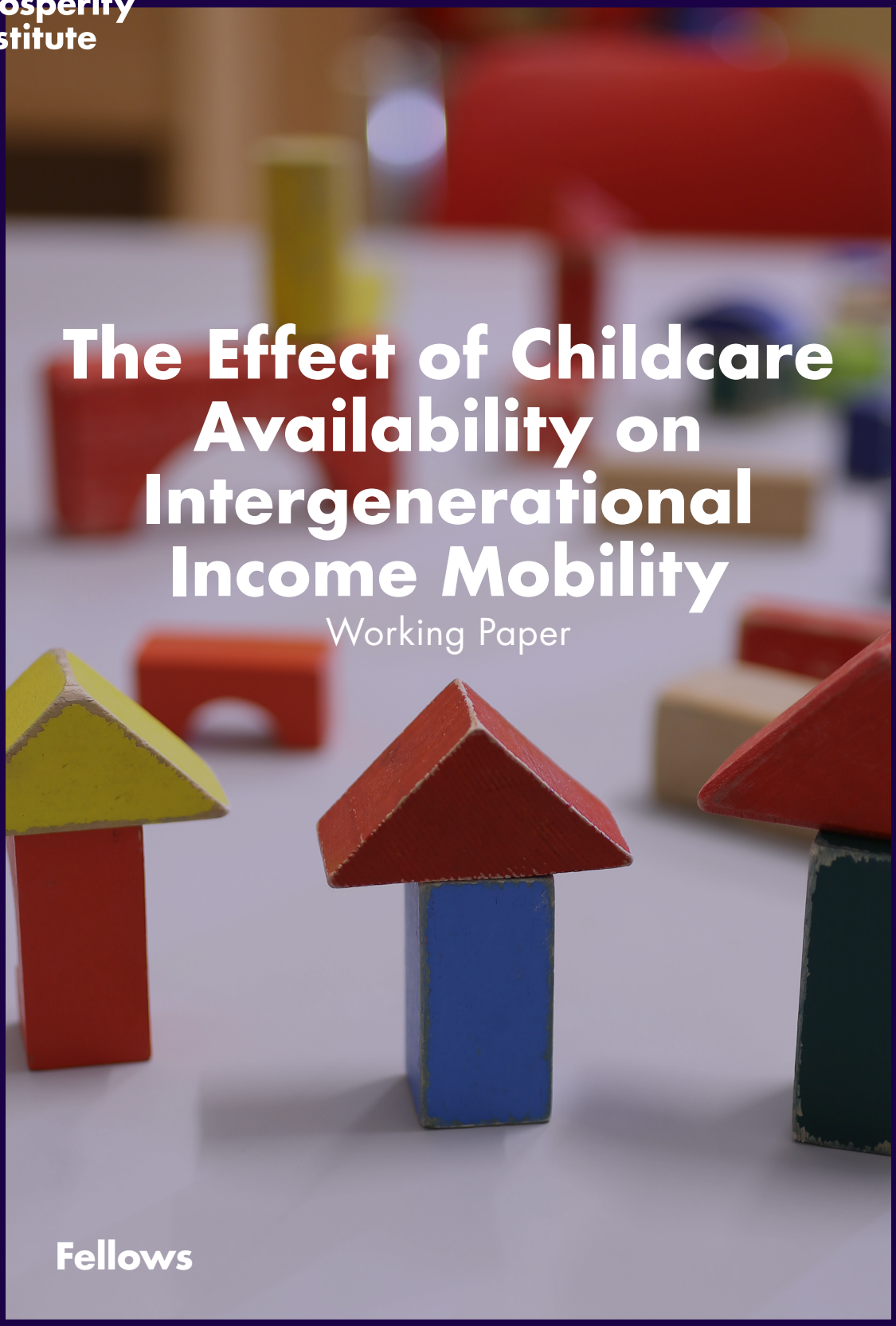
Martin Prosperity Institute

The Effect of Childcare Availability on Intergenerational Income Mobility

Working Paper



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Abstract

The chance that a child from a low income family will achieve economic prosperity varies significantly across the United States: economic mobility is more difficult if you are born or grow up in certain parts of the country. There is an urgent need to identify the features that generate mobility in certain places, and those that limit it in others. I explore the role that the availability of childcare plays in local economic mobility. Using county-level measures of intergenerational income mobility, I relate mobility for children from poor and rich families to the availability of center- and home-based childcare providers in a county. I find positive associations between the availability of home-based care and mobility of children from both poor and rich families. I also find negative associations between the availability of center-based care for children from poor families, especially boys. I also explore variation in the local childcare availability rate generated by regulations that require higher student-to-teacher ratios in center-based care. These regulations caused center-based facilities to close, especially in poor neighborhoods. I find that the regulations are associated with lower mobility among children from poor families who live in poor counties, suggesting that the closing of center-based facilities reduced mobility of children born in affected counties and years.

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"Childcare and Intergenerational Income Mobility"

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The Effect of Childcare Availability on Intergenerational Income Mobility

Working Paper

Lauren Jones

As middle incomes stagnate and inequality increases, there is growing concern that one of the fundamental values of western society — intergenerational income mobility — is disappearing. New evidence suggests that children do not enjoy equal chances of getting ahead. Children from higher income families are more likely than are children from low income families to complete college and earn high incomes themselves. Furthermore, the chance that a child from a low income family has of achieving economic prosperity varies significantly across the United States: economic mobility is more difficult if you are born or grow up in certain parts of the country (Chetty et al. 2014). The variation in mobility across areas suggests that mutable, community-level characteristics may foster intergenerational mobility, and that there may be policy approaches available to improve opportunities for children in low-mobility areas. As such, there is an urgent need to identify the features that generate mobility in certain places, and those that limit it in others.

The growing body of literature showing that very early life experiences have large effects on adulthood outcomes provides one clue as to which factors are important ingredients for mobility. Inequalities in adulthood outcomes manifest at very young ages. Children from high and low income families exhibit an achievement gap — a gap which is already large and apparent at five years old (Bradbury et al. 2005). While some of these inequalities are due to prenatal experiences (Currie 2011), childcare arrangements may also play an important role in cementing the opportunities children will enjoy over the lifespan. In this paper, I examine the extent to which local availability of childcare can improve intergenerational income mobility.

Childcare availability may improve adulthood outcomes through several potential mechanisms. First, availability and affordability of childcare options allow parents to work (Herbst 2017; Baker, Gruber and Milligan 2008). Parental employment can help children succeed because it provides economic stability to a household, allows for asset building and can reduce financial stress. In particular, work opportunities for mothers can improve child well-being by reducing maternal stress, and modeling economic independence, especially for girls (McGin 2015; Lucas-Thompson, Goldberg and Prause 2010).

Second, high-quality, enriching center-based childcare can improve developmental outcomes for children in the short-term. Many studies have uncovered short- and medium-term positive effects of wide-reaching childcare interventions on child outcomes (Currie and Thomas 1995; Gupta and Simonsen 2010; Black et al. 2014; Herbst and Tekin 2012; 2016; Gormley and Gayer 2005; Fitzpatrick 2008; Barnett et al. 2013; Cascio and Schanzenbach 2013; Weiland and Yoshikawa 2013). Across a large set of early childhood interventions — including both small demonstration programs like Perry Preschool, and larger, public preschool and pre-kindergarten programs — evaluations generally show improvements in cognitive outcomes (i.e. IQ, early reading skills, etc.) (Duncan and Magnuson, 2013; Camilli et al. 2010; Puma et al. 2005 etc.). Evidence on the noncognitive effects (i.e. socio-emotional development) of such programs is more mixed, but at least a few studies have found that attendance at a quality childcare facility can reduce hyperactivity and acting-out, and increase classroom engagement (Heckamn, Pinto and Savelyev 2012; Puma et al. 2005; Gormley et al. 2011). However, recent studies have also demonstrated some negative non-cognitive effects of large-scale public pre-school programs (Baker et al. 2008; Baker et al. 2015), suggesting that expansions of low-quality care may be damaging to children.

Finally, while high-quality childcare is associated with positive outcomes for all children, evaluations tend to demonstrate especially large gains for children from low income families (Gormley et al. 2008; Weiland and Yoshikawa 2013; Hill, Waldfogel, & Brooks-Gunn, 2002). If children from low income families disproportionately benefit from childcare programs, then such programs may help close achievement gaps between high and low income children as they enter adulthood. The effects of childcare could translate into later-life prosperity either directly, by changing developmental trajectories or establishing life-long habits, or indirectly, by increasing school readiness and allowing children to learn more and achieve additional educational qualifications. A self-productive model of human capital formation, where skills build on themselves over time, suggests that early childhood experiences may have a large bang-for-the-buck effect on narrowing adulthood gaps between children from rich and poor families (Cuhna and Heckman 2007).

While there is substantial evidence demonstrating positive short-run effects of high-quality, early childcare programs, fewer studies have explored the long-term impacts of such programs on adult outcomes. One curious fact is that many of the evaluations of landmark programs (i.e. Perry preschool, Abecedarian and Head Start) show that the positive gains of attendees disappear within a few years, at least in terms of test scores, which converge with those of their non-attendee peers (Campbell et al. 2002; Heckman et al. 2010; Currie and Thomas 1995). Yet, despite the convergence of test scores, the few existing evaluations of the long-term effects of these programs are promising. Studies of participants in small demonstration programs targeted at low income families like Perry Preschool and Abecedarian show positive effects as late as age 40 on educational attainment, earnings and criminal behavior (Campbell et al. 2002; Belfied et al. 2006; Heckman et al. 2010; Schweinhart et al. 2005).

An evaluation of a targeted preschool programs in Chicago revealed positive associations between program attendance and educational attainment at 24 (Reynolds, Temple and Suh-Ruu Ou 2010). Evaluations of the largest, U.S. to-scale program providing public quality childcare to low income families, Head Start, also found positive effects on young adult outcomes. Deming (2009) and Carneiro and Ginja (2015) showed that children who attend Head Start programs score better than their peers who did not attend on dimensions including educational attainment and delinquency behaviors in young adulthood. However, the oldest people exposed to the large Head Start expansions are not yet old enough to allow study of the effects of the program on earnings. Finally, a recent study by Herbst (2017) shows that expansions to publicly funded childcare during World War II resulted in significant economic gains over the lifecycle.

While these studies point to early childcare experiences as a driver of long-term economic wellbeing, the existing research is limited in several ways. First, the fact that it is difficult and costly to follow individual children from pre-school into adulthood means that there is a dearth of studies in this area. Existing studies on the Perry and Abecedarian programs are therefore limited in their small sample sizes. Studies on Head Start Participants offer a solution to the small sample problem, since Head Start serves about a 1 million children per year. However, because Head Start is targeted to children from low income families, even once graduates of the program begin earning income it will not be possible to evaluate whether the program disproportionately benefits children from low income families (since no higher income children participate). This is especially limiting if we hope to measure the relationship between preschool and intergenerational mobility across the income distribution.

Existing studies on the long-term effects of participation in the Perry and Abecedarian programs are also limited in their external validity because of the programs' high quality — quality levels that are expensive to replicate in programs that are widely available. In practice, even in large public pre-K programs and Head Start, instruction does not live up to the curricular and interpersonal standards that constitute high-quality experiences (Mashburn et al. 2008; Moiduddin et al. 2012). Recent studies on expansions of public childcare programs in Canada and in Europe suggest that such programs may even harm children, especially boys from low income families (Datta-Gupta and Simonsen 2010;Baker et al 2015; Kottelenberg and Lehrer 2018). Thus the question remains: how are adulthood outcomes affected when there is expanded access to the *average* available childcare, even when the quality of that care does not live up to standards?

I address several of these gaps by combining data from three sources in a novel way to estimate the relationship between early childcare availability and intergenerational mobility measures at the county level. Using data on county-level intergenerational income mobility compiled by Chetty et al. (2014; 2018a; 2018b) from IRS tax records of over 40 million children and their parents, combined with data on the number of center- and home-based childcare employees in each county during the 1980s, I begin by identifying the descriptive relationship between mobility measures and childcare availability. Next, I address the fact that the correlation between the availability of childcare and mobility measures is likely biased by unobserved county-level characteristics. If, for example, facilities tend to locate in higher income counties that have other mobility-generating amenities, then the descriptive relationship is unlikely to reflect a causal relationship. I employ several strategies to address this fact.

First, I progressively add other observable characteristics to a model relating local availability of childcare and local intergenerational mobility measures. Next, I estimate a model that relates changes in county-level mobility rates across cohorts to changes in the availability of childcare providers, thereby controlling for unobserved county-specific factors that could bias my results.

Finally, I capitalize on a finding from Hotz and Xiao (2011) that state-level regulations of student-teacher ratios that were implemented in the 1980s and 1990s caused center-based childcare facilities to shut down in poor neighborhoods. Using this exogenous source of variation in the number of center-based facilities at the state-level, I estimate instrumental variable models. Using the cohort-to-cohort variation in exposure to the regulations, I am able to control for cohort and state fixed-effects, and therefore to estimate the relationship between available center-based childcare and intergenerational mobility net of factors that may bias the estimation.

My findings show that there is a positive correlation between the number of home-based childcare providers per 100 children in a county and the average income mobility of children from that county. I find that one additional provider operating in the year a child is born is associated with about a 1.6 percentile increase in the expected rank of that child in the earning distribution at age 24 if she comes from a family at the 25th income percentile. If the child comes from a family at the 75th percentile, the additional childcare provider is associated with a 0.7 percentile increase in her expected rank. I also estimate a negative correlation between the availability of center-based care providers and income mobility of children from families at the 25th percentile. This relationship is driven by boys, for whom one additional center-based provider is associated with 0.7 lower expected rank in the age-24 income distribution. These estimated relationships are robust to the inclusion of other county-level covariates.

Despite the negative correlation I find between center-based care availability and mobility, two pieces of quasi-experimental evidence suggest the opposite relationship. First, I find a positive correlation between changes in center-based childcare availability and changes in mobility measures across cohorts. Finally, using the instrumental variables approach, I estimate a positive relationship between local childcare provider availability in poor counties and mobility measures of children from poor families. I find that one additional provider operating in the county where a child grows up leads to about a 1 percentile increase in her expected rank in the age 24 income distribution. Considering the fact that the regulations caused higher-quality center-based facilities to close in poor neighborhoods (demonstrated in Hotz and Xiao (2011) and confirmed herein), my results suggest that the harmful effects of limited supply trump any potential effects of higher quality, showing that regulations can have a perverse effect on children from poorer families.

I am able to contribute to several lines of literature. First, I add to the growing literature on the neighborhood determinants of social mobility measures. Second, I add to the few studies that demonstrate that early childhood education has effects that persist into adulthood, and that the effects are largest for children from poor families. My approach allows me to identify descriptive relationships between local availability of childcare and community-level mobility measures for affected children. It also allows me to add causal evidence on the long-run effects of the availability of childcare. While my approach does not capture individual trajectories from childhood to adulthood, it

does generate evidence on the long-term effects of childcare from a large-scale context, using data on millions of children from both poor and rich families spread over the entire United States.[1] It also shows that benefits accrue even in a "real world" contexts where the quality of childcare is unobservable, and likely below par. Finally, I add to the literature on childcare regulations, and show that well-intentioned regulatory efforts may have perverse effects on children from low income households.

2. Data

I use data from several sources. First, I use county-level intergenerational mobility data compiled by Raj Chetty, Nathanial Hendren and co-authors, and made available through the Equality of Opportunity Project. Second, I use data from the Economic Census and County Business Patterns programs on the number of childcare facilities and employees in a county between 1987 and 1992. Third, I use data on the regulation of teacher-student ratios in preschool programs. I detail my main data sources below. I additionally use a series of time-invariant county-level characteristics that I acquire from Chetty et al., and from IPUMS. I describe these variables in the appendix.

i. Intergenerational Mobility Measures

I use publicly available measures of county-level intergenerational mobility described in Chetty et al. (2014; 2018a; 2018b). These come from IRS data on all individuals with a Social Security Number or Tax Identification Number who were born between 1980 and 1991, and who were US citizens in 2013—approximately 40 million individuals. These records are linked to tax returns of individuals who first claim these children as dependents as of 1996 and who were between the ages of 15 and 40 when the child was born—individuals who are likely the parents.[2] Using these data, Chetty and co-authors compute county- and commuting zone (CZ) -measures of absolute and relative intergenerational income mobility.

To do this, they rank parents according to income in a national income distribution specific to each child cohort; they similarly rank children of each cohort in their own cohort-specific national income distribution. Then, for each county, they regress child income ranks on their corresponding parent income rank, producing a linear relationship. The estimated coefficients from this exercise provide two mobility measures. First, is the relationship between parent and child income ranks—or the county-specific slope of the linear regression line. The slope is a measure of *relative income mobility:* it reflects how children from families that fall lower in the income distribution fare relative to children from higher income families in a given region. The second measure that can be computed from the estimated regression coefficients is the expected rank of children from parents at the 25th or 75th percentile of the parent income distribution. This is a measure of *absolute income mobility:* it tells us the expected rank in the national child income distribution of a children from a given county, who grew up in poor (25th percentile) or rich (75th percentile) families.[3] For this study, I use this second measure, which I call local income mobility. Chetty et al. produce fixed estimates for each county

1 In this study, I use the terms `poor' and 'rich' to refer to families from the 25th and 75th percentiles of the income distribution, respectively. They are shorthand and do not imply value judgements about these families' merits.

2 See Chetty et al. (2014) for details on the data, how children and parents are linked, and other specifics of how the data were created.

3 Note that even though this measure uses ranks rather than dollar value of income, it still reflects a measure of absolute mobility because it reflects the expected rank in the national income distribution of children from a given county.

using children born in the 1980-1982 birth cohorts, as well as cohort-specific measures of mobility for each of the 1980 thought 1988 cohorts.[4] I use both the fixed county estimates, as well as the cohort-specific measures, which vary over birth years. Chetty et al. only release the cohort-specific measures for larger counties, and I limit my analysis to these. They also produce fixed estimates for subgroups of children: boys versus girls, and single-parent versus two-parent households.

One important caveat is that the measures I employ herein are not causal estimates of place. Any measure of intergenerational mobility of a place may either reflect the fact that families with inherently better prospects tend to group in places with better amenities *(the selection effect)* or the fact that a the features of a place (i.e. peers, characteristics, policies, etc.) improve the outcomes of children who grow up there *(causal effect).* Chetty et al. (2018b) generates better measures of the causal effects of place. However, due to the method utilized to create these measures — which relies on families who move to an area when their children are aged 9 or older — they are not suitable for an exploration of how very early life experiences (before age 9) shape mobility. As such, I use the overall estimates of local income mobility, which capture both the causal and selection effects, but are constructed using families who were more likely to have grown up in the given county.[5]

4 The fixed measure uses child incomes measured at age 26, while the cohort-specific measures use child income measured at age 24.

5 One additional flaw with these data for the present purpose is that among children in the main cohorts (1980-1982), the first observations in the IRS data occur at age 16. It is therefore not certain that children grew up in the county to which they are assigned, and thus it is not certain that they were exposed to the level of available childcare in that county. Chetty et al. (2014) note that 83.5 percent of 16-year olds live in the same commuting zone as when they were 5.

ii. Childcare availability data

I use two data sources to capture the availability of childcare in a given county. Accurate, specific measures of the childcare facilities at the county-level are not widely available going back to the 1980s. As such, I use data from the Economic Census of Services, a census of all establishments conducted every five years (in 1987 and 1992), and from the County Business Patterns data compiled annually by the Census Bureau from a variety of sources.

To measure the availability of home-based childcare facilities in a county I use the Economic Census. The sample includes all establishments that filed a tax return, regardless of whether they owed taxes. The benefit of these data is that they include counts on non-employer establishments where the only worker is an owner-operator. Home-based childcare establishments are included in this category as long as the owner-operator filed a tax return. The data are also limited in several ways. First, they are only reported every five years, meaning that measures only exist for 1987 and 1992. Further, in 1987, the data do not include fine enough measures of industry to capture childcare establishments; instead, they are included in the general social services category. However, at the state level, where childcare establishments are identified, I estimate that upwards of 90 percent of all non-employer social service establishments are childcare facilities, and I therefore proxy county-level childcare facilities with county-level social service facilities in 1987. Because these facilities are non-employer, they have only one childcare provider per facility.

For data on center-based childcare facilities — which would typically have a payroll — I use data from the County Business Patterns (CBP) program. These data are compiled annually by the Census Bureau from the Economic Census, several other surveys, and administrative data from the IRS, Social Security Administration and Bureau of Labor Statistics. The

CBP data cover employer companies and thus do not include home-based childcare facilities. The advantages of the CBP data is that they are provided yearly, and that, along with information on the number of local facilities, they also include information about the total number of employees at the county-level. Because centers differ in size and capacity, I use the number of employees in childcare facilities as my main measure of available center-based childcare in a county. Using the employee count also provides a better comparison to the home-based care measure, since home-based care facilities have only an owner-operator. The disadvantage of the CBP data is that prior to 1988 they do not include separate measures of employment in childcare services, instead including these employees in the general social services category. In some analyses, I use counts of employees in all social services in pre-1988 years.[6] However, unlike home-based care, the total number of social service employees is only a mediocre proxy for childcare employment: in post-1987 year, childcare employees represent on average 40 percent of total social services employees.

I convert the number of home-based care providers and center-based employees to rates by dividing each by the number of children under 5 years of age in each county-year and multiplying by 100. For convenience, I refer to each measure as the home-based and center-based childcare employee rate. I am left with the following measures: the home-based employee rate in 1992 and 1987 (where the 1987 measure is proxied by the total social services employee rate); the center-based employee rate for 1988 through 1992; and the center-based employee rate from 1981 through 1987, which I proxy with the total social services employee rate. I also generate measures of county-level changes in employee rates by subtracting the 1987 (or 1988 in the case of the center-based measure) from the 1992 measures.

iii. Student-Teacher Ratio Regulation Data

The third data source I employ is data on state-level regulations on center-based childcare facilities between 1983 and 1992. These data were used in Hotz and Xiao (2011) and are publicly available on the American Economic Association website. The data indicate the minimum allowable teacher-student ratios for children of different age groups (infants, 1, 2, 3 and 4 year olds) in each state and each year. I convert these data into cohort-specific exposure measures for each cohort from 1980 through 1988 as follows:

$$E_{cs} = \frac{\sum_{a=0}^{a=4} TSR_{s,y=c+a}}{5} \qquad (1)$$

This measure captures the average 5-year exposure of individuals born in year c and state s to the state-level regulations governing the minimum teacher-student ratio (TSR) for children. It is constructed by summing the annual regulation for children of age a in year y over the first five years of life, and then dividing by five.[7] I convert the continuous measure of average exposure into three categories: low regulatory restrictiveness, with a rule requiring 1 or fewer teachers per 10 students; moderate restrictiveness, with a rule of 1 to 1.5 teachers per 10 students; and strict restrictiveness, with average exposure to rules that require over 1.5 teachers per 10 students.

6 Along with childcare services, total social services include individual and family services, job training and related services, residential care, and other.

7 Note that because the regulation data are only available starting in 1983, I do not accurately capture the 5-year exposure for individuals born before 1983. This is a source of measurement error in the policy exposure variable.

3. Methods

i. Descriptive Relationship between Childcare Facilities and Mobility Measures

I begin by estimating a naïve, descriptive correlation between the rate of childcare availability in each county and the local income mobility measure according to model (2).

$$M_{k,g} = \alpha + \beta_{ols} Childcare_{k,l} + \eta X_k + \varepsilon \quad (2)$$

The model relates the mobility measure for county k and subgroup g ($M_{k,g}$) to the county-level childcare availability measure, $Childcare_{kl}$, where l indexes the two types of care (center- and home-based). I estimate Ordinary Least Square (OLS) models. For the full population, I estimate a model relating the 1987 (or 1988 for center-based) childcare rate measures to the corresponding cohort-specific mobility measure. Chetty et al. data do not include cohort-specific measures for subgroups, and I therefore relate the cohort-invariant measures to the 1987 and 1988 measures of childcare providers.[8] For each approach, I estimate the basic correlation and then add a series of control variables (X_k) that Chetty et al. (2014) show are relevant predictors of mobility.[9] I weight all regression models by county-level population in 2000, and I cluster all standard errors at the state level.

8 This is not an ideal approach, since the cohort-invariant measures are constructed using the 1980 through 1982 cohorts. These cohorts were only exposed to the 1987 and 1988 childcare environments for the tail-end of their under-5 years.

9 I control for the female labor force participation rate, the unemployment rate, the poverty rate, the college graduation rate, the divorce rate, the fraction of the population who identify as black, an indicator for metro counties, average population density, the Gini coefficient, a measure of the affordability of place for the median family and the local tax rate. These are all measured using different data sources, and are measured at some point between 1980 and 1988. More details in the appendix.

ii. Causal Relationship between Childcare Regulations and Mobility

The estimated relationships above are descriptive in nature and do not reflect the causal effect of availability of local childcare on mobility. It may be that counties with more or less available childcare differ in unobserved ways for other counties, or that families that locate in counties with more available childcare produce inherently more or less mobile children. To overcome this issue, I use two approaches.

First, I estimate a model relating changes in local income mobility between the 1983 and 1988 cohorts to changes in the childcare rates between 1987 (or 1988) and 1992. The benefit of estimating the model in differences is that it will net out some time-invariant unobserved county-level characteristics that could bias estimation. I estimate a model similar to (2), and show results for models with and without controls. Of course, this approach is not a perfect solution, since counties that are adding childcare capacity may be doing so in response demographic shifts that also impact mobility.

As such, I also employ an instrumental variables approach intended to address this issues. I exploit a finding from Hotz and Xiao (2011), who study the effects of state-level regulations governing the necessary child-teacher ratio in center-based childcare. The regulations that Hotz and Xiao study were intended to improve the quality of childcare by regulating inputs to quality (i.e. teacher training and attention to individual children). However, their primary findings show that increasingly stringent requirements in the number of staff per student in childcare centers substantially decreases the number of open facilities, especially in low income neighborhoods. Home-based childcare providers increased their revenue when the policy passed, suggesting that children moved into home-based care in response to the reduced supply of center-based spots. They also show that while reducing quantity, the regulations

increased accreditation rates in center-based care. In sum, the regulation likely decreased supply of center-based care in low income neighborhoods, but also increased the quality in centers that remained operational.

I use this source of variation in the quantity and quality of the center-based childcare market to help tease out the causal effect of center-based care on mobility measures. I begin by estimating reduced form models, where I relate the cohort-specific measure of exposure to the staff-per-student requirements (E_{cs}) that I construct above in (1) to the cohort-specific local mobility measure using the following model:

$$M_{ck,s} = \alpha + \beta_{rf} E_{cs} + \eta X_k + \gamma_s + \delta_c + \varepsilon \quad (3)$$

This model estimates the relationship between the mobility of cohort c from county k (in state s) ($M_{ck,s}$)and exposure to the state-level cohort-specific childcare regulations (E_{cs}). The model includes state (γ_s) and cohort (δ_c) fixed-effects, and some specifications include county-level covariates (X_k). The estimate β_{rf} therefore captures the change in county-specific mobility between one cohort and the next when regulations become increasingly stringent. Controlling for the fixed effects means that the estimate of β_{rf} is not biased by any cohort- or state-specific unobserved factors that are related to the mobility measures and available childcare, and could produce a spurious correlation between the two.

In the reduced form model, β_{rf} captures the total effect of the regulation—including both supply and quality effects—on mobility measures. Thus, I also estimate an instrumental variables model that uses the changing regulation as an exogenous source of variation in the supply of centers to estimate the causal effect of available centers on mobility. I estimate (3) on the rate of center-based childcare employees in a county in each year (although because I do this for the pre-1988 cohorts, I am required to use the total social services employees as a proxy).[10] Next, using the predicted childcare employee measure, I estimate (4):

$$M_{ck,s} = \alpha + \beta_{iv} \widehat{Childcare}_{ck,s} + \eta X_k + \gamma_s + \delta_c + \varepsilon \quad (4)$$

In the IV model, βiv captures the effect of adding one additional childcare employee per 100 children in a county on mobility measures between cohorts from that county. To the extent that the regulations are independent of other county-level factors that could simultaneously affect mobility and childcare markets, βiv should provide an estimate of the causal effect of childcare availability on intergenerational income mobility.

4. Results

i. Descriptive Relationship

Figure 1 shows the distribution of center- and home-based employees per 100 children in US counties in 1988 and 1987, respectively. There is significant variation across counties in both home- and center-based childcare employee rates. On average, there are about 1.9 home-based childcare providers per 100 children in a county, and about 1.6 center-based providers. By 1992, the number of center-based providers per 100 children in a county had grown to 1.9, while the number of home-based providers had grown to 3.9.

Figure 2 shows the descriptive relationships between local absolute mobility measures for children from families at the 25th and 75th percentiles of the income distribution, and the

10 Hotz and Xiao (2011) confirm that the regulations cause a significant decrease in the number of available childcare centers in low income neighborhoods. They use microdata from the Economic Census, data that is used in part to construct the CBP data I employ herein.

measures of center- and home-based childcare availability. The figures reveal a negative correlation between the center-based employee rate and mobility, and a positive correlation between the home-based facility rate and mobility. For center-based care, the relationship between mobility and availability is similar for rich and poor families; for home-based care, however, the correlation appear stronger for lower-income families.

Tables 1a and *1b* describe the same relationship parametrically, using regression. Table 1a shows the relationships between the center-based and home-based rates and the mobility measure. The left side show the results for children from families at the 25th percentile of the income distribution, while the right side shows results for children from 75th percentile families. Each column represents the results of a separate regression; odd-numbered columns report the raw relationships while even-numbered columns show the results after controlling for county-level covariates.

Two facts emerge from the results for children from poor families. First, there is a strong negative relationship between mobility measures and the availability of center-based childcare for children from poorer families. One additional center-based childcare employee per 100 children in a county is associated with about a 0.64 percentile decrease in the expected rank of a child in the national income distribution. Second, the relationship is extremely stable to the inclusion of other covariates. Once I control for covariates, the estimated coefficient changes to -0.57 and remains significant at the 0.01 level. Second, I estimate the opposite relationship between home-based childcare availability and mobility. One additional home-based childcare provider per 100 children is associated with a 1.6 percentile higher rank in the national income distribution at age 24. Again, the estimated coefficient is relatively stable to the inclusion of other county-level covariates.

The right side of *Table 1a* shows the parallel results for children from families at the 75th percentile of the income distribution. I do not estimate a significant relationship between the availability of center-based care and mobility among children from richer families. For home-based care, I find a positive relationship between availability and mobility, but the relationship is weaker than among children from poor families. For children from higher income families, one additional home-based childcare provider per 100 children is associated with a 0.72 percentile higher income rank.

In *Table 1b*, I report the estimated coefficients obtained from estimating model (2) on the mobility measures for various subgroups. I only report the main coefficient of interest from each model; thus, each number in Table 1b comes from a different regression. In all cases, I report the coefficient obtained from estimating the model after including county-level covariates. The left panel of the table shows the results for children from families at the 25th percentile. I find the same negative relationships between center-based care and mobility, although the coefficient is only significant for boys. I find that one additional center-based provider per 100 children leads to a 0.72 percentile lower expected rank for boys, and a 0.49 percentile lower rank for girls (although the coefficient for girls is marginally insignificant). These coefficient estimates are statistically different from one another. I also estimate marginally insignificant but negative relationships between center-based care availability and mobility among children from both single- and two-parent families. Turning to the home-based care estimates among children from lower-income families, I find heterogeneous effects by subgroup. Additional home-based childcare results in higher mobility among boys than among girls. One additional center-based provider per 100 children leads to a 1.56 percentile higher expected rank for boys, whereas an additional provider leads to a 1.32 percentile higher expected rank

for girls. The coefficient estimates are significantly different from each other. I also estimate positive relationships between available homecare and mobility among single- and two-parent families, but the estimated coefficients are statistically equivalent.

The right panel of *Table 1b* shows the same results for children from families at the 75th percentile. I do not estimate significant relationships between available center-based childcare and mobility for any of the subpopulations among children from richer families. For home-based care, I find a stronger relationship between availability and mobility for boys than for girls. One additional home-based care provider per 100 children in a county is associated with a significant 0.58 percentile higher income rank for boys, and an insignificant 0.44 percentile higher rank for girls (although the coefficient estimates are not statistically different from each other). I also find a large and statistically significant difference between the estimates for children from single- versus two-parent families. One additional home-based care provider is associated with 0.96 percentile increase in expected rank of children from single-parent families; I do not estimate a significant relationship for children from two-parent families.

ii. Causal Results

The estimated relationships described above likely suffer from omitted variable bias. There are likely differences in underlying characteristics between counties with more or less available childcare, and these differences may also affect mobility. To help alleviate this concern, I also report results from the model estimated in changes in *Tables 2*. this tables mirror *Tables 1a*, with the exception that the independent variables capture changes in employee rates in a county between 1987 (or 1988 for center-based care) and 1992, and the dependent variable captures the change in mobility measures between the 1983 and 1988 cohorts. The left panel of *Table 2* shows the results for children from families at the 25th percentile of the income distribution. I estimate positive relationships between changes center-based care availability and changes mobility measures; the estimated relationship between changes in home-based care and mobility is positive but insignificant. A one-employee increase in the number of center-based care providers in a county per 100 children is associated with a 0.01 percentile increase in the expected income rank of the 1988 cohort versus 1983 cohort from that county. For children from richer families, I estimate positive relationships between changes in both center- and home-based care availability and change in mobility measures. A one-employee increase in the number of center-based providers in a county is associated with a 0.01 percentile increase in the average income rank of the 1988 versus 1983 cohort. A similar increase in home-base care providers is associated with 0.01 percentile increase in expected ranks between the two cohorts.

I also report results from models that use changes in cohort-specific exposure to regulations as a way to capture exogenous variation in the availability of childcare facilities in a county. I report results from this exercise in *Tables 3*, *4* and *5*. *Table 3* shows results of estimating the reduced form model on children from both 25th and 75th percentile families across all counties. I show results from models that include only the measures of exposure to the regulation, along with state- and cohort- fixed effects (columns (1) and (3)), as well as results from models when I add the county-level covariates (columns (2) and (4)). In columns (1) and (2) I show how cohort-specific income mobility for children from families at the 25th percentile changes when regulations become more stringent. I report results for the categorical measure of the regulation, where low regulatory restrictiveness is the omitted category. The results indicate that, after controlling for state and cohort fixed effects, children from poor

families who are exposed to moderate restrictions have a 0.45 percentile lower expected rank in the adult income distribution relative to children exposed to the least restrictive regulation. Children exposed to the most restrictive regimes have on average a 1.14 percentile lower rank than unexposed children. In column (2) I show that the estimated relationship is stable to the inclusion of covariates. In columns (3) and (4), I show the same results for families from the 75th percentile of the income distribution. I do not estimate statistically significant relationships between the regulations and income mobility for children from richer families.

In *Table 4*, I report results for low income families after partitioning my sample by average county-level household income. Hotz and Xiao (2011) find that the regulations led to the biggest losses in center-based care facilities in low income areas. As such, I repeat the analysis on the sample of counties in the bottom 25 percent in terms of average household income (columns (1) and (2)), as compared to the top 75 percent of counties (columns (3) and (4)). I find that strict regulations are especially limiting for the mobility of children from low income families who live in lower income counties. The most restrictive regulations are associated with 1.54 percentile lower expected income rank in poorer counties, and a 0.86 percentile lower expected rank in richer counties (although the coefficients are not statistically different from each other).

The results in *Table 3* and *4* show that, overall, the regulations lowered mobility. I also estimate an IV model to illustrate the extent to which the lower mobility originates from restricted supply of the center-based childcare providers. I report results of this exercise in *Table 5*. Again, I focus on children from families at the 25th percentile of the income distribution, and partition the data by average county household income (bottom 25 percent in columns (1) and (2) vs. top 75 percent in columns (3) and (4)). I again report results without controls (columns (1) and (3)) and with (columns (2) and (4)). In the bottom panel of the table, I show the results from the first stage model where I estimate the relationship between the regulations and the number of childcare employees per 100 children in a county.

The results show that the regulations predict the number of providers, but only in low income counties. The strictest regulation is associated with about 1.4 fewer local providers per 100 children in a county. The top panel of the of the table shows the second stage estimates, where I estimate the relationship between available providers and mobility measures using the predicted rate of employees from the first stage. I find that a one-employee increase in the rate of childcare providers per 100 children in a county leads to a 1 percentile increase in the expected rank of exposed children. The inclusion of county-level characteristics does not significantly affect the estimate. The results in columns (3) and (4) show that the regulations are not significant predictors of the number of childcare providers in higher income counties; the second stage estimates are therefore also insignificant.

5. Conclusions

In this paper, I explore the relationship between county-level measures of income mobility and availability of childcare. Childcare availability may improve mobility if it allows parents to work, or if it encourages healthy development in children. Childcare options may also be more important for children from low income families, since such families may be required to have both parents working, or may face more time constraints than richer families. Because of the difficulty of tracking people over the long-term, however, there is limited existing research linking childcare to adulthood outcomes in large, representative samples.

The results discussed here add to this literature. I find positive correlations between available home-based childcare providers and mobility measures, relationships that are generally stronger for children from families at the 25th percentile of the income distribution than from families at the 75th percentile. I also find that for center-based care, there is a negative correlation between available childcare providers and income mobility for children from lower-income families. The estimated relationships are relatively stable to the inclusion of a wide set of county-level covariates.

The estimated negative relationship between center-based childcare and mobility measures for children from lower-income families may reflect omitted variable bias. Counties that have more center-based capacity may differ from those with less in unobservable ways that bias the estimated relationships. Alternatively, families who live in counties with more capacity may tend to have different characteristics than families who live elsewhere, and may therefore produce less mobile children. However, I uncover some evidence to discredit this possibility. I find interesting heterogeneity in effects that suggest that omitted variables may not necessarily account for the negative correlation. The negative estimate only holds for children from low income family and only for boys from low income families. There is a growing body of literature suggesting that low quality childcare may be especially harmful for boys from lower income households (Datta-Gupta and Simonsen 2010; Kottelenberg and Lehrer 2018). In that sense, the correlation aligns with predictions from existing literature. Furthermore, I do not find a similarly negative relationship for home-based care. If omitted county-level characteristics were responsible for the negative estimate of the relationship between center-based care and mobility, one might imagine that they would cause a similar bias for home-based care. However, the two pieces of quasi-experimental evidence I uncover suggest that omitted variable bias may be responsible for the negative correlation. When I estimate the model in changes, I uncover positive — but small — associations between the change in available childcare providers and the cohort-to-cohort change in mobility for children from both low- and higher-income families. Of course, the model in changes may also be biased and reflect trends in the demographic composition of some areas. However, I also estimate a positive relationship between available center-based providers (which I proxy with social service providers) and mobility when I use the instrumental variables approach. Using variation in regulations that limited the supply of childcare providers in low income communities, I estimate that a one-unit increase in available care providers leads to a one-percentile increase in the expected rank of children from low income families who live in low income counties. Further, the main causal evidence I present originates from a natural experiment that reduced supply, but also increased quality. The reduced form estimations show that, on net, the regulations reduced mobility for children from low income families. Thus, while higher quality care may be good for children, the effect of availability appears to swamp any effect associated with improved quality.

While I am not able to test for causal effects of the availability of home-based care, I do find interesting correlations between county-level availability and mobility measures. I estimate positive correlations between the availability of home-based care, which are stronger for children from low income families. I also find especially strong, positive correlations between home-based care availability and mobility among boys relative to girls. Further, we might expect to find that childcare plays a more important role in mobility for children

from single- versus two-parent families. My results show that this is indeed true, but only among children from higher-income families, for whom the availability of home-based care is much more important for single-parent children than two-parent children. For children from lower income households, the relationships between home-based care availability and mobility are similar for children from single- and two-parent households. This makes sense if single and two-parent families with lower incomes use similar types of care — namely, informal care — while higher income families with different family structures use different care arrangements. However, I am ultimately unable to identify the extent to which the estimated relationships reflect causal effects.

The results of this study should be interpreted in light of several additional limitations. Firstly, the childcare availability data are limited. They only exist for select years, and as a result, some models relate outcomes and treatment variables that capture the world in different years. Data limitations also mean that I am required to proxy for total center-based childcare employees in the IV regression. Second, because the outcome data are taken from Chetty et al. and are reported at the county level, I am only able to estimate average effects. Thus, all estimates should be interpreted as intent-to-treat, capturing the average effects of childcare on all children in a county regardless of whether they use childcare or not. Despite these limitations, the results add to the literature estimating the long-run effects of childcare, a task that is often difficult to do. I find evidence to support the theory that childcare availability may be a good tool to help remedy the mobility gap between children from poor and rich families. I also show that regulating childcare markets may have unintended consequences on poor children from low income areas where regulations may restrict supply.

6. References

Baker, Michael, Jonathan Gruber, and Kevin Milligan. "Universal child care, maternal labor supply, and family well-being." *Journal of Political Economy* 116, no. 4 (2008): 709–745.

Baker, Michael, Jonathan Gruber, and Kevin Milligan. "Non-cognitive deficits and young adult outcomes: The long-run impacts of a universal child care program." No. w21571. *National Bureau of Economic Research* (2015).

Barnett, W. Steven, Kwanghee Jung, M. Youn, and Ellen C. Frede. "Abbott preschool program longitudinal effects study: Fifth grade follow-up." *National Institute for Early Education Research* 20 (2013).

Belfield, Clive R., Milagros Nores, Steve Barnett, and Lawrence Schweinhart. "The high/scope perry preschool program cost–benefit analysis using data from the age-40 followup." *Journal of Human Resources* 41, no. 1 (2006): 162–190.

Black, Sandra E., Paul J. Devereux, Katrine V. Løken, and Kjell G. Salvanes. "Care or cash? The effect of child care subsidies on student performance." *Review of Economics and Statistics* 96, no. 5 (2014): 824–837.

Bradbury, Bruce, Miles Corak, Jane Waldfogel, and Elizabeth Washbrook. "Too many children left behind." *Schools and Society: A Sociological Approach to Education* (2017): 456.

Camilli, Gregory, Sadako Vargas, Sharon Ryan, and W. Steven Barnett. "Meta-analysis of the effects of early education interventions on cognitive and social development." *Teachers college record* 112, no. 3 (2010): 579–620.

Campbell, Frances A., Craig T. Ramey, Elizabeth Pungello, Joseph Sparling, and Shari Miller-Johnson. "Early childhood education: Young adult outcomes from the Abecedarian Project." *Applied developmental science* 6, no. 1 (2002): 42–57.

Carneiro, Pedro, and Rita Ginja. "Long-term impacts of compensatory preschool on health and behavior: Evidence from Head Start." *American Economic Journal: Economic Policy* 6, no. 4 (2014): 135–73.

Cascio, Elizabeth U., and Diane Whitmore Schanzenbach. *"The impacts of expanding access to high-quality preschool education."* No. w19735. National Bureau of Economic Research (2013).

Chetty, Raj, Nathaniel Hendren, Patrick Kline, and Emmanuel Saez. "Where is the land of opportunity? The geography of intergenerational mobility in the United States." *The Quarterly Journal of Economics* 129, no. 4 (2014): 1553–1623.

Chetty, Raj, and Nathaniel Hendren. "The impacts of neighborhoods on intergenerational mobility I: Childhood exposure effects." *The Quarterly Journal of Economics* 133, no. 3 (2018): 1107–1162.

Chetty, Raj, and Nathaniel Hendren. "The impacts of neighborhoods on intergenerational mobility II: County-level estimates." *The Quarterly Journal of Economics* 133, no. 3 (2018): 1163–1228.

Currie, Janet, and Duncan Thomas. "Does head start make a difference?" *The American Economic Review* 85, no. 3 (1995): 341.

Currie, Janet. "Inequality at birth: Some causes and consequences." *American Economic Review* 101, no. 3 (2011): 1–22.

Deming, David. "Early childhood intervention and life-cycle skill development: Evidence from Head Start." *American Economic Journal: Applied Economics* 1, no. 3 (2009): 111–34.

Duncan, Greg J., and Katherine Magnuson. "Investing in preschool programs." *Journal of Economic Perspectives* 27, no. 2 (2013): 109–32.

Fitzpatrick, Maria D. "Starting school at four: The effect of universal pre-kindergarten on children's academic achievement." *The BE Journal of Economic Analysis & Policy* 8, no. 1 (2008).

Garces, Eliana, Duncan Thomas, and Janet Currie. "Longer-term effects of Head Start." *American Economic Review* 92, no. 4 (2002): 999–1012.

Gormley, William T., and Ted Gayer. "Promoting school readiness in Oklahoma an evaluation of Tulsa's pre-k program." *Journal of Human Resources* 40, no. 3 (2005): 533–558.

Gupta, Nabanita Datta, and Marianne Simonsen. "Non-cognitive child outcomes and universal high quality child care." *Journal of Public Economics* 94, no. 1-2 (2010): 30–43.

Haeck, Catherine, Pierre Lefebvre, and Philip Merrigan. "Canadian evidence on ten years of universal preschool policies: The good and the bad." *Labour Economics* 36 (2015): 137–57.

Havnes, Tarjei and Magne Mogstad. "Is universal childcare leveling the playing field?" *Journal of Public Economics* 127 (2015): 100–114.

Heckman, James J., Seong Hyeok Moon, Rodrigo Pinto, Peter A. Savelyev, and Adam Yavitz. "The rate of return to the HighScope Perry Preschool Program." *Journal of Public Economics* 94, no. 1–2 (2010): 114–128.

Heckman, James, Rodrigo Pinto, and Peter Savelyev. "Understanding the mechanisms through which an influential early childhood program boosted adult outcomes." *American Economic Review* 103, no. 6 (2013): 2052–86.

Herbst, Chris M., 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* 35, no. 1 (2016): 94–116.

Herbst, Chris M. "Universal child care, maternal employment, and children's long-run outcomes: Evidence from the US Lanham Act of 1940." *Journal of Labor Economics* 35, no. 2 (2017): 519–564.

Hill, Jennifer, Jane Waldfogel, and Jeanne Brooks-Gunn. "Differential effects of high-quality child care." *Journal of Policy Analysis and Management*, 21, no. 4 (2002): 601–627.

Hotz, V. Joseph, and Mo Xiao. "The impact of regulations on the supply and quality of care in child care markets." *American Economic Review* 101, no. 5 (2011): 1775–1805.

Kottelenberg, Michael J., and Steven F. Lehrer. "Does Quebec's subsidized child care policy give boys and girls an equal start?" *Canadian Journal of Economics/Revue canadienne d'économique* 51, no. 2 (2018): 627–659.

McGinn, Kathleen L., Mayra Ruiz Castro, and Elizabeth Long Lingo. "Learning from mum: Cross-national evidence linking maternal employment and adult children's outcomes." *Work, Employment and Society* (2018): 0950017018760167.

Peisner-Feinberg, E., Burchinal, M., Clifford, R., Culkin, M., Howes, C., Kagan, S., et al. "The relation of preschool child-care quality to children's cognitive and social development trajectories through second grade." *Child Development*, 72 (2001): 1534–1553.

Puma, Michael, Stephen Bell, Ronna Cook, Camilla Heid, and Michael Lopez. "Head Start Impact Study: First Year Findings." *Administration for Children & Families* (2005).

Reynolds, Arthur J., Judy A. Temple, and Suh-Ruu Ou. "Preschool education, educational attainment, and crime prevention: Contributions of cognitive and non-cognitive skills." *Children and Youth Services Review* 32, no. 8 (2010): 1054–1063.

Schweinhart, Lawrence J., Jeanne Montie, Zongping Xiang, W. Steven Barnett, Clive R. Belfield, and Milagros Nores. "Lifetime effects: The high/scope perry preschool study through age 40 (monographs of the high/scope educational research foundation, 14)." *Ypsilanti, MI: High Scope Educational Research Foundation* (2005).

Weiland, Christina, and Hirokazu Yoshikawa. "Impacts of a prekindergarten program on children's mathematics, language, literacy, executive function, and emotional skills." *Child Development* 84, no. 6 (2013): 2112–2130.

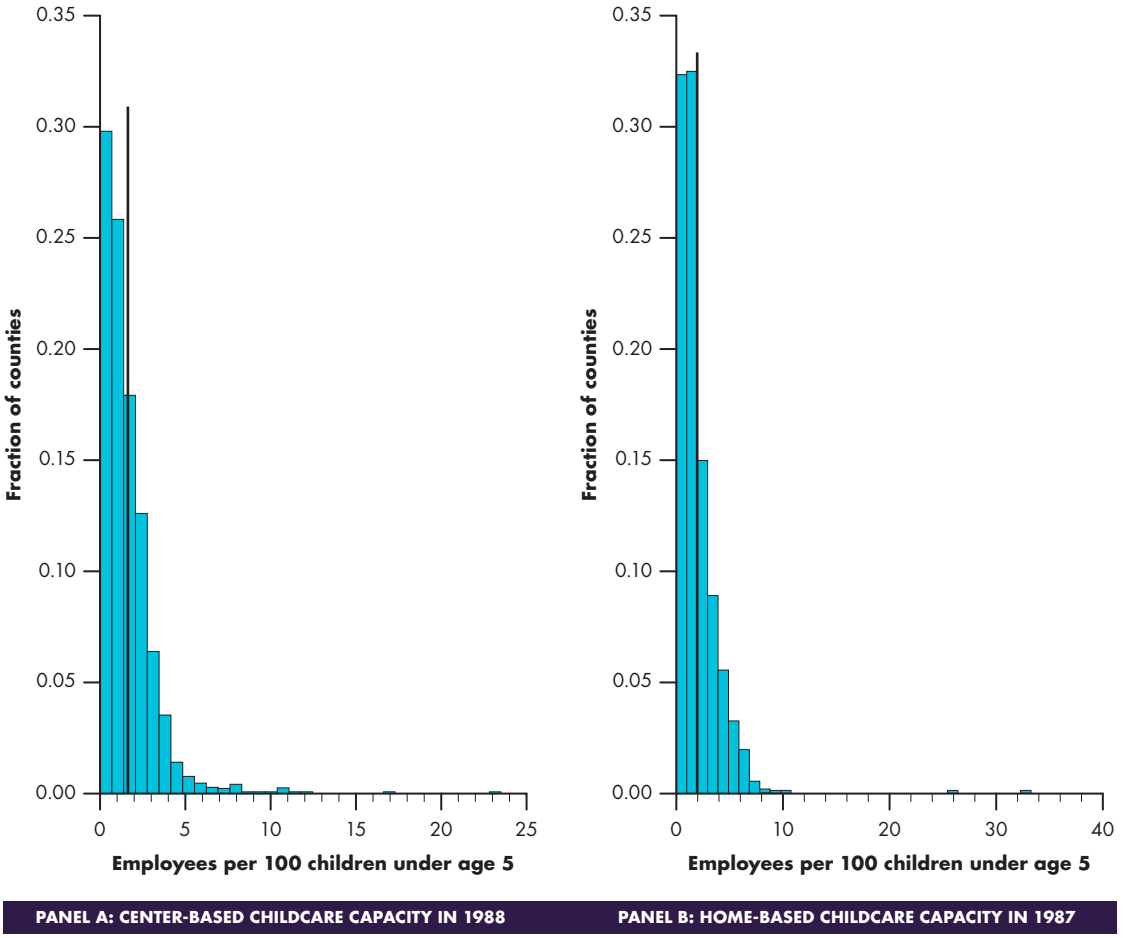
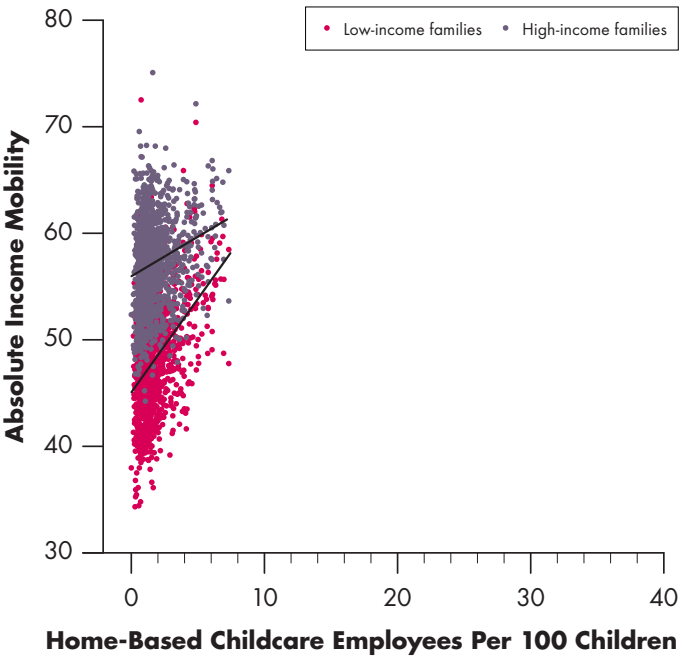
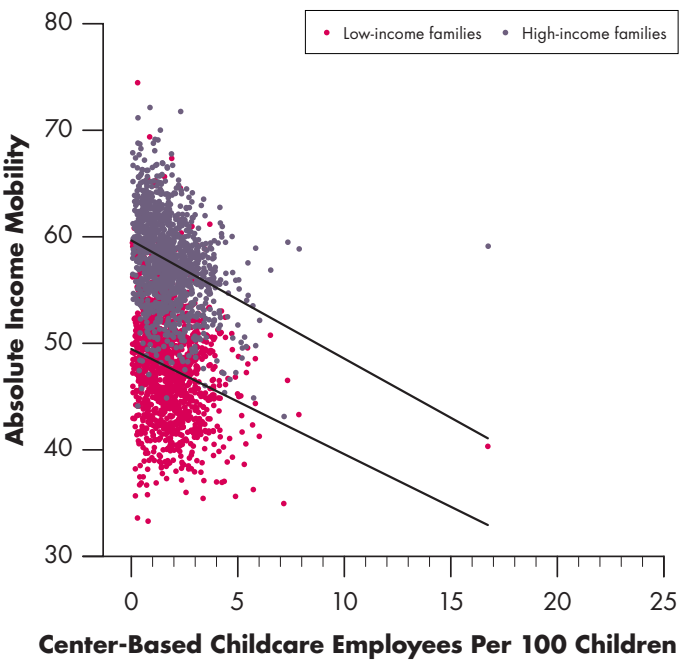


Figure 1. Distribution of home-based and center-based childcare facilities



PANEL C: RELATIONSHIP BETWEEN COUNTY-LEVEL HOME-BASED CARE AND MOBILITY



PANEL D: RELATIONSHIP BETWEEN COUNTY-LEVEL CENTER-BASED CARE AND MOBILITY

Figure 2. Scatterplots of income mobility measures and total facility rates, by parent income rank

Table 1a. Naïve relationship between childcare availability and mobility measures

	Income Mobility 25th percentile				Income Mobility 75th percentile			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Center-based Employee Rate	**-0.64****	**-0.57****			**-0.57**	**-0.17**		
	(0.23)	**(0.24)**			**(0.29)**	**(0.38)**		
Home-based Employee Rate			**1.73*****	**1.60*****			**0.82*****	**0.72*****
			(0.16)	**(0.24)**			**(0.16)**	**(0.19)**
Female Labor Force Part.		0.99**		-0.41		0.44		-0.16
		(0.30)		(0.39)		(0.38)		(0.32)
Unemployment Rate		0.14		0.64***		0.39*		0.55**
		(0.18)		(0.15)		(0.16)		(0.19)
Poverty Rate		-0.62**		-0.89***		-0.38*		-0.49**
		(0.19)		(0.18)		(0.17)		(0.18)
College Grad Rate		0.02		0.01		-0.07		-0.08
		(0.07)		(0.09)		(0.08)		(0.08)
Divorce Rate		-0.64***		-0.71***		-0.10		-0.12
		(0.13)		(0.11)		(0.13)		(0.11)
Fraction Black		-1.14***		-0.98***		-0.57**		-0.50**
		(0.23)		(0.21)		(0.18)		(0.16)
Metro		0.71		0.08		1.38***		1.09**
		(0.40)		(0.40)		(0.35)		(0.32)
Population Density		-0.39		-0.31		-0.47*		-0.42
		(0.21)		(0.20)		(0.19)		(0.22)
Gini		-0.50		-0.47*		-0.54*		-0.49**
		(0.27)		(0.18)		(0.22)		(0.15)
Location Affordability		0.01		-0.03		-0.09		-0.09
		(0.15)		(0.14)		(0.11)		(0.10)
Local Tax Rate		-0.47***		-0.20		0.03		0.08
		(0.08)		(0.12)		(0.10)		(0.09)
N	1274	968	1288	973	1274	968	1288	973
adj. R-sq.	0.03	0.44	0.20	0.55	0.03	0.27	0.07	0.31

* p<0.05; ** p<0.01; *** p<0.001

Notes: Data from Chetty et al. (2011), Economic Census and County Business Patterns. Each column reports results from an independent regression. Models exploring center-based care use data from 1988; models of home-based care use data from 1987. All models use the cohort-specific mobility measures from Chetty et al. for the corresponding year and reflect income measured at age 24. Robust standard errors clustered at the state level.

Table 1b. Naïve relationship between childcare availability and mobility measures for subgroups

	Income Mobility 25th percentile				Income Mobility 75th percentile			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	boys	girls	single parent	two parent	boys	girls	single parent	two parent
Center-based Employee Rate	**-0.72***	**-0.49**	**-0.53**	**-0.44**	**-0.24**	**0.03**	**0.03**	**-0.07**
	(0.30)	**(0.25)**	**(0.28)**	**(0.25)**	**(0.44)**	**(0.36)**	**(0.35)**	**(0.42)**
Home-based Employee Rate	**1.56*** **	**1.32*** **	**1.34*** **	**1.09*** **	**0.58***	**0.44**	**0.96*** **	**0.40**
	(0.28)	**(0.25)**	**(0.24)**	**(0.27)**	**(0.23)**	**(0.22)**	**(0.21)**	**(0.23)**

* p<0.05; ** p<0.01; *** p<0.001

Notes: Data from Chetty et al. (2011), Economic Census and County Business Patterns. Each cell reports results from an independent regression. Models exploring center-based care use childcare data from 1988; models of home-based care use data from 1987. All models use the cohort-invariant mobility measures from Chetty et al. and reflect income measured at age 26. Robust standard errors clustered at the state level.

Table 2. Relationships between changes in childcare availability and changes in mobility measures

	Income Mobility 25th percentile				Income Mobility 75th percentile			
	(1)	(2)	(3)	(4)	(1)	(2)	(3)	(4)
Center-based Employee Rate	**0.010***	**0.010***			**0.010***	**0.008***		
	(0.005)	**(0.004)**			**(0.004)**	**(0.003)**		
Home-based Employee Rate			**0.004**	**0.003**			**0.008****	**0.008****
			(0.003)	**(0.003)**			**(0.003)**	**(0.002)**
Female Labor Force Part.		-0.284		-0.344		-0.090		-0.278
		(0.177)		(0.226)		(0.212)		(0.233)
Unemployment Rate		-0.180		-0.213		-0.098		-0.072
		(0.107)		(0.111)		(0.113)		(0.103)
Poverty Rate		-0.065		-0.034		-0.166		-0.178
		(0.117)		(0.119)		(0.135)		(0.137)
College Grad Rate		-0.040		-0.033		0.006		0.024
		(0.083)		(0.085)		(0.061)		(0.061)
Divorce Rate		0.247*		0.238*		0.137		0.110
		(0.100)		(0.089)		(0.079)		(0.067)
Fraction Black		0.190*		0.208		0.077		0.116
		(0.089)		(0.107)		(0.104)		(0.092)
Metro		0.471		0.441*		0.905***		0.641**
		(0.257)		(0.214)		(0.216)		(0.189)
Population Density		0.285**		0.317**		0.065		0.120
		(0.105)		(0.097)		(0.093)		(0.095)
Gini		0.071		0.070		-0.011		0.044
		(0.117)		(0.166)		(0.101)		(0.106)
Location Affordability		-0.003		-0.003		-0.035		0.001
		(0.107)		(0.114)		(0.106)		(0.098)
Local Tax Rate		0.109		0.144		0.105*		0.148*
		(0.074)		(0.093)		(0.044)		(0.062)
N	1261	965	1275	970	1261	965	1275	970
adj. R-sq.	0.042	0.104	0.015	0.077	0.044	0.127	0.096	0.160

* p<0.05; ** p<0.01; *** p<0.001

Notes: Data from Chetty et al. (2011), Economic Census and County Business Patterns. Each column reports results from an independent regression. Models exploring center-based care use the change in the local employee rate between 1988 and 1992; models of home-based care use the change in the local employee rate between 1987 and 1992. All models use the change in cohort-specific mobility measures between the 1983 and 1988 cohorts from Chetty et al. and reflect income measured at age 24. Robust standard errors clustered at the state level.

Table 3. Reduced form estimates of the effects of regulation on mobility

	25th Percentile Parents		75th Percentile Parents	
	(1)	(2)	(5)	(6)
Moderate Regulation	**-0.46***	**-0.45***	**-0.09**	**-0.10**
	(0.22)	**(0.22)**	**(0.29)**	**(0.29)**
Strict Regulation	**-1.16****	**-1.13****	**-0.24**	**-0.24**
	(0.35)	**(0.36)**	**(0.52)**	**(0.53)**
Controls	N	Y	N	Y
N	11549	8670	11549	8670
adj. R-sq	0.32	0.70	0.36	0.61

* p<0.05; ** p<0.01
Notes: Data from Chetty et al. (2014), and Hotz and Xiao (2011). Each column reports results from an independent regression. All models use the cohort-specific mobility measures for the 1980 through 1988 cohorts from Chetty et al. and reflect income measured at age 24. All models include state and cohort fixed-effects. Robust standard errors clustered at the state level.

Table 4. Reduced form estimates of the effects of regulation on mobility by county income

	25th Percentile Parents		75th Percentile Parents	
	Poorest 25% Counties		Richest 75% Counties	
	(1)	(2)	(3)	(4)
Moderate Regulation	**-0.43**	**-0.44**	**-0.40**	**-0.39**
	(0.37)	**(0.36)**	**(0.23)**	**(0.24)**
Strict Regulation	**-1.49***	**-1.53***	**-0.90***	**-0.86***
	(0.72)	**(0.73)**	**(0.36)**	**(0.37)**
Controls	N	Y	N	Y
N	2879	2221	8670	6449
adj. R-sq	0.57	0.74	0.35	0.68

* p<0.05; ** p<0.01
Notes: Data from Chetty et al. (2014), and Hotz and Xiao (2011). Each column reports results from an independent regression. All models use the cohort-specific mobility measures for the 1980 through 1988 cohorts from Chetty et al. and reflect income measured at age 24. All models include state and cohort fixed-effects. Robust standard errors clustered at the state level. Income split according to average household income in county in 1980.

Table 5. Instrumental variables estimation

	25th Percentile Parents			
	Poorest 25% Counties		Richest 75% Counties	
	(1)	(2)	(3)	(4)
SS Employee Rate	**1.01***	**0.94***	**-0.72**	**-0.15**
	(0.48)	**(0.44)**	**(1.25)**	**(0.97)**
Controls	N	Y	N	Y
N	2869	2212	8659	6446
adj. R-sq	–	0.29	0.26	0.67
First Stage				
Moderate Regulation	**-0.83****	**-0.91****	**-0.14**	**-0.18**
	(0.28)	**(0.29)**	**(0.16)**	**(0.17)**
Strict Regulation	**-1.40****	**-1.59*****	**0.03**	**-0.03**
	(0.41)	**(0.41)**	**(0.28)**	**(0.30)**
F-stat	49.19	1319.23	106.12	1982.74

* p<0.05; ** p<0.01

Notes: Data from Chetty et al. (2014), Hotz and Xiao (2011), County Business Patterns. Each column reports results from an independent regression. All models use the cohort-specific mobility measures for the 1980 through 1988 cohorts from Chetty et al. and reflect income measured at age 24. All models include state and cohort fixed-effects. Robust standard errors clustered at the state level. Income split according to average household income in county in 1980.

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