# The Price of Parenthood: Childcare Costs and Fertility *

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January 8, 2026

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**Abstract**

Across the developed world, fertility rates have fallen below replacement level, raising concerns over shrinking workforces and ageing[1] populations. U.S. birthrates have reached historic lows, and high childcare costs pose a financial barrier to parenthood. This paper studies how childcare prices shape fertility decisions - whether to have children, when to have them, and how many to have. Using an instrumental variables approach that exploits changes in U.S. state-level childcare regulations that effectively shift the price of childcare, I find that higher prices reduce birth rates, delay first births, and lengthen the interval between first and second births. A 10% increase in the price of childcare leads to a 5.7% decrease in the birth rate (4 births per 1000 women). Reduced form results show that changes in the regulations directly impact birthrates. Declines are largest amongst women aged 30 and above. I propose a theoretical model to explain this age gradient: older women earning higher wages face a greater opportunity cost of their time and thus outsource childcare, making them more sensitive to its price. Consistent with the model's predictions, older parents spend more on formal childcare, and more educated women (as a proxy for income) exhibit greater price sensitivity. Additionally, older mothers are more likely to be considering higher order births, which I find to be more price sensitive.

*I am grateful to Kevin Lang, Patricia Cortés, Anna Sinaiko and Tal Gross for invaluable mentorship, advice, and encouragement. I thank Maggie McConnell, Daniele Paserman, Pauline Mourot, Johannes Schmieder, Daniel Dench, Peter Blair, Mayra Pineda-Torres, Jessica Cohen, Taylor Watson, Danielle Graves Williamson, James Dow, as well as seminar participants at SEHO (2025), ASHEcon (2025), APPAM (2025), the BU empirical micro workshop (2025), and the Harvard Health Economics PhD seminar (2025) for valuable comments. Kyle Gillard provided helpful research assistance. The opinions, findings, and conclusions presented/reported in this article/presentation are those of the author(s), and are in no way meant to represent the corporate opinions, views, or policies of the National Association for the Education of Young Children (NAEYC). NAEYC does not warrant nor assume any liability or responsibility for the accuracy, completeness, or usefulness of any information presented in this article.

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[1]Please note that I use British English spelling throughout.

# 1 Introduction

Developed countries across the world are experiencing a fertility crisis, as fertility rates drop further below replacement level. Low fertility rates, absent increased immigration, lead to a shrinking future workforce and an ageing population, which will slow economic growth and strain social services.

Would-be parents cite financial pressures as a key barrier to starting or expanding a family (Institute for Family Studies, 2022), with childcare one of the earliest and largest costs of child-rearing. Childcare costs represent a substantial financial burden in the U.S; families spend 9% to 16% of median income on full-time care for one child alone (U.S. Department of Labor, 2024), and low-income families are particularly strained. Furthermore, high childcare costs can push mothers to reduce their working hours or drop out of the labour market (Haan and Wrohlich, 2011). Yet evidence on the relationship between childcare costs and fertility remains limited.

In this paper, I study how childcare prices affect mothers' decisions to have children, how many to have, and when to have them. To my knowledge, this is the first paper to study the causal relationship between childcare *prices* and fertility, allowing me to estimate price elasticities. Prior work on the cost of childcare is limited, particularly in the U.S., reflecting the difficulty of finding plausibly exogenous cost variation.

To answer this question, I assemble a unique dataset on U.S. childcare regulations to construct a novel instrument for childcare prices. I compile state-level data on maximum group size and minimum child-staff ratios for 2010 and 2022, collecting data directly from historical state administrative codes and licensing regulations to address gaps and errors in existing sources. These regulations affect prices by limiting capacity and dictating staffing requirements. This instrumental variables (IV) strategy departs from the quasi-experimental approaches employed in prior work. An additional contribution of this project is the regulation dataset itself, which can be used in a wide range of other research settings and questions. I link these data to administrative birth records and the first national dataset on childcare prices, the National Database of Childcare Prices (NDCP).

I document key facts about childcare prices in the U.S., which are substantial for many families. The average cost of childcare as a share of median household income ranged from 5% to 35% across counties in 2022. I highlight that there is significant geographical variation in childcare prices, with higher prices on the West Coast and in the Northeast. However, the cost of childcare as a share of median household income shows that there are areas throughout the U.S. where childcare costs represent more than 20% of median household income. There has been much public discussion of rising childcare prices (The Guardian, 2025). Yet annual childcare costs as a share of median household income have not changed substantially since 2008.

I show that childcare facility regulations significantly impact the price of childcare for children under three. This relationship is both a useful input into policy debates around regulating the childcare market, and indicates that these regulations are relevant instruments for prices. An increase in the maximum group size by one child (6% of the mean) is associated with a reduction in the weekly price of childcare of $1. As these regulations dictate staffing requirements, they may also affect employment in the childcare sector. Moreover, by changing operating costs, regulations could influence market size through provider entry and exit. In additional difference-in-differences analysis that exploits variation across states and time, I analyse the effects of changes in the regulations on the childcare market. I find that changes that loosen the regulations lead to falls in employment in the childcare sector and increases in earnings. Although we may expect earnings to fall rather than rise, this finding could reflect remaining staff being more experienced or of higher quality. I do not find evidence that more stringent changes have statistically significant effects on employment or the number of childcare establishments, which may reflect heterogeneity in the extent of regulatory shifts across the treated states. Null effects could also arise if regulatory changes trigger offsetting demand responses.

The core of my paper analyses the effects of childcare prices on birthrates. A simple OLS regression of birthrates on childcare prices would likely suffer from statistical endogeneity. Price changes can reflect either a supply or demand response, or both. Such simultaneity would bias my estimates towards zero, and indeed, I find null effects with OLS. To overcome endogeneity, I instrument childcare prices with the childcare facility regulations.

My quasi-experimental results show that fertility is sensitive to childcare prices. I find that a 10% increase in the price of childcare for 0 to 2 year olds leads to a 5.7% decrease in the birthrate of women aged 20 to 44 (4 births per 1000 women). Births to White, Black, and Hispanic mothers are all price sensitive. Reduced form estimates show that increases in the maximum group size directly impact birthrates. An increase in the maximum group size by 10 children leads to a rise in birthrates of 3.7%. I also find that a rise in childcare prices leads mothers to delay their first birth, and increase the time between their first and second birth. A 10% increase in the childcare price shifts age at first birth by 4 months and the time between the first and second birth by half a month.

These estimates are robust to a battery of sensitivity analyses and alternative approaches. I defend the validity of my instrument by assessing the plausibility of the identifying assumptions. One potential concern with this identification strategy is that the childcare regulations may affect the quality of childcare, and quality may directly impact fertility decisions. To respond to this concern, I first show that the results are robust to controlling for a measure of quality - staff turnover. I also conduct a bounding exercise. If quality does in fact impact birthrates, I show that my Instrumental Variables (IV) estimates represent a lower bound. I decompose the size and components of the bias, and estimate the size of the true population parameter using a unique dataset on childcare quality.

I show that birthrate responses to price changes vary considerably by age. Older women, aged 30 and above, are more price responsive than younger women. I outline a theoretical model that provides a framework for understanding this age gradient. One may expect younger women to be more price responsive than older women, given that they are more likely to be financially constrained. However, I show that older mothers can be more price sensitive than younger mothers. Through human capital accumulation from work experience, older women earn a higher wage, and so the opportunity cost of their time is higher. Women earning higher wages will outsource a larger share of childcare, if not all. High levels of outsourcing make mothers more exposed to price changes, driving increased price sensitivity. Additionally, second births to older mothers are more price sensitive simply because the total spending on childcare rises.

I test my model predictions and demonstrate several potential mechanisms driving the age heterogeneity. First, higher-earning women are more price sensitive. Using education as a proxy for income, I show that birthrates for women with an undergraduate degree are more price sensitive than those for women without. Second, using Consumer Expenditure Survey data, I confirm that older parents do spend more on formal childcare. Finally, consistent with the prediction that older mothers with two children are price sensitive because total childcare spending rises, I show that second and third birthrates are more affected by price changes than first birthrates.

This paper builds on several strands of the literature. Broadly, by studying childcare prices, I contribute to the literature studying how financial barriers and incentives affect fertility. Child subsidies (Cohen et al., 2013; Milligan, 2005), cash transfers (González, 2013; Ang, 2015), paid maternity leave (Raute, 2019), housing credits (van Doornik et al., 2024), and tax incentives (Laroque and Salanié, 2014; Whittington et al., 1990) have pro-natal effects. Car seat laws that require parents with three children to purchase a larger car also reduce fertility (Nickerson and Solomon, 2024). Welfare reforms have null to small effects on childbearing (Kearney, 2004; Rosenzweig, 1999; Joyce et al., 2003; Moffitt, 1998), except for a reform that reduced welfare for immigrants (Amuedo-Dorantes et al., 2016). Furthermore, Kearney and Wilson (2018), Cumming and Dettling (2024), and Dettling and Kearney (2014) show that economic conditions, monetary policy, and families' assets causally impact U.S. birthrates.

The causal effects of childcare costs on fertility remain understudied outside of the structural modelling literature[2]. In European settings, where public provision of childcare is more common and spending on policies to support families is high, prior research has documented notable fertility responses to childcare policy reforms. The introduction of universal childcare in Germany led to an expansion in fertility, for second and third births in particular (in line with my findings) (Bauernschuster et al., 2016). A reform that capped childcare costs increased first births in Sweden, with stronger effects for low-income families (Mörk et al., 2013). Using simulation models, Rindfuss et al. (2010) estimate that increased availability of childcare spaces in Norway would lead to higher childbearing. These papers have focused on policy reforms that shift the cost of childcare, whilst I bring new evidence on the effects of childcare prices themselves, which allows me to quantify price elasticities.

While important and informative, the conclusions and magnitudes from these papers may not carry across to the U.S., where childcare is chiefly delivered through the private market, the responsibility for paying for childcare is placed on parents (Davis and Sojourner, 2021), and the population is more racially diverse. The U.S. spends 0.33% of GDP on public early care and education for 0 to 5 year olds relative to 1.3% or more in France, Norway and Sweden and the OECD average of 0.74% (OECD, 2019)[3]. The cost of childcare as a share of household income is substantially higher in the U.S. than other OECD countries (OECD,

[2] There is a large structural literature that models female labour force participation and fertility decision making (e.g. Keane and Wolpin (2010); Blundell et al. (2016)), some of which also study childcare costs or policies (e.g. Haan and Wrohlich (2011); Bick (2016); Guner et al. (2024)). These papers find that reducing the cost of childcare encourages fertility, except for when subsidies require tax increases.

[3] Public expenditure on early-childhood education and care defined as all public spending towards formal day-care services and pre-primary education services. Data adjusted for cross-national differences in school starting age.

2022). Early work by Blau and Robins (1989) suggests that childcare costs are birthrate reducing in the U.S. Averett and Wang (2023) find that the Child and Dependent Care Tax Credit (CDCTC) has no effect on fertility, which the authors attribute to an increase in female labour force participation. Evidence from the marketisation of childcare in the U.S., though, suggests that the relationship between childcare costs and fertility rates holds. The marketisation of childcare and immigrant inflows has allowed educated women to remain in the labour force and work longer hours (Cortes and Tessada, 2011). A few authors explore the fertility responses (Furtado, 2016; Furtado and Hock, 2010; Bar et al., 2018; Hazan and Zoabi, 2015), finding that immigrant inflows are associated with an increased likelihood of having a child and that changes in the relative cost of childcare can explain highly educated women's ability to have more children and increase their working hours. To this empirical literature, I contribute new causal evidence on the childcare price elasticity of fertility in a setting where access to high-quality, affordable childcare is limited for most.

The decline in U.S. fertility rates is driven by both an increase in childlessness and declines in total number of children, and observed across demographic groups. Replicating the fertility rates of cohorts before 2007 would necessitate more births occurring after age 30 among today's women (Kearney and Levine, 2021). My results suggest that birthrates, and higher order birthrates in particular, are sensitive to childcare price changes. These findings indicate that containing childcare costs is important for policymakers seeking to mitigate continued fertility declines.

## 2 Background

In the U.S., there is limited public involvement in the provision of childcare. The childcare market is mostly made up of small private businesses (both profit and non-profit) (Tekin, 2021) and can be divided into formal and informal markets.

Formal childcare settings include day care centres, preschool, nurseries and family childcare homes. Centre-based care options are usually provided by businesses, places of worship, or community-based organisations. Centre-based childcare is typically split up into classrooms by child age (infants, toddlers, preschool, school-age) with teaching staff members overseeing the children (Brown and Herbst, 2022). High-quality, centre-based care has been found to have positive effects on children's education, future earnings (Bailey et al., 2021; Garces et al., 2002) and health (Carneiro and Ginja, 2014). However, there is a low supply of high-quality care and it is often the most expensive option for parents. In family childcare homes, the childcare takes place in the provider's home and children are typically in mixed age groups. Often, the provider also cares for their own children alongside the other children.

Formal childcare facilities are licensed and regulated by state and federal governments to ensure that they meet minimum health and safety requirements. These requirements span a range of domains, including building safety, sanitation, health, background checks, and staff qualifications, training, and supervision. They are designed to support child safety, well-being and development. Family childcare homes tend to face less stringent regulations than childcare centres.

Informal childcare is care that is unlicensed and unregulated, and provided in the child or caregiver's home by nannies, babysitters, au-pairs, family members or friends. Informal care can often be cheaper, particularly if there are multiple children being cared for at the same time, and a more flexible option for mothers and families.

Public funding for childcare is targeted at low-income families and comes chiefly from the federal government. The main childcare assistance programme is the Childcare and Development Fund (CCDF), a subsidy scheme for low-income households. Eligibility is based on income and child age (under 13). Furthermore, households must need the childcare to work or engage in work-related activities (Tekin, 2021). In 2022, 1.4 million children were served by the CCDF (Administration for Children and Families, Office of Child Care, 2022a). 96% of these children were funded through vouchers (Administration for Children and Families, Office of Child Care, 2022c), which parents can use to purchase private childcare from their choice of provider (formal and informal). Of families with income that were served by the CCDF, 31% paid no additional copayment for their childcare (Administration for Children and Families, Office of Child Care, 2022b).

Government funding for childcare is also directed towards the Temporary Assistance to Needy (TANF) and Head Start programmes for low-income families. Head Start is the only federal public provider of childcare, and serves a small proportion of the population. Head Start associated programmes (Head Start, American Indian and Alaska Native Head Start, and Migrant and Seasonal Head Start) served 249,094 children under three in 2023 (Administration for Children and Families, 2023), or 2% of the U.S. under three population (U.S. Census Bureau, 2025b).

Parents who pay for childcare to work or search for work are eligible to claim a tax credit of up to $1,050 for one child, or $2,100 for two or more children (under 13)[4]. Parents can also save money for childcare services in a Dependent Care Flexible Spending Account (DCFSA) - if offered by their employer. A DCFSA is a pre-tax benefit account that can be used for spending on before and after school care, babysitting, nannies, formal childcare, and summer day camps. Both parents must be working, looking for work, or full-time students.

Data from the Early Childhood Program Participation (ECPP) component of the National Household Education Surveys (NHES) in 2019 show that 53% of children under 3 participate in some form of non-parental care or programme arrangement, for an average (mean) of 16 hours a week. Amongst these children, for their primary form of care, 37% went to a centre-based programme, 13% received care from a relative, 40% were in a family childcare home, and 6% received other non-relative care (e.g. friends or nannies).

# 3 Data and sample construction

## 3.1 Data

### 3.1.1 Birthrates

My source of data on fertility is the restricted use National Vital Statistics System (NVSS) birth records data. The NVSS contains information on the universe of births in the U.S., making it the most comprehensive source of fertility data available. These administrative data are derived from birth certificates and contain detailed demographic information on the mother (e.g. marital status, age, race, ethnicity, and birth history). I use these data to conduct individual and county-level analysis. The NVSS has county identifiers, so I combine these data with Census population counts to calculate age-specific county-level birth rates for the years 2010 to 2022 inclusive. For the heterogeneity analysis by education, I calculate population counts for women with and without an undergraduate degree by age band using the 5-year American Community Survey (ACS). Fertility decisions take place at the time of conception, rather than at birth. I calculate the estimated date of conception by subtracting the mother's gestation length in weeks from the midpoint of the month of birth. Using the

[4] The percent of childcare expenses that is eligible for the tax credit varies by household income and subject to a maximum that depends on the number of children. Households with gross income of up to $15,000 can claim 35% of $3,000 (one child), or $6,000 (two or more children). Households with gross income of $43,001 and over can claim 20% of these same maximum amounts.

individual-level data I can also explore whether potential mothers delay births or increase time between births (in order to save money) in response to higher costs of childcare [5].

I exclude 2020 due to the global COVID-19 pandemic. Childcare facilities were closed or had reduced capacity during the pandemic, and stay-at-home orders may have affected fertility decisions.

### 3.1.2 Childcare prices

The childcare price data is from the National Database of Childcare Prices (NDCP), which provides county-level prices for formal childcare by child age. I use the median price of full-time centre-based care, aggregated for 0 to 2 year olds inclusive. I focus on prices for children under 3 as these are the initial costs that prospective parents would face.

The NDCP is collated by the U.S. Department of Labor (DOL) Women's Bureau (WB) and sourced from historic market surveys conducted by U.S. states. States have collected data on childcare market prices since 1998, as a requirement by the Administration for Children and Families (ACF) at the U.S. Department of Health and Human Servies. The ACF needs these data to calculate state reimbursement rates for the CCDF grants, and in order for states to receive funding they must provide information on the prices charged at childcare facilities across the counties in their state. Thus, it is in the states' interest to collect these data. The ACF demands that states conduct the surveys every three years (this figure was 2 years until 2016), but some states provide annual data. The market surveys focus on the regulated, formal childcare market, and data is most complete for childcare centres. Despite the requirement to collect these data, and the incentives to do so, there are missing data at the county, year, and child-age level. Furthermore, states varied in their approach to collecting these data. For example, not all states collected the price data by all ages. As a result of these inconsistencies and missingness, the DOL WB has imputed data for missing years, counties, and ages. I discuss how I handle the imputed data in the sample construction subsection.

[5] Note that I cannot link mothers across births.

### 3.1.3 Childcare regulations

My empirical strategy relies on state-level regulations that shift the cost of providing childcare. A public dataset that tracks the regulations placed on formal childcare facilities by year across my study period does not exist, so I assemble a hand-collected, novel dataset on childcare facility regulations. Specifically, I collect the maximum group size (the maximum number of children allowed in a room) and minimum ratio (the ratio of children per staff member) by age group of child for each U.S. state-year in my sample. This data collection process requires finding historical copies of the administrative code or childcare facilities licensing regulation for a state. In addition, I use legal research resources such as "Casetext" to help identify the history of law changes. With the regulations in hand, I then search the text for any references to the a) maximum group size, and b) ratio for childcare centres, and extract the data for these two regulations by the age group of the child.

### 3.1.4 Additional datasets

I supplement these data with the 5-year American Community Survey (ACS) to capture information on county-level socioeconomic and demographic characteristics, and the U.S. Federal Housing Finance Agency House Price Index to control for single-family house prices.

For exploring mechanisms, I rely on data from the U.S. Bureau of Labor Statistics Consumer Expenditure Surveys (CES). The CES provides detailed information on categories of expenditures for individual survey respondents, as well as demographic characteristics of these respondents. I use the 2010 and 2022 surveys, as these years bookend my study period. In these data I can observe spending on childcare centres by respondent age. I define spending on childcare centres as any spending tagged with the uniform commercial code of "670310" for day care centres, nursery, and preschools.

For evaluating robustness and analysis of the impacts of the childcare facility regulations on childcare markets, I utilise data from the Census County Business Patterns (CBP) and Quarterly Workforce Indicators (QWI) series. The CBP provides data on the number of establishments at various geographical levels, disaggregated by industry. The CBP is derived from the Census Business Register, which tracks all establishments with paid employees in the U.S. The QWI contains data on local labour market conditions by industry. It is sourced from the Longitudinal Employer-Household Dynamics linked employer-employee microdata.

I restrict these datasets to the childcare industry, conditioning on NAICS codes "6244//" for 'Child Day Care Services'. I aggregate the QWI quarterly data to the annual level by taking the mean, as advised in the QWI methodology guide.

For robustness analysis, I use the CBP data and Census population estimates to calculate the share of childcare establishments per 0 to 5 year old. Additionally, I estimate the share of high-quality childcare establishments, which I describe in more detail in Appendix A. I use the QWI data to obtain a proxy for childcare quality: staff turnover.

### 3.2 Sample construction

The birth records sample consists of women aged 20 to 49 who gave birth between 2010 and 2019, 2021 or 2022 inclusive. I then create a county-level sample for analysing birth rates, and individual-level samples to analyse birth timing decisions.

In order to accurately measure when birthing decisions are made and the prices facing potential mothers, I must use the non-imputed childcare price data. I restrict my sample to state-years for which the NDCP data is not imputed on the following criteria: year, geography, and child age. First, I exclude imputed years of data from my sample as they will not reflect the actual prices facing mothers in those years. This is particularly important given that my empirical approach relies on childcare regulatory changes over time. Second, I drop observations where the county-level prices are imputed, to ensure that I am capturing the local-area prices facing potential mothers. A subset of states only provided the price data at the state level. The majority of the childcare price data is at the county level, and there is sufficient geographical variation in prices within a state to conduct county-level analysis. Third, I exclude observations that impute data based on child age. To impute missing prices for age groups, the DOL WB assigned the price for a different age group. As I focus on childcare prior to age 3, I don't want imputed prices that reflect older ages (particularly school age) to be in my analytical sample.

This exercise leaves me with data on births and birthrates for 30 states[6], 1,415 unique counties, and 7,495 county-years for the main county-level analysis. For the individual-level analysis, I create separate samples of first, second and third time mothers to analyse

[6] Alaska, Alabama, Arizona, California, Connecticut, Delaware, Florida, Idaho, Illinois, Kansas, Kentucky, Louisiana, Massachusetts, Maryland, Maine, Minnesota, Nevada, Ohio, Oregon, Pennsylvania, South Carolina, South Dakota, Tennessee, Texas, Utah, Virginia, Vermont, Washington, Wisconsin

birth spacing decisions for these subgroups. I drop any second (third) births that occur less than 9 months after the first (second) birth. I also remove multiple births to ensure that I am comparing births of the same parity in my first, second, and third birth samples. I have 4,178,730 first time mothers, 3,418,884 second time mothers, and 1,864,605 third time mothers.

Table 1 shows summary statistics for my sample of counties. The sample counties have lower earnings and more unemployment than the whole U.S. The weighted mean earnings in the sample is $32,969, and the median is $28,265. In 2022, the sample median earnings was $38,087. The median for the whole U.S. in 2022 was $47,960 (U.S. Census Bureau, 2023). The unemployment rate for the whole U.S. in 2022 was 3.6 percent of the labour force (U.S. Bureau of Labor Statistics, 2023). In the sample counties, the weighted mean is 6.9 percent.

The sample is broadly representative of the wider U.S. population with regards to race and ethnicity. Across the whole U.S., in 2022, 75% of the population identified as White, 14% identified as Black, 6% identified as Asian, and 19% identified as Hispanic (U.S. Census Bureau, 2025a). The sample weighted mean share of Whites is 74%, for Black individuals the share is 11%, for Asians the share is 5% and for Hispanics, 21%.

The sample mean childcare price for full-time care at a childcare centre for 0 to 2 year olds in Table 1 is winsorised at the 99th percentile, as this is what is used in later analysis, and adjusted for inflation using base year 2010. The unadjusted mean childcare price in 2022 was $200, and the median $188. For 2010, these figures were $143 for the mean and $137 for the median.

Table 1. Descriptive statistics

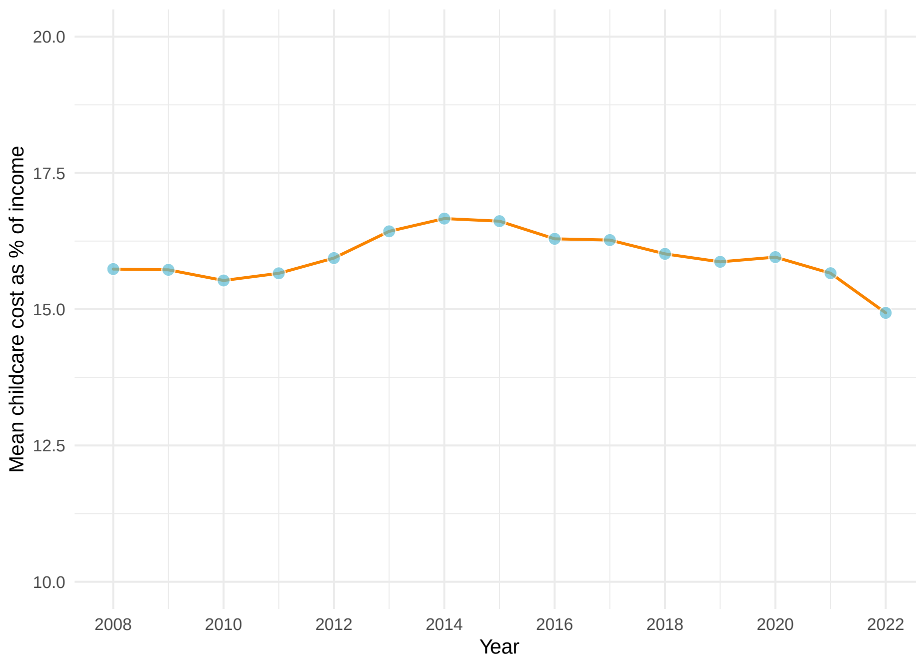
| | Mean | Weighted Mean | St. Dev. | Min | Max |
|---|---|---|---|---|---|
| Total Births per 1000 (20-44) | 69.76 | 65.49 | 18.02 | 1.93 | 177.30 |
| Maximum Group Size | 16.10 | 17.87 | 7.55 | 8.00 | 30.00 |
| Staff-to-Child Ratio | 0.20 | 0.20 | 0.03 | 0.14 | 0.33 |
| Childcare Price | 146.66 | 189.38 | 49.20 | 69.71 | 317.34 |
| Earnings | 29,544 | 32,969 | 6,414 | 4,725 | 69,937 |
| Median Household Income | 52,041 | 60,396 | 14,000 | 22,333 | 136,268 |
| Unemployment Rate | 6.57 | 6.88 | 2.83 | 0.10 | 22.70 |
| Male–Female Ratio | 1.07 | 1.02 | 0.17 | 0.76 | 3.12 |
| Male LFP (%) | 79.68 | 83.18 | 9.19 | 16.00 | 96.90 |
| Female LFP (%) | 70.74 | 72.44 | 6.89 | 39.90 | 94.10 |
| White (%) | 85.18 | 73.43 | 12.74 | 15.00 | 99.50 |
| Black (%) | 7.20 | 11.30 | 10.82 | 0.00 | 82.20 |
| Asian (%) | 1.53 | 5.15 | 2.60 | 0.00 | 35.90 |
| Hispanic (%) | 11.18 | 21.29 | 15.41 | 0.00 | 95.60 |

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, American Community Survey 5-year estimates, for 2010-2019, 2021-2022. "Total Births per 1000 (20-44)" is the county-level birthrate per 1000 women aged 20 to 44. "Maximum Group Size" is the maximum group size average for 0-2 year olds. "Staff-to-Child Ratio" is the average staff-to-child ratio for 0-2 year olds. "Childcare Price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, adjusted for inflation using base year 2010 and winsorised at the 99th percentile. "Earnings" is the median earnings for the population aged 16 and above. "Median Household Income" is the median household income. "Unemployment rate" is the unemployment rate of the population aged 16 and above. "Male-Female ratio" is the ratio of men to women aged 20 to 49 years old. "Female LFP (%)" is the labour force participation rate of the female population aged 20 to 64 years old. "Male LFP (%)" is the labour force participation rate of the male population aged 20 to 64 years old. "White (%)" is the percent of the population that identifies as White. "Black (%)" is the percent of the population that identifies as Black. "Asian (%)" is the percent of the population that identifies as Asian. "Hispanic (%)" is the percent of the population that identifies as Hispanic or Latino regardless of race. Weighted means weighted by population.

### 3.3 Descriptive patterns in the cost of childcare

I document several patterns in the cost of childcare in the U.S. between 2010 and 2022. First, although the price of childcare has risen over time, the estimated annual cost of childcare for 0 to 2 year olds as a share of median household income has not changed markedly since 2010 (see Figure 1).

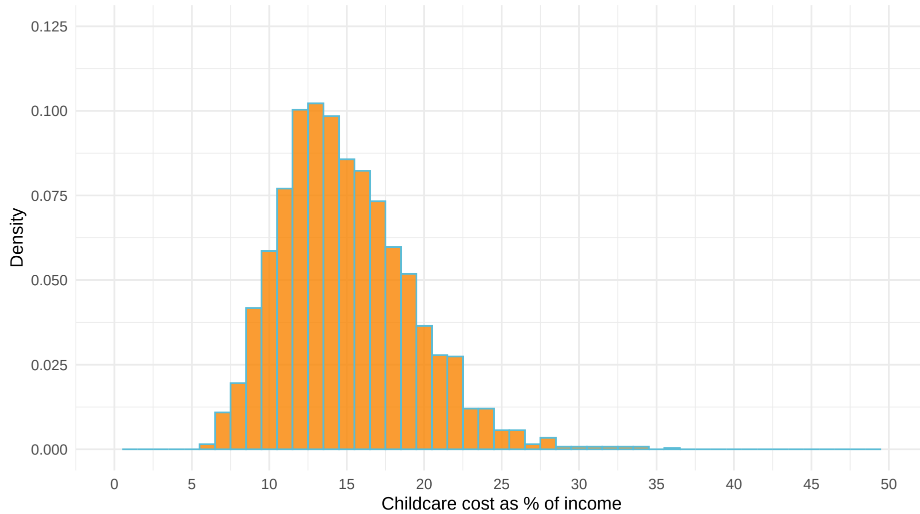
Figure 1. Avg. annual cost of full-time centre-based childcare for 0-2 years as a share of median household income over time




Notes: Data: National Database of Childcare Prices (including imputed data), American Community Survey, for 2010-2022. This plot shows a time series of the average annual cost for full-time care at a childcare centre for 0 to 2 year olds, as a percentage of median household income at the U.S. county level.

In most counties, the annual cost of childcare falls between 10 to 20% of median household income, but can reach up to 35% of median household income. Figure 2 plots the distribution of the annual cost of childcare as a share of household income for 2022 (See Appendix Figure D1 for the 2010 plot).

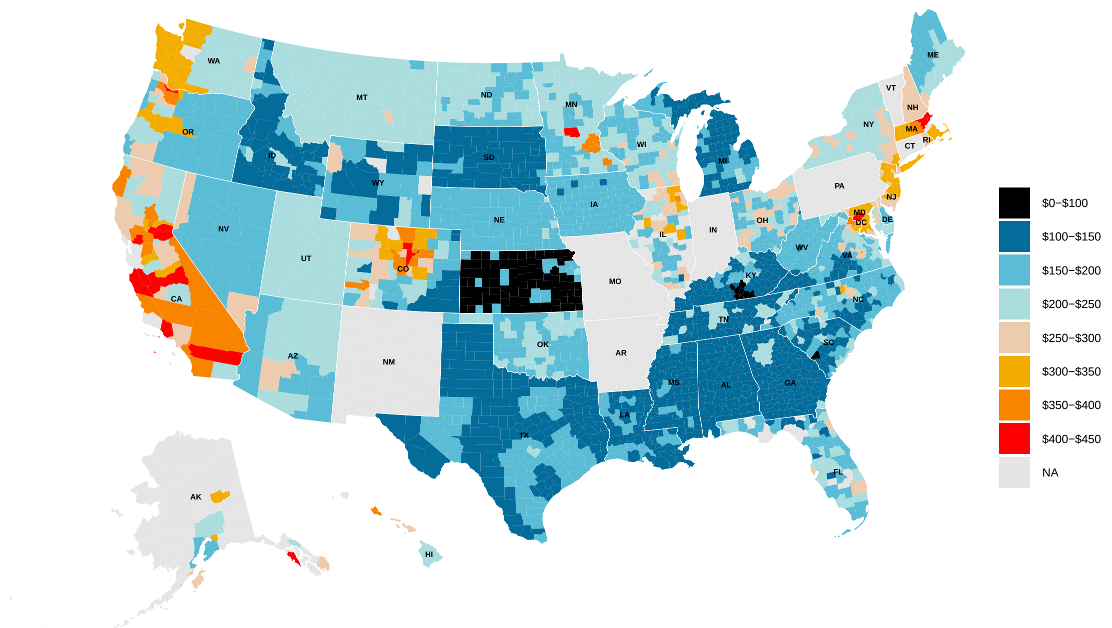
Figure 2. Distribution of avg. annual cost of full-time centre-based childcare for 0-2 years as a share of median household income, 2022




Notes: Data: National Database of Childcare Prices (including imputed data), American Community Survey, for 2022. The plots show the distribution of the average annual cost for full-time care at a childcare centre for 0 to 2 year olds, as a percentage of median household income at the U.S. county level.

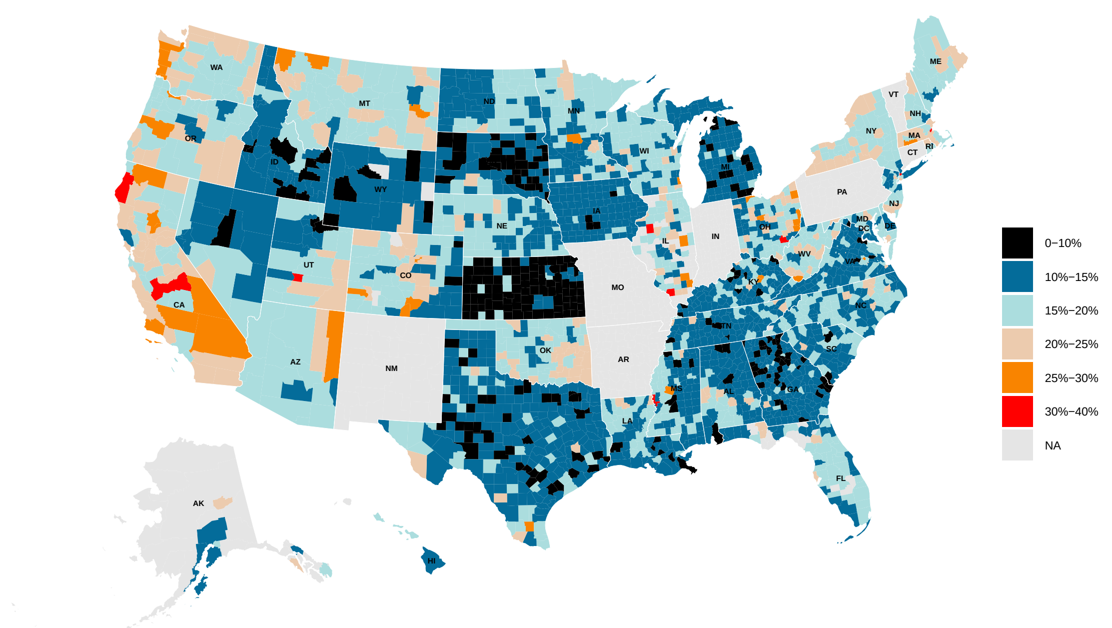
There is substantial geographical variation in the cost of childcare, with parents living on the West Coast and in the Northeast facing much higher prices. Figure 3 shows the geographical distribution of childcare prices for full-time centre-based care for children under 3 across the U.S. in 2022. We also observe this pattern in the geographical distribution of the annual cost of childcare as a share of median household income, but to a lesser extent. There are counties spread across the U.S. where this share is at 20% or higher. Figure 4 shows the annual cost of childcare as a percentage of median household income.

Figure 3. Avg. weekly price of full-time centre-based childcare for 0-2 years, 2022




Notes: Data: National Database of Childcare Prices (including imputed data), for 2022. This map shows the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, by U.S. county.

Figure 4. Avg. annual cost of full-time centre-based childcare for 0-2 years as a share of median household income, 2022




Notes: Data: National Database of Childcare Prices (including imputed data), American Community Survey, for 2022. This map shows the average annual cost for full-time care at a childcare centre for 0 to 2 year olds, as a percentage of median household income, by U.S. county.

## 4 Empirical strategy

I evaluate the causal effect of childcare prices on birth outcomes using a two-stage least squares (2SLS) approach. A naive Ordinary Least Squares (OLS) regression of birth outcomes on childcare prices could suffer from statistical endogeneity. One source of such endogeneity is simultaneity. Childcare prices are determined in equilibrium, thus price changes can reflect either a supply or demand response (or both). A lower birth rate would lead to reduced demand for childcare and could lead to lower prices, and/or a shock to the cost of childcare could increase prices and reduce the birth rate. Measurement error may also arise from imprecise measurement of childcare prices. As discussed in Section 3, the NDCP dataset is constructed from state surveys of childcare facilities. We can imagine that this is an imperfect process, with limitations on collecting fully accurate information. To overcome these issues, I instrument childcare prices with regulations placed on formal childcare facilities.

Regulations placed on childcare facilities affect the cost of providing childcare. Increasing health and safety requirements, setting stricter staff-child ratios and limiting the number of children allowed in a room can all raise the cost of running a childcare centre. In the main analysis, I instrument the price of childcare in a county with the state-mandated maximum number of children permitted in a room, the maximum group size, in a given year. To test the robustness of the results, I use both the state-mandated maximum group size and staff-child ratio as instruments. These regulations apply to all formal childcare centres and I use the average group size and staff-child ratio for children less than 3 years old. When the mandated maximum group size is reduced, the childcare facility has to decrease the number of children they can cater for, which can lead the childcare price to rise. When the staff-child ratio increases, fewer children per staff member are permitted, which can also lead the price to increase. This is the intuition behind the instruments.

My IV identification strategy rests on two assumptions: relevance and the exclusion restriction. I establish relevance and address the exclusion restriction in Section 5.

### 4.1 Specification

The empirical model for analysing effects on birth rates is described by the following equation:

$$ln(Birthrate)_{ct} = \zeta + \beta \cdot CostofChildcare_{ct} + \eta \cdot X_{ct} + \gamma_{1t} + \delta_{1c} + \epsilon_{ct} \tag{1}$$

$$CostofChildcare_{ct} = \alpha + \mu \cdot Z_{st} + \kappa \cdot X_{ct} + \gamma_{2t} + \delta_{2c} + \varepsilon_{ct} \tag{2}$$

The subscript $c$ denotes county and $t$ denotes year. $Z_{st}$ is the state-level maximum group size in place for childcare centres, or both the maximum group size and the staff-child ratio, averaged for 0 to 2 year olds. I control for time varying county-level characteristics $X_{ct}$, which includes median earnings, the unemployment rate, female labour force participation, the male-female ratio, the house price index, and the racial and ethnic composition (Black, White, Asian and Hispanic) of the county. I control for county fixed effects $\delta_c$ and year fixed effects $\gamma_t$ to account for time-invariant differences across counties and time trends. I cluster standard errors at the state-year level[7]. The coefficient of interest is $\beta$, which captures the local average treatment effect (LATE). The LATE is the causal effect of the cost of childcare on birthrates in counties where the regulations led to a change in prices for formal childcare, weighted by the change in prices.

The empirical model for analysing effects on individual mother $i$'s birth timing outcomes is given by:

$$Y_{ict} = \zeta + \cdot\beta CostofChildcare_{ct} + \eta \cdot X_{ict} + \gamma_{1t} + \delta_{1c} + \epsilon_{ct} \tag{3}$$

$$CostofChildcare_{ct} = \alpha + \mu \cdot Z_{st} + \kappa \cdot X_{ict} + \gamma_{2t} + \delta_{2c} + \varepsilon_{ict} \tag{4}$$

$Y_{ict}$ is either age at first birth (in years), time between the first and second birth (in months), or time between the second and third birth (in months). $Z_{st}$ is as before. I control for the same county-level characteristics as in Equations 1 and 2[8]. In addition, I control for the following additional individual-level characteristics: race and ethnicity (non-Hispanic White, non-Hispanic Black, Hispanic), marital status, and month of birth. Again, I include county ($\delta_c$) and year ($\gamma_t$) fixed effects and cluster standard errors at the state-year level. The coefficient of interest $\beta$ captures the local average treatment effect. Here, the LATE is the causal effect of the cost of childcare on birth timing outcomes amongst mothers living

[7] Appendix Table C9 shows that the results are robust to clustering at the state level, but doing so makes the number of clusters small given that I do not have all 50 states in my sample.

[8] In the individual-level analysis I do not control for racial and ethnic composition at the county level. Instead I control for these variables at the individual level.

in counties where the regulations led to a change in prices for formal childcare, weighted by the change in prices.

This approach exploits variation in the presence and strength of childcare facility regulations across time and states. In my data, I observe regulatory changes in three states: Delaware (2011), Nevada (2015), and Vermont (2016). For the main analysis with the maximum group size as the instrument, I exploit regulatory changes in Nevada and Vermont. For the robustness analysis with both instruments, I exploit changes in Nevada, Vermont, and Delaware. Across my study period there were four more states (Arizona, Virginia, Louisiana, Utah) that made changes to the mandated maximum group size or staff-child ratio for children under 3, but due to missing data in the NDCP (as described Section 3) I only observe price data before and after the regulatory changes in Delaware, Nevada, and Vermont. Although the missingness constrains the analysis, I am nonetheless able to exploit multiple policy changes across my sample period and provide new causal evidence on childcare prices and fertility.

# 5 Results

## 5.1 Effect of regulations on childcare prices

Table 2 shows that an increase in the maximum group size reduces childcare prices; an increase by one child reduces the weekly childcare price for 0 to 2 year olds by $1.05. This provides evidence of a strong first stage, supporting instrument relevance. I show both the raw childcare price (adjusted for inflation using base year 2010) and the log of the childcare price as outcome variables. The former is simpler to interpret as a first stage, but the latter is what is used in the IV analysis. Both specifications deliver a large F statistic. For the robustness analysis I use both instruments, which also has a large F statistic (See Appendix Table C1).

Table 2. First stage

| | Childcare Price | |
|---|---|---|
| | Price | Log(Price) ×100 |
| Maximum Group Size | -1.05*** | -0.64*** |
| | (0.23) | (0.13) |
| Mean (Childcare Price) | 146.66 | 146.66 |
| Mean (Maximum Group Size) | 16.10 | 16.10 |
| F-stat | 21.07 | 25.27 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NDCP childcare prices, hand-collected regulation data, for 2010-2019, 2021-2022. This table shows the first stage of childcare prices on the maximum group size. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, adjusted to 2010 dollars and winsorised at the 99th percentile. The Log(Price) is unadjusted. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. "F-stat" is the first-stage F statistic. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to women aged 20-44. Standard errors, clustered at the state-year level, in parentheses.

## 5.2 Effects of childcare prices and regulations on fertility

### 5.2.1 Birthrates

Table 3 shows the OLS, IV and reduced form estimates of the effects of childcare prices on birthrates, broken down by age bands. The top panel shows the OLS results, which we fear suffer from endogeneity and bias estimates towards zero due to reverse causality and measurement error, as discussed in Section 4. The OLS estimates confirm this fear: they are imprecise and close to null in absolute terms.

The second panel presents the IV results estimated using the maximum group size as the instrument. The IV estimates show a statistically significant reduction in birthrates. Column 1 shows the main outcome: the log birthrate for women aged 20 to 44. A 10% increase in the weekly price of childcare leads to a 5.7% decrease in the birthrate of women aged 20 to 44. Relative to the mean birthrate of 70 births per 1000 women, this amounts to 4 births per 1000. We see that this reduction in birthrates is more pronounced amongst women aged 30 and above in Columns 2 to 7; a 10% price increase has a 6 percentage point larger effect on birthrates for women aged 30 to 34 than birthrates for women aged 20 to 24. This difference increases with age. The results estimated using both instruments, shown in Appendix Table C5, are consistent in coefficient size and significance.

The IV estimates rest on the exclusion restriction, which I discuss in Section 5.3. In the third panel, the reduced form estimates show that changes in the maximum group size regulations on their own lead to statistically significant effects on birthrates. An increase in the maximum group size average for 0 to 2 year olds by 10 children, which could allow childcare centres to reduce prices, increases birthrates by 3.7%. These effects are concentrated amongst mothers aged 30 and above.

Table 3. Effects of childcare prices on birthrates, by age

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | 0.01 | 0.02 | 0.03 | 0.02 | 0.02 | -0.02 |
| | (0.02) | (0.04) | (0.03) | (0.02) | (0.02) | (0.03) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.89 |
| *IV* | | | | | | |
| Log(Childcare Price) | -0.57*** | -0.14 | -0.12 | -0.74*** | -0.88*** | -0.81*** |
| | (0.14) | (0.18) | (0.20) | (0.15) | (0.21) | (0.19) |
| $R^2$ | 0.95 | 0.98 | 0.97 | 0.92 | 0.93 | 0.88 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.37*** | 0.10 | 0.08 | 0.46*** | 0.54*** | 0.49*** |
| | (0.13) | (0.12) | (0.13) | (0.12) | (0.11) | (0.07) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.89 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the log of the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Birthrates and preferences for non-parental childcare differ across various groups within a population, due to a range of factors such as cultural norms, career expectations, and access to childcare. Table 4 shows the effects of childcare prices on birthrates for women aged 20 to 44 decomposed by race and ethnicity. Birthrates for White, Black and Hispanic women all reduce in response to increased childcare prices. The reduced form estimates suggest that increasing the maximum group size by 10 children increases the birthrate by 4.3% for White mothers, 3% for Black mothers, and 9% for Hispanic mothers.

Table 4. Effects of childcare prices on birthrates, by race and ethnicity

| | White, 20-44 | Black, 20-44 | Hispanic, 20-44 |
|---|---|---|---|
| *OLS* | | | |
| Log(Childcare Price) | -0.00 | 0.06 | 0.03 |
| | (0.03) | (0.05) | (0.03) |
| $R^2$ | 0.96 | 0.93 | 0.96 |
| *IV* | | | |
| Log(Childcare Price) | -0.78*** | -0.51** | -0.90*** |
| | (0.05) | (0.25) | (0.22) |
| $R^2$ | 0.92 | 0.92 | 0.92 |
| *Reduced Form* | | | |
| Maximum Group Size | 0.43*** | 0.30*** | 0.69*** |
| | (0.11) | (0.11) | (0.10) |
| $R^2$ | 0.96 | 0.93 | 0.96 |
| Mean | 66.75 | 58.75 | 81.32 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women, by race and ethnicity. Reduced form coefficients and standard errors multiplied by 100. "White, 20-44" is the log of the county-level birthrate per 1000 white women aged 20 to 44, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that race-age group. Standard errors, clustered at the state-year level, in parentheses.

### 5.2.2 Birth timing

Next, I explore whether birth timing responds to changes in childcare prices using the individual-level sample of births. Table 5 displays the OLS, IV, and reduced form results for mother's age at first birth and spacing between births. I caveat this analysis by noting that these estimates also reflect compositional change in the sample of mothers. Mothers who choose to not have a first, second, or third child in response to price increases may differ in unobservable characteristics to those who remain in the sample, and so these estimates should be viewed as descriptive and suggestive of behavioural responses.

I find that a rise in childcare prices is associated with mothers shifting their first birth into the future. The IV estimates reveal that a 10% increase in the weekly price of centre-based care is associated with age at first birth rising by 0.3 years, or roughly 4 months. I also find evidence of an increase in time between the first and second birth; a 10% increase in the weekly price of childcare increases the time between the first and second birth by 0.4 months. There is a negative statistically significant effect on time between the second and third birth, which is the opposite direction to the prediction that higher childcare prices may lead parents to delay births. This effect, however, could be explained by sample changes. It may reflect mothers who would otherwise have had longer birth intervals deciding not to have a third child. In addition, the mothers who do choose to have a third birth may be more likely to have shorter birth intervals and also live in high price areas.

The reduced form estimates also show a statistically significant effect of maximum group size regulations on age at first birth and spacing between the first and second birth. An increase in the maximum group size by 10 children is associated with a decrease in the age of first time mothers of 0.19 years (2.2 months), and a decrease in the first birth interval by 0.26 months. We see an effect in the opposite direction for the interval between the second and third birth; the discussion in the previous paragraph on sample compositional change applies here too.

Table 5. Effects of childcare prices on birth spacing outcomes

| | Age at 1st birth | | Birth spacing (1-2) | | Birth spacing (2-3) | |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | -0.16 | -0.14 | -0.02 | -0.08 | 0.38 | 0.34 |
| | (0.11) | (0.10) | (0.19) | (0.14) | (0.50) | (0.52) |
| $R^2$ | 0.12 | 0.22 | 0.03 | 0.04 | 0.02 | 0.02 |
| *IV* | | | | | | |
| Log(Childcare Price) | 1.72** | 3.34*** | 6.20*** | 4.43*** | -7.29** | -8.46*** |
| | (0.77) | (0.52) | (0.33) | (0.54) | (2.88) | (2.87) |
| $R^2$ | 0.12 | 0.22 | 0.03 | 0.04 | 0.02 | 0.02 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | -0.95** | -1.85*** | -3.60*** | -2.57*** | 4.48** | 5.19*** |
| | (0.47) | (0.44) | (0.58) | (0.87) | (1.82) | (1.62) |
| $R^2$ | 0.12 | 0.22 | 0.03 | 0.04 | 0.02 | 0.02 |
| Mean | 27.60 | 27.60 | 50.52 | 50.52 | 52.71 | 52.71 |
| Controls | Cty | Cty+Ind | Cty | Cty+Ind | Cty | Cty+Ind |
| N | 4,178,730 | 4,178,730 | 3,418,884 | 3,418,884 | 1,864,605 | 1,864,605 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: Data: NVSS birth records, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on birth spacing outcomes. Reduced form coefficients and standard errors multiplied by 100. "Age at 1st birth" is the age at which the mother has their first child in years. "Birth spacing (1-2)" is the number of months between the first and second birth. "Birth spacing (2-3)" is the number of months between the second and third birth. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. "Cty" controls include county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, the mother's race and ethnicity, and county and year fixed effects. "Cty&Ind" controls also include the mother's date of birth and marital status. Standard errors, clustered at the state-year level, in parentheses.

### 5.3 Threats to identification

#### 5.3.1 Exclusion restriction

One may question whether the changes in the regulations on childcare centres also affect prices of family childcare and informal care. Rising prices of centre-based care may lead parents to substitute to other forms of care, with subsequent effects on prices. In this paper, I view the price of centre-based childcare as a proxy for the price of childcare more broadly. The NDCP data indicate that childcare centre prices are representative of the formal care market. In Appendix Figure D2 I show that centre and family-based care prices in the NDCP are highly and statistically significantly correlated. Yet a limitation of these data is that I cannot see prices of informal care, and another publicly available dataset of informal childcare prices does not exist. This data constraint limits my ability to directly test the informal care channel. That said, I can assess this channel indirectly. If there were spillover effects onto the informal and family care markets, we would still expect to observe effects on birth rates amongst groups that rely less on centre-based childcare. However, in Subsection 5.2.1, I show evidence of no statistically significant effects on younger mothers, and I show that these mothers consume less centre-based care in Section 7. These data are consistent with the identifying assumption that the childcare facility regulations affect birthrates chiefly through the formal care channel, rather than shifts in the informal care market.

One may worry that childcare regulations may impact not only the price of childcare, but also the viability of childcare businesses. A reduction in the number of providers could, in turn, influence fertility decisions. For example, whether the closure of a local provider leads families to reconsider having a child. In Appendix Table C2, I present evidence that mitigates this concern; my estimates are robust to controlling for the share of childcare establishments per child aged 0 to 5.

In addition, childcare regulations not only affect the price of childcare, but also the quality. If potential parents care sufficiently about childcare quality, their fertility choices may respond to changes in quality. If such a channel exists, my estimates of the effect of the price of childcare on birthrates may be biased. One approach to mitigate this concern is to control for a measure of childcare quality. However, obtaining data on childcare quality is not trivial as there is a dearth of publicly available, nationally representative data on childcare quality[9].

[9] A system of childcare quality rating does exist in the U.S. - the Quality Rating and Improvement System (QRIS). However, QRIS systems are designed and monitored at the state level, so vary across states, and

I can, however, control for a proxy of childcare quality - staff turnover. Research in the early-childhood literature indicates that staff turnover in the childcare centre can create instability in the care environment, disrupting relationships (Howes and Hamilton, 1992; Doromal et al., 2022). Stable relationships are important for child development (Lally and Mangione, 2017). In addition, directors' attention may get directed away from the children towards hiring, and until open jobs are filled, remaining staff may need to adjust their activities, take on more children, or work overtime (Whitebook and Sakai, 2004). Each of these factors could lead to reduced quality in the provision of care. In Appendix Table C3 I control for the staff turnover rate in the childcare sector; the estimates are robust to this inclusion.

Nonetheless, I proceed to quantify the effect of the quality channel. To do so, I conduct a bounding exercise in Appendix A to explore how such a quality channel affects the size and direction of my estimates. To quantify the potential bias, I secure data for a subset of sample years on a measure of childcare quality - childcare programme accreditation - from the National Association for the Education of Young Children (NAEYC) (National Association for the Education of Young Children, 2025). As the NAEYC was unable to share data prior to 2017, I cannot use these data as a control variable in robustness analysis. First, I show that my IV estimates represent a lower-bound of the effect of childcare prices on birthrates. Next, using the NAEYC data, I estimate the magnitude of the true $\beta$ under the assumption that quality of childcare directly impacts birthrates. I describe the NAEYC data and set out the bounding analysis in Appendix A.

### 5.3.2 Additional assumptions

The instrument must also address conditional independence. Conditional on covariates and fixed effects, the childcare regulations must be as good as randomly assigned with respect to fertility outcomes. Including county fixed effects absorbs time-invariant local factors (e.g. cultural norms), whilst year fixed effects account for national level shocks or trends. To further strengthen the credibility of conditional independence, I include a rich set of time-varying control variables that could affect family formation. I control for county-year changes in socioeconomic factors such as earnings and the unemployment rate, racial and ethnic composition, and house prices. These controls help address potential confounding from within-county trends that may be correlated with the regulations and birthrates.

not all states have a QRIS system. Furthermore, states do not publish their historical QRIS data.

Moreover, given declining rates of fertility in the U.S., one might be concerned that states may relax these regulations to encourage fertility. However, reporting and discussion of the regulations highlights the key goal of these regulations: to protect child health and safety and encourage learning (See Appendix Figure D3). Mandated group size and staff-child ratio requirements support child safety. They ensure staff can adequately supervise and care for the children they are responsible for, reducing the risk of injuries or accidents. The requirements also support child development. Sufficient room space limits overcrowding and promotes increased staff-child and safe peer interactions, which can enhance learning and development. Additionally, two of the three regulatory changes that I observe increase the stringency of the mandates on childcare providers (e.g. introducing a maximum group size requirement).

In the presence of heterogeneous treatment effects, to interpret the instrumental variables (IV) estimates as the LATE, we also require the monotonicity assumption. In this setting, the monotonicity assumption demands that a decrease in the maximum group size weakly increases or weakly decreases childcare prices for all counties. Given that a decrease in the maximum group size will reduce profits for childcare providers, I expect such a change to increase childcare prices for all. It seems implausible that the regulations would have the opposite effect. Nonetheless, to assess this assumption, I conduct one-sided Kolmogorov-Smirnov tests comparing childcare price distributions in treated and untreated county-years. The null hypothesis is that the prices for treated county-years come from the same distribution as prices for untreated county-years. The alternative hypothesis is that the price distribution of treated county-years stochastically dominates that of untreated county-years. The null hypothesis is rejected with $p < 0.001$. A second Kolmogorov-Smirnov test reversing the direction of the alternative fails to reject the null. Together, these results give additional reassurance that the monotonicity assumption is reasonable.

The Stable Unit Treatment Value Assumption (SUTVA) states that the potential outcome for one unit must be unaffected by the assignment of treatment to the other units. In my setting, this implies that birthrates in a given county are unaffected by changes in maximum group size or child–staff ratio regulations in other counties. Where we may have concerns about this assumption is at state borders. If childcare regulations shift the price of childcare within a state, families in counties bordering a state with lower childcare prices may choose to send their children to childcare providers across the state border. Such cross-border substitution would violate SUTVA. To address this concern, I drop bordering counties from my sample. As shown in Appendix Table C4, the magnitude and significance of the estimates remain unchanged.

Given that I have a small number of "treated" states - states which experience changes in the regulations in my sample - one may worry that there is effect heterogeneity and that the LATE does not closely approximate the Average Treatment Effect. The LATE that I estimate is the weighted causal effect on women in counties in the treated states. In Section 5.4, I show that the results are not sensitive to dropping states one at a time, which provides some assurance that effect size heterogeneity is not a substantial issue. One may also question whether the treated and control states were on different paths. In Appendix Figures D4, D5, and D6, I plot the event study estimates of the effect of the introduction of childcare facility regulations and birthrates for women aged 30 to 34 (a group driving the results) for each of the three treated states[10]. For Nevada and Delaware, the regulations introduced were more stringent on childcare centres, and in these two states we see no evidence of pre-trends and evidence of reductions in birthrates. In Vermont, the state relaxed the group size requirement for 18 month olds, so we may expect to see increases in birthrates. The estimates are noisy, but point in this direction. Overall, these event studies provide some reassurance that counties in control states in combination with covariates are providing a suitable control for counties in treated states.

### 5.4 Robustness

I explore the sensitivity of my findings to various specifications and approaches. Overall, the estimates and quantitative conclusions remain stable. First, the IV and reduced form results are robust in effect size and significance to the inclusion of both instruments, rather than just the maximum group size instrument (see Appendix Table C5). The estimates are also robust to weighting by population rather than number of births (See Appendix Table C6). Next, in Appendix Table C7, I repeat the IV analysis of the effects of childcare prices on birthrates for women aged 20 to 44 on subsamples of states, dropping one state at a time. This exercise demonstrates that the results are not driven by any one state; they are consistent and statistically significant across all subsamples. My main analytical approach winsorises childcare prices at the 99% level as there are notable outliers, as shown in Appendix Figure D7. Appendix Table C8 illustrates that my main results are robust to different levels of

[10]Note that this is not exactly the same approach as the reduced form analysis I present in Section 5, where I use the continuous variables of the maximum group size (e.g. 15) and staff-child ratio (e.g. 0.25) rather than a binary indicator for presence of a policy.

winsorising of childcare prices, and not winsorising at all. The IV estimates are slightly larger when I don't winsorise prices, but once the influence of the outliers is reduced, there is little difference in coefficient values from winsorising at the 95th, 98th, or 99th percentile. My primary approach is to cluster standard errors at the state-year level, given concerns for the bias that can result from having too few clusters (clustering at the state level delivers 30 clusters). Appendix Table C9 shows that the results withstand a more stringent approach to clustering. The estimates remain significant at the 1 percent level if I cluster standard errors at the state level. I also test the sensitivity of my estimates to alternative ways of handling states without maximum group size regulations. Some states have no maximum group size restrictions in place, including states which experience changes in the regulations across the study period. In order to retain county observations in these states in my analytical sample, I set these missing values to 30 in my baseline specification. This number seems reasonable given that the maximum value in my data is 22. Appendix Table C10 demonstrates that the estimates are not sensitive to setting these missing values to alternative numbers. Finally, the estimates are robust to excluding control variables that may themselves be outcomes. In Table C11, I replace the unemployment rate and median earnings with their male-specific counterparts and remove female labour force participation as a covariate.

# 6 A model of fertility choices

In this section, I use a theoretical model of household decision making to outline mechanisms behind the age gradient in price elasticities. The model is built on work by Doepke et al. (2023); I allow for part-time childcare and build in human capital accumulation with two periods to consider age heterogeneity. Most detail can be found in Appendix B; here I set up the model and outline the key model predictions.

## 6.1 Setup

I model the household from the perspective of an individual who gives birth, who has a working partner, and whom I assume represents the views of the household. Henceforth, I will assume that this individual is a woman to align with the birth records analysis. In this model, the woman derives utility from consumption and having children, and either a benefit or disutility from caring for her child(ren) at home. There are two periods, $t \in \{1, 2\}$. In each period, a woman decides whether she will have a child. She can have at most one child each period: $n \in \{0, 1\}$. The preferences of the women are described by the following utility function:

$$u = c_1 + c_2 + (2n_1 + n_2)v - \mu((1 - s_1)^\gamma n_1 + (1 - s_2)^\gamma n_2)$$

Each period lasts for several years, such that childcare is only required for the child born in that period. This setup allows us to consider fertility responses of younger and older mothers. I assume no time discounting.

The mother's budget constraints for periods one and two are given by:

$$c_1 + ps_1n_1 \leq w\,(1 - (1 - s_1)n_1)$$

$$c_2 + ps_2n_2 \leq w(1 + \alpha h_1)\,(1 - (1 - s_2)n_2)$$

Each mother is endowed with one unit of time, which can be allocated between employment and childcare ($s$). The mother can choose to care for the child at home, or purchase childcare in the private market at price $p$ per unit of time. She selects the desired share of private childcare, $s$, in each period. If the woman works, she earns a wage $w$ in $t = 1$. Working in the first period allows the woman to build human capital $h_1$, which delivers a wage increase in the second period - her period $t = 2$ wage is $w(1 + \alpha h_1)$. The parameter $\alpha$ captures productivity.

Women can experience either a positive benefit or some disutility from caring for their child at home. I initially present the utility function with a disutility from self-care, but in subsection B.4 I model a positive benefit of self-care and my key model predictions are unchanged. The disutility term puts a greater penalty on longer periods of self-childcare at home ($\gamma > 1$). This term reflects a preference for working rather than home-making (Gallup, 2019). Note that this does not mean that the woman does not enjoy any child-rearing, only that she has a preference for spending her weekdays working, rather than caring for her child at home.

In this simple model, I assume that the woman takes her partner's labour supply as fixed, and her partner is able to support the household if the woman decides not to outsource any childcare. I abstract from savings.

### 6.2 Model predictions

At first glance, it is unclear whether younger or older women would be more sensitive to changes in the price of childcare. One on hand, younger women are more likely to earn less than their older counterparts, which could make them disproportionately affected by price hikes. Yet there are mechanisms that could drive greater price responsiveness amongst older women. For example, older mothers may be on their second or third birth and higher parity births may be more price reactive. Additionally, the higher wages and developed careers of older women raise the opportunity cost of having a child. My model explores these mechanisms for older women and delivers the following propositions:

**Proposition 1.** *Women who earn higher wages will outsource more, if not all, childcare and remain in the labour market.*

Higher wages increase the opportunity cost of time, raising the incentive to outsource more childcare. In comparison, women with lower wages will provide more self-childcare at home and decrease their labour supply. In this way, women with lower wages will be less exposed to childcare prices and in turn less reactive to price changes. Formally, the first order condition for the optimal private childcare share $s^*$ yields

$$\frac{\partial s^*}{\partial w} > 0,$$

so that as $w$ increases, $s^*$ rises and exposure to childcare prices grows. This result can be found in Appendix B.

**Proposition 2.** *An increase in the childcare price reduces the probability of (older) mothers having a birth in the second period.*

Amongst mothers with one child, price increases decrease the probability of a second-period birth and raise the probability of a first period birth. As work experience builds human capital, second-period wages are higher. This leads older mothers to purchase a larger share of private childcare than mothers who give birth earlier. Thus price increases will hurt older mothers with greater reliance on paid childcare more than their younger counterparts. Formally,

$$\frac{dP_{01|1}}{dp} < 0$$

This result is derived in Appendix B.

**Proposition 3.** *Second births are more price sensitive than first births, as total childcare spending rises with additional children.*

A mother with two children is exposed to paid childcare in both periods, so total spending increases (if a mother outsources some share of private childcare in the first period, she will also outsource in the second period). This effect is amplified by the fact that due to the wage uplift in period two, private childcare is more attractive in the second period. Formally, the difference in the elasticities between having two children and having one child is

$$\eta_{11,p} - \eta_{10,p} = -\, p\, s_2^* < 0$$

which shows that the marginal impact of a price increase is larger for higher parity births. The proof can be found in Appendix B.

# 7 Mechanisms

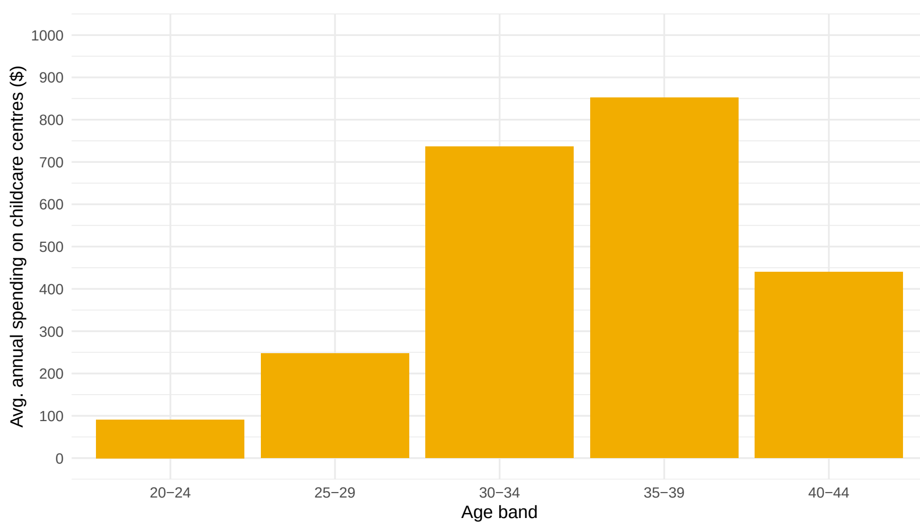
Next, I test my key model predictions for why older women are more childcare price responsive than younger women. I provide evidence that higher-income women are more price responsive, and that within income groups this responsiveness increases with age. I also find that older women allocate more spending to formal childcare, and that higher parity births exhibit greater responsiveness to childcare costs. Together, these mechanisms help to explain the age gradient in price sensitivity.

## 7.1 Older parents spend more on childcare

My model predicts that older women with higher incomes will outsource more childcare. This could explain the age gradient in my analysis of birthrates to some degree, if the price responsiveness of older mothers is driven by the fact that they are more likely to use formal care in the first place. Younger mothers may rely more on informal care, perhaps by parents or relatives, or may be more likely to drop out of the labour market to care for the child themselves. Indeed, I do not see much of a birthrate response to childcare price increases for younger women.

I explore whether older mothers tend to use more formal childcare by examining spending on childcare centres by age using spending data from the Consumer Expenditure Survey. Figure 5 shows the average annual spending on childcare centres in 2022 by age, and Appendix Figure D8 shows the same plot for 2010. We observe a noticeable pattern by age; spending on childcare centres remains low for parents in their early to mid twenties, rises sharply for those in their thirties, before falling for those in their forties. This age trend is seen in both 2010 and 2022, but there is a more pronounced increase in spending for parents in their thirties in the latter period.

Figure 5. Avg. annual spending on childcare centres for 2022, by age




Note: Data: Consumer Expenditure Survey, for 2022. This figure shows the average annual spending on childcare centres by age of the respondent, for respondents with any children under 3, adjusted for inflation using base year 2010. Childcare centres defined as day care centres, nurseries, and preschools.

### 7.2 Higher educated women (a proxy for income) are more price sensitive

A second prediction is that older women with higher incomes, through outsourcing more childcare, will be more price sensitive. The birth records data does not contain mother's income, but I observe education, which I explore as a proxy for income[11]. Indeed, I find that women with an undergraduate/Bachelor's degree are more responsive to childcare price changes than women without a Bachelor's degree[12]. Furthermore, within education, the coefficient sizes increase with age, further supporting the conclusions from my model. We also observe these patterns in the reduced form.

[11]Note that due to exclusion of the education variable for many states prior to 2014 by NVSS, I run this heterogeneity analysis on a subsample of years with low rates of missingness.

[12]Note that the 5-year ACS only provides population counts by age and education for women aged 18 to 24, and then by 10 year age bands, hence why the age bands in Table 6 differ from other analysis in this paper.

Table 6. Effects of childcare prices on birthrates, by education

| | BA | | | No BA | | |
|---|---|---|---|---|---|---|
| | 18-44 | 25-34 | 35-44 | 18-44 | 25-34 | 35-44 |
| *OLS* | | | | | | |
| Log (Childcare Price) | -0.00 | -0.00 | -0.01 | -0.00 | 0.02 | -0.04 |
| | (0.04) | (0.05) | (0.03) | (0.04) | (0.04) | (0.05) |
| $R^2$ | 0.96 | 0.96 | 0.93 | 0.98 | 0.96 | 0.93 |
| *IV* | | | | | | |
| Log (Childcare Price) | -2.00*** | -2.10** | -3.62 | -1.29** | -1.37*** | -2.95 |
| | (0.53) | (0.64) | (2.41) | (0.52) | (0.31) | (1.70) |
| $R^2$ | 0.83 | 0.86 | 0.59 | 0.91 | 0.86 | 0.62 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.37*** | 0.45** | 0.42*** | 0.32** | 0.33* | 0.53*** |
| | (0.10) | (0.14) | (0.08) | (0.13) | (0.16) | (0.15) |
| $R^2$ | 0.96 | 0.96 | 0.93 | 0.98 | 0.96 | 0.93 |
| Mean | 71.83 | 127.60 | 32.10 | 63.93 | 99.48 | 19.63 |

* p < 0.10, ** p < 0.05, *** p < 0.01.

Notes: N = 4,823. Data: NVSS birth records, ACS population by education counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women, by education. Reduced form coefficients and standard errors multiplied by 100. "18-44" is the log of the county-level birthrate per 1000 women aged 18 to 44, "25-34" the log of the birthrate per 1000 women aged 25-34, and so on. "BA" is women with a Bachelor's degree. "No BA" is women with less than a Bachelor's degree. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age and education band. Standard errors, clustered at the state-year level, in parentheses.

### 7.3 Higher order birthrates are more price sensitive

A third prediction is that mothers with more children are more price sensitive, because total childcare spending rises. Older mothers are more likely to be having their second or third child than younger mothers. I test this mechanism through analysis of birthrates by parity.

Table 7 present the OLS, IV and reduced form estimates for the effect of childcare prices on birthrates for the first birth, by age bands. Tables 8 and 9 show the same estimates for the second and third birthrates, respectively. We see that for the same increase in childcare prices, second and third birthrates fall by more than first birthrates. Furthermore, the lack of an age gradient in the second and third birthrate results indicates that parity is an important factor underlying the age gradient in total birthrates. The estimates for the second and third birthrates are less precise and thus interpreted as suggestive, but are statistically significant at the 10% level when the price variable is in levels rather than logs (see Appendix Tables C12 and C13). For a 10% increase in the weekly price of childcare, there is a fall in first birthrates for women aged 20 to 44 by 2.4%. This is a decline in 0.5 births per 1000 relative to the mean of 22.7. For second birthrates, this figure is 27.7% (5 births per 1000) and for third birthrates, 24.5% (3 births per 1000). We see a similar pattern in the reduced form results.

Table 7. Effects of childcare prices on first birthrates, by age

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | -0.00 | 0.00 | -0.00 | -0.00 | -0.04 | -0.05 |
| | (0.03) | (0.03) | (0.04) | (0.04) | (0.04) | (0.05) |
| $R^2$ | 0.94 | 0.95 | 0.90 | 0.93 | 0.91 | 0.86 |
| *IV* | | | | | | |
| Log(Childcare Price) | -0.24*** | 0.01 | 0.28 | -0.44*** | -0.82*** | 0.85*** |
| | (0.07) | (0.17) | (0.20) | (0.09) | (0.20) | (0.11) |
| $R^2$ | 0.94 | 0.95 | 0.90 | 0.93 | 0.90 | 0.84 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.16*** | -0.01 | -0.18 | 0.27*** | 0.50*** | -0.51*** |
| | (0.06) | (0.11) | (0.12) | (0.09) | (0.11) | (0.05) |
| $R^2$ | 0.94 | 0.95 | 0.90 | 0.93 | 0.91 | 0.86 |
| Mean | 22.66 | 48.14 | 39.64 | 19.92 | 6.40 | 1.16 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of first birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. “20-44” is the log of the county-level first birthrate per 1000 women aged 20 to 44, “20-24” the log of the first birthrate per 1000 women aged 20-24, and so on. “Childcare price” is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. “Maximum Group Size” is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by total births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Table 8. Effects of childcare prices on second birthrates, by age

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | -0.28 | -0.34 | -0.29 | -0.23 | -0.23 | -0.15 |
| | (0.32) | (0.32) | (0.35) | (0.35) | (0.31) | (0.17) |
| $R^2$ | 0.55 | 0.70 | 0.60 | 0.58 | 0.71 | 0.78 |
| *IV* | | | | | | |
| Log(Childcare Price) | -2.77 | -3.44* | -2.95 | -2.25 | -2.32 | -1.58** |
| | (1.70) | (2.08) | (2.09) | (1.93) | (1.42) | (0.63) |
| $R^2$ | 0.45 | 0.62 | 0.52 | 0.53 | 0.66 | 0.74 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 1.78 | 2.28 | 1.92 | 1.40 | 1.42 | 0.95** |
| | (1.19) | (1.45) | (1.45) | (1.29) | (0.97) | (0.47) |
| $R^2$ | 0.55 | 0.70 | 0.60 | 0.58 | 0.71 | 0.78 |
| Mean | 20.64 | 29.82 | 38.36 | 26.39 | 9.15 | 1.43 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of second birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level second birthrate per 1000 women aged 20 to 44, "20-24" the log of the second birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by total births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Table 9. Effects of childcare prices on third birthrates, by age

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | -0.24 | -0.23 | -0.23 | -0.25 | -0.18 | -0.17 |
| | (0.27) | (0.25) | (0.31) | (0.32) | (0.27) | (0.15) |
| $R^2$ | 0.64 | 0.77 | 0.68 | 0.61 | 0.63 | 0.66 |
| *IV* | | | | | | |
| Log(Childcare Price) | -2.45* | -1.58 | -2.93 | -2.83* | -2.04 | -1.42** |
| | (1.42) | (1.63) | (1.79) | (1.68) | (1.27) | (0.62) |
| $R^2$ | 0.56 | 0.75 | 0.60 | 0.51 | 0.56 | 0.61 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 1.57 | 1.05 | 1.91 | 1.77 | 1.25 | 0.86** |
| | (1.00) | (1.11) | (1.25) | (1.16) | (0.86) | (0.39) |
| $R^2$ | 0.64 | 0.77 | 0.68 | 0.61 | 0.63 | 0.66 |
| Mean | 12.09 | 10.68 | 22.27 | 19.20 | 8.01 | 1.34 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of third birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level third birthrate per 1000 women aged 20 to 44, "20-24" the log of the third birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by total births to that age band. Standard errors, clustered at the state-year level, in parentheses.

# 8 Effect of childcare regulations on the childcare market

The first stage of my 2SLS analysis tells us how the childcare regulations impact the price of childcare. Yet the regulations may impact other aspects of the childcare market that are of interest too. For example, employment of staff, staff wages, and the number of childcare facilities. Therefore I conduct additional analysis of the causal effects of changes in childcare facility regulations on employment and establishments in the U.S. childcare industry using a reduced form approach.

### 8.1 Empirical strategy

To do so, I use a Difference-in-Differences (DiD) strategy, exploiting variation in regulatory changes across time and states. I use the Callaway and Sant'Anna (2021) stacked DiD estimator to address concerns about contamination from already-treated units and effect heterogeneity across states and time.

I evaluate the effect of a change in the maximum group size or staff-child ratio in Delaware, Vermont, Nevada, Louisiana, Utah, Virginia, Arizona, Idaho, and South Carolina between 2008 and 2022[13]. In my sample, the change is either an increase/decrease in the staff-child ratio, an increase/decrease in the maximum group size, or an introduction of a maximum group size. Given that these changes move in two different directions, I split them into either a change that is more strict (e.g. higher staff-child ratio), or a change that is less strict (e.g. increasing the maximum group size)[14]. Note that this approach differs from the instrument used in my 2SLS analysis, where I use the continuous value of the maximum group size and staff-child ratio as doing so allows me to exploit additional variation in the size of the regulatory change. The continuous treatment stacked DiD literature is still nascent, so to evaluate the effects of the regulations on childcare employment and market size, I rely on using a binary treatment variable.

#### 8.1.1 Specification

The empirical model for the DiD approach is as follows:

$$Y_{ct} = \alpha + \beta \cdot D_{st} + \kappa \cdot X_{ct} + \gamma_t + \delta_s + \epsilon_{st} \tag{5}$$

where outcome $Y$ is county $c$ in year $t$ is regressed on the binary treatment variable $D_{st}$, covariates $X_{ct}$, and state ($\delta_s$) and year ($\gamma_t$) fixed effects. Outcomes $Y_{ct}$ include: the log number of childcare establishments (by number of employees), log employment (the count of beginning of quarter employment), log earnings (average monthly earnings for beginning-of-quarter employment), log new hires (the count of new hires), the hiring rate (the end-

[13] The IV analysis limits my sample of states with regulatory changes due to missingness in the childcare price data, but in this reduced form analysis I am able to take advantage of additional regulatory changes across my study period.

[14] The states that experience more strict changes are: DE, LA, NV, VA, ID, and SC. The states that experience less strict changes are: VT, UT, and AZ.

of-quarter hiring rate), log separations (the count of separations), the separation rate (the beginning-of-quarter separation rate), and staff turnover (stable turnover). $D_{st}$ equals 1 the years of and following a change in the maximum group size or staff-child ratio in state $s$. The coefficient $\beta$ captures the causal effect of a change in the maximum group size or staff-child ratio on childcare market outcomes $Y_{ct}$. I control for covariates $X_{ct}$: county median earnings, the unemployment rate, and racial and ethnic composition.

To examine the effects of the regulatory changes over time, and assess the presence of any pre-trends, I estimate event studies as well. The two-way fixed effects event study model is given by:

$$Y_{ct} = \alpha + \sum_{k=-5,k\neq 1}^{k=5} \beta_k \cdot D_{sk} + \kappa \cdot X_{ct} + \gamma_t + \delta_s + \epsilon_{st} \tag{6}$$

I estimate the $\beta$s in these two equations using the Callaway and Sant'Anna (2021) estimator, which estimates disaggregated state-time average treatment effects for each time period. I use the doubly robust estimation method. I then aggregate these state-time effects into an event study plot that depicts the average effects across different lengths of exposure to a childcare facility regulation change. I set the reference year as $t = -1$, weight estimates by the population of children under 5 years olds, and cluster standard errors at the state-year level (as above). I set the control group to be "never-treated" mothers.

I estimate these models for two treatment groups: a) states that experience a change in the staff-child ratio or maximum group size that is *less strict*, and b) states that experience a change that is *more strict*.

### 8.1.2 Identification

The critical assumption required for DiD estimation is parallel trends: the treatment and control states must have parallel trends in outcomes absent treatment. We cannot observe these counterfactual outcomes, but we can assess pre-treatment trends in outcomes using event study plots. If we see that the DiD coefficients in the pre-treatment periods are not statistically different from zero, then we cannot reject the hypothesis that changes in the childcare regulations have no effect on childcare market outcomes.

I am evaluating the effects of *changes* in the regulations on childcare market outcomes, so the control states are states that did not observe a regulatory change between 2008 and

2022. I argue that these are valid control states because all of the states in my sample had some form of childcare regulation in place across my time period (all states in my sample had a minimum staff-child ratio in place in 2008, and only three control states did not have a maximum group size in 2008.)

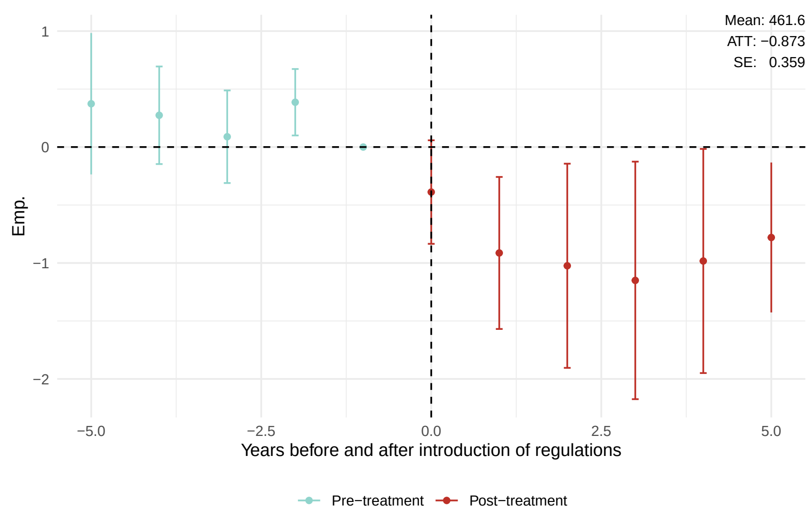
### 8.2 Results

I have shown that changes in childcare centre regulations impact the price of childcare. One might also ask whether the regulations impact other aspects of the childcare market. In this section I explore how changes in the maximum group size and minimum staff-child ratio affect the childcare labour market and market size.

I find that the childcare market is responsive to loosening childcare regulations. Reducing the stringency of the maximum group size and/or staff-child ratio leads to a reduction in employment, new hires, and job separations in the childcare sector (see Figures 6, 7, 8). Loosening of the staff-child ratio can allow childcare providers to operate with fewer staff for a given number of children, which could explain the reduction in employment and new hires. Separations may fall if the remaining staff are more stable hires. I also find evidence of increased earnings, as shown in Figure 9. This finding could be driven by remaining staff being more experienced or of higher quality. The aggregated effects across the post-treatment period are shown in Table 10. There is a decrease in employment by 58%, in new hires by 52%, and in separations by 58%. These effect sizes are large, and appear particularly so relative to the mean. However, there is a large mass of counties with less than 25 employees (See Appendix Figure D9). In these counties, small changes in absolute terms will lead to large changes in percentage terms, which could be driving the results. I find a small increase in earnings of 7%. I do not find statistically significant effects on the separation rate, hiring rate, or on staff turnover (see Appendix Figures D10, D11, and D12 for the event studies). I do not find evidence that loosening childcare regulations impacts the size of the childcare market; there are no statistically significant effects on the number of childcare establishments (see Table 11 and Appendix Figures D13 to D17).

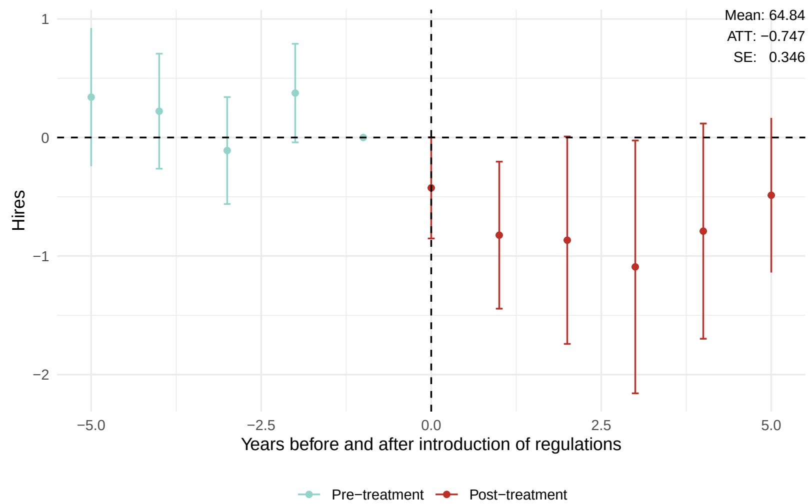
I find that across the states in my sample, increasing the stringency of the maximum group size and/or staff-child ratio requirements has no statistically significant effect on employment outcomes in the childcare market, nor on the number of childcare establishments. These results can be found in Tables 10 and 11, and Appendix Figures D18 to D29. The event study estimates are quite noisy, though, suggesting that there is variation in the post-change outcomes across states. There are 3 states in the "less stringent" treatment group, whilst there are 6 states in the "more stringent" treatment group. One can imagine that these changes can have differing effects across states, particularly given that the size, or "dosage", of the maximum group size and/or staff-child ratio change varies across the treated states. So the combination and number of states in each group could be a factor behind why we see results for the "less stringent" group and not the "more stringent" group. Furthermore, a demand response from parents could counteract the effects of regulatory changes.

Figure 6. The effect of loosening childcare regulations on employment



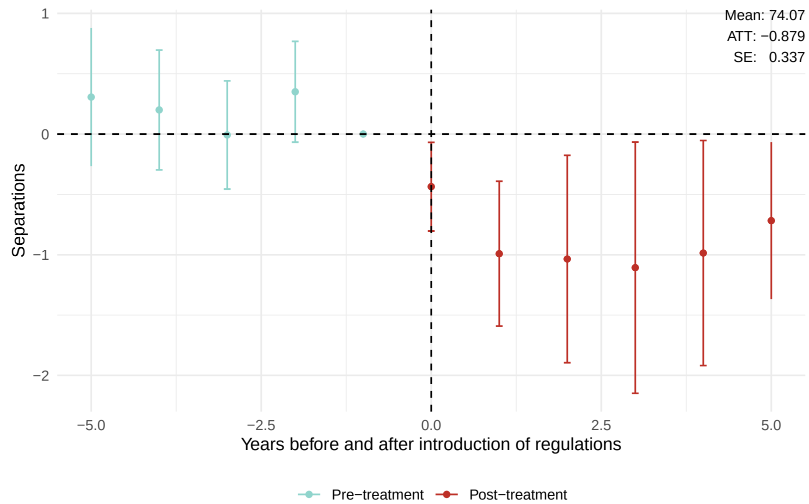

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log of employment in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Figure 7. The effect of loosening childcare regulations on new hires



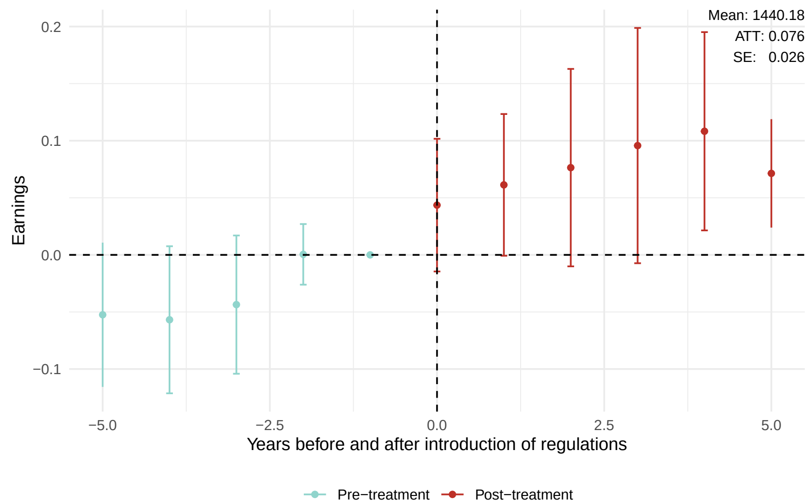

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log of new hires in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Figure 8. The effect of loosening childcare regulations on job separations




Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log of job separations in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Figure 9. The effect of loosening childcare regulations on earnings




Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log of earnings in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Table 10. Effects of childcare regulations on employment outcomes

| | Emp. | Earnings | Hires | Separations | Hiring Rate | Sep. Rate | Turnover |
|---|---|---|---|---|---|---|---|
| Less Strict | -87.31** | 7.61*** | -74.71** | -87.92*** | 1.43*** | -0.99 | -0.56 |
| | (35.88) | (2.63) | (34.56) | (33.74) | (0.52) | (0.66) | (0.53) |
| More Strict | -43.91* | -2.77 | -37.92 | -35.03 | 0.62 | 0.58 | 0.39 |
| | (24.98) | (6.57) | (26.36) | (23.46) | (1.42) | (0.45) | (0.38) |
| Mean (Less Strict) | 461.6 | 1440.2 | 64.8 | 74.1 | 0.2 | 0.2 | 0.1 |
| Mean (More Strict) | 411.2 | 1433.9 | 58.0 | 66.5 | 0.2 | 0.2 | 0.1 |

*p<0.10; **p<0.05; ***p<0.01

Notes: N (Less Strict) = 19,634; N (More Strict) = 24,010. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. This table shows the estimated effects of introducing childcare facility regulations on employment outcomes for the childcare industry. Coefficients and standard errors multiplied by 100. "Emp." is the log of employment. "Earnings" is the log of earnings. "Hires" is the log of new hires. "Separations" is the log of separations. "Hiring rate" is hires as a percent of average employment. "Sep. rate" is separation as percent of average employment. "Turnover" is the rate at which stable jobs begin and end. "Less Strict" is for the sample of counties in states which experienced loosening of regulations, in addition to control counties. "More Strict" is for the sample of counties in states which experienced tightening of regulations, in addition to control counties. The means are of the non-logged variables. All models control for county median earnings, the unemployment rate, and racial and ethnic composition. Estimates weighted by the population under five. Standard errors, clustered at the state-year level, in parentheses.

Table 11. Effects of childcare regulations on childcare establishments

| | Log of Number of Childcare Establishments | | | | |
|---|---|---|---|---|---|
| | Total | <5 Employees | 5-9 Employees | 10-49 Employees | 50+ Employees |
| Less Strict | -45.55 | -31.84 | -44.13 | -40.72 | -35.75 |
| | (32.72) | (29.30) | (38.01) | (35.85) | (45.52) |
| More Strict | -17.32 | -11.48 | -14.36 | -49.29** | 6.24 |
| | (50.77) | (55.21) | (29.35) | (21.38) | (45.39) |
| Mean (Less Strict) | 29.4 | 10.9 | 5.7 | 11.7 | 0.5 |
| Mean (More Strict) | 26.6 | 9.8 | 5.2 | 10.6 | 0.4 |

*p<0.10; **p<0.05; ***p<0.01

Notes: N (Less Strict) = 22,740; N (More Strict) = 27,433. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. This table shows the estimated effects of introducing childcare facility regulations on the number of childcare establishments. Coefficients and standard errors multiplied by 100. "Total" is the log of the total number of childcare establishments. "<5 Employees" is the log of the number of childcare establishments with less than 5 employees. "5-9 Employees" is the log of the number of childcare establishments with 5-9 employees, and so on. "Less Strict" is for the sample of counties in states which experienced loosening of regulations, in addition to control counties. "More Strict" is for the sample of counties in states which experienced tightening of regulations, in addition to control counties. The means are of the non-logged variables. All models control for county median earnings, the unemployment rate, and racial and ethnic composition. Estimates weighted by the population under five. Standard errors, clustered at the state-year level, in parentheses.

# 9 Comparison to literature

The price elasticity estimates that I find appear large. Recall that I find that a 10% increase in the price of childcare (approximately $990 a year) leads to a 5.7% decrease in the birthrate (4 births per 1,000 aged 20 to 44).

However, these estimates broadly align with magnitudes found by Mörk et al. (2013), who study the introduction of a childcare cost cap in Sweden in 2002. The authors estimate that a reduction in the present value of future marginal childcare costs of approximately $10,000 (or $12,200 in 2010 prices) over 10 years would increase fertility rates by 5.8%. Assuming uniform responses over time (a simplification), this corresponds to an approximate annual cost reduction of $1,000 (or $1,220 in 2010 prices) producing a comparable fertility response.

Another benchmark for comparison is the literature on income shocks, although price and income elasticities may not be directly comparable. Kearney and Wilson (2018) study the U.S. fracking boom between 1997 and 2012, finding that a 10% increase in earnings ($\approx$ $7,900 in 2010 prices) leads to $\approx$ 15.8% higher birth rates (or 15.8 births per 1,000 women aged 18 to 34). This suggests a smaller income response than the price elasticity estimates I find.

## 10 Back of the envelope calculation

To illustrate the potential policy implications of my estimates, I conduct a simple back-of-the-envelope calculation of the cost and fertility effects of a childcare price subsidy for parents of children under age three.

Using a childcare centre participation rate of 19.61% (53% of children under 3 are in non-parental care, 37% of these are in centre care (National Center for Education Statistics, 2020)) and a population estimate of 11 million children under 3 in 2023, I estimate that 2.16 million children are enrolled in centre-based care. The weighted mean weekly price of childcare is \$190 in my sample, or \$9,880 annually. A 10% annual subsidy would therefore cost approximately \$2.13 billion.

Applying my estimated elasticity, such a subsidy would raise birthrates by 5.7%, implying approximately 205,000 additional births in the first year (relative to a baseline of 3,596,017 births in 2023). This implies a cost of approximately \$10,400 per additional birth in the first year.

## 11 Conclusion

Low and falling fertility rates across the developed world are generating concern about future economic growth and the financial viability of social support systems. In this paper I explore how the price of childcare, a large and early cost facing potential parents, affects the decision to have children in the U.S. I provide the first causal evidence on how changes in childcare *prices* affect fertility behaviour, and extend a limited reduced form literature exploring the causal effects of childcare costs on fertility.

I find that higher childcare prices reduce birthrates, delay the first birth, and increase spacing between the first and second births. Heterogeneity analysis reveals varying effects by age: the price elasticity for women aged 30 and above is larger than that for younger women. I develop a simple theoretical model to explain this age gradient. I demonstrate that older women can be more price responsive than younger women because they earn a higher wage, and so the opportunity cost of their time is higher. This higher opportunity cost leads them to outsource more, if not all, childcare. This high level of outsourcing makes women more sensitive to price changes. Older women are also more likely to be having a second, or higher, birth. Having additional children increases spending on childcare, increasing price sensitivity.

I test the model predictions and demonstrate that, indeed, higher-income women (proxied by education) are more price responsive, and that older parents spend more on formal childcare. Additionally, I find that price elasticities are larger for higher-order births, indicating stronger responses from women along the intensive margin.

These results suggest that preventing rising childcare costs and expanding financial support for childcare are promising avenues for policymakers seeking to address low fertility rates in the U.S. In particular, sustaining birthrates among women aged 30 and above is critical for any recovery in completed fertility as current cohorts of women will need to have more births after age 30 to match total fertility rates of cohorts prior to 2007 (Kearney and Levine, 2021) [15].

[15] The total fertility rate is the number of children a woman is expected to have over her childbearing years, given current age-specific fertility rates.

# A Appendix A: Bounding exercise

In this section, I conduct a bounding exercise to explore how the quality of childcare may affect my IV estimates. I show that my IV estimates represent a lower-bound, and estimate the size of the bias in the case where quality of childcare directly impacts birthrates.

## A.1 Decomposition of the IV Estimator

In the two stage-least squares equation I set out in section 4, I assume that:

$$Y = \beta P + X'\eta + \epsilon \tag{7}$$

Where $Y$ is the log of the birthrate, $P$ is the cost of childcare, and $X'$ contains covariates including county and year fixed effects. As $P$ is endogenous, I instrument the variable with $Z$:

$$P = \mu Z + X'\kappa + \varepsilon \tag{8}$$

However, let us consider the possibility that the structural model is in fact:

$$Y = \beta P + \delta Q + X'\eta + e \tag{9}$$

Where $Q$ is the quality of childcare, and the regulations that I use as a instrument for $P$ also affect $Q$. If we estimate equation 9 using equation 7, then the error term may include the quality of childcare component:

$$\epsilon = \delta Q + e$$

By the Frisch-Waugh-Lovell theorem, I partial out the observed covariates $X$:

$$\tilde{Y} = \beta \tilde{P} + \delta \tilde{Q} + \tilde{e},$$
$$\tilde{P} = \mu \tilde{Z} + \tilde{\varepsilon}$$

Then the instrumental variables estimator of $\beta$ can be written as:

$$\hat{\beta}_{IV} = \frac{\text{Cov}(\tilde{Z}, \tilde{Y})}{\text{Cov}(\tilde{Z}, \tilde{P})}$$

$$= \frac{\text{Cov}(\tilde{Z}, \beta\tilde{P} + \delta\tilde{Q} + \tilde{e})}{\text{Cov}(\tilde{Z}, \tilde{P})}$$

$$= \frac{\beta\ \text{Cov}(\tilde{Z}, \tilde{P}) + \delta\ \text{Cov}(\tilde{Z}, \tilde{Q}) + \text{Cov}(\tilde{Z}, \tilde{e})}{\text{Cov}(\tilde{Z}, \tilde{P})}.$$

With the assumption that $\text{Cov}(\tilde{Z}, \tilde{e}) = 0$,

$$\hat{\beta}_{IV} \to \beta + \delta \cdot \frac{\text{Cov}(\tilde{Z}, \tilde{Q})}{\text{Cov}(\tilde{Z}, \tilde{P})}$$

Therefore, to bound $\hat{\beta}_{IV}$, we must estimate $\text{Cov}(\tilde{Z}, \tilde{Q})$ and $\text{Cov}(\tilde{Z}, \tilde{P})$. We can estimate $\text{Cov}(\tilde{Z}, \tilde{P})$ using the first stage, equation 8. If:

$$\tilde{P} = \mu\tilde{Z} + \tilde{\varepsilon}$$

It follows that:

$$\hat{\mu} = \frac{\text{Cov}(\tilde{Z}, \tilde{P})}{\text{Var}(\tilde{Z})}$$

$$\Rightarrow \text{Cov}(\tilde{Z}, \tilde{P}) = \hat{\mu} \cdot \text{Var}(\tilde{Z})$$

Say the regulations ($Z$) also affect the quality of childcare ($Q$), then we can consider the following equation to estimate $\text{Cov}(\tilde{Z}, \tilde{Q})$:

$$\tilde{Q} = \omega\tilde{Z} + \tilde{u} \tag{10}$$

It follows that:

$$\hat{\omega} = \frac{\text{Cov}(\tilde{Z}, \tilde{Q})}{\text{Var}(\tilde{Z})}$$

$$\Rightarrow \text{Cov}(\tilde{Z}, \tilde{Q}) = \hat{\omega} \cdot \text{Var}(\tilde{Z})$$

Substituting in these expressions for $\text{Cov}(\tilde{Z}, \tilde{Q})$ and $\text{Cov}(\tilde{Z}, \tilde{P})$, we can bound the estimate of $\beta$ using the following equation:

$$\hat{\beta}_{IV} - \hat{\delta} \cdot \frac{\hat{\omega}}{\hat{\mu}} \to \beta$$

Where $\hat{\delta}$ is an estimate of the effect of childcare quality on birthrates, $\hat{\omega}$ is an estimate of the effect of the instrument (childcare regulations) on childcare quality, and $\hat{\mu}$ is an estimate of the effect of the instrument on childcare prices.

### A.2 Signing the bias

Let us first consider the sign of this bias. I find that an increase in childcare prices reduces birthrates, so the estimator $\hat{\beta}_{IV} < 0$. For the main instrument, the maximum group size, I find that an increase in the maximum group size reduces prices, so $\hat{\mu} < 0$. We would expect that loosening the regulations, by increasing the maximum group size, could reduce the quality of childcare. This would leave $\hat{\omega} < 0$. Finally, if childcare quality were to affect birthrates, we would anticipate that raising quality would have a positive effect on birthrates ($\hat{\delta} > 0$). Putting these together, we get:

$$\underset{(<0)}{\hat{\beta}_{IV}} - \underset{(>0)}{\hat{\delta}} \cdot \frac{\underset{(<0)}{\hat{\omega}}}{\underset{(<0)}{\hat{\mu}}} \longrightarrow \underset{(<0)}{\beta}$$

If we instead consider the minimum staff-child ratio, an increase in the staff-child ratio increases prices, so $\hat{\mu} > 0$. An increase in the staff-child ratio makes the regulations stricter, so we would expect this to increase the quality of childcare. Thus $\hat{\omega} > 0$. As before, we would anticipate that raising quality has a positive effect on birthrates; $\hat{\delta} > 0$. Combining these we get:

$$\underset{(<0)}{\hat{\beta}_{IV}} - \underset{(>0)}{\hat{\delta}} \cdot \frac{\underset{(>0)}{\hat{\omega}}}{\underset{(>0)}{\hat{\mu}}} \longrightarrow \underset{(<0)}{\beta}$$

This analysis reveals that if quality of childcare is a pertinent omitted variable, the estimator $\hat{\beta}_{IV}$ is an underestimate of the true value of $\beta$. Next, I will estimate the magnitude of the bias term.

### A.3 Estimating the magnitude of the bias

To estimate the effect of childcare quality on birthrates ($\hat{\delta}$) and the effect of childcare regulations on childcare quality ($\hat{\omega}$), I utilise data on a measure of childcare quality: childcare programme accreditation.

My data on childcare programme accreditation comes from the National Association for the Education of Young Children (NAEYC) (National Association for the Education of Young Children, 2025). The NAEYC has been an independent accreditator of early learning programmes for over thirty years, working with facilities across the U.S. to improve quality and implement best practices. NAEYC accreditation provides a signal to families that the childcare programme is reputable and high quality. Early learning programmes, including childcare centres, apply for NAEYC accreditation voluntarily. During my sample period, there were four stages of the NAEYC early learning accreditation process (National Association for the Education of Young Children, 2023). First, a programme will enrol and undertake self-study in preparation. Next, they will apply for accreditation and conduct a self assessment to demonstrate that they meet the NAEYC standards. If the programme has sufficiently evidenced that they are ready to progress to the next stage, they will receive a site visit by a NAEYC assessor. During the site visit, programmes are marked against several categories of quality: curriculum; teaching; relationships with children, families, and communites; child learning and development, health and safety, staff competencies, the physical environment, programme management, and collaboration with communities. Accredited programmes are awarded accreditation for five years (subject to meeting annual maintenance requirements). I have obtained data on programme accreditation for 2017 to 2022 inclusive (the NAEYC was unable to share data prior to 2017). The lack of earlier data is a limitation of my analysis, but the remaining sample still allows me to estimate the effect of childcare quality on birthrates for the purposes of this bounding exercise.

With these data, I can construct a measure of childcare quality. I estimate the fraction of childcare establishments that are NAEYC accredited at the state level. To do so, I divide the number of NAEYC accredited programmes by the number of childcare establishments in the Census CBP data at the state level for each of the years from 2017 to 2022 inclusive. Across this time period and sample, the average share of childcare establishments that are NAEYC accredited is 8.4%. A caveat is in order. I may underestimate the number of accredited programmes prior to 2022, as the NAEYC were unable to share information on programmes that lost accreditation status. However, I do not see a large jump in the share of accredited programmes in 2022 when I plot the mean share over time (See Appendix Figure D30). Further, to test the sensitivity of my estimates, I drop states where I observe a noticeable rise in the number of programmes in 2022. Reassuringly, the coefficients' significance, direction, and rough magnitude remain consistent.

First, I estimate the effect of childcare quality on birthrates ($\hat{\delta}$). I present OLS estimates of the effect of childcare quality on birthrates in Table A1. The share of NAEYC programmes has an insignificant positive effect on log birthrates.

Next, I must estimate the effect of the childcare regulations on childcare quality ($\hat{\omega}$). For this component, I have two approaches. First, I can estimate the effect of maximum group sizes/staff-child ratio changes on the NAEYC accreditation rate using my hand-collected data on childcare facility regulations. Across the years 2017 to 2022 there were two changes: Virginia introduced group size requirements (2021), and Utah relaxed their group size requirements (2022). As I only have pre- and post- years for Virginia, I exploit the change in Virginia. The results are shown in Table A2. I find that increasing the maximum group size has a significant but small effect on the share of NAEYC accredited programmes. For my second approach, I can look to prior work by Hotz and Xiao (2011). The authors estimate the effect of the minimum staff-child ratio for infants on the NAEYC accreditation rate; they estimate a significant positive coefficient of 0.639[16].

[16] Please see "Table 12 - Estimated Effects of State Regulations on the Accreditation of Child Care Centers" on page 1802.

Appendix Table A1. Bounding exercise: Effects of childcare quality on birthrates

| | (1) | (2) | (3) |
|---|---|---|---|
| Log(Childcare Price) | -0.02 | -0.01 | -0.01 |
| | (0.02) | (0.01) | (0.02) |
| NAEYC Share | 0.23 | 0.21 | 0.34 |
| | (0.45) | (0.40) | (0.33) |
| Mean (Price) | 148.98 | 148.98 | 148.24 |
| Mean (NAEYC Share, %) | 6.81 | 6.81 | 7.12 |
| N | 2,678 | 2,678 | 1,948 |
| Controls | No | Yes | Yes |

* p < 0.10, ** p < 0.05, *** p < 0.01

Notes: Data: NVSS birth records, SEER county population counts, NDCP childcare prices, National Association for the Education of Young Children (NAEYC), Census County Business Patterns, for 2017-2019, 2021-2022. This table shows estimated effects of childcare price and quality on the log of the birthrate per 1000 women aged 20 to 44 from OLS regressions. Columns (1) and (2) include all states in the sample. Column (3) is sensitivity analysis that drops AR, AZ, CA, IL, MD, ME, SC, and TN. "Log(Childcare Price)" is the log of the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "NAEYC Share" is the number of NAEYC accredited childcare programmes out of the number of childcare establishments in the state. Columns (2) and (3) control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, and racial and ethnic composition. All models control for county and year fixed effects. Estimates weighted by births to women aged 20 to 44. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table A2. Bounding exercise: Effects of childcare regulations on quality

| | (1) | (2) |
|---|---|---|
| Maximum Group Size | -0.10*** | -0.10*** |
| | (0.01) | (0.02) |
| Mean (Maximum Group Size) | 16.74 | 16.26 |
| Mean (NAEYC Share, %) | 6.85 | 6.88 |
| N | 7,175 | 5,305 |

* p < 0.10, ** p < 0.05, *** p < 0.01

Notes: Data: Hand-collected maximum group size data, National Association for the Education of Young Children (NAEYC), Census County Business Patterns, for 2017-2019, 2021-2022. This table shows estimated effects of childcare regulations on childcare quality from OLS regressions. Coefficients and standard errors multiplied by 100. Column (1) includes all states in the sample. Column (2) is sensitivity analysis that drops AR, AZ, CA, IL, MD, ME, SC, and TN. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. "NAEYC Share" is the number of NAEYC accredited childcare programmes out of the number of childcare establishments in the state. Both models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, and racial and ethnic composition. Both models control for county and year fixed effects. Standard errors, clustered at the state-year level, in parentheses.

I now have estimates for the effect of childcare quality on birthrates ($\hat{\delta}$), the effect of the instrument (childcare regulations) on childcare quality ($\hat{\omega}$), and the effect of the instrument on childcare prices ($\hat{\mu}$) (recall that we already have the estimator $\hat{\mu}$ in hand, as this is the first stage coefficient shown in Table 2.) Thus I can estimate the size of the potential bias, as shown below. Recall from Table 3 that my estimate for $\hat{\beta}_{IV}$ is -0.57. Both approaches deliver bias terms of similar magnitudes.

*Maximum group size instrument:*

$$\hat{\beta}_{IV} \; - \; 0.215 \cdot \frac{-0.000951}{-0.01} \; \longrightarrow \; \beta$$

$$\Rightarrow \beta \in [\hat{\beta} - 0.0316, \hat{\beta}]$$

*Staff-child ratio instrument:*

$$\hat{\beta}_{IV} \; - \; 0.215 \cdot \frac{0.639}{3.99} \; \longrightarrow \; \beta$$

$$\Rightarrow \beta \in [\hat{\beta} - 0.0344, \hat{\beta}]$$

# B Appendix B: Theoretical model

## B.1 Optimisation problem

The woman's optimisation problem is:

$$\max_{\{c,n,s\}} u = c_1 + c_2 + (2n_1 + n_2)v - \mu((1 - s_1)^{\gamma} n_1 + (1 - s_2)^{\gamma} n_2) \tag{11}$$

She is subject to the following budget and time constraints:

$$c_1 + ps_1 n_1 \leq w\,(1 - (1 - s_1)n_1) \tag{12}$$

$$c_2 + ps_2n_2 \leq w(1 + \alpha h_1)\left(1 - (1 - s_2)n_2\right) \tag{13}$$

Where $h_1$ is the woman's work hours in $t = 1$: $h_1 = 1 - (1 - s_1)n_1$.

$$1 - (1 - s_1)n_1 \geq 0 \tag{14}$$

$$1 - (1 - s_2)n_2 \geq 0 \tag{15}$$

Equations 12 and 13 are the budget constraints for periods one and two respectively. The budget constraints reflect the fact that the woman can spend on consumption and private childcare, and that this expenditure must be at most her labour income in that period. Equations 14 and 15 are the mother's time constraints for each period. Her time spent on employment and self-childcare must be less than or equal to one unit of time.

## B.2 Optimal choice

### B.2.1 Optimal share of childcare

We can derive the optimal share of private childcare purchased in each period $(s_1, s_2)$. Conditional on having a child in the relevant period, the first order conditions for $s_1, s_2$ are given by:

$$(w - p) + \mu\gamma(1 - s_1)^{\gamma-1} = 0$$

$$(w(1 + \alpha h_1) - p) + \mu\gamma(1 - s_2)^{\gamma-1} = 0$$

We can then derive the optimal share of childcare in periods one and two:

$$s_1^* = \begin{cases} 0, & \text{if } p > \mu\gamma + w, \\ 1 - \left(\frac{(p-w)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } w \leq p \leq \mu\gamma + w, \\ 1, & \text{if } p < w. \end{cases}$$

$$s_2^* = \begin{cases} 0, & \text{if } p > \mu\gamma + w(1+\alpha h_1^*), \\ 1 - \left(\frac{(p-w(1+\alpha h_1^*))}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } w(1+\alpha h_1^*) \leq p \leq \mu\gamma + w(1+\alpha h_1^*), \\ 1, & \text{if } p < w(1+\alpha h_1^*). \end{cases}$$

$$\text{and where } h_1^* = \begin{cases} 0, & \text{if } s_1^* = 0 \text{ and } n_1 = 1 \\ 1 - (\frac{(p-w)}{\mu\gamma})^{\frac{1}{\gamma-1}}, & \text{if } s_1^* = 1 - (\frac{(p-w)}{\mu\gamma})^{\frac{1}{\gamma-1}} \text{ and } n_1 = 1, \\ 1, & \text{if } s_1^* = 1 \text{ and } n_1 = 1, \text{ or } n_1 = 0 \end{cases}$$

Optimal $s_1^*, s_2^*$ depend on the wage $w$, price of childcare $p$, productivity $\alpha$, and disutility from self-childcare parameters $\gamma$ and $\mu$. An increase in the price of childcare reduces the share of private childcare purchased, while wage increases raise it. If the wage that period exceeds the childcare price, the woman will fully outsource childcare. Conversely, if prices are too high relative to wages, some women exit the labour market to provide full-time care for their child. Human capital accumulation interacts with these decisions: outsourcing childcare in period one allows for more labour supply, raising human capital and wages in period two, making outsourcing in the second period more attractive.

Note that if $p < w + \mu\gamma$, then $s_1^* > 0$. Since the period two wage $w_2 \equiv w(1 + \alpha h_1^*) \geq w$, it follows that $p < w_2 + \mu\gamma$ and thus $s_2^* > 0$. Moreover, holding $p$ (and $\mu, \gamma$) fixed, $s^*(\cdot)$ is weakly increasing in the effective wage, so $s_2^* \geq s_1^*$. Mothers with second period births will purchase a weakly larger share of private childcare than mothers who have a first period birth. Intuitively, this arises because the period 2 wage uplift makes outsourcing relatively more attractive.

### B.2.2 Optimal fertility choices

As $n$ takes discrete values of 0 or 1, we can set out equations for the woman's utility under each of the four fertility scenarios with $s_1^*$ and $s_2^*$ as above. Utility $u(n_1, n_2)$ for $n_1, n_2 \in \{0, 1\}$ is denoted by:

$$u(0,0) = w(2+\alpha)$$

$$u(1,0) = w(1-(1-s_1^*)) - ps_1^* - \mu(1-s_1^*)^\gamma + w(1+\alpha) + 2v$$

$$u(0,1) = w + w(1+\alpha)(1-(1-s_2^*)) - ps_2^* - \mu(1-s_2^*)^\gamma + v$$

$$u(1,1) = w(1-(1-s_1^*)) \; - \; p\,s_1^* + w(1+\alpha h_1^*)(1-(1-s_2^*)) \\ - \; p\,s_2^* \; - \; \mu\left((1-s_1^*)^\gamma + (1-s_2^*)^\gamma\right) \; + \; 3v$$

Based on optimal choices $s_1^*, s_2^*$ (which depend on the wage $w$, price of childcare $p$, and disutility from self-childcare $\mu, \gamma$), a woman will compare her utility in each fertility scenario to determine whether to have children, and how many to have.

### B.2.3 The utility gain from having a child

We can denote the utility gain from having a child as:

$$\Delta u(1,0) = u(1,0) - u(0,0) = 2v - w(1-s_1^*) - ps_1^* - \mu(1-s_1^*)^\gamma$$

$$\Delta u(0,1) = u(0,1) - u(0,0) = v - w(1+\alpha)(1-s_2^*) - ps_2^* - \mu(1-s_2^*)^\gamma$$

$$\Delta u(1,1) = u(1,1) - u(1,0) = v - w(1+\alpha h_1^*)(1-s_2^*) - ps_2^* - \mu(1-s_2^*)^\gamma + w\alpha(h_1^* - 1)$$

For women who do some self-childcare ($0 < s_i^* < 1$), they will have a child if the value, or joy, from having a child, is greater than three components: (i) the opportunity cost of time, $w_t(1-s_i^*)$, (ii) the cost of private childcare, $ps_i^*$, and (iii) the disutility of self-care, $\mu(1-s_i^*)^\gamma$. Here $w_1 = w$ in $t = 1$ and $w_2 = w(1 + \alpha h_1^*)$ in $t = 2$. For women that purchase part-time childcare, the foregone wage is scaled by $(1 - s_i^*)$ and the childcare price by the share of private childcare $s_i^*$. As discussed above, increases in the wage that period and productivity raise the share of private childcare, so will increase the private childcare cost term but reduce the foregone wage term. Women who fully outsource ($s_i^* = 1$) only weigh the child value against the cost of private childcare. Each of the cases are discussed in more detail below.

*Case 1: Stay at home mothers ($s_1^*, s_2^* = 0$).* Mothers who will not outsource any childcare will have a child if the benefit from having a child outweighs the opportunity cost of foregone wages from full-time self-childcare. They will have a first and second period birth respectively when:

$$2v \geq w + \mu$$

$$v \geq w(1 + \alpha h_1^*) + \mu$$

*Case 2: Mothers with part-time private childcare in both periods.* These mothers will have a child if the benefit is greater than the foregone wages (weighted by share of self-childcare), cost of private childcare, and disutility from self-childcare. They will have a first and second period birth respectively when:

$$2v \geq w(1 - s_1^i) + ps_1^i + \mu(1 - s_1^i)^\gamma$$

$$v \geq w(1 + \alpha h_1^*)(1 - s_2^i) + ps_2^i + \mu(1 - s_2^i)^\gamma$$

where

$$s_1^i = 1 - \left(\frac{(p - w)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, s_2^i = 1 - \left(\frac{(p - w(1 + \alpha h_1^*))}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}$$

*Case 3: Mothers with part-time private childcare in $t = 1$, full-time childcare in the second period in $t = 2$.* These mothers will have a child in the first period if the benefit is greater than the foregone wages (weighted by share of self-childcare), cost of private childcare, and disutility from self-childcare. They will have a child in the second period if the benefit outweighs the cost of private childcare for that second period. They will have a first and second period birth respectively when:

$$2v \geq w(1 - s_1^i) + ps_1^i + \mu(1 - s_1^i)^\gamma$$

$$v \geq p$$

where

$$s_1^i = 1 - \left(\frac{(p - w)}{\mu\gamma}\right)^{\frac{1}{\gamma - 1}}$$

*Case 4: Mothers who fully outsource childcare ($s_1^*, s_2^* = 1$).* Mothers who purchase as much as private childcare as possible have a child in the first and second period if the benefit is greater than the monetary cost of private childcare. They will have a first and second period birth respectively when:

$$2v \geq p$$

$$v \geq p$$

## B.3 Response to price changes

### B.3.1 Utility responses

Next, I consider how utility at different fertility outcomes varies with respect to the childcare price:

$$\frac{\partial u(1,0)}{\partial p} = -\ s_1^* = \begin{cases} 0, & \text{if } p \geq \mu\gamma + w, \\ -\Big(1 - \left(\frac{(p-w)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}\Big), & \text{if } w \leq p \leq \mu\gamma + w, \\ -1, & \text{if } p \leq w. \end{cases}$$

$$\frac{\partial u(0,1)}{\partial p} = -s_2^* = \begin{cases} 0, & \text{if } p \geq \mu\gamma + w(1+\alpha), \\ -\Big(1 - \left(\frac{(p-w(1+\alpha))}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}\Big), & \text{if } w(1+\alpha) \leq p \leq \mu\gamma + w(1+\alpha), \\ -1, & \text{if } p \leq w(1+\alpha). \end{cases}$$

$$\frac{\partial u(1,1)}{\partial p} = -(s_1^* + s_2^*) = -\left(\begin{cases} 0, & \text{if } p \geq w + \mu\gamma, \\ 1 - \left(\dfrac{(p-w)}{\mu\gamma}\right)^{\dfrac{1}{\gamma-1}}, & \text{if } w \leq p \leq w + \mu\gamma, \\ 1, & \text{if } p \leq w \end{cases} \right.$$
$$\left. + \begin{cases} 0, & \text{if } p \geq w(1+\alpha h_1^*) + mu\gamma, \\ 1 - \left(\dfrac{(p - w(1+\alpha h_1^*))}{\mu\gamma}\right)^{\dfrac{1}{\gamma-1}}, & \text{if } w(1+\alpha h_1^*) \leq p \leq w(1+\alpha h_1^*) + \mu\gamma, \\ 1, & \text{if } p \leq w(1+\alpha h_1^*) \end{cases}\right)$$

**Number of children** By comparing $\frac{\partial u(1,0)}{\partial p}$ and $\frac{\partial u(0,1)}{\partial p}$, and recalling that $s_2^* \geq s_1^*$, we see that second period births (to older women) are more price responsive than first period births (to younger women) for interior solutions. The wage uplift in period 2 raises $s_2^*$, which in turn increases the price sensitivity of utility. Delaying birth therefore makes utility more price sensitive: human capital accumulation raises wages, leading mothers to outsource more childcare in the second period. This higher level of outsourcing exposes mothers more strongly to price changes.

**Birth timing amongst one-child mothers** A comparison of $\frac{\partial u(1,0)}{\partial p}$ and $\frac{\partial u(1,1)}{\partial p}$ yields a straightforward prediction. Consider mothers who purchase some share of private childcare in the first period. As shown above, they will purchase at least that amount in the second period. Thus mothers who have two children, rather than one, will have utility that is more price sensitive because they face childcare costs in both periods.

### B.3.2 Child-state responses

However, sufficiently large price changes can also shift mothers between the optimal $s_1^*$ and $s_2^*$ values. For example, a price increase can move a mother towards part-time private childcare or full-time self-childcare. Ultimately, we are interested in how the probability of choosing one of the four utility states $(u(0,0), u(1,0), u(0,1), u(1,1))$ varies with respect to the price of childcare, $p$. To capture reallocation across fertility states, I model the probability of being in one of the four states using multinomial logit. This requires the assumption that the unobserved taste errors for each state follow independent extreme-value distributions. This delivers tractable choice probabilities, but is a strong assumption as it rules out correlation in unobserved preferences across states.

$$P_{n_1,n_2} = \frac{e^{u_{n_1,n_2}}}{\sum_{k\in\{(0,0),(1,0),(0,1),(1,1)\}} e^{u_k}}$$

where each utility $u_{n_1,n_2}$ state is evaluated at the optimal childcare shares $s_1^*, s_2^*$.

Using the fact that:

$$\frac{\partial P_{n_1,n_2}}{\partial u_{k_1,k_2}} = P_{n_1,n_2}\big(\mathbf{1}\{(n_1,n_2)=(k_1,k_2)\} - P_{k_1,k_2}\big),$$

We can derive the following:

$$\frac{dP_{n_1,n_2}}{dp} = \sum_{k\in\{(0,0),(1,0),(0,1),(1,1)\}} \frac{\partial P_{n_1,n_2}}{\partial u_k}\frac{du_k}{dp} = P_{n_1,n_2}(\frac{du_{n_1,n_2}}{dp} - \sum_{k\in\{(0,0),(1,0),(0,1),(1,1)\}} P_k\frac{du_k}{dp})$$

Recall that the within state derivatives are given by:

$$\frac{du_{0,0}}{dp} = 0, \quad \frac{du_{1,0}}{dp} = -s_1^*, \quad \frac{du_{0,1}}{dp} = -s_2^*, \quad \frac{du_{1,1}}{dp} = -(s_1^* + s_2^*).$$

Which we can use to derive:

$$\begin{aligned}
\frac{dP_{00}}{dp} &= P_{00}\Big[s_1^*\,(P_{10} + P_{11}) + s_2^*(P_{01} + P_{11})\Big],\\
\frac{dP_{10}}{dp} &= P_{10}\Big[s_1^*\,(P_{10} + P_{11} - 1) + s_2^*(P_{01} + P_{11})\Big],\\
\frac{dP_{01}}{dp} &= P_{01}\Big[s_1^*\,(P_{10} + P_{11}) + s_2^*(P_{01} + P_{11} - 1)\Big],\\
\frac{dP_{11}}{dp} &= P_{11}\Big[s_1^*\,(P_{10} + P_{11} - 1) + s_2^*(P_{01} + P_{11} - 1)\Big].
\end{aligned}$$

With the optimal private childcare shares $s_1^*, s_2^*$ as before.

**Having no children** First, observe that $\frac{dP_{00}}{dp} \geq 0$ whenever $s_1^*(p) > 0$ or $s_2^*(p) > 0$, a childcare price increase weakly raises the probability of having no children.

**Number of children** Computing the price elasticities $\eta_{\{n_1,n_2\},p}$ aids a comparison of the one-child versus two-child states:

$$\begin{aligned}
\eta_{10,p} &= p\Big[s_1^*\,(P_{10} + P_{11} - 1) + s_2^*\,(P_{01} + P_{11})\Big],\\
\eta_{11,p} &= p\Big[s_1^*\,(P_{10} + P_{11} - 1) + s_2^*\,(P_{01} + P_{11} - 1)\Big]
\end{aligned}$$

$$
\begin{aligned}
\eta_{11,p} - \eta_{10,p} = \; & p\Big\{ s_1^* \big[ (P_{10} + P_{11} - 1) - (P_{10} + P_{11} - 1) \big] \\
& \qquad\qquad + \; s_2^* \big[ (P_{01} + P_{11} - 1) - (P_{01} + P_{11}) \big] \Big\} \\
= & - \, p \, s_2^*
\end{aligned}
$$

The probability of having two children has a (weakly) more negative price elasticity than that of having one child, because of the additional private care exposure.

**Birth timing amongst one-child mothers** To evaluate how price changes impact delays to birth, I consider birth timing amongst mothers with one child. Conditional on having one child, the probability of choosing a first-period birth is: $P_{10|1} \equiv \frac{P_{10}}{P_{10}+P_{01}}$. A marginal increase in the childcare price $p$ shifts this probability by:

$$
\frac{dP_{10|1}}{dp} = \frac{P_{01}\,\frac{dP_{10}}{dp} - P_{10}\,\frac{dP_{01}}{dp}}{(P_{10} + P_{01})^2} = - \; \frac{P_{10} P_{01}}{(P_{10} + P_{01})^2} \left( s_1^* - s_2^* \right) = - \; P_{10|1} \left( 1 - P_{10|1} \right) \left( s_1^* - s_2^* \right)
$$

By the result established above that $s_2^*(p) \geq s_1^*(p)$, it follows that

$$
\frac{dP_{10|1}}{dp} \; \geq \; 0 \quad \text{and} \quad \frac{dP_{01|1}}{dp} \; = \; - \frac{dP_{10|1}}{dp} \; \leq \; 0
$$

A marginal price increase reduces the probability of a second-period birth; it shifts timing toward the first period amongst one-child mothers. The term $P_{10|1}(1 - P_{10|1})$ scales the magnitude of the derivative; it captures how indifferent between the two timings the mother is, and is small when one option dominates. If $s_1^* = s_2^*$, birth timing is insensitive to price.

### B.4 Extension: taste for self-caring for the child

The model presented above incorporates a distaste for self-childcare, particularly in large quantities. The disutility term captures that a share of mothers have a preference for a career, and that caring for their child at home limits their ability to progress in the workplace. However, not all parents may feel this way about caring for their own child, and in fact may enjoy spending a portion of their working hours caring for their child. The model can easily be adjusted to reflect a taste for self-childcare. We simply flip the sign of the disutility parameter and require that $0 < \gamma < 1$ so that the taste for self-childcare is concave: the marginal benefit from self-childcare is diminishing. This adjustment does not change the model predictions, but pushes the interior solution (part-time childcare) away from more private childcare and towards more self child-care.

We can replace Equation 6.1 with the following utility function:

$$u = c_1 + c_2 + (2n_1 + n_2)v + \mu((1 - s_1)^{\gamma} n_1 + (1 - s_2)^{\gamma} n_2)$$

The budget and time constraints remain the same. To derive the optimal share of private childcare purchased in each period $(s_1, s_2)$ we take first order conditions:

$$(w - p) - \mu\gamma(1 - s_1)^{\gamma-1} = 0$$

$$(w(1 + \alpha h_1^*) - p) - \mu\gamma(1 - s_2)^{\gamma-1} = 0$$

From these we determine the optimal share of childcare in periods one and two:

$$s_1^* = \begin{cases} 0, & \text{if } p \geq w - \mu\gamma, \\ 1 - \left(\dfrac{(w-p)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w - \mu\gamma. \end{cases}$$

$$s_2^* = \begin{cases} 0, & \text{if } p \geq w(1 + \alpha h_1^*) - \mu\gamma, \\ 1 - \left(\dfrac{\big(w(1+\alpha h_1^*) - p\big)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w(1 + \alpha h_1^*) - \mu\gamma. \end{cases}$$

$$\text{and where } h_1^* = \begin{cases} 1, & \text{if } s_1^* = 0 \text{ and } n_1 = 1 \\ 1 - (\frac{(w-p)}{\mu\gamma})^{\frac{1}{\gamma-1}}, & \text{if } s_1^* = 1 - (\frac{(w-p)}{\mu\gamma})^{\frac{1}{\gamma-1}} \text{ and } n_1 = 1, \\ 1, & \text{if } n_1 = 0 \end{cases}$$

Note that due to the positive utility, or joy, that the mother receives from self-childcare, mothers never choose full outsourcing ($s_i^* = 1$). Instead they either select part-time private childcare or provide all care themselves.

As before, increases in the price of childcare reduce the share of private childcare purchased. Increases in the wage and productivity lead the share of private childcare to rise. Because the wage in period two is at least as high as in period one ($w(1 + \alpha h_1^*) \geq w$), if a mother chooses part-time private childcare in the first period she will also choose part-time in the second.

Examining how mothers now respond to price changes, we see that:

$$\frac{\partial u(1,0)}{\partial p} = -\, s_1^* = \begin{cases} 0, & \text{if } p \geq w - \mu\gamma, \\ -\left(1 - \dfrac{(w-p)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w - \mu\gamma. \end{cases}$$

$$\frac{\partial u(0,1)}{\partial p} = -\, s_2^* = \begin{cases} 0, & \text{if } p \geq w(1+\alpha) - \mu\gamma, \\ -\left(1 - \dfrac{(w(1+\alpha)-p)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w(1+\alpha) - \mu\gamma. \end{cases}$$

$$\frac{\partial u(1,1)}{\partial p} = -(s_1^* + s_2^*) = -\left(\begin{cases} 0, & \text{if } p \geq w - \mu\gamma, \\ 1 - \left(\dfrac{(w-p)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w - \mu\gamma \end{cases} + \begin{cases} 0, & \text{if } p \geq w(1+\alpha h_1^*) - \mu\gamma, \\ 1 - \left(\dfrac{(w(1+\alpha h_1^*)-p)}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w(1+\alpha h_1^*) - \mu\gamma \end{cases}\right)$$

The model predictions remain unchanged with this modification to the utility function. Second births (to older women) are more price responsive than first period births (to younger women). Again, this reflects the higher effective wage in period two, which leads to more outsourcing of childcare. This greater reliance on private childcare increases the magnitude of price sensitivity. Similarly, women with higher wages are more responsive to childcare price changes, as they outsource more childcare. Finally, for mothers with two children, utility is more price sensitive than for those with one child, since private childcare is purchased in both periods.

# C Appendix Tables

Appendix Table C1. First stage

| | Childcare Price | |
|---|---|---|
| | Price | Log(Price) ×100 |
| Maximum Group Size | -0.04 | -0.08 |
| | (0.16) | (0.08) |
| Staff-Child Ratio | 732.42*** | 397.31*** |
| | (2.88) | (32.14) |
| Mean (Childcare Price) | 146.54 | 146.54 |
| Mean (Maximum Group Size) | 16.26 | 16.26 |
| Mean (Staff-Child Ratio) | 0.20 | 0.20 |
| F-stat | 32532.22 | 627.28 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 8,094. Data: NDCP childcare prices, hand-collected regulation data, for 2009-2019, 2021-2022. This table shows the first stage of childcare prices on the maximum group size and staff-child ratio. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, adjusted to 2010 dollars and winsorised at the 99th percentile. The Log(Price) is unadjusted. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. "Staff-Child Ratio" is the state-level child-staff ratio average for 0 to 2 year olds. "F-stat" is the first-stage F statistic. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to women aged 20-44. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C2. Robustness of estimates to controlling for share of childcare establishments

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | 0.01 | 0.01 | 0.03 | 0.01 | 0.01 | -0.02 |
| | (0.02) | (0.04) | (0.03) | (0.02) | (0.02) | (0.03) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.89 |
| *IV* | | | | | | |
| Log(Childcare Price) | -0.53*** | -0.11 | -0.10 | -0.67*** | -0.79*** | -0.75*** |
| | (0.13) | (0.17) | (0.19) | (0.14) | (0.20) | (0.19) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.93 | 0.93 | 0.88 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.35*** | 0.07 | 0.06 | 0.43*** | 0.50*** | 0.47*** |
| | (0.12) | (0.11) | (0.12) | (0.12) | (0.10) | (0.08) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.89 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the log of the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, the share of childcare establishments, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C3. Robustness of estimates to controlling for staff turnover

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | 0.01 | 0.03 | 0.03 | 0.02 | 0.02 | -0.02 |
| | (0.02) | (0.04) | (0.03) | (0.02) | (0.02) | (0.03) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.92 |
| *IV* | | | | | | |
| Log(Childcare Price) | -0.59*** | -0.17 | -0.23 | -0.75*** | -0.86*** | -0.93*** |
| | (0.14) | (0.18) | (0.17) | (0.13) | (0.19) | (0.17) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.93 | 0.93 | 0.89 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.40*** | 0.12 | 0.16 | 0.49*** | 0.55*** | 0.60*** |
| | (0.12) | (0.12) | (0.12) | (0.12) | (0.11) | (0.06) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.92 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. “20-44” is the log of the county-level birthrate per 1000 women aged 20 to 44, “20-24” the log of the birthrate per 1000 women aged 20-24, and so on. “Childcare price” is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. “Maximum Group Size” is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, the share of childcare establishments, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C4. Robustness of estimates to dropping bordering counties

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log (Childcare Price) | 0.01 | 0.02 | 0.03 | 0.02 | 0.02 | -0.01 |
| | (0.02) | (0.04) | (0.03) | (0.02) | (0.02) | (0.03) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.90 |
| *IV* | | | | | | |
| Log (Childcare Price) | -0.57*** | -0.15 | -0.13 | -0.73*** | -0.87*** | -0.79*** |
| | (0.14) | (0.18) | (0.20) | (0.15) | (0.21) | (0.20) |
| $R^2$ | 0.95 | 0.98 | 0.97 | 0.92 | 0.93 | 0.88 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.37*** | 0.10 | 0.09 | 0.46*** | 0.54*** | 0.48*** |
| | (0.13) | (0.12) | (0.13) | (0.12) | (0.11) | (0.08) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.90 |
| Mean | 69.70 | 97.53 | 122.30 | 89.94 | 37.62 | 7.41 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,395. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. The sample does not contain counties bordering Nevada and Vermont. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the log of the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C5. Effects of childcare prices on birthrates, by age (both instruments)

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log (Childcare Price) | 0.02 | 0.02 | 0.03 | 0.01 | 0.02 | 0.01 |
| | (0.02) | (0.03) | (0.03) | (0.02) | (0.02) | (0.03) |
| $R^2$ | 0.98 | 0.98 | 0.96 | 0.95 | 0.96 | 0.89 |
| *IV* | | | | | | |
| Log (Childcare Price) | -0.64*** | -0.28** | -0.22 | -0.80*** | -0.93*** | -0.70*** |
| | (0.16) | (0.12) | (0.18) | (0.17) | (0.21) | (0.24) |
| $R^2$ | 0.94 | 0.97 | 0.96 | 0.91 | 0.92 | 0.88 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.16*** | 0.31*** | 0.34*** | 0.19*** | 0.17*** | -0.62*** |
| | (0.03) | (0.08) | (0.05) | (0.06) | (0.04) | (0.04) |
| Child-Staff Ratio | -157.12* | 146.91 | 203.04* | -200.02** | -280.54** | -823.51*** |
| | (86.28) | (125.81) | (103.99) | (78.94) | (113.81) | (74.66) |
| $R^2$ | 0.98 | 0.98 | 0.96 | 0.95 | 0.96 | 0.89 |
| Mean | 69.78 | 99.21 | 122.42 | 89.62 | 37.34 | 7.40 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 8,094. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2009-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. Coefficients and standard errors multiplied by 100. “20-44” is the log of the county-level birthrate per 1000 women aged 20 to 44, “20-24” the log of the birthrate per 1000 women aged 20-24, and so on. “Log (Childcare Price)” is the log of the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. “Maximum Group Size” is the state-level maximum group size average for 0 to 2 year olds. “Child-Staff Ratio” is the state-level child-staff ratio average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C6. Robustness of estimates to weighting by population

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log (Childcare Price) | -0.00 | 0.00 | 0.03 | -0.00 | 0.01 | -0.03 |
| | (0.03) | (0.04) | (0.04) | (0.03) | (0.03) | (0.03) |
| $R^2$ | 0.99 | 0.99 | 0.98 | 0.98 | 0.96 | 0.88 |
| *IV* | | | | | | |
| Log (Childcare Price) | -0.63*** | -0.30 | -0.27 | -0.81*** | -0.88*** | -0.79*** |
| | (0.15) | (0.19) | (0.20) | (0.15) | (0.21) | (0.21) |
| $R^2$ | 0.98 | 0.99 | 0.98 | 0.96 | 0.95 | 0.87 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.38*** | 0.18* | 0.16 | 0.48*** | 0.54*** | 0.49*** |
| | (0.11) | (0.11) | (0.12) | (0.08) | (0.11) | (0.12) |
| $R^2$ | 0.99 | 0.99 | 0.98 | 0.98 | 0.96 | 0.88 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the log of the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by population in that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C7. Robustness of IV estimates of the effect of childcare prices on birthrates to leave-one-state-out analysis

| Dropped State | Coefficient | Standard Error | P-value |
|---|---|---|---|
| *All states* | -0.57 | (0.14) | 0.00 |
| AK | -0.57 | (0.14) | 0.00 |
| AL | -0.57 | (0.14) | 0.00 |
| AZ | -0.63 | (0.15) | 0.00 |
| CA | -0.70 | (0.09) | 0.00 |
| CT | -0.56 | (0.14) | 0.00 |
| DE | -0.57 | (0.14) | 0.00 |
| FL | -0.37 | (0.20) | 0.09 |
| ID | -0.57 | (0.14) | 0.00 |
| IL | -0.43 | (0.13) | 0.01 |
| KS | -0.57 | (0.14) | 0.00 |
| KY | -0.57 | (0.14) | 0.00 |
| LA | -0.57 | (0.14) | 0.00 |
| MA | -0.63 | (0.13) | 0.00 |
| MD | -0.56 | (0.14) | 0.00 |
| ME | -0.57 | (0.14) | 0.00 |
| MN | -0.58 | (0.15) | 0.00 |
| NE | -0.57 | (0.15) | 0.00 |
| NV | -0.57 | (0.15) | 0.00 |
| OH | -0.56 | (0.13) | 0.00 |
| OR | -0.58 | (0.13) | 0.00 |
| PA | -0.57 | (0.14) | 0.00 |
| SC | -0.57 | (0.14) | 0.00 |
| SD | -0.58 | (0.14) | 0.00 |
| TN | -0.56 | (0.14) | 0.00 |
| TX | -0.58 | (0.24) | 0.03 |
| UT | -0.57 | (0.14) | 0.00 |
| VA | -0.56 | (0.14) | 0.00 |
| VT | -0.57 | (0.14) | 0.00 |
| WA | -0.60 | (0.21) | 0.02 |
| WI | -0.61 | (0.14) | 0.00 |

Notes: Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated IV effects of log childcare prices on the log of the birthrate per 1000 women aged 20 to 49 for the full sample of states ("All states"), and for subsamples where I drop one state at a time. The childcare price is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at 99th percentile. The instrumental variable is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to women aged 20 to 44. Standard errors are clustered at the state-year level.

Appendix Table C8. Robustness of IV estimates of the effects of childcare prices on birthrates to winsorising

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *95 percentile* | | | | | | |
| Log (Childcare Price) | -0.47*** | -0.12 | -0.10 | -0.59*** | -0.69*** | -0.62*** |
| | (0.15) | (0.16) | (0.17) | (0.17) | (0.20) | (0.15) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.94 | 0.94 | 0.88 |
| *98 percentile* | | | | | | |
| Log (Childcare Price) | -0.54*** | -0.14 | -0.12 | -0.70*** | -0.83*** | -0.76*** |
| | (0.15) | (0.18) | (0.19) | (0.16) | (0.21) | (0.18) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.93 | 0.93 | 0.88 |
| *99 percentile* | | | | | | |
| Log (Childcare Price) | -0.57*** | -0.14 | -0.12 | -0.74*** | -0.88*** | -0.81*** |
| | (0.14) | (0.18) | (0.20) | (0.15) | (0.21) | (0.19) |
| $R^2$ | 0.95 | 0.98 | 0.97 | 0.92 | 0.93 | 0.88 |
| *No winsorising* | | | | | | |
| Log (Childcare Price) | -0.69*** | -0.16 | -0.15 | -0.91*** | -1.11*** | -1.03*** |
| | (0.18) | (0.20) | (0.23) | (0.19) | (0.27) | (0.28) |
| $R^2$ | 0.94 | 0.98 | 0.97 | 0.91 | 0.91 | 0.86 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women for different levels of winsorising of prices. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 95th percentile, 98th percentile, and 99th percentile and with no winsorising. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C9. Robustness of estimates to clustering standard errors at state level

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *IV* | | | | | | |
| Log (Childcare Price) | -0.57*** | -0.14 | -0.12 | -0.73*** | -0.87*** | -0.80*** |
| | (0.21) | (0.21) | (0.23) | (0.23) | (0.30) | (0.31) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.92 | 0.93 | 0.88 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.37*** | 0.10 | 0.08 | 0.46*** | 0.54*** | 0.49*** |
| | (0.11) | (0.15) | (0.16) | (0.11) | (0.13) | (0.11) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.89 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state level, in parentheses.

Appendix Table C10. Robustness of IV estimates of the effects of childcare prices on birthrates to instrument missing values

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *NA = 25* | | | | | | |
| Log (Childcare Price) | -0.57*** | -0.13 | -0.12 | -0.73*** | -0.88*** | -0.81*** |
| | (0.15) | (0.19) | (0.20) | (0.15) | (0.21) | (0.20) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.92 | 0.93 | 0.88 |
| *NA = 30* | | | | | | |
| Log (Childcare Price) | -0.57*** | -0.14 | -0.12 | -0.73*** | -0.87*** | -0.80*** |
| | (0.14) | (0.18) | (0.20) | (0.15) | (0.21) | (0.19) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.92 | 0.93 | 0.88 |
| *NA = 35* | | | | | | |
| Log (Childcare Price) | -0.57*** | -0.15 | -0.13 | -0.73*** | -0.87*** | -0.80*** |
| | (0.14) | (0.17) | (0.20) | (0.15) | (0.21) | (0.19) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.92 | 0.93 | 0.88 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated instrumental variable effects of log childcare prices on the log of birthrates per 1000 women for three different approaches to treating states with no maximum group size restrictions. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "NA=25" sets the maximum group size to 25 for states with no regulation, "NA=30" sets the maximum group size to 30 (baseline specification), and "NA=35" sets the maximum group size to 35. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C11. Robustness of estimates to removing bad controls

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Log(Childcare Price) | 0.01 | 0.02 | 0.03 | 0.01 | 0.01 | -0.02 |
| | (0.02) | (0.04) | (0.03) | (0.02) | (0.02) | (0.03) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.89 |
| *IV* | | | | | | |
| Log(Childcare Price) | -0.51*** | -0.11 | -0.04 | -0.59*** | -0.74*** | -0.75*** |
| | (0.12) | (0.16) | (0.18) | (0.14) | (0.18) | (0.17) |
| $R^2$ | 0.96 | 0.98 | 0.97 | 0.93 | 0.93 | 0.88 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 0.33*** | 0.07 | 0.02 | 0.38*** | 0.47*** | 0.47*** |
| | (0.09) | (0.11) | (0.12) | (0.09) | (0.10) | (0.08) |
| $R^2$ | 0.98 | 0.98 | 0.97 | 0.96 | 0.96 | 0.89 |
| Mean | 69.76 | 97.57 | 122.42 | 89.99 | 37.71 | 7.45 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of log childcare prices on the log of birthrates per 1000 women. Reduced form coefficients and standard errors multiplied by 100. "20-44" is the log of the county-level birthrate per 1000 women aged 20 to 44, "20-24" the log of the birthrate per 1000 women aged 20-24, and so on. "Childcare price" is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, winsorised at the 99th percentile. "Maximum Group Size" is the state-level maximum group size average for 0 to 2 year olds. All models control for male county median earnings, the male unemployment rate, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C12. Effects of childcare prices on second birthrates, by age

| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Childcare price | -0.08 | -0.12 | -0.11 | -0.08 | -0.07 | -0.04 |
| | (0.14) | (0.14) | (0.15) | (0.16) | (0.13) | (0.07) |
| $R^2$ | 0.55 | 0.70 | 0.60 | 0.58 | 0.71 | 0.78 |
| *IV* | | | | | | |
| Childcare price | -1.69* | -2.03* | -1.76 | -1.36 | -1.46* | -1.03*** |
| | (0.98) | (1.17) | (1.20) | (1.13) | (0.82) | (0.28) |
| $R^2$ | 0.39 | 0.59 | 0.48 | 0.49 | 0.62 | 0.70 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 1.78 | 2.28 | 1.92 | 1.40 | 1.42 | 0.95** |
| | (1.19) | (1.45) | (1.45) | (1.29) | (0.97) | (0.47) |
| $R^2$ | 0.55 | 0.70 | 0.60 | 0.58 | 0.71 | 0.78 |
| Mean | 20.64 | 29.82 | 38.36 | 26.39 | 9.15 | 1.43 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of childcare prices on the log of second birthrates per 1000 women. Coefficients and standard errors multiplied by 100. “20-44” is the log of the county-level second birthrate per 1000 women aged 20 to 49, “20-24” the log of the second birthrate per 1000 women aged 20-24, and so on. “Childcare price” is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, adjusted for inflation using base year 2010 and winsorised at the 99th percentile. “Maximum Group Size” is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by total births to that age band. Standard errors, clustered at the state-year level, in parentheses.

Appendix Table C13. Effects of childcare prices on third birthrates, by age

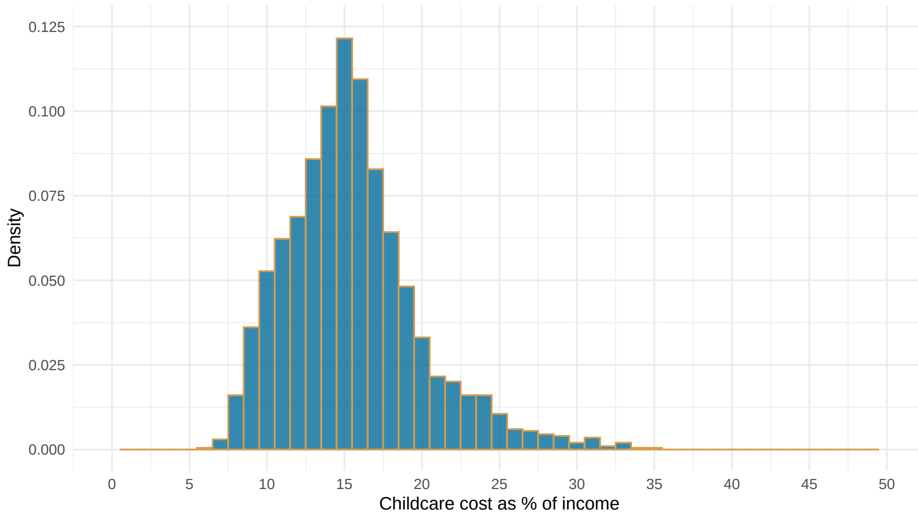
| | 20-44 | 20-24 | 25-29 | 30-34 | 35-39 | 40-44 |
|---|---|---|---|---|---|---|
| *OLS* | | | | | | |
| Childcare price | -0.07 | -0.08 | -0.07 | -0.10 | -0.04 | -0.04 |
| | (0.11) | (0.11) | (0.13) | (0.14) | (0.11) | (0.06) |
| $R^2$ | 0.64 | 0.77 | 0.68 | 0.61 | 0.63 | 0.66 |
| *IV* | | | | | | |
| Childcare price | -1.49* | -0.93 | -1.75* | -1.71* | -1.28* | -0.92*** |
| | (0.82) | (0.94) | (1.02) | (0.96) | (0.73) | (0.35) |
| $R^2$ | 0.50 | 0.74 | 0.56 | 0.45 | 0.50 | 0.56 |
| *Reduced Form* | | | | | | |
| Maximum Group Size | 1.57 | 1.05 | 1.91 | 1.77 | 1.25 | 0.86** |
| | (1.00) | (1.11) | (1.25) | (1.16) | (0.86) | (0.39) |
| $R^2$ | 0.64 | 0.77 | 0.68 | 0.61 | 0.63 | 0.66 |
| Mean | 12.09 | 10.68 | 22.27 | 19.20 | 8.01 | 1.34 |

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Notes: N = 7,495. Data: NVSS birth records, SEER county population counts, NDCP childcare prices, hand-collected maximum group size data, for 2010-2019, 2021-2022. This table shows the estimated effects of childcare prices on the log of third birthrates per 1000 women. Coefficients and standard errors multiplied by 100. “20-44” is the log of the county-level third birthrate per 1000 women aged 20 to 49, “20-24” the log of the third birthrate per 1000 women aged 20-24, and so on. “Childcare price” is the median weekly price for full-time care at a childcare centre averaged for 0 to 2 year olds, adjusted for inflation using base year 2010 and winsorised at the 99th percentile. “Maximum Group Size” is the state-level maximum group size average for 0 to 2 year olds. All models control for county median earnings, the unemployment rate, female labour force participation, the male-female ratio, a housing price index, racial and ethnic composition, and county and year fixed effects. Estimates weighted by total births to that age band. Standard errors, clustered at the state-year level, in parentheses.

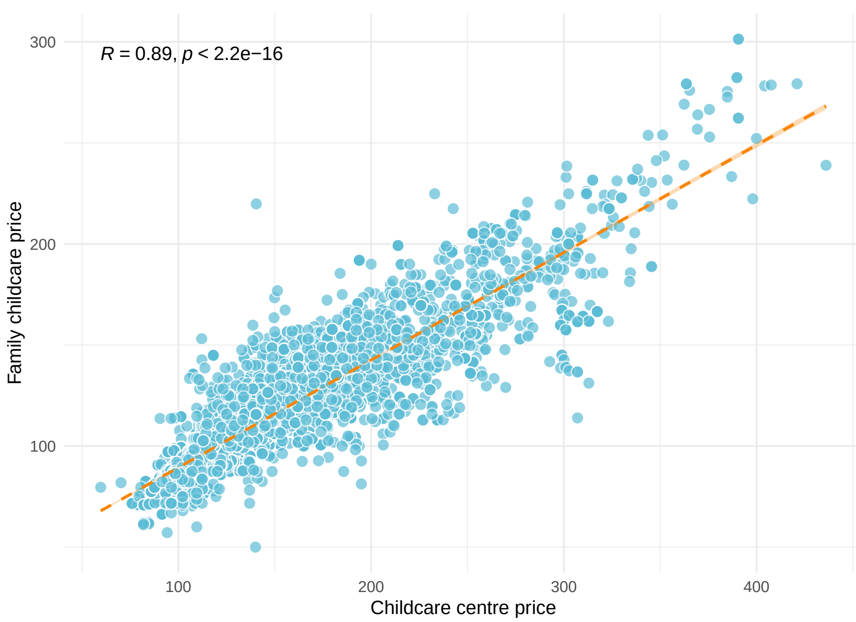
# D Appendix Figures

Appendix Figure D1. Distribution of avg. annual cost of full-time centre-based childcare for 0-2 years as a share of median household income, 2010




Notes: Data: National Database of Childcare Prices (including imputed data), American Community Survey, for 2010. The plot shows the distribution of the average annual cost for full-time care at a childcare centre for 0 to 2 year olds, as a percentage of median household income at the U.S. county level.

Appendix Figure D2. Scatterplot of centre-based childcare and family childcare prices




Notes: N=11,789. Data: NDCP childcare prices. This figure shows a scatterplot of the median weekly price for full-time care averaged for 0 to 2 year olds, adjusted for inflation using base year 2010, at childcare centres and at family childcare homes. $R$ is the Pearson correlation coefficient and $p$ is the two-sided p-value from testing the null hypothesis that $R = 0$.

Appendix Figure D3. Newspaper article on childcare regulations in Nevada

LAS VEGAS SUN

## Day care concerns: Staffing standards in Nevada below national averages

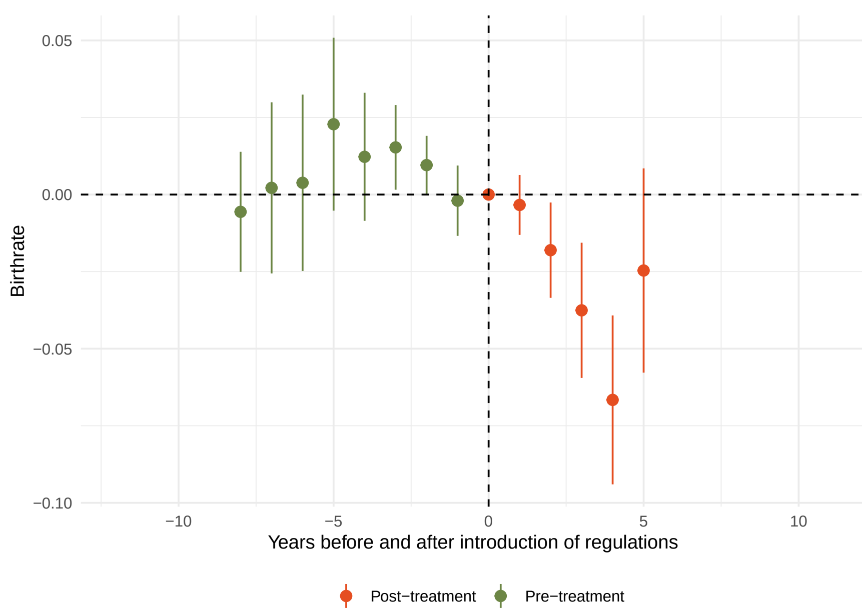
**Thursday, May 15, 2003 | 11:24 a.m.**

Nevada doesn't do as much as most other states to ensure that children are safe at day care centers, studies and experts say.

When it comes to child care staffing ratios, Nevada has some of the loosest regulations in the nation.

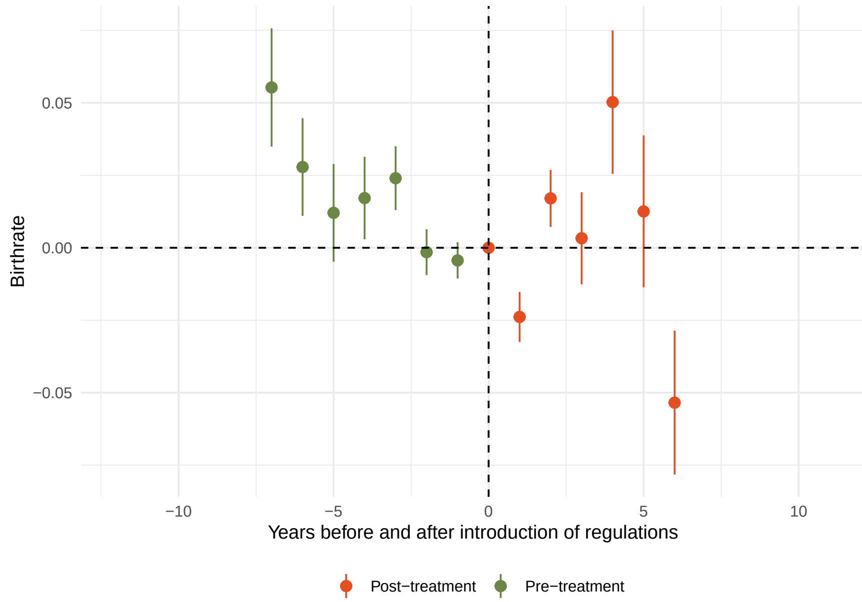
Nevada also ranks low in the number of licensed child care centers and in children served by government-subsidized child care, according to national comparisons. A state study last summer found that there were at least 6,000 children on waiting lists for child care.

Appendix Figure D4. Event study plot of childcare facility regulations on birthrates, Nevada



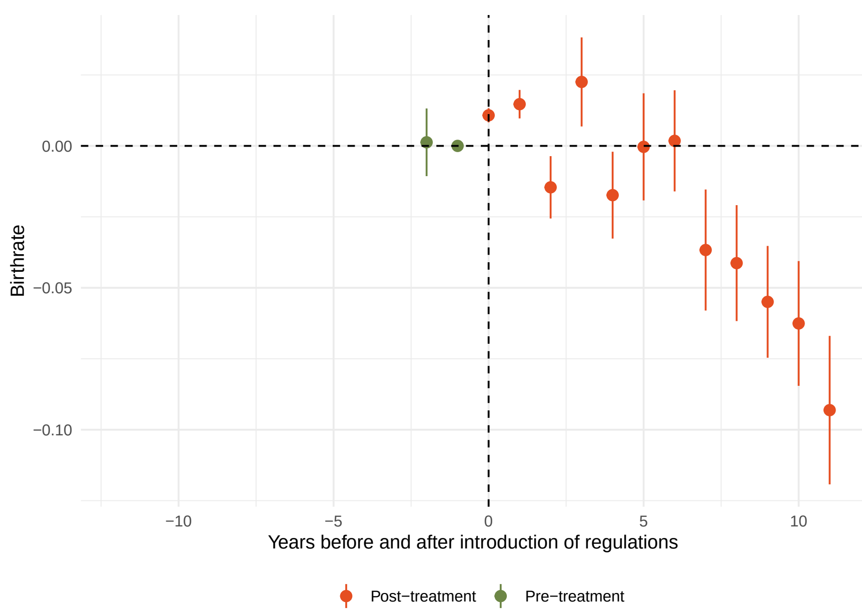

Notes: N=14,805. This figure shows an event study plot of effects of the introduction of childcare centre regulations in Nevada relative to control states on birthrates. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of the regulations. The y-axis is the log birthrates for women aged 30 to 34. In 2017 NV introduced group size requirements for the first time and increased staff-child ratios for 18 month and 3 year olds. The reference year is $t = 0$ as the regulations were introduced in September.

Appendix Figure D5. Event study plot of childcare facility regulations on birthrates, Vermont



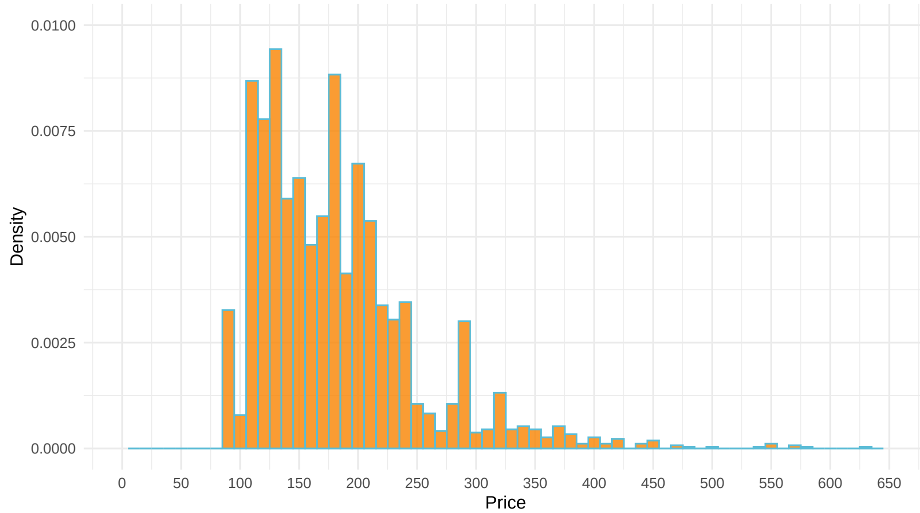

Notes: N=14,794. This figure shows an event study plot of effects of the introduction of childcare centre regulations in Vermont relative to control states on birthrates. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of the regulations. The y-axis is the log birthrates for women aged 30 to 34. In 2016 VT relaxed group size requirements for 18 month olds. The reference year is $t = 0$ as the regulations were introduced in September.

Appendix Figure D6. Event study plot of childcare facility regulations on birthrates, Delaware



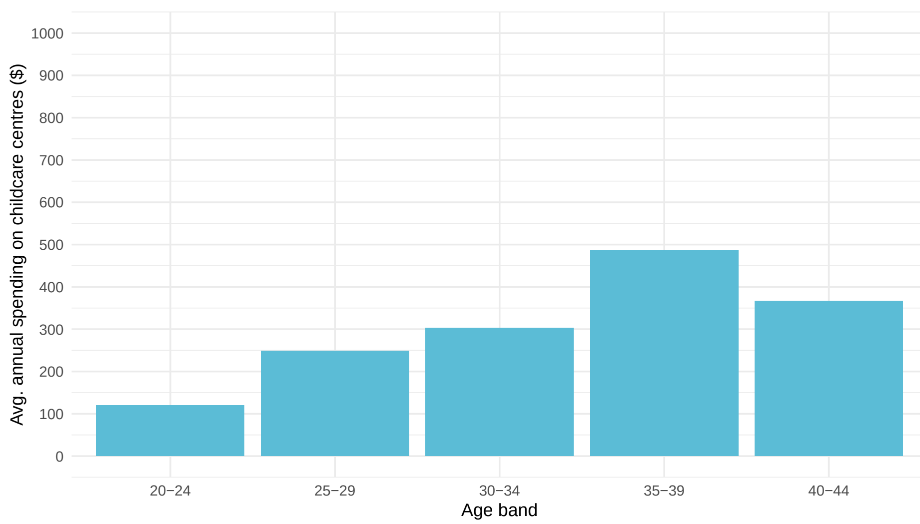

Notes: N=14,668. This figure shows an event study plot of effects of the introduction of childcare centre regulations in Delaware relative to control states on birthrates. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of the regulations. The y-axis is the log birthrates for women aged 30 to 34. In 2011 DE introduced group size requirements for the first time. The reference year is $t = -1$ as the regulations were introduced in January.

Appendix Figure D7. Distribution of median price of full-time centre-based childcare for 0-2 years, 2022




Notes: Data: National Database of Childcare Prices (including imputed data), for 2022. The plot shows the distribution of the median price for full-time care at a childcare centre for 0 to 2 year olds at the U.S. county level.

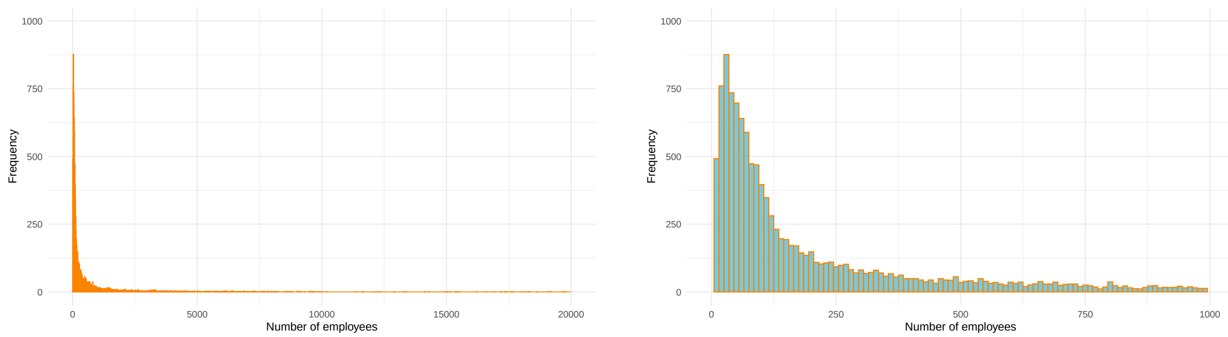
Appendix Figure D8. Avg. annual spending on childcare centres for 2010, by age




Note: Data: Consumer Expenditure Survey, for 2010. This figure shows the average annual spending on childcare centres by age of the respondent, for respondents with any children under 3. Childcare centres defined as day care centres, nurseries, and preschools.

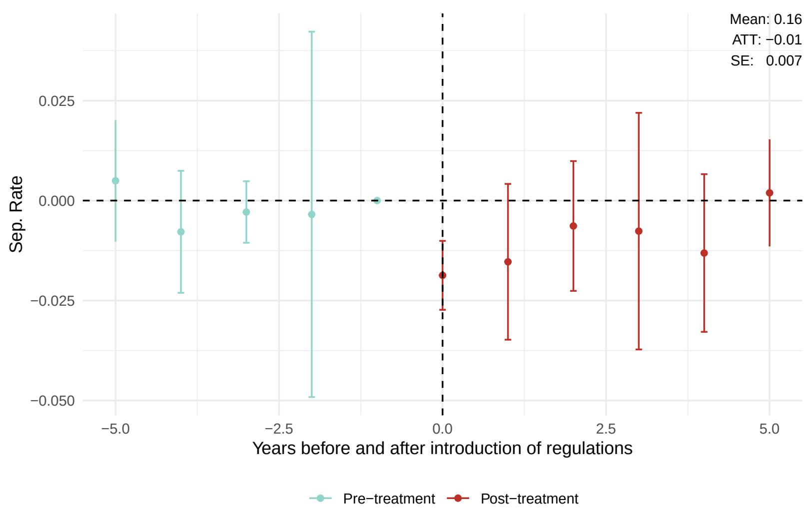
Appendix Figure D9. Distribution of number of employees in the childcare industry

(a) Full sample (b) Counties with <1000 employees



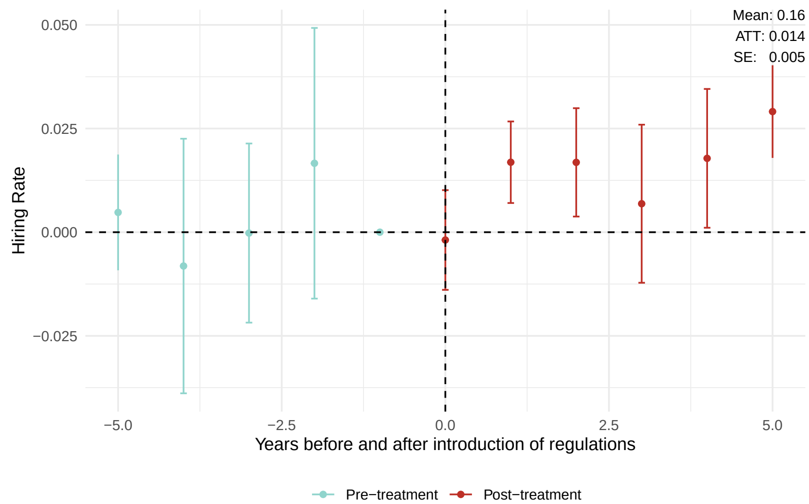

Note: N=22,740. Data: Census County Business Patterns, for 2008-2022. The plots show the distribution of the number of employees in the childcare industry at the U.S. county level.

Appendix Figure D10. The effect of loosening childcare regulations on the separation rate



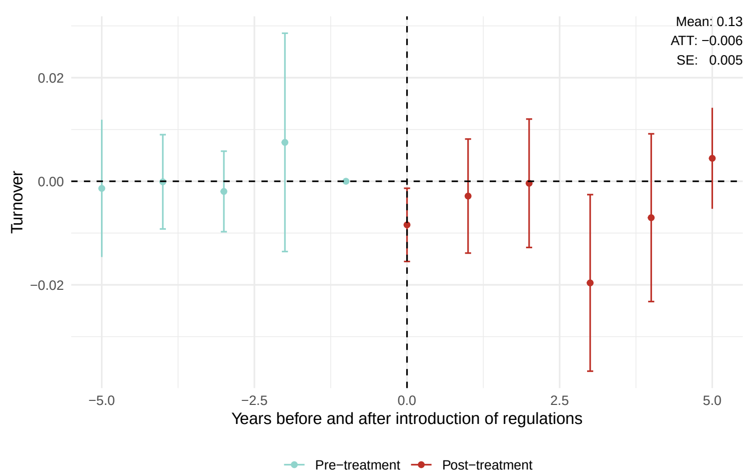

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the job separation rate in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D11. The effect of loosening childcare regulations on the hiring rate



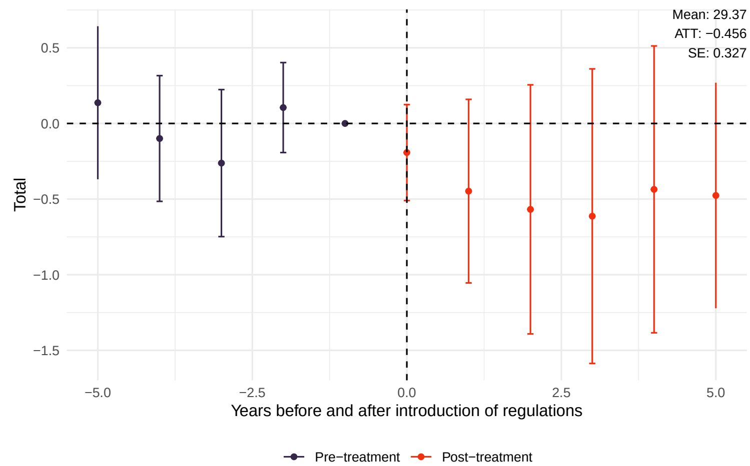

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the hiring rate in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D12. The effect of loosening childcare regulations on staff turnover



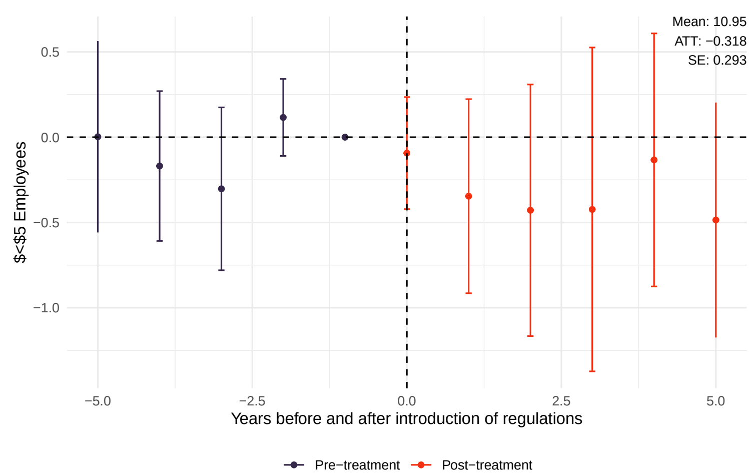

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is staff turnover in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D13. The effect of loosening childcare regulations on the total number of childcare establishments



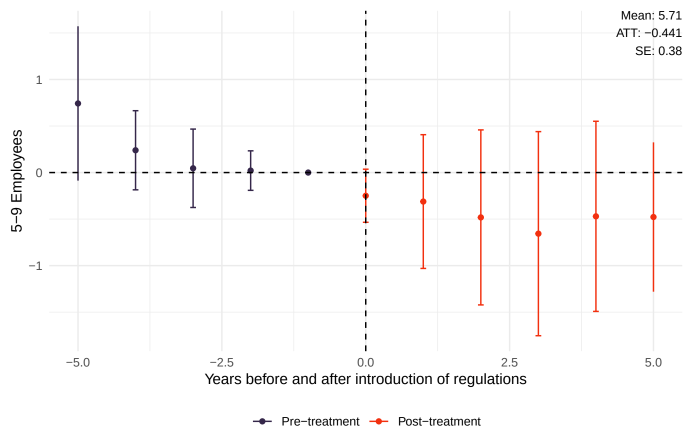

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D14. The effect of loosening childcare regulations on the total number of childcare establishments with fewer than 5 employees



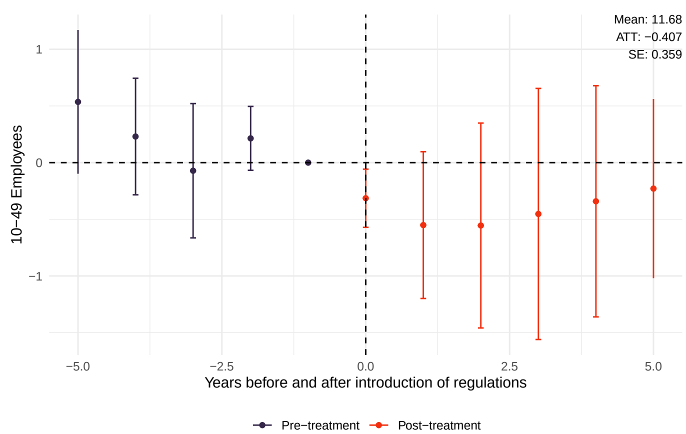

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with fewer than 5 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D15. The effect of loosening childcare regulations on the total number of childcare establishments with 5-9 employees



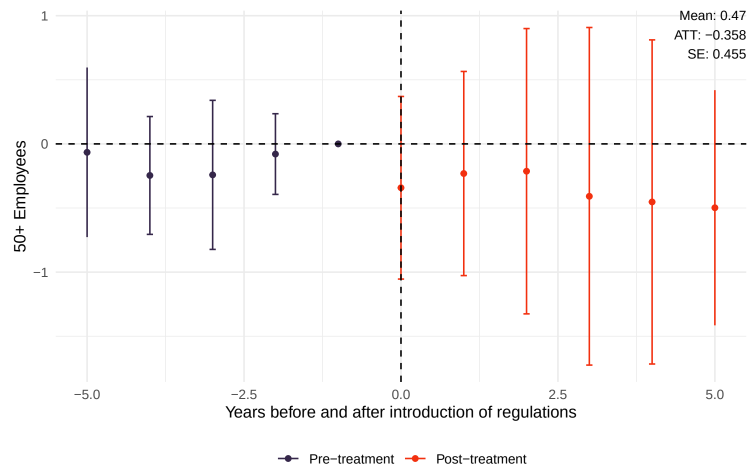

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with 5 to 9 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D16. The effect of loosening childcare regulations on the total number of childcare establishments with 10-49 employees



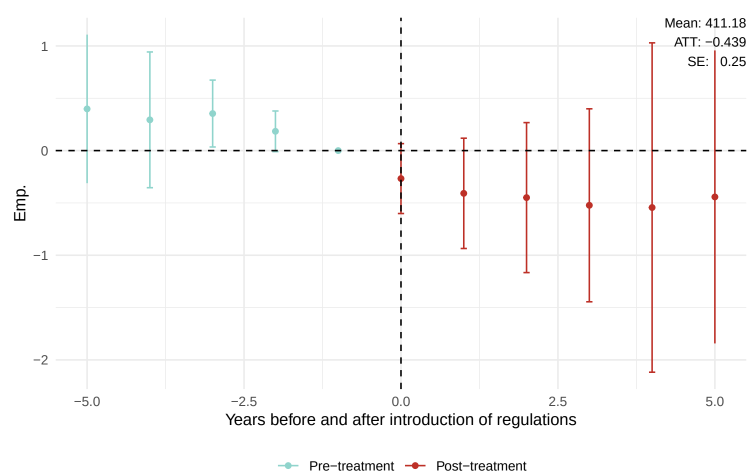

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with 10 to 49 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D17. The effect of loosening childcare regulations on the total number of childcare establishments with over 50 employees



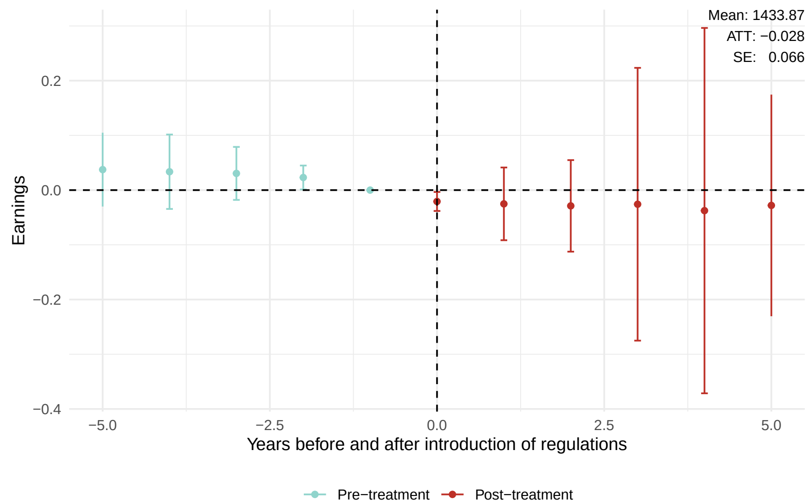

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a less stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with more than 50 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D18. The effect of more stringent childcare regulations on employment



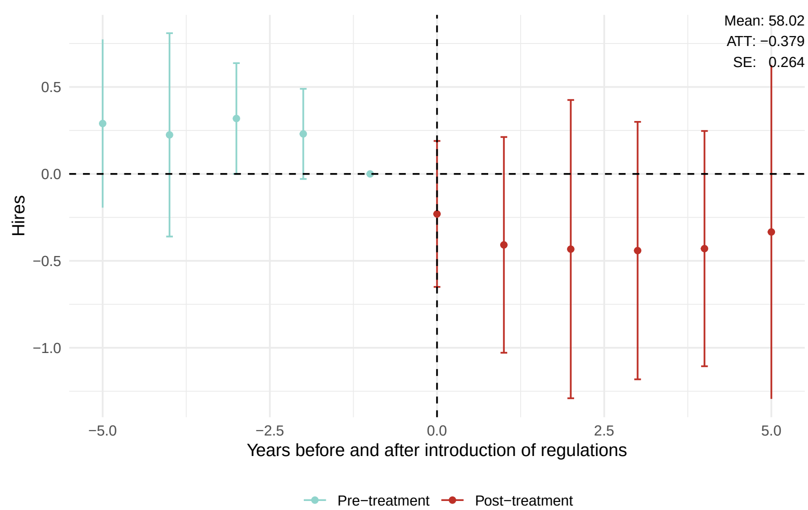

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log of employment in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D19. The effect of more stringent childcare regulations on earnings



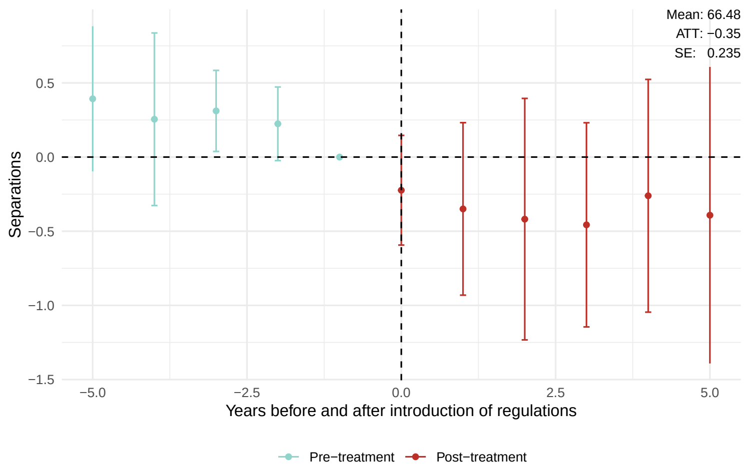

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log of earnings in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D20. The effect of more stringent childcare regulations on new hires



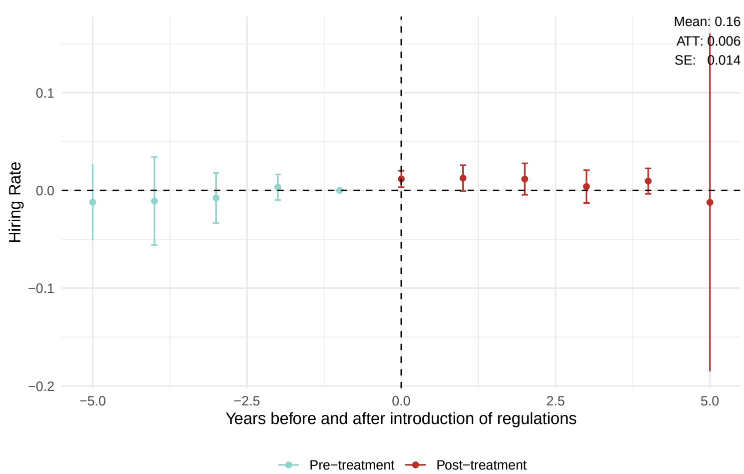

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log of new hires in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D21. The effect of more stringent childcare regulations on job separations



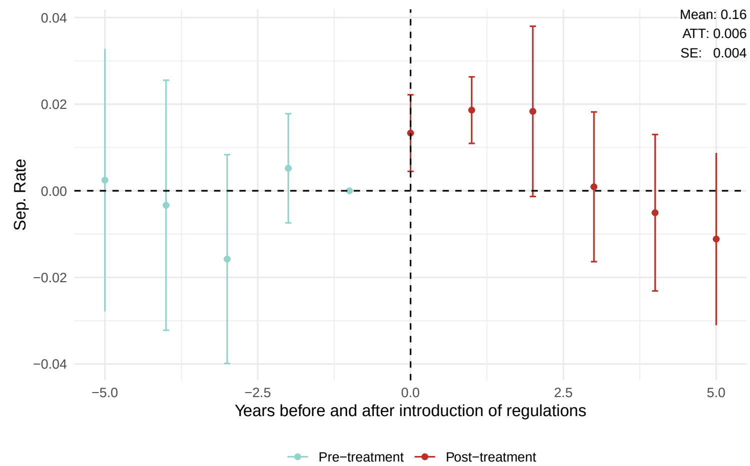

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log of job separations in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D22. The effect of more stringent childcare regulations on the hiring rate



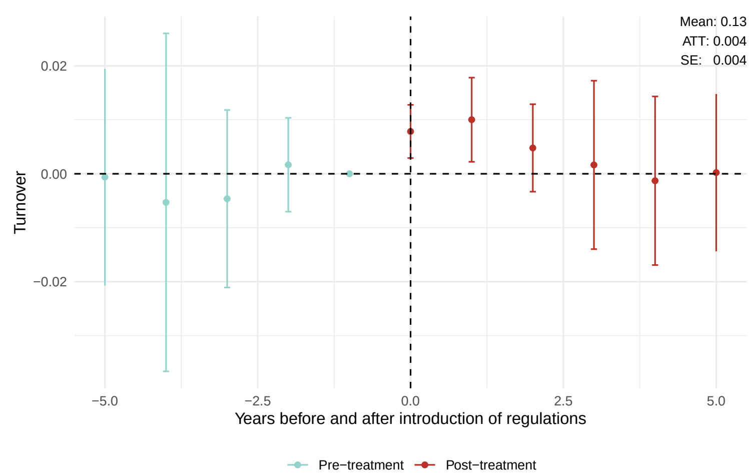

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the hiring rate in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D23. The effect of more stringent childcare regulations on the separation rate



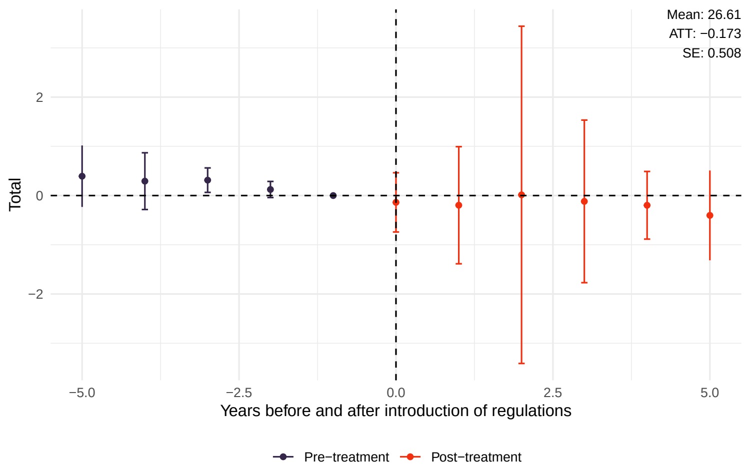

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the job separation rate in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D24. The effect of more stringent childcare regulations on staff turnover



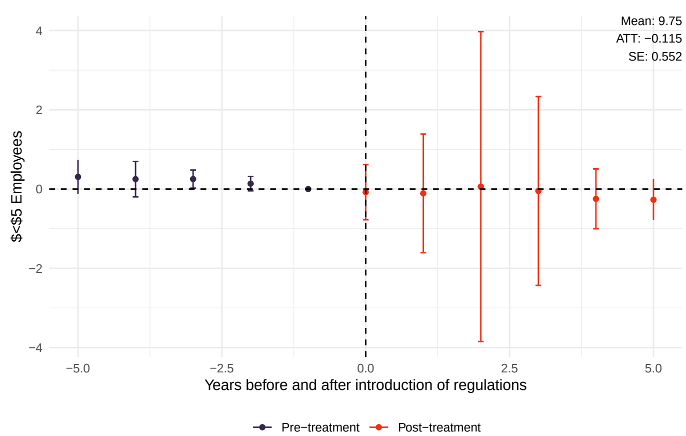

Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is staff turnover in the childcare industry. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D25. The effect of more stringent childcare regulations on the total number of childcare establishments



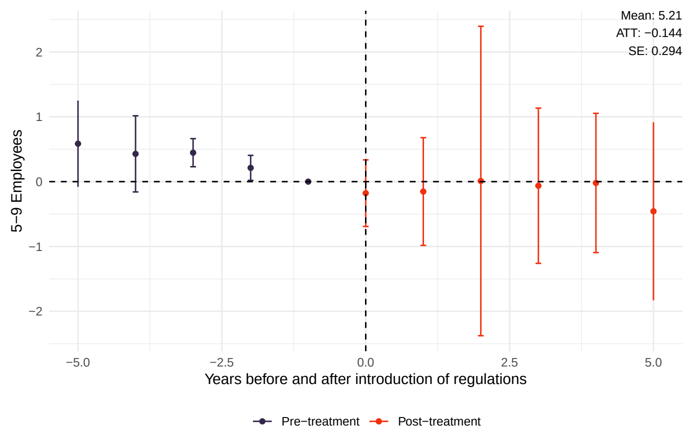

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D26. The effect of more stringent childcare regulations on the total number of childcare establishments with fewer than 5 employees



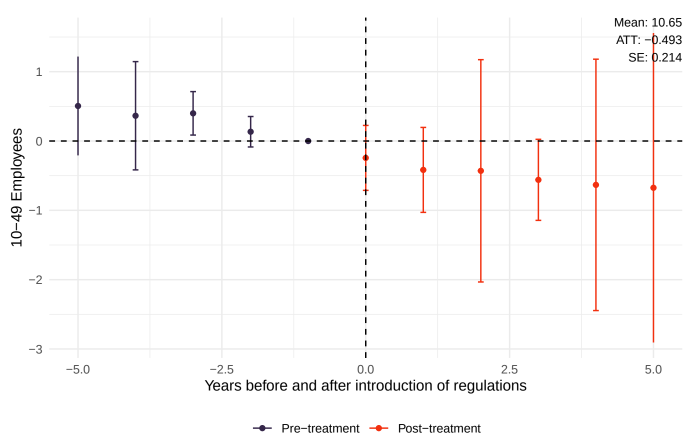

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with fewer than 5 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D27. The effect of more stringent childcare regulations on the total number of childcare establishments with 5-9 employees



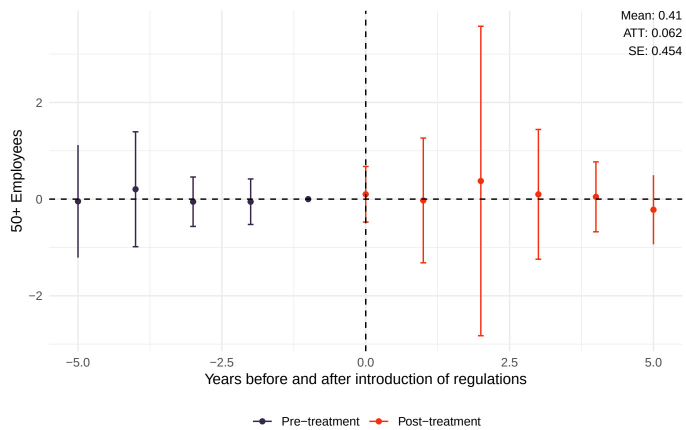

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with 5 to 9 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D28. The effect of more stringent childcare regulations on the total number of childcare establishments with 10-49 employees



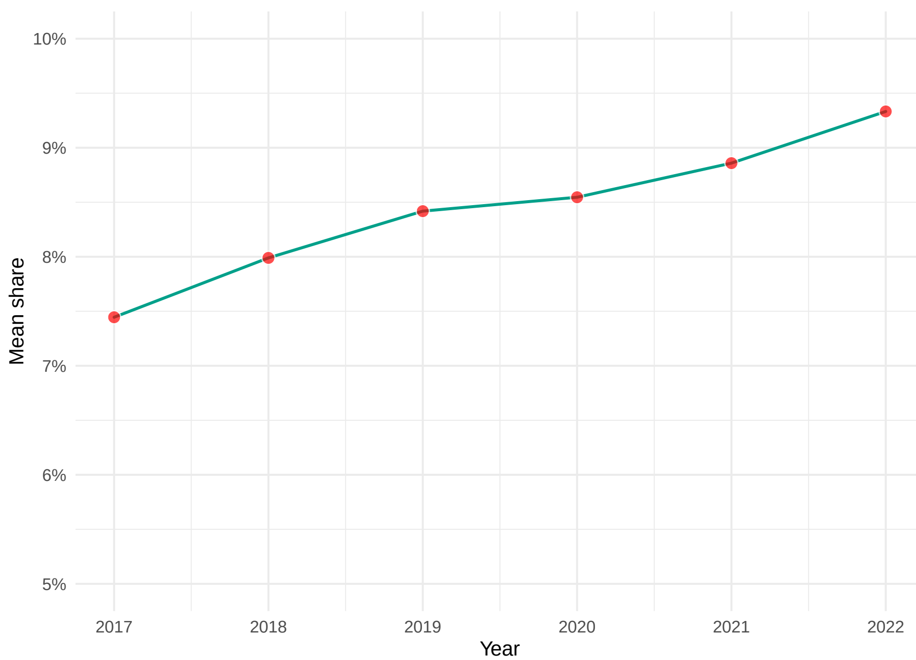

Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with 10 to 49 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D29. The effect of more stringent childcare regulations on the total number of childcare establishments with over 50 employees




Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 6 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical line is the year of regulatory change. The x-axis is relative time to a more stringent change in the maximum group size or staff-child ratio. The y-axis is the log number of childcare establishments with more than 50 employees. Controls for median earnings, unemployment rate, and racial and ethnic composition. The model includes state and year fixed effects. Estimates weighted by the population under five. Standard errors clustered at the state-year level.

Appendix Figure D30. Mean share of NAEYC accredited programmes over time




Notes: N=30. Data: National Association for the Education of Young Children (NAEYC). This figure shows the mean share of NAEYC accredited programmes at the state level between 2017 and 2022.

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