The Price of Parenthood: Childcare Costs and Fertility *

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Abstract

Across the developed world, fertility rates have fallen below replacement level, raising concerns over shrinking workforces and ageing populations. In the U.S., the rate has fallen to a historic low, and potential parents cite financial constraints as a barrier to having children. A substantial and early cost for parents is childcare. 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 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). Additionally, reduced form results show that changes in the regulations directly impact birthrates. Declines are largest amongst women aged 30 and above, which can be partly explained by reductions in second and third births. I propose a theoretical model to further explain the 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, I show that older parents spend more on formal childcare, and that more educated women (with higher incomes) exhibit larger price responses.

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1 Introduction

Developed countries across the world are experiencing a fertility crisis, as fertility rates drop further below replacement level. Low fertility rates can precipitate a shrinking future workforce and ageing population, which will slow economic growth and strain social services, if not addressed through increased immigration.

Would-be parents cite financial pressures as a top factor inhibiting them from starting or expanding their family (Institute for Family Studies, 2022), with childcare representing 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 burdened. 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 childcare costs is limited, reflecting the difficulty of finding plausibly exogenous cost variation. In the U.S. context, only one paper has examined the causal effect of changes in childcare costs on fertility. The remaining literature has focused on policy reforms that shift the cost of childcare (e.g. cost caps), in European settings characterised by far higher levels of public childcare spending and provision than in the U.S.

To answer this question, I assemble a unique dataset on childcare facility regulations that allows me to construct a novel instrument for childcare prices. Specifically, I compile state-level data on the mandated maximum group size and minimum child–staff ratios by child age between 2010 and 2022. Because existing sources are incomplete and contain errors, I collect data directly from historical state administrative codes and licensing regulations. These regulations affect childcare prices by limiting capacity and dictating staffing requirements. This instrumental variables (IV) strategy differs from quasi-experimental approaches used 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 this dataset to Vital Statistics birth records and the first national dataset on childcare prices, the National Database of Childcare Prices (NDCP).

I document key facts about prices in the U.S. using the NDCP. Childcare costs 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, plotting 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 begin by showing that childcare facility regulations significantly impact the price of childcare for children under 3, evidencing instrument relevance. 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 for 0 to 2 year olds 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 (which could reflect remaining staff being more experienced or of higher quality). However, I do not find evidence that changes that tightened the regulations had statistically significant effects on employment or market size, which may reflect the heterogeneity in the extent of regulatory shifts across the treated states.

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. Indeed, I find null effects when I run an OLS regression, suggesting that endogeneity is a problem. 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 weekly price of childcare for 0 to 2 year olds leads to a 5.7% decrease in the birthrate of women aged 20 to 44. This is equivalent to 4 births per 1000 women. Reduced form estimates show that increases in the maximum group size impact birthrates. An increase in the maximum group size by 10 children is associated with a rise in birthrates of 3.7%. Births to White, Black, and Hispanic mothers are all price sensitive. 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 weekly 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 impacts fertility decisions. To respond to this concern, I first show that my 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 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. This price sensitivity is reinforced if mothers dislike providing the majority of childcare themselves. Additionally, second births to older mothers are more price sensitive simply because the total spending on childcare rises.

I test my model predictions and identify 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, 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., 2002; 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. There is less work examining the cost of childcare, as discussed above. This paper brings novel evidence on the causal relationship between childcare prices and fertility.

Most empirical evidence on childcare costs and fertility comes from the European context, where public provision of childcare is more common and spending on policies to support families is higher. The cost of childcare as a share of household income is substantially higher in the U.S. than other OECD countries (OECD, 2022). The introduction of universal childcare in Germany led to an expansion in fertility, for second and third births in particular (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. However, 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)[1].

The causal effects of childcare costs on fertility in the U.S. remain understudied outside of the structural modelling literature[2]. Early work by Blau and Robins (1989) suggests that

[1] 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.

[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 studies 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.

childcare costs are birthrate reducing in the U.S. Averett and Wang (2023) finds 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 bring novel evidence on how childcare price elastic potential mothers and parents are with respect to childbearing in a setting where access to high quality, affordable childcare is limited for most.

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 (less than 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)[3]. 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

[3]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.

Household Education Surveys (NHES) in 2019 shows 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 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 [4].

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.

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

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 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.

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, which is non-trivial as many states do not publish historical versions of their regulations/code along with the current version. Additionally, it is unclear from the documents when the regulations last changed. To help assemble the time series and be confident in the exact year of any change, I use legal research resources such as "Casetext", which often highlight the history of changes in laws. Identifying the exact year of the change allows me to search for updated regulation documents for that year, or bulletins with the revisions. 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 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. Specifically, 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 Section **??**. I use the QWI data to obtain a proxy for childcare quality: staff turnover.

For analysis of the impacts of the childcare facility regulations on childcare markets, I use the number of childcare establishments (total, and by number of employees) from the CBP. I use employment (the count of beginning of quarter employment), earnings (average monthly earnings for beginning-of-quarter employment), new hires (the count of new hires), job separations (the count of separations), the hiring rate (the end-of-quarter hiring rate), the separation rate (the beginning-of-quarter separation rate), and staff turnover (stable turnover) from the QWI.

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[5], 1,415 unique counties, and 7,495 county-years for the main county level analysis. For the individual

[5] 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

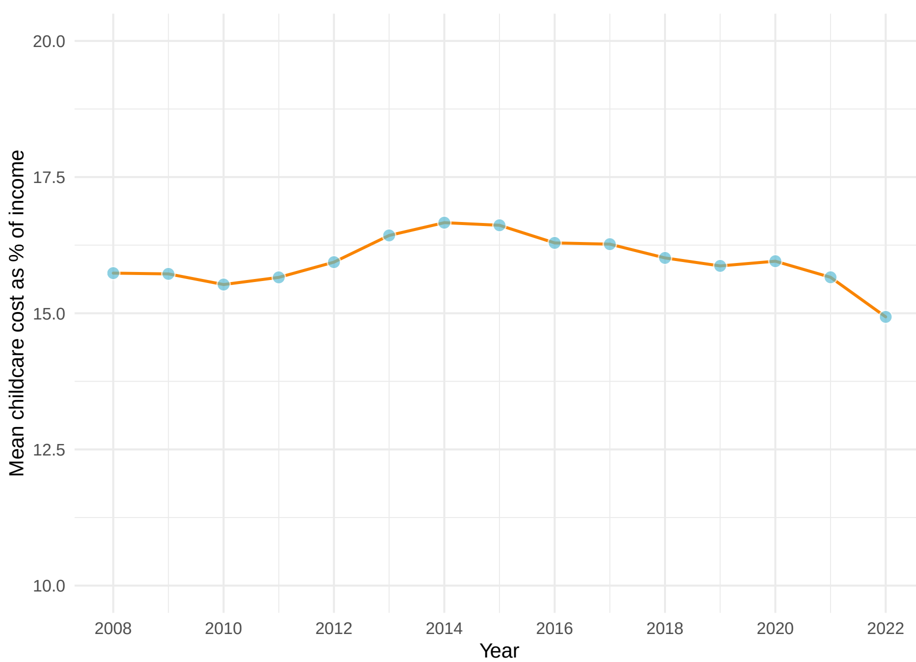
level analysis, I create separate samples of first, second and third time mothers to analyse birth spacing decisions for these subgroups. I drop any second (third) births that occur less than 9 months after the first (second) birth. I also remove multiple births to ensure that I am comparing births of 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.

3.3 Descriptive statistics

3.3.1 Descriptive patterns in the cost of childcare

We observe several patterns and facts about 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).

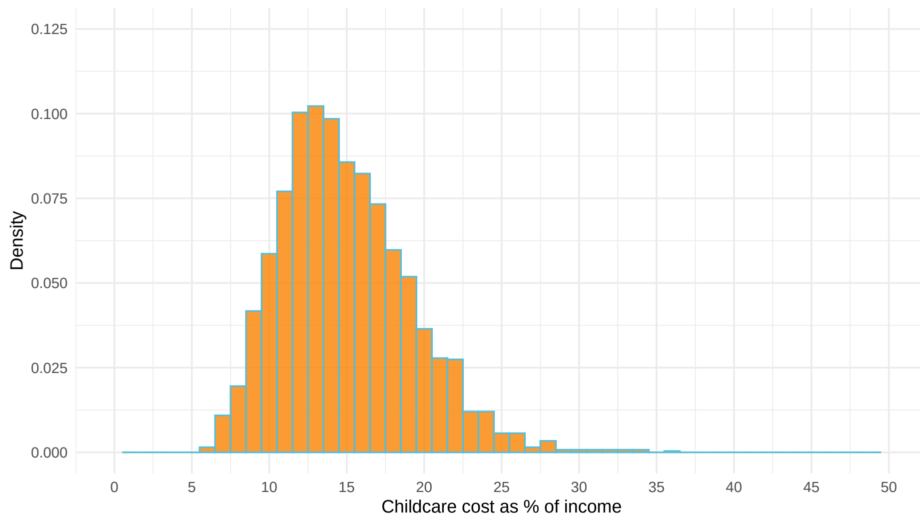
Figure 1. Avg. annual cost of full-time centre based childcare for 0-2 years as a share of median household income over time



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 E1 for the 2010 plot).

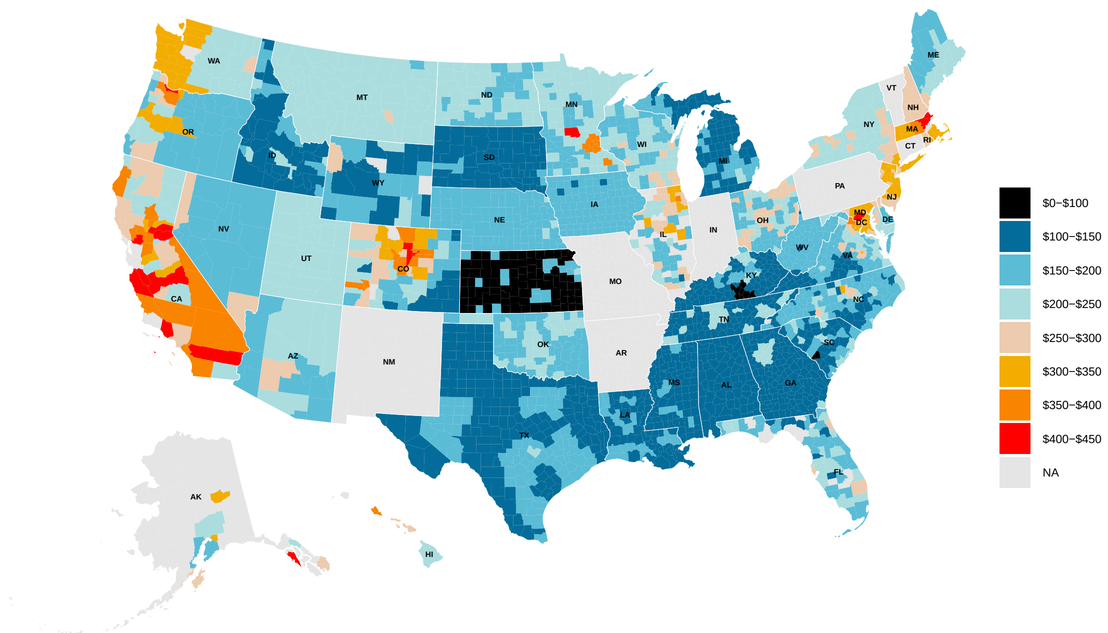
Figure 2. Distribution of avg. annual cost of full-time centre based childcare for 0-2 years as a share of median household income, 2022



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.

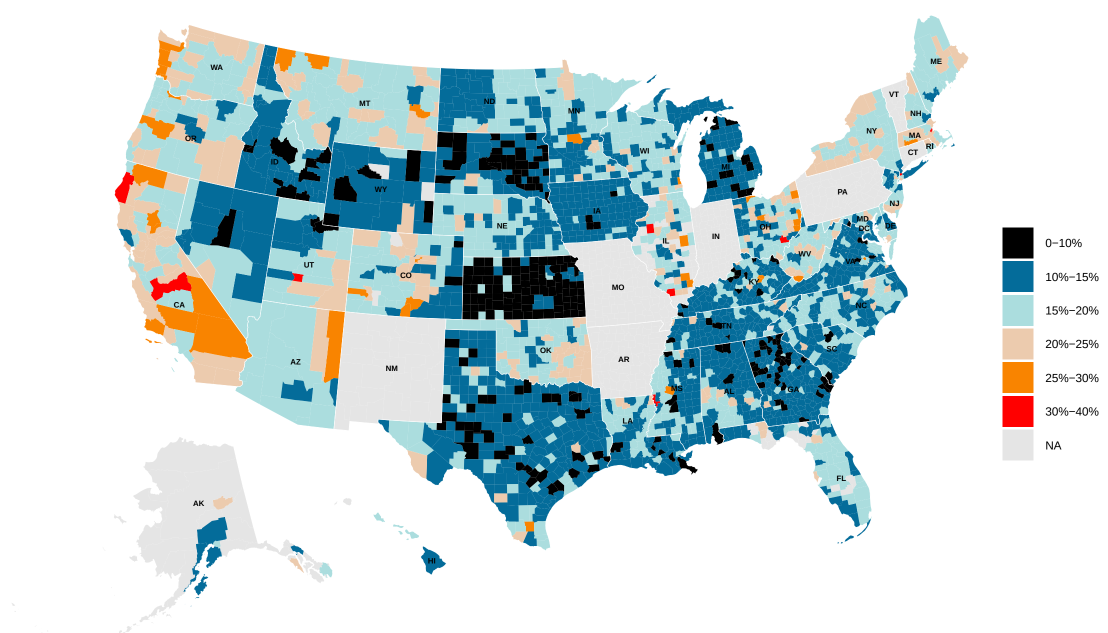
There is substantial geographical variation in the cost of childcare, with parents living on the West Coast and in the Northeast facing much higher prices. We also observe this pattern in the geographical distribution of the annual cost of childcare as a share of median household income, but to a lesser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

3.3.2 Sample

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.

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.

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 δ_c and time fixed effects γ_t to account for time-invariant differences across counties and time trends. I cluster standard errors at the state-year level[6]. The coefficient of interest is β, 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 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[7]. 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 (δ_c) and time (γ_t) fixed effects and cluster standard errors at the state-year level. The coefficient of interest β 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 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

[6]Appendix Table D2 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.

[7]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.

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.

4.2 Identification

The key identifying assumptions for 2SLS are relevance and the exclusion restriction. I first discuss relevance, then present my results, then discuss the exclusion restriction and additional assumptions in Subsection 5.3.

4.2.1 Relevance

The instrument is relevant if it is highly correlated with the endogenous regressor, childcare prices, in our empirical specification. I show evidence of a strong first stage in Table 2. I show both the raw childcare price (adjusted for inflation using base year 2010) as the outcome variable, and the log of the childcare price. The former is simpler to interpret as a first stage, but the latter is what I use in the two-stage least squares analysis. Table 2 shows that an increase in the maximum group size by one child reduces the weekly childcare price for 0 to 2 year olds by $1.05. 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 D1).

Table 2. First stage

	Childcare Price	
	Price	Log(Price) $\times$100
Maximum Group Size	-1.05***	-0.57***
	(0.23)	(0.03)
Mean (Childcare Price)	146.66	146.66
Mean (Maximum Group Size)	16.10	16.10
F-stat	21.07	369.72

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

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 Results

5.1 Birthrate results

5.1.1 Main results

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 D4, are consistent in coefficient size and significance.

The IV estimates rest on the exclusion restriction, which I discuss in Section 4. However, 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 would 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.

5.1.2 Heterogeneity analysis

Birthrates and preferences for non-parental childcare differ across various groups within a population, due 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 estimates differ in absolute value, but are not statistically significant from each other. 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 Birth timing results

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 be the result of mothers who would have had larger intervals between births deciding to not have a third birth at all. 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

The exclusion restriction is satisfied if the childcare regulations impact birth outcomes only through the price of childcare, and not via other channels. It is not possible to directly test this assumption, but we can consider potential violations.

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 indicates that childcare centre prices are representative of the formal care market. In Appendix Figure E4 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 5.1.1, I show evidence of no statistically significant effects on younger mothers, and I show that these mothers consume less centre based care in Section 8. 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 D12, 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. 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 not all states have a QRIS system. Furthermore, states do not publish their historical QRIS data.

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 D13 I control for the staff turnover rate in the childcare sector; this has limited impact on my estimates.

Nonetheless, I proceed to quantify the effect of the quality channel. To do so, I conduct a bounding exercise in Appendix A.1 to explore how such a quality channel affects the size and direction of my estimates. To quantify the potential bias, I secured data from 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 β under the assumption that quality of childcare directly impacts birthrates. I describe the NAEYC data and set out the bounding analysis in Appendix A.1.

5.3.2 Additional assumptions

The instrument must also address conditional independence. Other than through their effect on price, the childcare facility regulations must be uncorrelated with birthrates and individual birth timing outcomes (conditional on covariates). Including county fixed effects accounts for time-invariant local factors (e.g. cultural norms), and time fixed effects accounts 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 control variables help address potential confounding from within-county trends that may be correlated with the regulations and birthrates.

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 E5). 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. Rooms with sufficient space limit overcrowding and can promote increased staff-child interaction and safe child-to-child interaction, 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. To assess this assumption, in Appendix Figure E6, I plot the cumulative distribution functions (CDF) of the birthrates for counties in treated and untreated, or not yet treated, states. The CDFs do not cross, which shows stochastic dominance; the birthrates for counties without regulatory changes are stochastically larger than those for counties with regulations. Further, a Kolmogorov-Smirnov test confirms stochastic dominance. I test the null hypothesis that the prices for post-treatment counties come from the same distribution as prices for pre-treatment counties, against the alternative hypothesis that the former stochastically dominates the second. The null hypothesis is rejected with $p < 0.001$. I then run a second Kolmogorov-Smirnov test where the null is the same, but the alternative hypothesis is that distribution of the price for pre-treatment counties lies above the same distribution for post-treatment counties. I cannot reject the null hypothesis. These tests 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 D3, 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 6, 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 E7, E8, and E9, 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[8]. 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.

[8] 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.

6 Robustness analysis

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 D4). The estimates are also robust to weighting by population rather than number of births (See Appendix Table D8). Next, in Appendix Table D9, 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 E3. Appendix Table D10 illustrates that my main results are robust to different levels of 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 D2 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 D11 demonstrates that my estimates are not sensitive to setting these missing values to alternative numbers.

7 Model

In this section, I use a theoretical model of household decision making to outline mechanisms that can explain why older women are more responsive to childcare price changes than younger women. The model is built on work by Doepke et al. (2023); I allow for part-time childcare and introduce two periods to consider age heterogeneity.

7.1 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: $n \in \{0, 1\}$. She also decides what share of childcare she will outsource to private childcare providers, denoted by s. Specifically, the preferences of the women are described by the following utility function:

$$u = c_1 + c_2 + (2n_1 + n_2)v - \mu((1 - s_1)^\gamma n_1 + (1 - s_2)^\gamma n_2) \tag{5}$$

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.

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. A child requires care for a portion ϕ of each unit of time. This assumption reflects that parents exclusively devote some hours of the day to child-rearing or other activities in the presence of their child. For example, weekends and the evening. 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 α captures productivity.

Aside from the time devoted solely to child-rearing, $(1 - \phi)$, 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 7.6 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 their 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.

7.2 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, some of which are discussed earlier in this paper. 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 makes the following predictions:

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

   Higher wages allow women 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. Therefore women who outsource some childcare will be more price responsive than these lower paid women.

2. *The utility of older mothers with one child is more price sensitive than that of younger mothers with one child*

   Delaying birth will make mothers more sensitive to price increases. As work experience builds human capital, second-period wages are higher. This leads mothers to purchase a larger share of private childcare than mothers who have an earlier (first period) birth. Thus price increases will hurt older mothers with greater reliance on paid childcare more than their younger counterparts.

3. *The utility of mothers with two children is more price sensitive than that of mothers with one child*

Having two children makes mothers more responsive to price increases than mothers with one child, because the mother is exposed to paid childcare in both periods (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.

7.3 Optimisation problem

This woman's optimisation problem is:

$$\max_{\{c,n,s\}} u = c_1 + c_2 + (2n_1 + n_2)v - \mu((1-s_1)^\gamma n_1 + (1-s_2)^\gamma n_2) \tag{6}$$

She is subject to the following budget and time constraints:

$$c_1 + \phi p s_1 n_1 \leq w\,(1 - (1-s_1)\phi n_1) \tag{7}$$

$$c_2 + \phi p s_2 n_2 \leq w(1 + \alpha h_1)\,(1 - (1-s_2)\phi n_2) \tag{8}$$

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

$$1 - (1-s_1)\phi n_1 \geq 0 \tag{9}$$

$$1 - (1-s_2)\phi n_2 \geq 0 \tag{10}$$

Equations 7 and 8 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 9 and 10 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.

7.4 Optimal choice

7.4.1 Optimal share of childcare

We can derive the optimal share of private childcare purchased in each period (s_1, s_2). The first order conditions for s_1, s_2 are given by:

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

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

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

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

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

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

Optimal s_1^*, s_2^* depend on the wage w, price of childcare p, productivity α, share of total childcare required ϕ, and disutility from self-childcare parameters γ and μ. 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 price 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 $p < w + \frac{\mu\gamma}{\phi}$, then $s_1^* > 0$. Since the period two wage $w_2 \equiv w(1 + \alpha h_1^*) \geq w$, it follows that $p < w_2 + \frac{\mu\gamma}{\phi}$ and thus $s_2^* > 0$. Moreover, holding p (and μ, γ, ϕ) 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.

7.4.2 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:

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

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

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

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

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

7.4.3 The utility gain from having a child

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

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

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

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

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, $w_t(1-s_i^*)\phi$, (ii) the cost of private childcare, $p\,\phi\,s_i^*$, 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:

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

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

Case 2: Stay at home mother in $t = 1$, part-time private childcare in $t = 2$. Mothers who provide full-time self-childcare in $t = 1$, but are able to purchase childcare in period $t = 2$ due to human capital accumulation, will have a first period child if the benefit from having a child for two periods is greater than the foregone wage. They will have a child in the second period if the benefit outweighs the opportunity cost of working, disutility of self-childcare, and cost of purchasing private childcare.

They will have a first and second period birth respectively when:

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

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

where

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

Case 3: Stay at home mother in $t = 1$, full-time private childcare in $t = 2$. These mothers will have a child in the first period if the benefit from having a child for two periods outweighs the opportunity cost of foregone wages from full-time self-childcare. They will have a child in the second period if the benefit from having a child for one-period is greater than the cost of private childcare. They will have a first and second period birth respectively when:

$$2v \geq w\phi + \mu \tag{11}$$

$$v \geq \phi p \tag{12}$$

Case 4: 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:

$$2v \geq w(1 - s_1^i)\phi + \phi p s_1^i + \mu(1 - s_1^i)^\gamma \tag{13}$$

$$v \geq w(1 + \alpha h_1^*)(1 - s_2^i)\phi + \phi p s_2^i + \mu(1 - s_2^i)^\gamma \tag{14}$$

where

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

Case 5: 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:

$$2v \geq w(1 - s_1^i)\phi + \phi p s_1^i + \mu(1 - s_1^i)^\gamma \tag{15}$$

$$v \geq \phi p \tag{16}$$

where

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

Case 6: 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:

$$2v \geq \phi p \tag{17}$$

$$v \geq \phi p \tag{18}$$

7.5 Response to price changes

7.5.1 Utility responses

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

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

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

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

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.

7.5.2 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, assume that the probability of being in one of the four states follows a multinomial logit:

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

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:

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

Recall that the within state derivatives are given by:

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

Which we can use to derive:

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

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:

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

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

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:

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

By the result established above that $s_2^*(p) \geq s_1^*(p)$, it follows immediately 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 raises the probability of a second-period birth, it shifts timing toward the second 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.

7.6 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 5 with the following utility function:

$$u = c_1 + c_2 + (2n_1 + n_2)v + \mu((1 - s_1)^{\gamma} n_1 + (1 - s_2)^{\gamma} n_2) \tag{19}$$

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:

$$(w - p)\phi - \mu\gamma(1 - s_1)^{\gamma - 1} = 0 \tag{20}$$

$$(w(1 + \alpha h_1^*) - p)\phi - \mu\gamma(1 - s_2)^{\gamma - 1} = 0 \tag{21}$$

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

$$s_1^* = \begin{cases} 0, & \text{if } p \geq w - \frac{\mu\gamma}{\phi}, \\ 1 - \left(\dfrac{(w-p)\phi}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w - \frac{\mu\gamma}{\phi}. \end{cases} \tag{22}$$

$$s_2^* = \begin{cases} 0, & \text{if } p \geq w(1+\alpha h_1^*) - \frac{\mu\gamma}{\phi}, \\ 1 - \left(\dfrac{(w(1+\alpha h_1^*)-p)\phi}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w(1+\alpha h_1^*) - \frac{\mu\gamma}{\phi}. \end{cases} \tag{23}$$

$$\text{and where } h_1^* = \begin{cases} 1-\phi, & \text{if } s_1^* = 0 \text{ and } n_1 = 1 \\ 1 - (\frac{(w-p)\phi}{\mu\gamma})^{\frac{1}{\gamma-1}}\phi, & \text{if } s_1^* = 1 - (\frac{(w-p)\phi}{\mu\gamma})^{\frac{1}{\gamma-1}} \text{ and } n_1 = 1, \\ 1, & \text{if } n_1 = 0 \end{cases} \tag{24}$$

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:

$$\frac{\partial u(1,0)}{\partial p} = -\phi\, s_1^* = \begin{cases} 0, & \text{if } p \geq w - \frac{\mu\gamma}{\phi}, \\ -\phi\Big(1 - \dfrac{(w-p)\phi}{\mu\gamma}\Big)^{\frac{1}{\gamma-1}}, & \text{if } p < w - \frac{\mu\gamma}{\phi}. \end{cases} \tag{25}$$

$$
\frac{\partial u(0,1)}{\partial p} = -\phi\, s_2^* = \begin{cases} 0, & \text{if } p \geq w(1+\alpha h_1^*) - \frac{\mu\gamma}{\phi}, \\ -\phi\Big(1 - \dfrac{(w(1+\alpha h_1^*) - p)\phi}{\mu\gamma}\Big)^{\frac{1}{\gamma-1}}, & \text{if } p < w(1+\alpha h_1^*) - \frac{\mu\gamma}{\phi}. \end{cases} \tag{26}
$$

$$
\begin{aligned}
\frac{\partial u(1,1)}{\partial p} = -\phi(s_1^* + s_2^*) = -\phi \Bigg(& \begin{cases} 0, & \text{if } p \geq w - \dfrac{\mu\gamma}{\phi}, \\ 1 - \left(\dfrac{(w-p)\phi}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w - \dfrac{\mu\gamma}{\phi} \end{cases} \\
& + \begin{cases} 0, & \text{if } p \geq w(1+\alpha h_1^*) - \dfrac{\mu\gamma}{\phi}, \\ 1 - \left(\dfrac{(w(1+\alpha h_1^*) - p)\phi}{\mu\gamma}\right)^{\frac{1}{\gamma-1}}, & \text{if } p < w(1+\alpha h_1^*) - \dfrac{\mu\gamma}{\phi} \end{cases} \Bigg)
\end{aligned} \tag{27}
$$

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.

8 Mechanisms

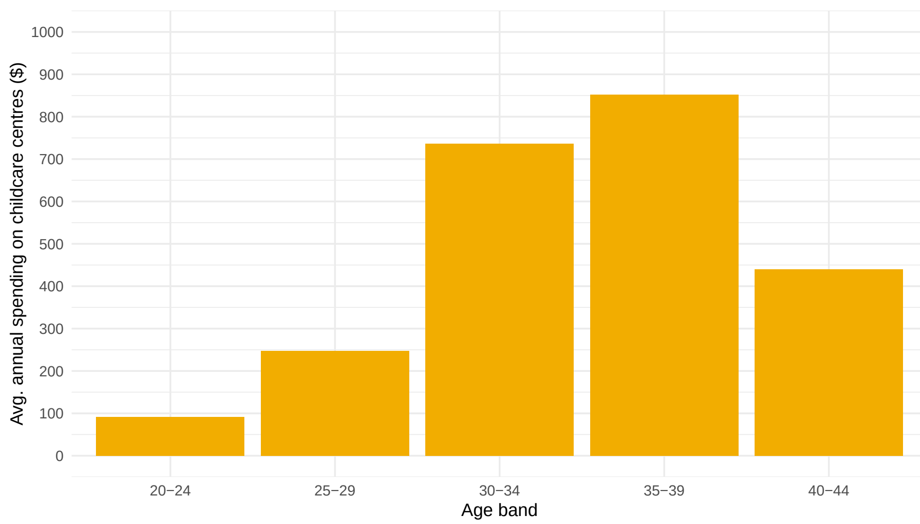
Next, I test my key model predictions for why older women are more childcare price responsive than younger women.

8.0.1 Spending 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 E2 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.

8.0.2 Heterogeneity by education, a proxy for income

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[9]. 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 [10]. 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.

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.

[9] 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.

[10] 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.

8.0.3 Birthrates by parity

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. The IV point estimates indicate that older women are more price responsive than younger women across the first, second, and third births. We also see that for the same increase in childcare prices, second and third birthrates fall by more than first 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 D6 and D7). 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.

9 Childcare market analysis

The first stage of my 2SLS analysis tells us how the childcare regulations impact the price of childcare. Yet the regulations may have impacted 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.

9.1 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[11]. 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)[12]. 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. 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.

9.1.1 Specification

The empirical model for the DiD approach is as follows:

$$Y_{ct} = \alpha + \beta \cdot D_{st} + \kappa \cdot X_{ct} + \gamma_t + \delta_s + \epsilon_{st} \tag{28}$$

where outcome Y is county c in year t is regressed on the binary treatment variable D_{st}, covariates X_{ct}, and state (δ_s) and year (γ_t) fixed effects. Outcomes Y_{ct} include: the log number of childcare establishments (by size), log employment, log earnings, log new hires, the hiring rate, log separations, the separation rate, and staff 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

[11]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.

[12]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.

coefficient β 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:

$$Y_{ct} = \alpha + \sum_{k=-5,k\neq 1}^{k=5} \beta_k \cdot D_{sk} + \kappa \cdot X_{ct} + \gamma_t + \delta_s + \epsilon_{st} \tag{29}$$

I estimate the βs 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 on two subgroups: a) a subgroup consisting of states that experience a change in the staff-child ratio or maximum group size that is *less strict*, plus control states, and b) a subgroup made up of states that experience a change that is *more strict*, and control states.

9.1.2 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 had 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.)

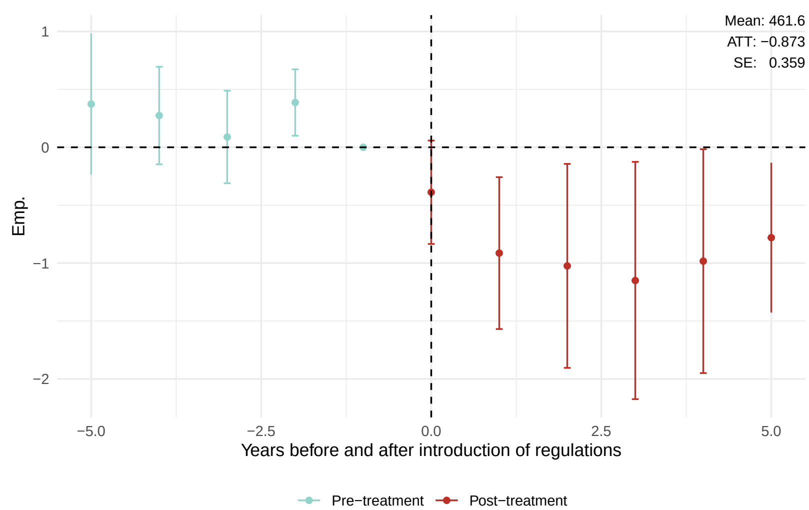
9.2 Results

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. I find evidence that 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 can 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 employed in the childcare sector 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 E31). 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, nor on staff turnover (see Appendix Figures E12 and E13 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 E21 to E25).

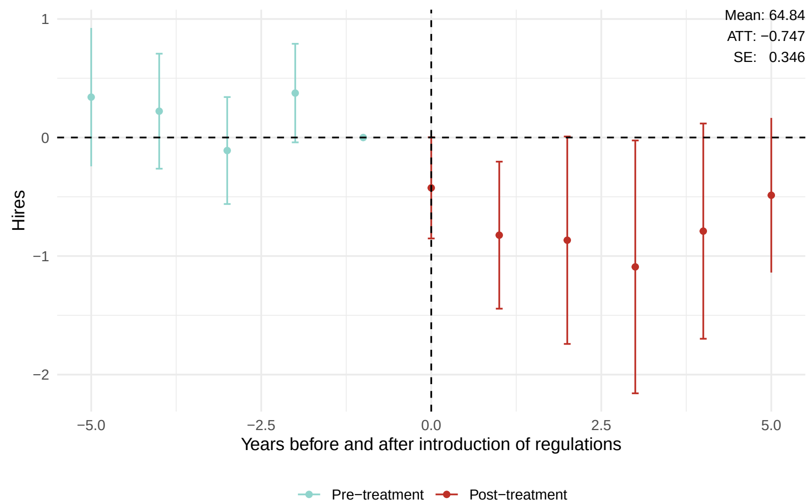
I find that across the states in my sample, increasing the stringency of the maximum group size and/or staff-child ratio requirements has no statistically significant effect on employment outcomes in the childcare market, nor on the number of childcare establishments. These results can be found in Tables 10 and 11, and Appendix Figures E14 to E30. 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" group, whilst there are 6 states in the "more stringent" 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.

Figure 6. The effect of loosening childcare regulations on employment



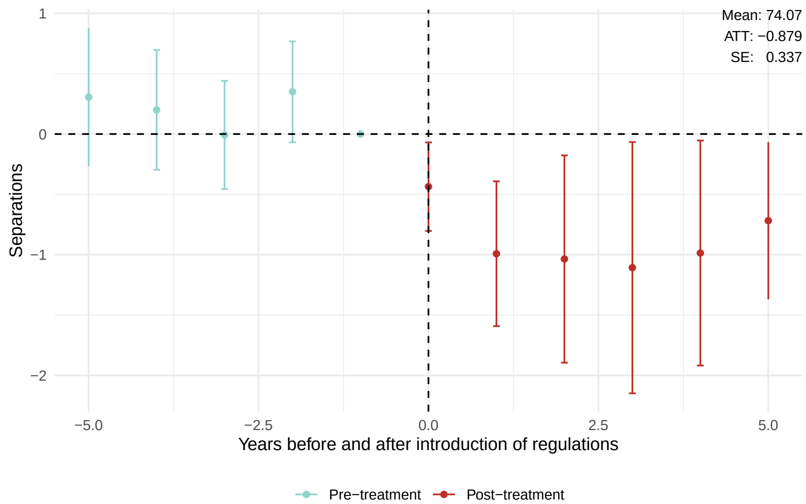
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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



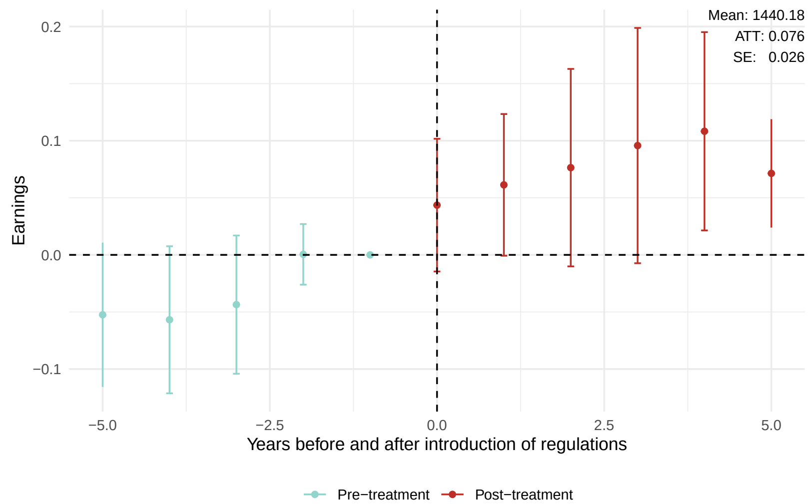
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 29 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 29 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) = 19634; N (More Strict) = 24010. 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) = 22740; N (More Strict) = 27433. 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.

10 Cost-benefit analysis of a childcare subsidy

Finally, I explore the cost and fertility benefit of a childcare price subsidy for parents of children under 3. 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 there to be 2.16 million children in centre-based care. The weighted mean weekly price of childcare is \$190 in my sample, or \$9,880 annually. To subsidise childcare costs by 10% annually would cost \$2.13 billion. Such a subsidy would raise birthrates by 5.7%, implying $\approx$ 205,000 additional births in the first year (from a baseline of 3,596,017 births in 2023). The cost per additional birth is thus $\approx$ \$10.4k. Aides in the current administration have proposed a baby bonus of \$5k. For double this cost, this simple back of the envelope calculation estimates a childcare subsidy could increase birthrates by 5.8%.

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. Policymakers looking to boost birthrates are considering a wide range of policies. Prior work has shown that financial support for families has positive effects on family formation (González, 2013; Ang, 2015; van Doornik et al., 2024; Cohen et al., 2013; Milligan, 2005). In this paper I explore how the cost of childcare, a large and early cost facing potential parents, affects the decision to have children.

This paper makes several contributions to the literature. I provide the first causal empirical evidence on how changes in childcare *prices* affect fertility, and bring early evidence on the cost of childcare in the U.S. The majority of empirical papers studying the cost of childcare to parents and fertility focus on European settings, where public provision of childcare is widespread and public spending on childcare high.

I find that higher childcare prices reduce birthrates, and that mothers respond on a second margin: by delaying their first birth. Heterogeneity analysis reveals varying effects by age; births to women aged 30 and above have a greater price elasticity than those for younger women. I show that this age gradient in the results can be explained by existing mothers choosing to forgo their second or third child. A second factor may also be at play: that older parents are more likely to use formal childcare in the first place. I provide supportive evidence to this theory by showing that spending on childcare centres is higher amongst older parents.

I explore further explanations for this age gradient with a theoretical model. I demonstrate that older mothers can be more price responsive than younger mothers because they earn a higher wage, and so the opportunity cost of their time is higher. Women earning higher wages will outsource more, if not all, childcare. This high level of outsourcing will drive greater price responsiveness. Further, simply having more than one child increases spending on childcare, which makes mothers more sensitive to price changes.

A few papers allow for a comparison of estimates. Kearney and Wilson (2018) study the U.S. fracking boom between 1997 and 2012, finding that a 10% increase in earnings ($\approx$ \$7,900) leads to $\approx$ 15.8% higher birth rates (or 15.8 births per 1,000 women aged 18 to 34). My price elasticity estimates suggest stronger fertility responses. I find that a 10% increase in the price of childcare (≈\$19 a week, or a cost of ≈ \$990 a year) leads to a 5.7% decrease in the birthrate (4 births per 1,000 aged 20 to 44). Note that Kearney and Wilson (2018) estimate *income* elasticities, whereas I estimate *price* elasticities. Thus a caveat applies: individuals may differ in their response to price and income changes. My elasticity estimates are also larger than the magnitudes found by Mörk et al. (2013) from Sweden, where childcare costs went from \$400 per month to \$290 for a two-parent household with two pre-school children in 2000. The authors find that a childless couple facing an average reduction in costs of SEK 111,000 (≈ \$13,000) increased fertility by 9.8%. However, this comparison should be made with the acknowledgement that the childcare policy context in Sweden and the U.S. differs greatly. At the time, Swedish families only contributed 15 to 20% of childcare costs, with the government covering the rest. The policy lever was operating on a smaller private cost margin than it would have been in the U.S.

The decline in U.S. fertility rates is seen across demographic groups and cannot be solely explained by women delaying children to later years. Total fertility rates, which measure births over women's lifetime, are also falling (Kearney and Levine, 2022). Current cohorts of women will need to have more births after age 30 than previous cohorts to match total fertility rates of cohorts prior to 2007 (Kearney and Levine, 2021). Considering my findings against this broader context, reductions in birthrates, particularly declines in second and higher order birthrates, paint a poor outlook for returning to replacement level birthrates. Thus preventing rising childcare costs and considering more financial support for childcare in the U.S. are avenues worth exploring for policymakers looking to address low fertility rates.

A Appendix

A.1 Bounding exercise

In this section, I conduct a bounding exercise to explore how such a quality channel affects my estimates. I show that my IV estimates represent a lower-bound, and estimate the upper bound of the true β in the case of a quality channel.

A.1.1 Decomposition of the IV Estimator

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

$$Y = \beta P + X'\eta + \epsilon \tag{30}$$

Where Y is the log of the birthrate, P is the cost of childcare, and for simplicity, X' includes county and year fixed effects. As P is endogenous, I instrument the variable with Z:

$$P = \mu Z + X'\kappa + \varepsilon \tag{31}$$

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

$$Y = \beta P + \delta Q + X'\eta + e \tag{32}$$

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 32 using equation 30, then the error term may include the quality of childcare component:

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

By the Frisch-Waugh-Lovell, 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 β can be written as:

$$\begin{aligned}
\hat{\beta}_{IV} &= \frac{\text{Cov}(\tilde{Z}, \tilde{Y})}{\text{Cov}(\tilde{Z}, \tilde{P})} \\
&= \frac{\text{Cov}(\tilde{Z}, \beta\tilde{P} + \delta\tilde{Q} + \tilde{e})}{\text{Cov}(\tilde{Z}, \tilde{P})} \\
&= \frac{\beta\ \text{Cov}(\tilde{Z}, \tilde{P}) + \delta\ \text{Cov}(\tilde{Z}, \tilde{Q}) + \text{Cov}(\tilde{Z}, \tilde{e})}{\text{Cov}(\tilde{Z}, \tilde{P})}.
\end{aligned}$$

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 31. 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 $\text{Cov}(\tilde{Z}, \tilde{Q})$:

$$\tilde{Q} = \omega\tilde{Z} + \tilde{u} \tag{33}$$

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 β using the following equation:

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

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.1.2 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, would 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, I find that 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 β. Next, I will estimate the bias term in order to provide an upper bound estimate for β.

A.1.3 Estimating the magnitude of the bias

To estimate the effect of childcare quality on birthrates ($\hat{\delta}$) and the effect of 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 E10). 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[13].

[13]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 Tables

Appendix Table D1. First stage

	Childcare Price	
Maximum Group Size	-1.05***	-0.04
	(0.23)	(0.16)
Child-Staff Ratio		732.37***
		(2.89)
Mean (Childcare Price)	146.66	146.54
Mean (Maximum Group Size)	16.10	16.26
Mean (Child-Staff Ratio)	0.20	0.20
F-stat	21.05	32247.86
N	7,495	8,094

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

Notes: 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 child-staff ratio, with the single instrument in the first column (2010-2019, 2021-2022) and both instruments in the second columnn (2009-2019, 2021-2022). "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. "Child-Staff Ratio" is the state-level child-staff ratio average for 0 to 2 year olds. "F-stat" is the F statistic for the first stage. 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, clustered at the state-year level, in parentheses.

Appendix Table D2. 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 D3. 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 D4. 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 D5. Effects of childcare prices on first birthrates, by age

	20-44	20-24	25-29	30-34	35-39	40-44
OLS						
Childcare price	-0.02	-0.02*	-0.03	-0.02	-0.04**	-0.04**
	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.02)
R^2	0.94	0.95	0.90	0.93	0.91	0.86
IV						
Childcare price	-0.15***	0.01	0.17	-0.26***	-0.52***	0.55
	(0.02)	(0.10)	(0.12)	(0.06)	(0.09)	(0.61)
R^2	0.94	0.95	0.89	0.92	0.89	0.83
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 childcare prices on the log of first birthrates per 1000 women. Coefficients and standard errors multiplied by 100. "20-49" is the log of the county-level first birthrate per 1000 women aged 20 to 49, "20-19" the log of the first birthrate per 1000 women aged 20-19, 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 D6. 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. "20-49" is the log of the county-level second birthrate per 1000 women aged 20 to 49, "20-19" the log of the second birthrate per 1000 women aged 20-19, 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 D7. 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. “20-49” is the log of the county-level third birthrate per 1000 women aged 20 to 49, “20-19” the log of the third birthrate per 1000 women aged 20-19, 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 D8. 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 D9. 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 D10. 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 D11. 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 D12. 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 D13. Robustness of estimates to controlling for staff turnover

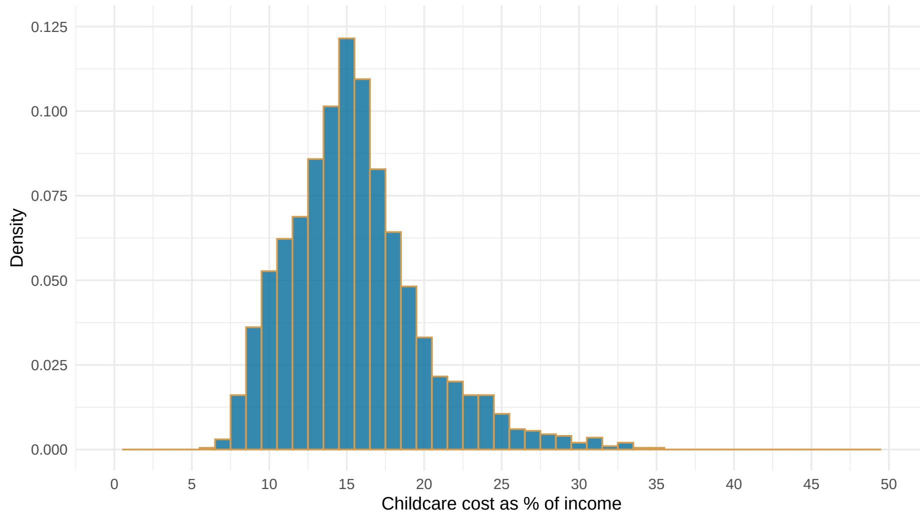
	20-44	20-24	25-29	30-34	35-39	40-44
OLS						
Log(Childcare Price)	0.01	0.03	0.03	0.02	0.02	-0.02
	(0.02)	(0.04)	(0.03)	(0.02)	(0.02)	(0.03)
R^2	0.98	0.98	0.97	0.96	0.96	0.92
IV						
Log(Childcare Price)	-0.59***	-0.17	-0.23	-0.75***	-0.86***	-0.93***
	(0.14)	(0.18)	(0.17)	(0.13)	(0.19)	(0.17)
R^2	0.96	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.

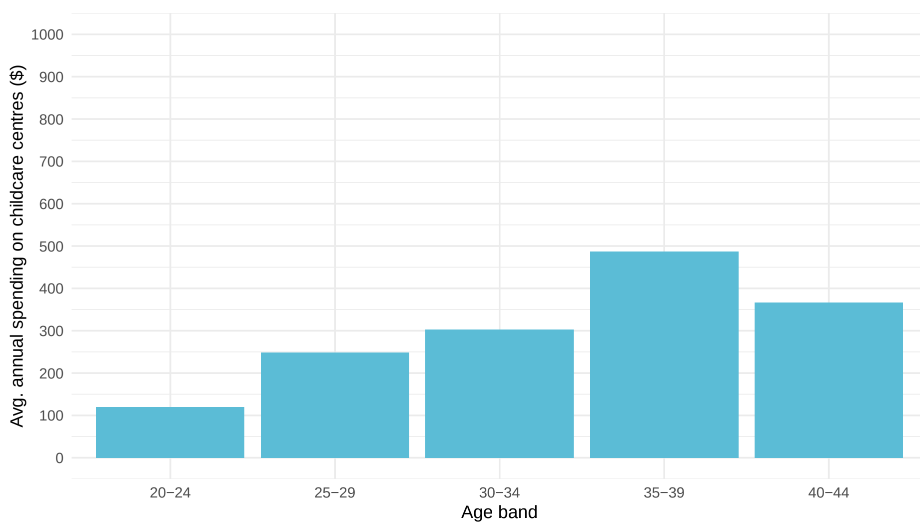
C Appendix Figures

Appendix Figure E1. Distribution of avg. annual cost of full-time centre based childcare for 0-2 years as a share of median household income, 2010



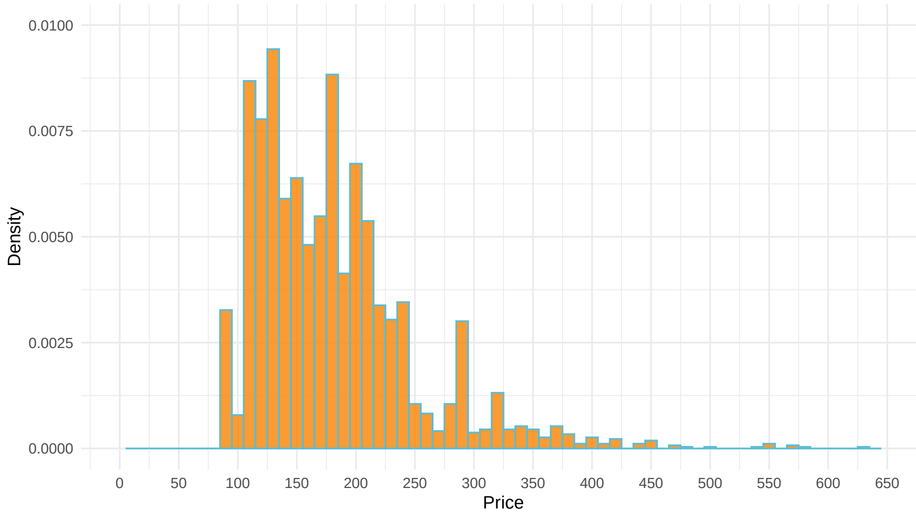
Notes: Data: National Database of Childcare Prices (including imputed data), American Community Survey, for 2010. The plot shows the distribution of the average annual cost for full-time care at a childcare centre for 0 to 2 year olds, as a percentage of median household income at the U.S. county level.

Appendix Figure E2. Avg. annual spending on childcare centres for 2010, by age



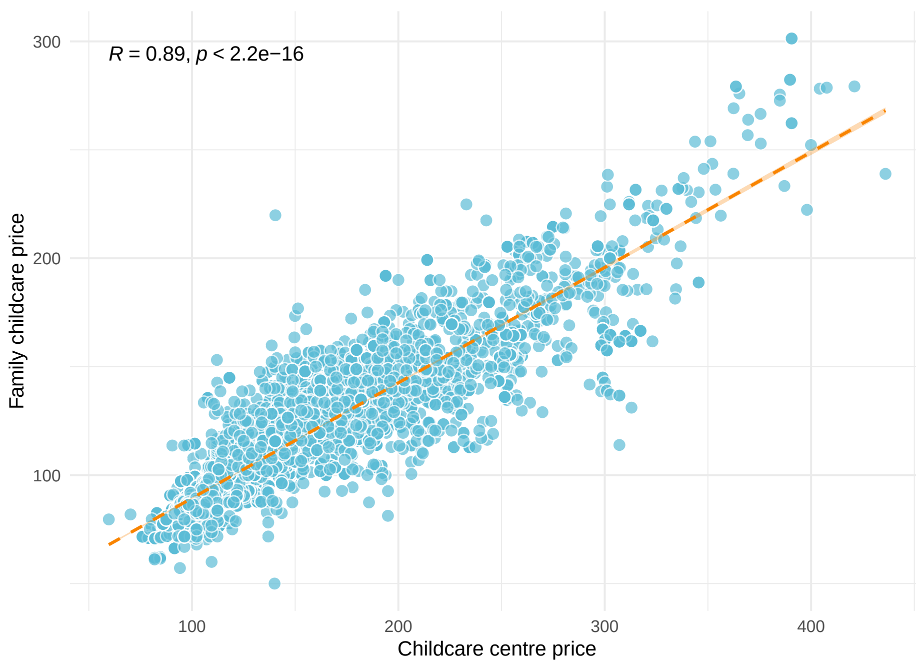
Note: Data: Consumer Expenditure Survey, for 2010. This figure shows the average annual spending on childcare centres by age of the respondent, for respondents with any children under 3. Childcare centres defined as day care centres, nurseries, and preschools.

Appendix Figure E3. 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 E4. 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 E5. Newspaper article on childcare regulations in Nevada

LAS VEGAS SUN

Day care concerns: Staffing standards in Nevada below national averages

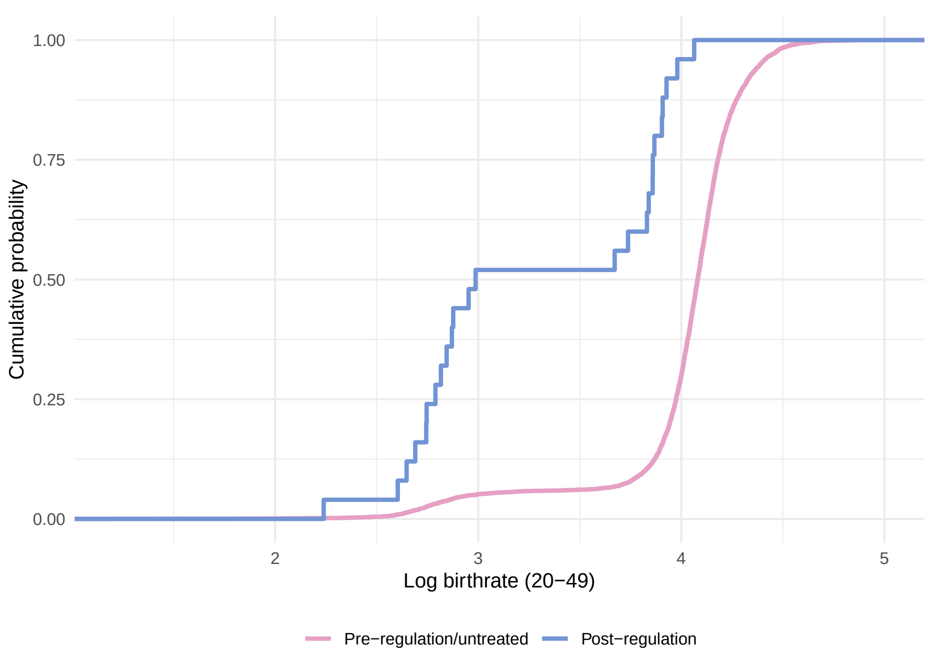
Thursday, May 15, 2003 | 11:24 a.m.

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.

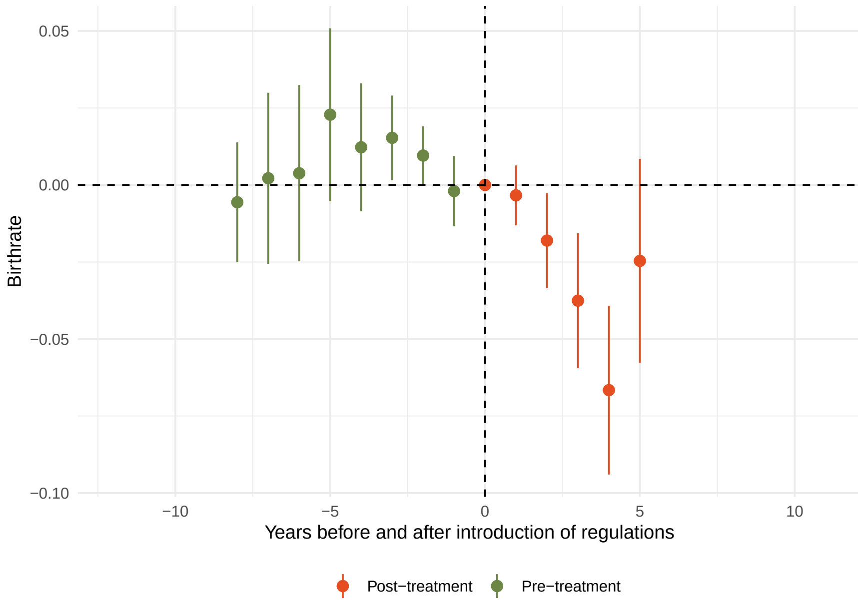
Nevada also ranks low in the number of licensed child care centers and in children served by government-subsidized child care, according to national comparisons. A state study last summer found that there were at least 6,000 children on waiting lists for child care.

Appendix Figure E6. Testing monotonicity



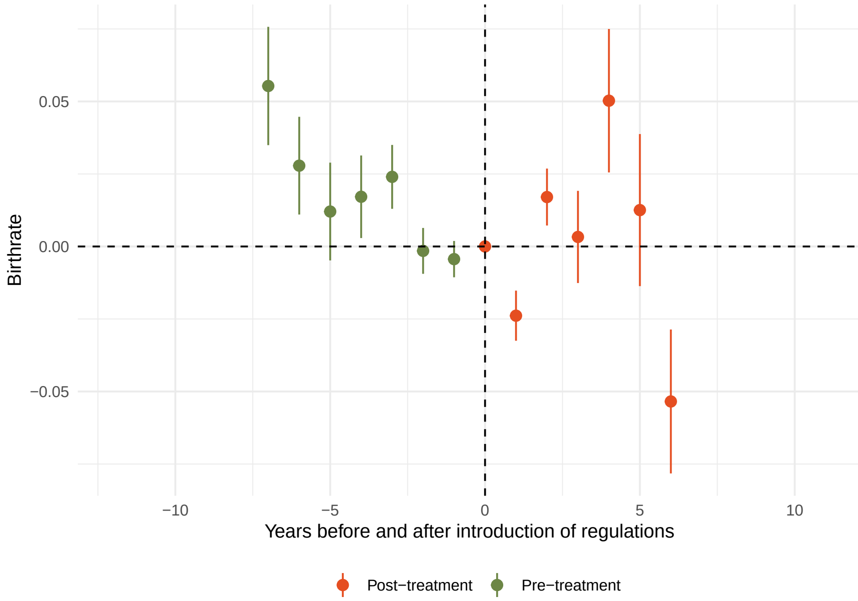
Notes: N=7,491. Data: NVSS birth records, SEER county population counts, hand-collected maximum group size data, for 2010-2019, 2021-2022. This figure shows the cumulative distribution functions for county-years after state-level childcare facility regulatory changes, and county-years before or without state-level childcare facility regulatory changes. The x-axis is log birthrate for women aged 20 to 44. The y-axis is the cumulative probability.

Appendix Figure E7. Event study plot of childcare facility regulations on birthrates, Nevada



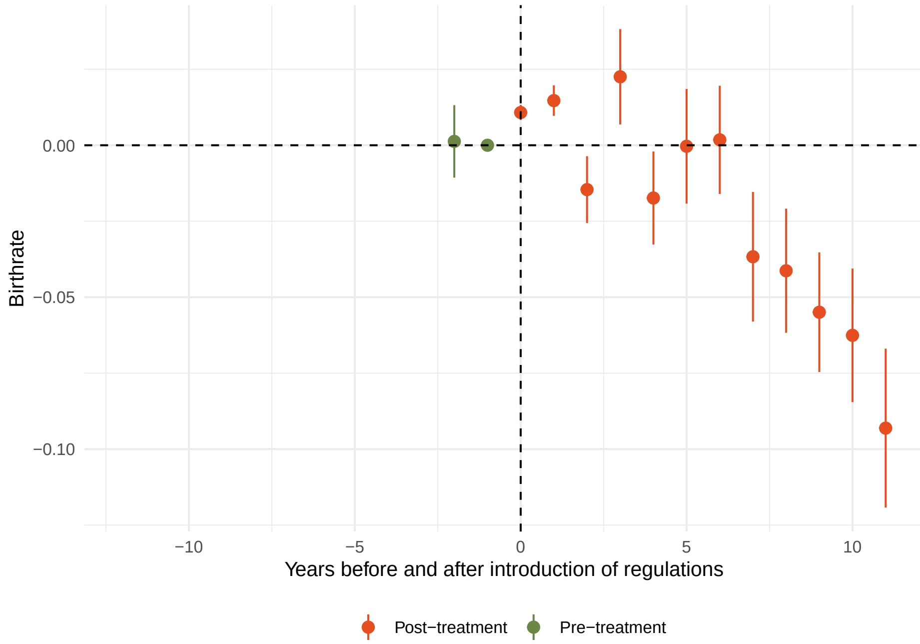
Notes: N=14,805. This figure shows an event study plot of effects of the introduction of childcare centre regulations in Nevada relative to control states on birthrates. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of the regulations. The y-axis is 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 E8. Event study plot of childcare facility regulations on birthrates, Vermont



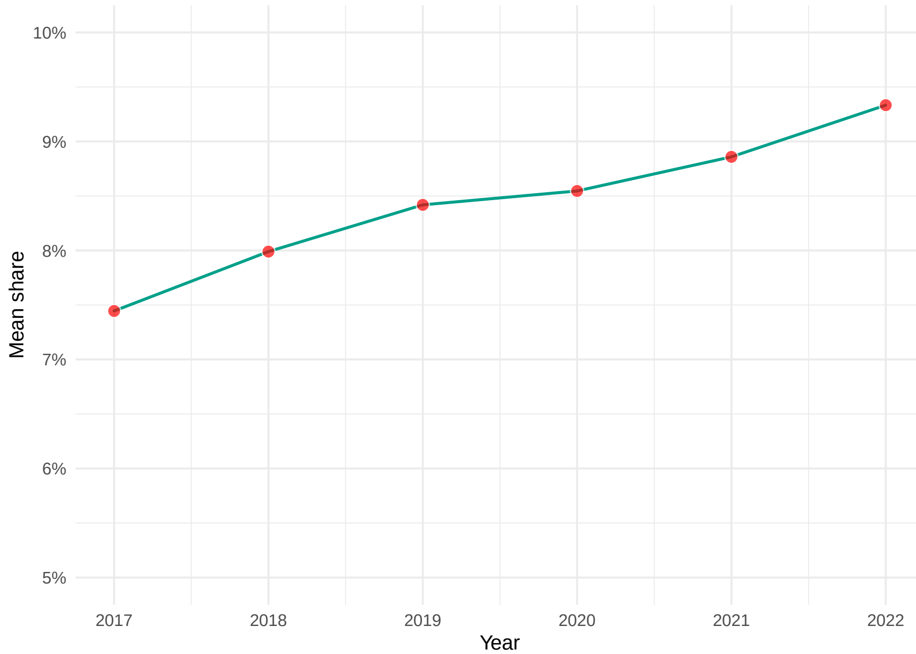
Notes: N=14,794. This figure shows an event study plot of effects of the introduction of childcare centre regulations in Vermont relative to control states on birthrates. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of the regulations. The y-axis 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 E9. Event study plot of childcare facility regulations on birthrates, Delaware



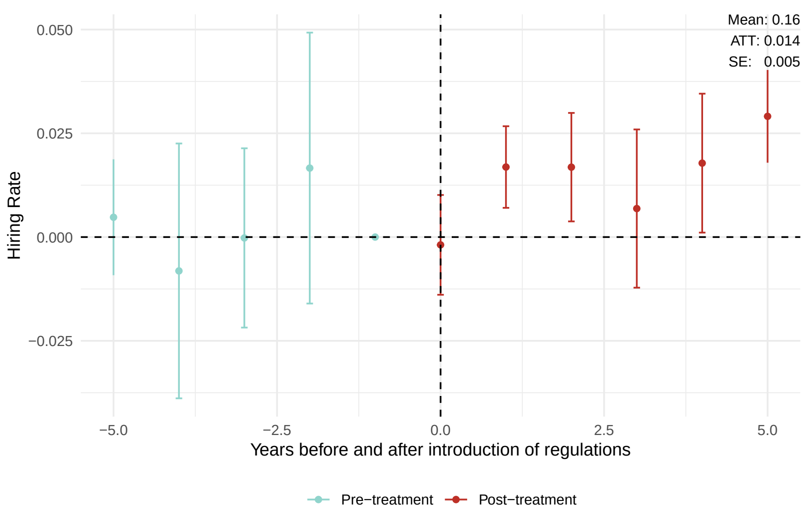
Notes: N=14,668. This figure shows an event study plot of effects of the introduction of childcare centre regulations in Delaware relative to control states on birthrates. The dotted vertical line is the year of treatment. The x-axis is relative time to the introduction of the regulations. The y-axis 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 E10. Mean share of NAEYC accredited programmes over time



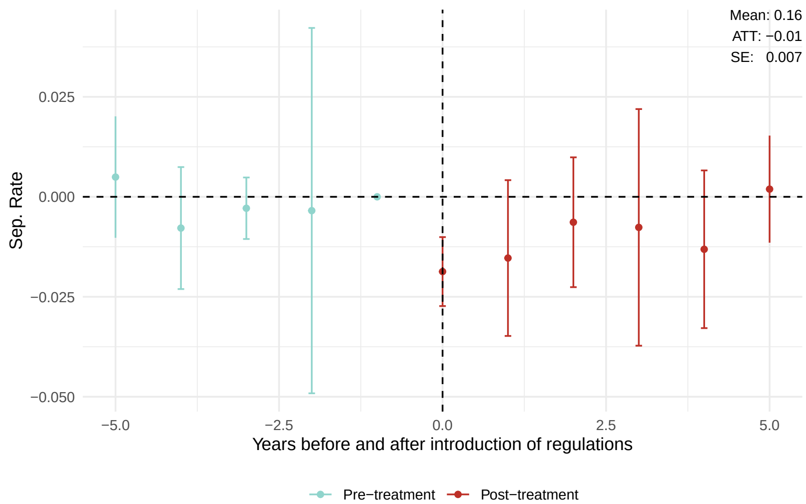
Notes: N=30. Data: National Association for the Education of Young Children (NAEYC). This figure shows the mean share of NAEYC accredited programmes at the state level between 2017 and 2022.

Appendix Figure E11. The effect of loosening childcare regulations on the hiring rate



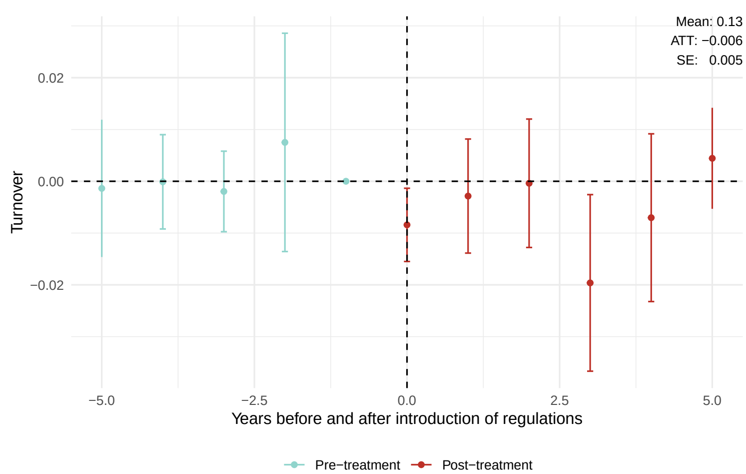
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E12. The effect of loosening childcare regulations on the separation rate



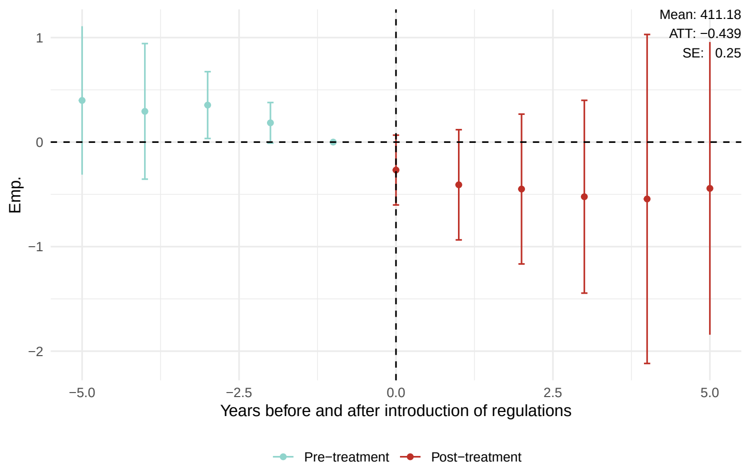
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E13. The effect of loosening childcare regulations on staff turnover



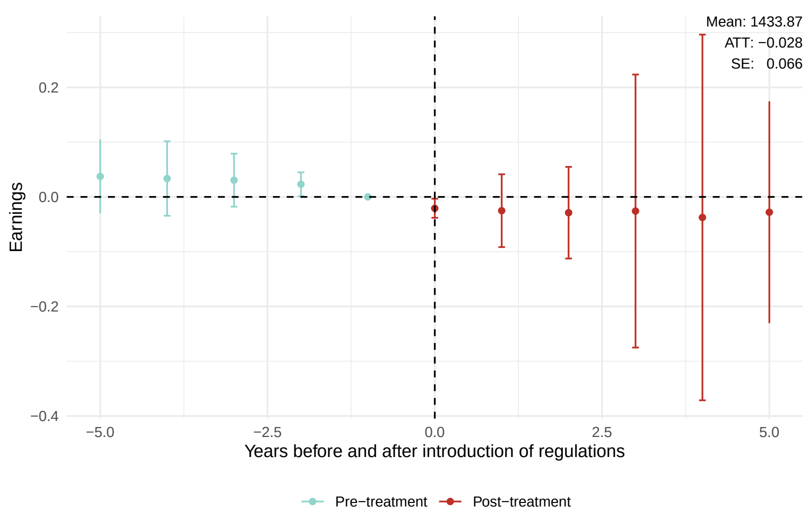
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E14. The effect of more stringent childcare regulations on employment



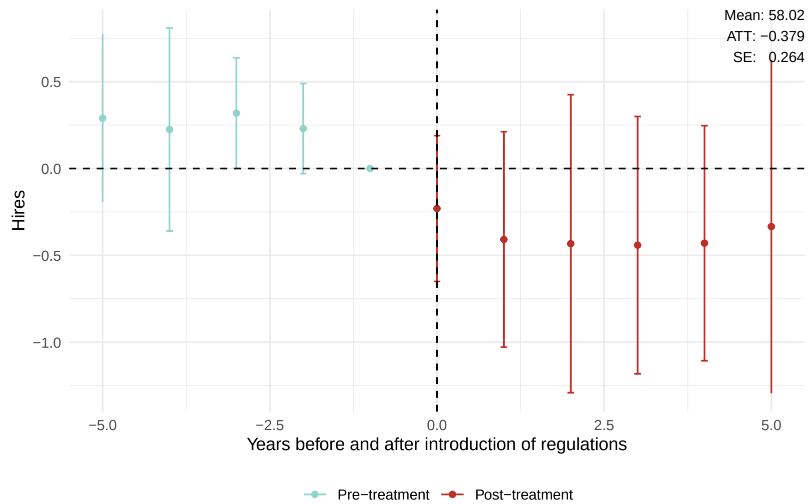
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E15. The effect of more stringent childcare regulations on earnings



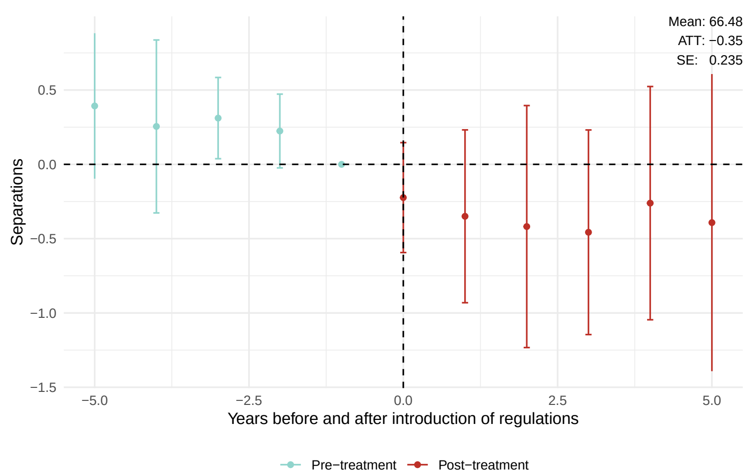
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E16. The effect of more stringent childcare regulations on new hires



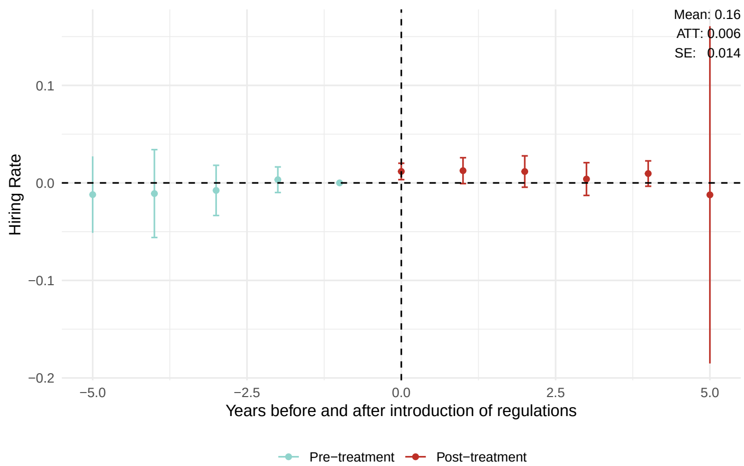
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E17. The effect of more stringent childcare regulations on job separations



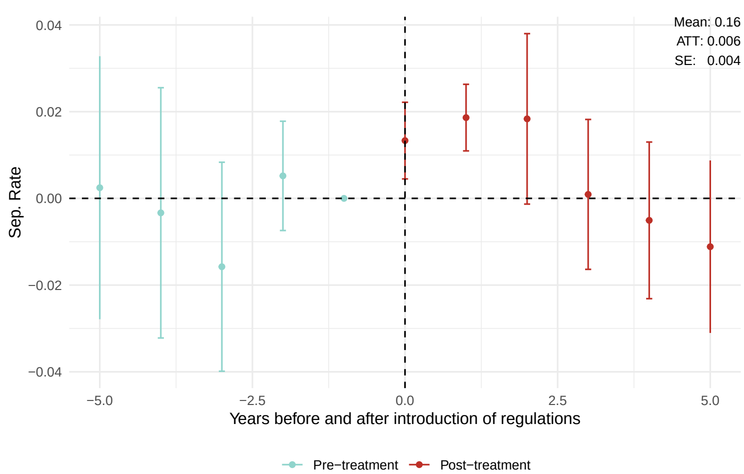
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E18. The effect of more stringent childcare regulations on the hiring rate



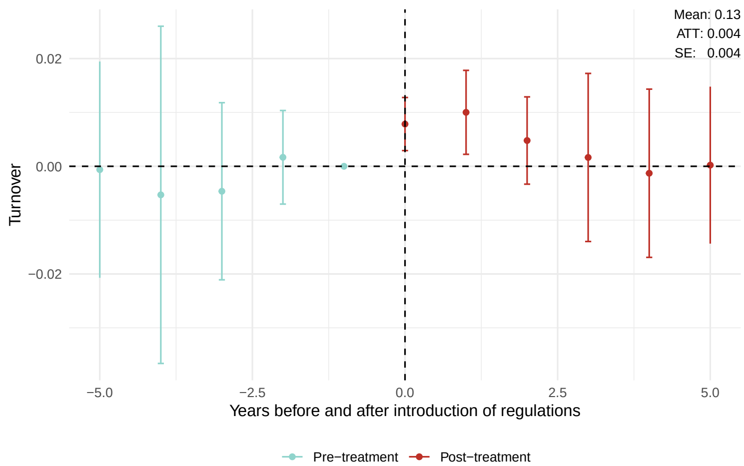
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E19. The effect of more stringent childcare regulations on the separation rate



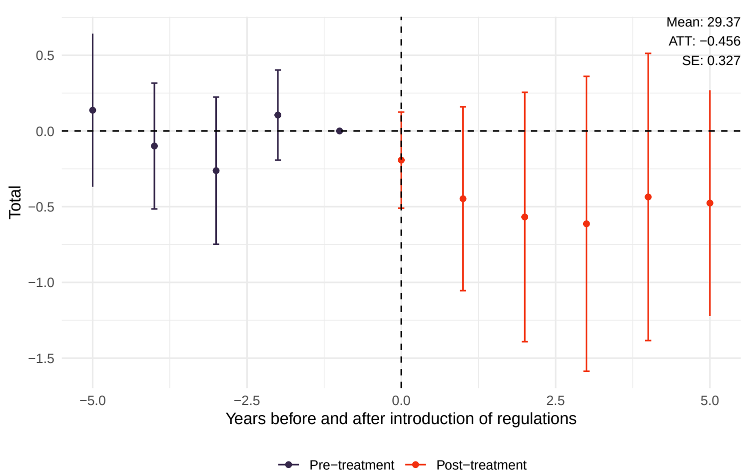
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E20. The effect of more stringent childcare regulations on staff turnover



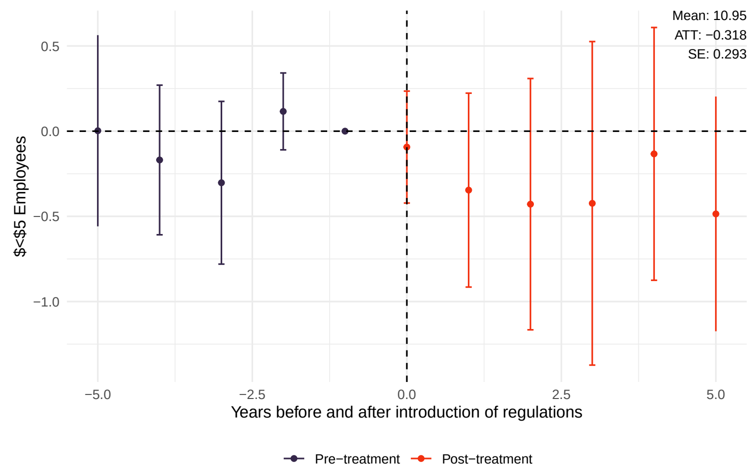
Note: N=19,634. Data: Census Quarterly Workforce Indicators, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted 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 E21. The effect of loosening childcare regulations on the total number of childcare establishments



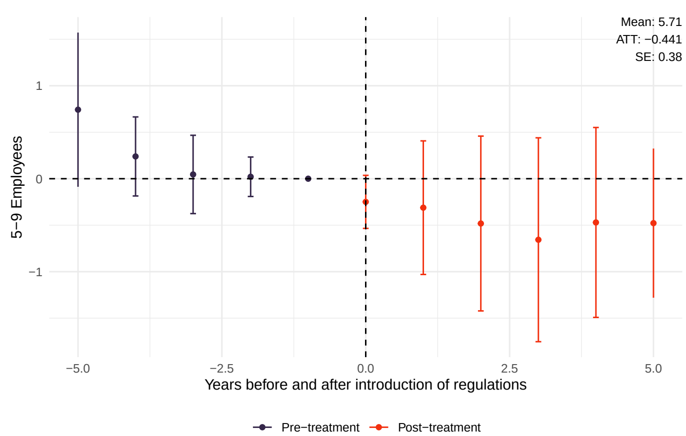
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E22. The effect of loosening childcare regulations on the total number of childcare establishments with fewer than 5 employees



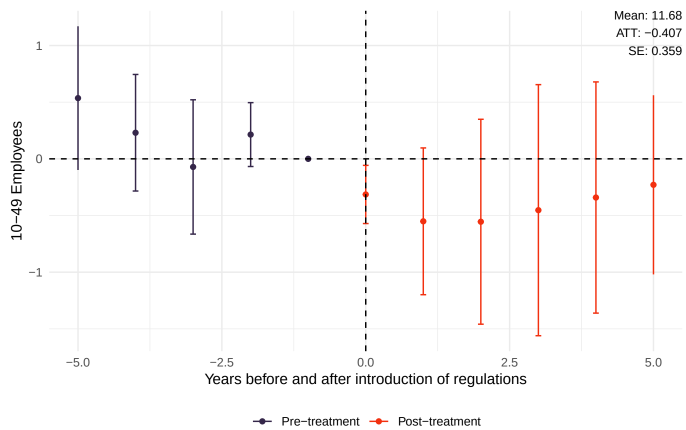
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E23. The effect of loosening childcare regulations on the total number of childcare establishments with 5-9 employees



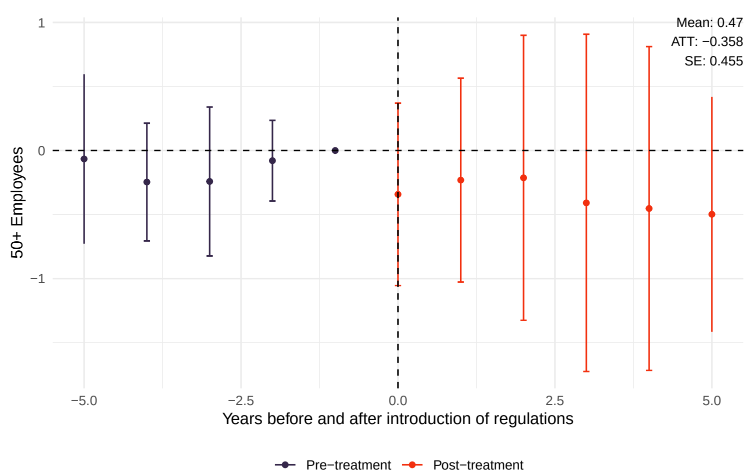
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E24. The effect of loosening childcare regulations on the total number of childcare establishments with 10-49 employees



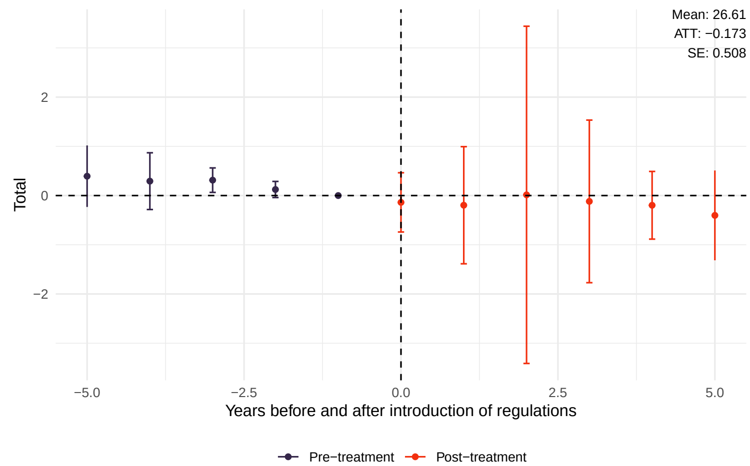
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E25. The effect of loosening childcare regulations on the total number of childcare establishments with over 50 employees



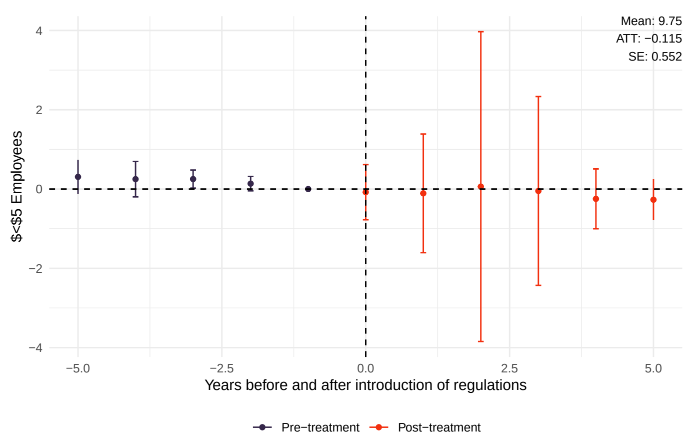
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E26. The effect of more stringent childcare regulations on the total number of childcare establishments



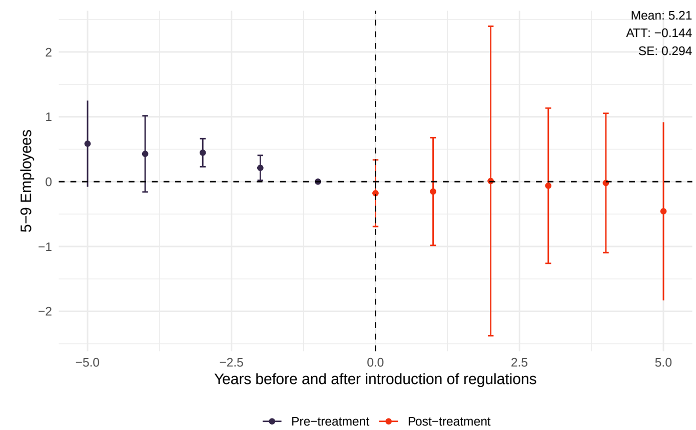
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E27. The effect of more stringent childcare regulations on the total number of childcare establishments with fewer than 5 employees



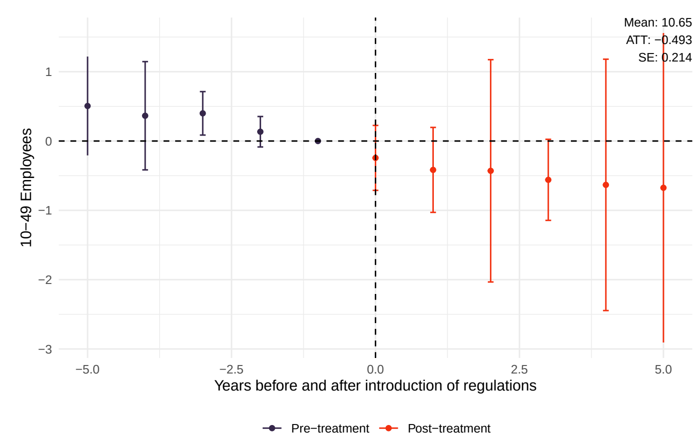
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E28. The effect of more stringent childcare regulations on the total number of childcare establishments with 5-9 employees



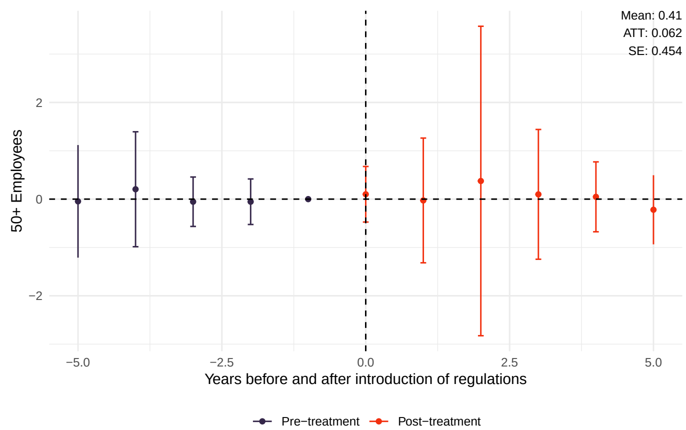
Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 event study coefficients and 95% confidence intervals estimated using Callaway and Sant'Anna (2021). ATT defined as the aggregate of the state-time average treatment effects. The dotted vertical 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 E29. 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 29 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.

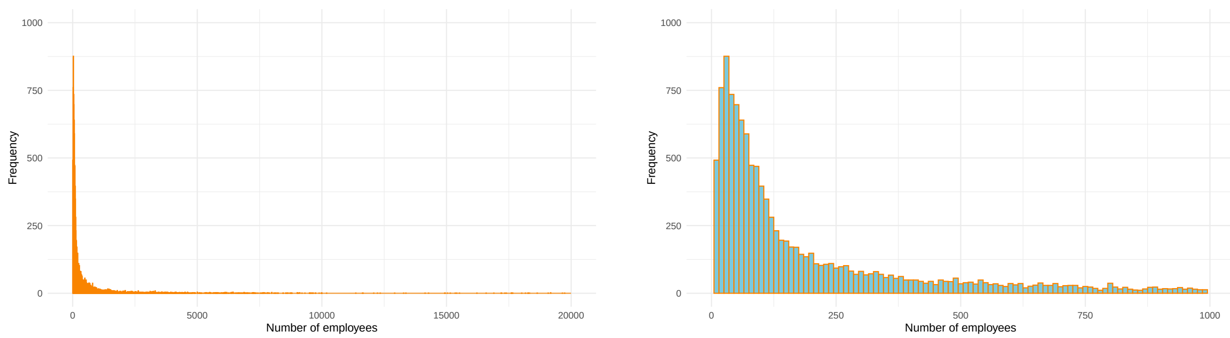
Appendix Figure E30. The effect of more stringent childcare regulations on the total number of childcare establishments with over 50 employees



Note: N=22,740. Data: Census County Business Patterns, hand-collected regulation data, for 2008-2022. Equation 29 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 E31. 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.

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