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ABSTRACT

Minimum Quality Regulations and the Demand for Child Care Labor*

Minimum quality regulations are often justified in the child care market because of the presence of information frictions between parents and providers. However, regulations can also have unintended consequences for the quantity and quality of services provided. In this paper, we merge new data on states' child care regulations for maximum classroom group sizes and child-to-staff ratios with the universe of online job postings to study the impact of regulations on the demand for and characteristics of child care labor. Our identification strategy exploits the unprecedented variation in regulatory reform during the COVID-19 pandemic, relying on changes both within states over time and across children's age groups. We find robust evidence that these regulations reduce the number of child care job postings and encourage providers to substitute away from higher-skilled postings, thereby increasing the number of positions that are out-of-compliance with state law. Furthermore, we show that regulations adversely affect mothers' labor force participation. In sum, the results imply that child care regulations may reduce the demand for child care labor, while simultaneously altering the composition of the workforce.

JEL Classification: H75, J21, I28
Keywords: child care, COVID-19, employment, state regulation, women

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1 Introduction

There is a large literature on the economics of licensing and minimum quality standards enacted in a variety of industries, including child care, for the purpose of increasing quality and ensuring the safety of market-provided goods and services (Leland, 1979). The key rationale for regulating the child care market is to mitigate the negative consequences of informational frictions between parents and providers, in which the former is poorly informed about the quality of care received by children. In such cases, regulations may be necessary to ensure that a minimally acceptable level of quality exists throughout the market. In addition, regulations may be desirable if any quality improvements translate into health and developmental benefits for children.

However, the benefits of child care regulations must be weighed against their potential costs. Indeed, the imposition of minimum quality standards may reduce the quantity child care services available, distort providers' input decisions, and lead to higher prices without improving quality (Shapiro, 1986; Blau, 2001). Over the last few decades, a large empirical literature has assessed the predictions of the canonical model of regulations in the center-based child care market.[1] This work shows that regulations reduce establishment-level supply and parental utilization of child care, but do not influence prices or quality. Furthermore, tougher regulations induce higher rates of non-compliance, in part because they encourage providers to substitute between inputs.

Nevertheless, estimating the impact of child care regulations is challenging because much of the variation exploited by previous studies is cross-sectional, raising concerns over whether the results are biased from unobserved state-level confounders. Furthermore, the studies relying on within-state over-time variation in regulatory policy are also limited because changes to regulations are fairly infrequent and restricted to a subset of states.[2] Thus, the estimates in these studies are generated using only a modest amount of variation from a small number of states, increasing the possibility that the results are either spurious or of limited generalizability.

In this paper, we study how the introduction and increased stringency of regulations in the market for center-based child care influence the demand for teacher labor, characteristics of the workforce, and compliance with other regulations. Our research covers the period surrounding the onset of the COVID-19 pandemic, when nearly all

[1] See, for example, Chipty and Witte (1999), Gormley (1991), Chipty (1995), Blau (2003), Blau and Currie (2006), Blau (2007), Boyd-Swan and Herbst (2018), and Hotz and Xiao (2011)

[2] For example, a study by Blau (2003) on group sizes and staff-to-child ratios over a 13-year period finds that such regulations changed only 0.44 times per state, on average. Similarly, Hotz and Xiao (2011) report that only nine states altered their staff-to-child ratios over their 10-year study period.

states enacted dramatic changes to the regulatory environment. Indeed, we study the impact of newly-enacted regulations as well as expansions to already-existing regulations. In particular, we consult several data sources to carefully code changes to maximum classroom group sizes, staff-to-child ratios, and ten (10) pandemic-related health and safety regulations. These policies are then matched to the universe of online child care teacher job postings in state-day-child age group cells over the period January 1 to September 30, 2020. The job postings provide detailed information on the rank of the teacher (assistant or lead), the child age group to be served (infants, toddlers, etc.), and the level of education required. Thus, these data allow us to estimate the impact of regulations on several dimensions of labor demand during the initial stage of the teacher hiring process.

In our most stringent specification, we exploit plausibly exogenous variation in the introduction and expansion of states' child care regulations across different child age groups, controlling for all shocks that are common to a state over time. We find that the introduction of a group size regulation (for providers not already exposed to such a requirement) reduces the number of child care job postings by 5.5% to 8.4% per day, which is indicative of a drop in labor demand. In addition, the introduction of a group size regulation increases the demand for lead teachers but reduces the demand for those with a bachelor's degree, and increases the odds that a posting's education requirement is out-of-compliance with the corresponding state education regulation. In contrast, increasing the stringency of group sizes (for providers already exposed to such a requirement) does not influence the demand for nor the characteristics of child care labor. Finally, we show that increasing the stringency of staff-to-child ratios (for providers already exposed to such a requirement) reduces the demand for labor, and encourages providers to hire fewer lead teachers and those with a bachelor's degree.

In an auxiliary analysis, we study the impact of regulations on maternal employment using monthly data from the Current Population Survey (CPS) along with a difference-in-differences estimator. We compare the change in labor force participation for mothers whose youngest child is ages 0 to 10 (who were exposed to the regulatory changes) with mothers whose youngest child is ages 11 to 17 (who were not exposed to such changes) before versus after the introduction of a group size regulation. Consistent with the labor demand results, we find that labor force participation rates for mothers with children ages 0 to 10 fell two percentage points following the enactment of a group size regulation. We find null effects on weekly hours of work.

Together, these results indicate that child care providers operating in states that did not regulate group sizes

prior to the pandemic–but began regulating them for the first time after the pandemic–experienced significant challenges adjusting to the new regulatory environment. Such providers not only hired fewer teachers, but sought to downskill the teacher positions being advertised, at least as it relates to education. Conversely, providers in states already regulating group sizes prior to the pandemic appear to have adapted well to the post-pandemic period, when these regulations became tougher. Indeed, increasing the strictness of group sizes altered virtually no aspect of providersâ hiring behavior. However, changes to child-to-staff ratios were costly for providers, leading to lower demand for teachers and a decrease in the skill requirements for the job. Furthermore, we show that the implications of introducing tougher regulations extend beyond the child care labor market and into broader labor market for mothers with young children.

Insofar as these new regulatory changes persist after the pandemic, our results shed light on how the child care labor market may continue to operate. Indeed, although Panel A of Figure 1 shows that child care job postings had already begun to return to trend levels toward the end of 2020, Panel B shows that the share of job postings requiring a bachelor's degree has fallen considerably, thereby influencing the share of postings that comply with the corresponding state education requirements (Panel C). Although educational attainment may be a noisy proxy for teacher quality, these descriptive patterns nonetheless point to the limits of regulations as a policy to improve child care quality (Boyd-Swan and Herbst, 2018).

Our paper builds on a large empirical literature in labor economics that studies the impact of regulations on the child care and maternal labor markets. In particular, previous work focuses on child care supply (e.g., Gormley, 1991; Hotz and Xiao, 2011) and quality (Blau, 2007; Hotz and Xiao, 2011; Boyd-Swan and Herbst, 2019), families' use of and expenditures on child care (Blau, 2003; Hotz and Kilburn, 1994), and parental employment (Blau, 2003). Far less attention has been given to how regulations influence the demand for and characteristics of child care labor. In fact, Blau (2007) is the only paper to our knowledge that examines these outcomes. Our paper contributes to this literature in several ways. First, we introduce a new data source–the universe of online job postings–to study how child care providers respond to regulations. These data, which reflect providers' contemporaneous preferences for teacher characteristics, are well-suited for assessing not just the labor-demand response to child care regulations, but also whether providers trade-off certain teacher characteristics as regulations become tougher. Second, our study period contains substantially more variation in regulatory policy than that exploited in previous studies.

Between January and October of 2020, 31 states changed their group sizes–with the average state making 1.3 changes over this period–and 18 states changed their staff-to-child ratios (0.73 changes per state). In addition, the magnitude of the changes are sizable, such that our parameter estimates reflect meaningful, not marginal, policy changes. Finally, our identification strategy exploits not just within state over time variation regulations, but also between child-age-group (within states and days) variation, which allows us to control for all time-varying shocks within states.

Our paper also contributes to a growing literature studying the effects of recessions generally and the recent pandemic specifically on the child care market. For example, Brown and Herbst (2021) examine how the supply and quality of child care varies over the business cycle. Other papers focus on the pandemic period, estimating changes in the supply of child care in specific states (e.g., Bryson, 2020; Sonnier-Netto et al., 2020). Similarly, Ali et al. (2021) show that states' pandemic containment policies, specifically stay-at-home orders, reduced the demand for child care labor. Finally, a parallel body of work work assesses how the pandemic influenced teachers' caregiving experiences, routines, and mental health (Delap et al., 2021; Carr, 2020), as well as parents' ability to manage their new (in-home) caregiving routines in tandem with changes to employment schedules (Del Boca et al., 2020).

The structure of the paper is as follows. Section 2 provides a summary of the regulatory landscape in the U.S. child care market. Section 3 introduces the data on child care teacher job postings along with newly collected data on child care regulations across age groups and states. Section 4 describes the identification strategy. Section 5 presents the main results. Section 6 examines several dimensions of heterogeneity and robustness. Section 7 concludes with a summary of policy implications.

2 The Child Care Regulatory Landscape

Child care in the U.S. is regulated at the state-level, with the goal of mitigating the risk of harm to young children from being exposed to low-quality providers. The risks targeted by regulations range from cognitive and social-emotional impairment to physical injury and disease-spreading (Blau, 2001). Regulations require providers to be licensed and to meet a series of requirements related to the physical attributes of the setting. Specifically, it is useful to characterize regulations as governing two broad areas of the child care environment: health/safety and

labor.

Those related to health and safety include immunizations, food safety, ventilation and lighting, and playground equipment, while the labor-related regulations generally include maximum classroom group sizes, child-to-staff ratios, and the experience and education of program staff. Such requirements vary extensively by state, program setting (i.e., center- versus home-based providers), children's age group, and type of staff. For example, infant and toddler classrooms are generally subject to tougher requirements on group sizes and ratios than those for older children, and lead teachers are required to have more experience and education than assistant teachers.

Table 1 sheds light on the extent of cross-state variation in the center-based child care regulatory environment. Specifically, it shows the maximum group sizes and child-to-staff ratios for three-year-olds as well as the education requirements for assistant teachers, lead teachers, and directors as of January 2020. Fourteen states did not regulate group sizes, and among those that did, the requirement varies substantially, ranging between eight and 30 children. Child-to-staff ratios were regulated in all but one state (Idaho), with the ratios ranging between seven and 15 children. There is similar variation in staff members' education requirements. Forty states either did not have an explicit education requirement or mandated only a high school diploma (or less) for assistant teachers, while six states required some college credits or a Child Development Associate (CDA) credential. As for lead teachers, all but nine states had an education requirement, and among those that did, the requirement varied from a high school diploma (17 states) to a completed associate's or bachelor's degree (three states). Finally, all but one state (Idaho) regulated education levels for program directors, with most states requiring either college credits or a completed college degree, although nine states required no more than a high school diploma.

Regulations are justified on the basis that they mitigate information asymmetries in the child care market where parents are poorly informed about the quality of care received by children. Parents may be poorly informed because they lack the resources to assess program quality or they cannot efficiently monitor staff. Thus, providers have an incentive to produce lower-quality services by reducing health and safety investments or hiring less productive workers than would be the case if parents were perfectly informed. Regulations may therefore be necessary because they ensure that a minimally acceptable level of quality exists throughout the market, primarily by forcing low-quality providers to improve or exit the market. However, even if parents were perfectly informed, regulations may be desirable if any quality improvements translate into health and developmental benefits for children.

The theoretical predictions from models of minimum quality standards depend crucially on whether child care providers engage in input substitution, whether the regulations are binding, and whether consumers are willing to pay for a higher price for regulated care. On the one hand, if regulations are binding, then providers face a higher cost of providing child care. Under a pass-through to the consumer, higher prices reduce the quantity of child care demanded, reduce the supply of such care, and cause a reduction in parental labor supply. On the other hand, if regulations raise the quality of child care, and consumers recognize and sufficiently value the increase, then the demand for and supply of child care can rise and lead to an increase in parental labor supply. Given that regulations do not dictate the level of quality per se—rather, they influence the measurable inputs to the production of quality—such requirements may distort provider behavior regarding the deployment of these inputs. For example, to comply with a tougher regulation on group sizes (leading to smaller classrooms), a provider may respond by hiring more teachers but favoring those with lower levels of education. Such input substitution means that program quality may not increase, and could in fact decrease.

If regulations are not binding on many child care providers, it is unlikely they would have a large impact on the market. For example, if a provider would chose a maximum group size of 15 in the absence of a regulation, then requiring group sizes to be 20 would not influence its behavior. The larger the number of providers that face a "binding regulation," the more that regulation will influence supply and prices within the market. Unfortunately, whether a regulation is binding has received only scant attention by researchers. Blau (2001) compares the observed child-to-staff ratios within center-based classrooms with the relevant state regulation and finds that most providers exceed (i.e., perform better than) the state ratio requirement. Boyd-Swan and Herbst (2018) also compare the experience and education requirements posted in online child care job advertisements with the corresponding state regulations, again finding that most providers are willing to exceed the state requirements.

Although this work suggests that regulations are not likely to be binding for many providers, some caution is warranted, particularly as it relates to the current study. Recall that this study examines the period surrounding the COVID-19 pandemic, during which states enacted unprecedented changes to their child care regulations. The magnitude of such changes, which will be detailed in a forthcoming section, likely means that a much larger share of providers face binding regulations than before the pandemic and, as a result, the new policy landscape may have forced providers to quickly alter their hiring and human capital decisions.

Finally, if parents are unwilling or unable to pay a higher price for regulated child care, perhaps because they have weak preferences for quality or because they cannot afford higher-quality services, then the demand for regulated care will unambiguously fall, thereby causing decreased demand for the regulated inputs as well as a reduction in supply. The evidence suggests that the demand for child care services and for quality are moderately sensitive to prices (Blau and Hagy, 1998), as are parental employment decisions (Anderson and Levine, 2000; Herbst, 2010), again implying a limited scope for regulation-effects. However, these price sensitivities may have increased significantly during the pandemic. For example, while parents may recognize the importance of a clean and safe child care environment, their ability to purchase such care during the pandemic—a period of rapid job loss—may be adversely affected. Moreover, as more information is now available about the relatively low risk of COVID-19 transmission among young children (Rothwell et al., 2021), parents may place a low valuation on these regulations. Insofar as any of these hypotheses hold, the demand for and quality of child care labor will fall as regulations become tougher.

3 Data and Measurement

3.1 Labor Demand for Child Care

Data on the demand for and characteristics of child care labor come from EMSI, an analytics company that scrapes every job that is posted across online job banks (e.g., Indeed, Glassdoor, and LinkedIn). From this database, we retrieve the universe of advertisements for center-based child care teacher positions, including those in private for- and non-profit centers and publicly-funded programs.[3] All job postings in the EMSI database include detailed information on the characteristics of the position, such as its name and title, the name of the hiring firm, and geographic identifiers for the city, county and state of the job location. Each job posting also lists requisite skills, education, and salary structure. Finally, posted positions are classified as part- or full-time jobs.

Relying on information in each job posting, we employ keyword search methods to classify all child care job postings in a variety of ways. Specifically, we search within the "position title" field to classify postings according to the sector in which the job is based (center-based child care, Head Start or pre-k), the level/type of teacher

[3] In the EMSI database, child care job postings are a subset of all education job postings identified with the two-digit Standard Occupational Classification Code (SOC) 25.

position (assistant or lead teacher), and the child age group with which the teacher will work (infants and toddlers, preschool-age children, or school-age children). We define infants and toddlers as children ages 0 to 2, preschool-age children as those ages 3 to 5, and school-age children as those ages 6 to 10.[4]

We use these job postings data to examine the impact of regulations on four key outcomes. We begin by studying the demand for child care labor, defined as the total number of child care job postings. For this analysis, we collapse the data into state × day × age group cells. The data thus consist of 41,922 observations (51 states × 274 days × 3 age groups) over the period January 1, 2020 to September 30, 2020.

We then turn our attention to studying the characteristics of the teacher job postings, thereby allowing us to shed light on the degree of skill-based input substitution. First, we estimate the demand for lead teachers as compared to the demand for assistant teachers. To do so, we classify each job posting as either a lead or an assistant teacher posting, as mentioned above, and create a binary indicator that equals one if a given posting is for a lead teacher. Second, we evaluate whether child care providers are hiring for similar roles, but altering the required skill level for the positions. We do so by examining if each job posting lists a bachelor's degree (or more) as a job requirement. Here again we construct a binary indicator equal to one if a given job posting requires a bachelor's degree and zero otherwise. The unit of analysis for these outcomes is the job posting, and the sample consists of a maximum of 49,045 observations, treating each job posting as an individual observation.

Finally, we examine whether compliance rates with other regulations change in response to increasingly strict group sizes and child-to-staff ratios. Specifically, we study compliance with state regulations on teachers' minimum education requirements. For this analysis, we begin by coding each state's center-based (minimum) education requirement for lead teachers. As shown in Table 1, we focus on lead teachers because most states regulate their education levels, and there is substantial variation in these regulations. Indeed, the lead teacher education requirements range from a high school diploma (17 states) to a college degree (4 states), with the remaining states requiring some number of college credits or a professional credential. We then compare the education requirement in each job posting with the corresponding state education regulation. We code compliance as a binary indicator, which takes a value of one if the posted education requirement meets or exceeds the state requirement. This analysis is conducted at the lead teacher job posting level, for which there is a total of 20,296 observations.

[4]It is important to note that the job postings data do not cover the home-based child care market, nor employment opportunities for au pairs or babysitters.

Figure 1 presents the daily time series for the four outcomes of interest over the study period (i.e., January 1 to September 30, 2020): total number of child care job postings (Panel A), share of lead teacher job postings (Panel B), share of job postings requiring a bachelor's degree or more (Panel C), and share of lead teacher job postings in compliance with the state education regulation (Panel D). Prior to the pandemic (in January and February), the U.S. averaged between 200 and 300 child care job postings each day, which then fell below 100 in the early months of the pandemic. However, job postings fully recovered to, and even exceeded, their pre-pandemic levels by the end of the summer. Interestingly, there was immediate increase after the pandemic began in the share of job postings for lead teachers and those requiring a bachelor's degree. However, the demand for bachelor's degrees fell throughout the summer to its pre-pandemic levels. Finally, nearly 70% of job postings in the pre-pandemic months (of January and February) were in compliance with the state education regulation, a share that increased between March and May before falling to (or even slightly below) its pre-pandemic levels by the end of the study period.

3.2 Maternal Employment

Following the child care labor market analysis, we conduct an auxiliary analysis of maternal employment, a focus of some previous work (e.g., Blau, 2003). Data for this analysis come from the Current Population Survey (CPS) for the months January to September (of 2020) (Ruggles et al., 2020). The analytic sample includes women ages 18 to 55 whose youngest child is ages 0 to 10 (the treatment group), as well as those whose youngest child is ages 11 to 17 (the comparison group). Consistent with our previous approach, we pay specific attention to the age group of the youngest child for each mother in the treated sample, differentiating across infants and toddlers (ages 0 to 2), preschool-age children (ages 3 to 5), and school-age children (ages 6 to 10). The sample consists of 97,756 observations. We examine two key outcomes related to maternal employment: an indicator variable equal to one if a given mother is in the labor force and logged weekly hours of work.

3.3 Child Care Regulations

Our analysis examines the impact of two labor-related child care regulations: center-based maximum classroom group sizes and child-to-staff ratios. A key feature of both regulations is that they vary by single-year of children's age, up to age 10. In order to exploit the substantial age-based variation in these regulations while keeping the

number of such variables at a manageable level, we create averages for group sizes and ratios across three age groups, as previously described: ages 0 to 2 (infants and toddlers), ages 3 to 5 (preschool-age children), and ages 6 to 10 (school-age children).[5] Thus, we code these regulations in state × day × age-group cells over the period January 1 to September 30, 2020.[6] We rely on multiple data sources to obtain an accurate and consistent time series in these regulatory changes, including Child Care Aware of America, National Governors Association (NGA), Hunt Institute, and state governor's office and Department of Health websites.[7]

We measure center-based maximum group size regulations in two ways. First, we examine whether any group size regulation is enacted within each state × day × age-group cell. Thus, this variable is coded as binary indicator, which takes a value of one if a group size regulation is in effect, and a value of zero when there is no group size regulation in effect. Second, we measure the actual value of the regulated group size within each state × day × age-group cell, making this a continuous measure of the stringency of the group size regulation. Furthermore, we assign a value of zero to cells without a group size regulation in effect and then invert the variable (i.e., 1/maximum group size), so that higher values indicate increasingly strict group size regulations. Finally, we standardize the variable to have a mean of zero and a standard deviation of one so that its coefficient can be interpreted as the change in a given outcome due to a one standard deviation increase in the stringency of the group size regulation.

Our final measure of child care regulations captures the stringency of center-based child-to-staff ratios. For this variable as well, we measure the maximum allowable classroom child-to-staff ratio within each state × day × age-group cell, again making this a continuous measure of the stringency of the ratio regulation. In addition, we impute a value of zero to cells without a ratio in effect, and we invert the variable so that it measures staff-to-child ratios with higher values indicating increasingly strict regulations. This variable is also standardized to have a mean of zero and a standard deviation of one.

Table 2 provides descriptive evidence on child-age-specific variation in group sizes and child-to-staff ratios, while

[5] For example, the value of group sizes and child-to-staff ratios for school-age children would represent the average of these regulations across 6-, 7-, 8-, 9-, and 10-year-olds.

[6] That our data exploits states' child-age-specific variation in regulations is advantageous for two reasons. First, it provides us with a third source of identifying variation, which can be used to generate estimates that rely on regulatory differences between child age-groups within states and days, thereby allowing us to control for time-varying unobservables. In contrast, most previous work relies on cross-sectional or within-state over time variation in child care regulations (e.g., Blau (2003), Boyd-Swan and Herbst (2019), and Hotz and Xiao (2011)). Second, the additional age-group variation reduces the correlation between the variables measuring group sizes and child-to-staff ratios, allowing us to separately identify the impact of both regulations. The presence of strong correlations between regulations has been noted elsewhere, and has forced previous studies to construct summary indices of multiple regulations to circumvent the problem (e.g., Blau (2003), Boyd-Swan and Herbst (2019), Hotz and Xiao (2011), and Currie and Hotz (2004)).

[7] Child Care Aware data are available here: https://www.childcareaware.org/coronavirus-hub/coronavirus-landing-page/state-policies-and-ratio-changes-during-covid-19/, NGA website resources are found here: https://education.nga.org/section-statetable, while the Hunt Institute's data summary can be seen here https://hunt-institute.org/covid-19-resources/state-child-care-actions-covid-19/

Figures 2 through 4 shed light on how these regulations evolved over the study period. It is clear from Table 2 that center-based classrooms serving younger children are subjected to more stringent labor regulations than those serving older children. For example, prior to the pandemic (that is, January and February of 2020), 79% of states enacted a group size regulation for infant/toddler classrooms, compared 63% for school-age classrooms (Panel A). Similarly, among states with a group size regulation in effect, the maximum classroom sizes were mandated to be considerably smaller in infant/toddler settings (11) than in school-age settings (31) (Panel B). Such differences are also quite large in states regulating child-to-staff ratios: the average ratio in infant/toddler classrooms was approximately 6:1, while that for school-age classrooms was nearly three times higher, at 17:1 (Panel C).

Figures 2 through 4 reveal how these pre-pandemic levels evolved throughout the first seven months of the pandemic. Specifically, Figure 2 documents the daily time series variation in the share of states regulating group sizes, both overall and by age group. Figure 3 shows the time series in the regulated value of group size (among states with a regulation in effect), while Figure 4 shows the analogous data for child-to-staff ratios. In each figure, the mean daily regulation across all ages (0 to 10) is displayed in the upper-left-hand corner, while the age-group-specific means are shown in the remaining graphs.

As shown in Figure 2, the share of states with any group size regulation enacted increased considerably in the early months of the pandemic, rising from 70% to 85% between March and June. Interestingly, some states subsequently allowed these regulations to lapse, such that by the end of the study period (September) the share of states regulating group sizes had fallen to around 80%. Furthermore, it is clear from the age-group-specific figures that the enactment and subsequent rescission of group size regulations affected classrooms serving all age groups in center-based programs. Figure 3 similarly shows that among states regulating group sizes, those regulations grew tougher throughout the pandemic, falling from an average of about 20 in March to a low of 14 in June, at which point some states allowed classroom sizes to increase gradually. However, it is noteworthy that, by the end of our study period (September 30), average group sizes still remain far below their pre-pandemic levels. Finally, Figure 4 reveals a similar time path for child-to-staff ratios: the enactment of tougher regulations between March and June, resulting in substantially smaller ratios, followed by a loosening of the regulations throughout the remainder of the study period (although the ratios do not return to their pre-pandemic levels).

In summary, states made substantial changes to their group size and child-to-staff ratio regulations during

the period covered by our analysis. Indeed, these policy changes were both widespread and numerous, providing substantially more policy variation than was available in previous studies. Between January and October of 2020, 31 states reformed their group size regulations, with five states making one change, 19 states making two changes, and seven states making three changes. Similarly, 18 states revised their child-to-staff ratios: three states made one change, 12 states made two changes, two states made three changes, and one state made four changes. We exploit this variation within and across states and age groups in the empirical models, as described in the next section.

3.4 Time-Varying State Covariates

This study controls for a number of state-level policies that were enacted concomitantly with the reforms to child care group sizes and child-to-staff ratios. Importantly, states implemented a series of COVID-19 health and safety requirements aimed at center-based providers. Therefore, all of the empirical models add controls for whether programs were (1) required provide sanitizing and disinfecting supplies to kids and staff on site, (2) required sanitize and disinfect facilities daily, (3) precluded from allowing inter-group (i.e., classroom) mixing for all activities, and (4) precluded from allowing all visitors to enter the facility. All of these health and safety requirements are coded as binary indicators equal to one if a given requirement is enacted in each state-day cell.[8]

The paper also obtains data for various COVID-19 containment polices, such as state of emergency declarations as well as the enactment of statewide stay-at-home orders (SAHO), public school closures, business closures (and re-closures), and statewide indoor mask mandates. All of these variables are coded as binary indicators equal to one if a given policy is in effect, and they vary within states over time.[9] One concern is that any changes in labor demand for child care might simply reflect a decline in the demand for market-based child care among households. Therefore, to ensure that demand-side changes do not confound the estimated effect of child care regulations, we include in the models Google Trends search intensity scores for the topic "child care" as a proxy for demand.

[8]Key resources used in the extraction of these data on health & safety regulations are relevant policy documents issued by state agencies, as outlined and summarized by Child Care Aware of America website, the National Governors Association (NGA) state-action tracker, and the Hunt Institute Database.

[9]These data have been obtained from the COVID-19 U.S. State Policy Database (CUSP) (Raifman et al., 2021), the National Governors Association (NGA) state-action tracker, and the Hunt Institute Database.

4 Empirical Strategy

To estimate the impact of regulations on the demand for child care labor, we use an identification strategy that exploits both within-state over-time and between age-group variation in the stringency of states' child care regulations. We begin by analyzing overall labor demand for child care, followed by an analysis of the demand for teacher characteristics, as well as compliance with regulations on teachers' education levels. We end with an auxiliary analysis of the impact of regulations on maternal employment.

4.1 Labor Demand for Child Care

To understand the relationship between regulations and the demand for child care labor, we start by estimating panel regressions of the following from:

$$Y_{sgt} = \gamma r^{e}_{sgt} + \phi r^{i}_{sgt} + X^{'}_{st} + \zeta_g + \xi_s + \eta_t + \varepsilon_{sgt} \tag{1}$$

where Y_{sgt} in Equation 1 denotes the log number of child care job postings in state s, child-age-group g, and day-of-the-year t. The key variables of interest are r^e, which denotes an indicator for whether the state has any group size regulation in place (i.e., the extensive margin), and r^i, which denotes a vector of standardized measures of group sizes and child-to-staff ratios (i.e., the intensive margin) within a given state-day-age group cell. The X' is a matrix of time-varying state controls, ζ denotes age-group fixed effects, ξ denotes state fixed effects, and η denotes day-of-the-year fixed effects. Whereas r^e captures whether any group size regulation is enacted, r^i focuses on the (continuous) regulated value of group size, conditional on having such a regulation in place. This allows us to distinguish between provider responses to newly-enacted regulations (i.e., regulations implemented for the first time during the pandemic) versus responses to incrementally increasing the stringency of existing regulations. Standard errors are clustered at the state $\times$ day level.

Our inclusion of age-group, state, and time fixed effects in Equation 1 is important for removing all time-invariant sources of unobserved heterogeneity. For example, states with tougher regulations may have other child care policies in place and/or have greater parental demand for child care, which may influence providers' labor

demand. Similarly, the importance of child care quality might vary across children's age groups, thereby leading to an age-specific component in the demand for regulated care (e.g., targeting younger children). Moreover, given the substantial macroeconomic volatility during the pandemic, changes to regulations may be correlated with demand for labor, including child care workers. By introducing these fixed effects, we isolate variation in regulations within the same state and age-group over time.

Despite the inclusion of fixed effects, there still could be time-varying shocks to the demand for child care labor. For example, the enactment and increased stringency of regulations could be a response to changing preferences for enhanced health/safety controls and supervision, which might have emerged during the pandemic as the risk of COVID-19 transmission changed. In addition, states enacted a number of policies (e.g., state-at-home and mandatory business closure orders) aimed at mitigating the spread of COVID-19, all of which likely influenced the demand for child care labor (Ali et al., 2021). It is also possible that these state quarantine restrictions caused households to migrate to another state or to work remotely, thereby reducing the demand for non-parental child care. Failure to control for these time-varying preferences and containment policies could bias the coefficients on regulations if they are correlated with child care providers' hiring behavior.

We address these potential time-varying confounders in three ways. First, we include a matrix of control variables, X', for state-specific COVID-19 containment policies that were enacted contemporaneously with the child care regulations, including a set of (four) health and safety requirements for child care providers as well as proclamations of state of emergency orders, stay-at-home orders, public school closures, business closures (and re-closures), and face mask mandates. We also include Google search intensity scores for the topic "child care", which may proxy any changes in parents' child care preferences and search behavior. Second, we consider specifications that include state $\times$ day fixed effects to purge all time-varying shocks to child care within a state that might not be captured by our state policy controls, such as changes in macroeconomic conditions or the spread of COVID-19.

Finally, to validate that we are not picking up any state $\times$ group $\times$ day shocks to the child care market, we implement a falsification test in which the number of child care job postings is replaced with the number of Head Start and pre-kindergarten job postings as the outcome. Although the labor markets for Head Start and pre-kindergarten teachers are comparable to that for child care (and are exposed to the same macroeconomic, policy, and pandemic conditions), changes to child care regulations should not influence labor demand in these publicly-

provided early education sectors, given that the regulations were directed only at center-based child care providers. Thus, Head Start and pre-kindergarten job postings offer a useful control group. In sum, our identification strategy offers substantial advantages compared to the existing literature since we not only exploit within-state variation and avoid cross-sectional comparisons, but also leverage heterogeneity in the response of child care providers that are subject to different age-group regulations.

4.2 Workforce Characteristics

Our identification strategy for the analysis of workforce characteristics differs from the one shown in Equation 1, relying only on within-state over-time variation in child care regulations. We estimate regressions for workforce characteristics as follows:

$$Y_{ist}^{k} = \gamma r_{st}^{e} + \phi r_{st}^{i} + X_{st}^{'} + \xi_s + \eta_t + \varepsilon_{ist} \tag{2}$$

where Y_{ist} in Equation 2 denotes an indicator variable for whether a given child care job posting i in state s and day-of-the-year t corresponds to a particular characteristic. Thus, the unit of analysis for these outcomes is the job posting, rather than the state $\times$ group $\times$ day panel structure used in the previous analysis. The r^e denotes the indicator for whether the state has any group size regulation in place (averaged over child ages 0 to 10), and r^i denotes a vector of standardized measures of group sizes and child-to-staff ratios (averaged over child ages 0 to 10). Our state-level variables, X', include the same set of observable policy characteristics outlined in Equation 1. As the with Equation 1, Equation 2 includes state and day fixed effects. However, this model does not include age group fixed effects, since we are interested in studying changes in the composition of job postings, rather than the within-group change in demand. Standard errors are clustered on state-day cells.

We study three outcomes using this specification. First, we differentiate across the level of each job posting i and create a binary indicator denoting whether the job posting corresponds to a lead teacher (1) or an assistant teacher (0). The second outcome examines whether each job posting requires at least a bachelor's degree (1) or not (0). For the third outcome, we attach state-specific minimum teacher education requirements to each job posting and define our outcome as a binary indicator for whether the job posting meets the state regulation (1) or not (0).

We rely on the full set of job postings for the first two outcomes on job characteristics, but limit the sample to only lead teacher job postings for the third outcome.[10]

4.3 Maternal Employment

In an extension of our main results, we consider a new specification in which we draw on monthly data on maternal employment from the Current Population Survey (CPS):

$$Y_{igst} = \xi c_{ist} + \gamma r_{gst} + \psi(c_{ist} \times r_{gst}) + \theta D_{ist}^{'} + \beta X_{st}^{'} + \xi_s + \eta_t + \varepsilon_{igst} \tag{3}$$

where Y_{ist} in Equation 3 denotes various measures of maternal employment for individual i with children in age group g in state s and month t. We explore two employment outcomes: labor force participation and log weekly number of hours worked. The c denotes an indicator variable equal to one if the mother's youngest child is between the ages of 0 and 10, and equal to zero if the youngest child is between the ages of 11 and 17. For brevity's sake, this analysis focuses on the impact of any group size regulation enacted (i.e., the extensive margin), denoted by r and measured through an indicator variable. The D denotes a vector of individual demographic controls, including a quadratic in age, marital status, race and ethnicity, education, and the presence of work-limiting physical and cognitive difficulties. The X denotes a vector of time-varying state controls, which includes the same set of COVID-19 containment policies in Equation 1. Finally, the ξ and η denote state and month fixed effects, respectively. The standard errors are clustered at the state-month level.

Women whose youngest child is ages 0 to 10 comprise the treatment group because, as discussed in the previous analyses, these women were exposed to the child care regulatory changes, given that the policy changes target center-based classrooms serving children in that age range. Those whose youngest child is ages 11 to 17 comprise the comparison group because women with older children are not exposed to the regulatory changes. Thus, the coefficient of interest is ψ, which represents the difference-in-differences employment estimator for mothers whose youngest child is ages 0 and 10, relative to those whose youngest child is ages 11 to 17, before versus after the implementation of any group size regulation.

[10] We limit the sample to lead teachers because for most states minimum state requirements for assistant teachers are either undefined or much more lenient.

Our primary identifying assumption is that labor market outcomes for mothers whose youngest child is ages 0 to 10 would have trended similarly to those mothers whose youngest child is ages 11 to 17 in the absence of a group size regulation, conditional on the observable controls and fixed effects. We verify the plausibility of this assumption by implementing an event study analysisâan explicit test the parallel trends assumptionâwhich investigates whether maternal employment was already shifting in states prior to the enactment of group size regulations. Another concern is that mothers with younger children were subject to more severe time constraints because of differences in their demands at home and work, or that these mothers were concentrated in occupations that were more adversely affected by states' COVID-19 containment policies. However, we control for a wide array of such policiesâincluding stay-at-home orders, school and business closures, and mask mandatesâthereby isolating variation that is unique to child care regulations. Furthermore, we allow for the presence of other time-varying confounders by estimating models that include Census region × month fixed effects, family income bin × month interactions, and state employment growth × month interactions. As will be shown, our baseline estimates are robust to these controls.

5 Main Results

5.1 The Demand for Child Care Labor

We now present the main results for child care labor demand in Table 3 associated with Equation 1. Panel A displays the baseline results based on models that include age group, state, and day fixed effects as well as the time-varying state covariates. Results in Panels B and C provide the robustness checks, with the former including state × day fixed effects and the latter implementing the falsification test. Recall that the falsification test uses the number of Head Start and pre-kindergarten (instead of child care) job postings as the outcome. Five models are estimated in each panel, each one varying the type and number of child care regulations included in the model. The final column in each panel estimates a model that incorporates all three regulation variables simultaneously.

Generally speaking, the results in Panel A indicate that the enactment and increased stringency of group sizes and child-to-staff ratios reduce the demand for child care labor, as proxied by the number of job postings. Column (1) shows that the enactment of any group size regulation is associated with a 5.5% decrease in the number of child

care job postings, while Column (2) shows that a one standard deviation (SD) reduction in the average group size is associated with a 1.2% decrease in the number of postings. Interestingly, Column (3), which includes both group size variables, reveals that the extensive margin of regulation remains statistically and economically significant. Column (4) shows that a one SD decrease in the child-to-staff ratio is associated with a 1% decline in job postings. When all three regulation variables are included together, as shown in column (5), only the extensive margin of group sizes remains economically and statistically significant.

Looking at Panel B, we now introduce state $\times$ day fixed effects, which exploit only age-group-specific variation in the child care regulations by controlling for all shocks that are common within the same state over time. The results are quite comparable to those in Panel A. In anything, the magnitude of the coefficients in Panel B are larger than their counterparts in the Panel A, implying that the estimates in Panel A are biased toward finding no impact of regulations. Thus, these results suggest that there are no time-varying state-specific sources of unobserved heterogeneity. Another source of bias is the presence of time-varying age-group shocks affecting the demand for child care in a state. As an additional robustness check, we implement a placebo test, exploring whether child care regulations influence the number of Head Start and pre-kindergarten job postings, as shown in Panel C. We find null associations: all of the coefficients are small in magnitude statistically insignificant. If our results in Panels A and B were simply a function of an unobserved age-group-specific shock, we would expect to see an effect here, which we do not. Overall, these results are consistent with those in Ali et al. (2021), who find that the decline in overall early care and education job postings throughout the pandemic was driven by the substantial reduction in the center-based child care sector.

To put our results in perspective, consider that the average daily number of child care job postings across states and age groups is 3.5. That means the enactment of group size regulations (i.e., the extensive margin effect) leads to a roughly 0.20 daily reduction in job postings, or nearly 5.7 fewer postings each month. Similarly, the 1.0 to 1.2% reduction in job postings associated with a SD reduction in group sizes would result in 1.1 to 1.3 fewer job postings each month. Given that there were less than 100 job postings per day nationally at the height of the pandemic in 2020, the estimated coefficients in this paper are economically meaningful.

In sum, the results indicate that the enactment of tougher regulations on classroom group sizes and child-to-staff ratios reduce the demand for child care labor, although the response appears to be especially strong at the extensive

margin of group sizes. That is, the reduction in labor demand is strongest among providers located in states that enacted a group size regulation for the first time during the pandemic. Indeed, we find smaller labor demand responses among providers in states that incrementally increased the stringency of already-existing regulations.

5.2 The Characteristics of Child Care Labor

We now turn to Table 4, which begins to study the impact of child care regulations on the characteristics of the job postings. In doing so, our goal is to understand whether child care providers respond to tougher regulations by engaging in input substitution, or varying the skill composition of the workforce. We begin by studying a binary indicator for whether a given job posting is for a lead or an assistant teacher. Our results consistently show that the enactment of a group size regulation increases the odds that a given job posting advertises for a lead teacher. Indeed, the estimate in column (5) shows that having a group size regulation in place increases the odds of advertising for a lead teacher by 3.6 percentage points. Among providers located in states with a group size regulation already enacted, increasing the stringency of that regulation does not appear to alter the demand for lead teachers. However, Table 4 also shows that increasing stringency of already-enacted child-to-staff ratios reduces the demand for lead teachers. Specifically, the coefficient in column (5) implies that a one SD decrease in the child-to-staff ratio reduces the probability of advertising for a lead teacher by 1.7 percentage points.

Table 5 further tests for input substitution by examining whether a given job posting requires at least a bachelor's degree. Panel A is restricted to the subset of assistant teacher postings, Panel B is restricted to lead teacher postings, and Panel C is restricted to preschool-age lead teacher postings. We conduct the analysis separately on the subset of lead preschool-age job postings because this is the most prominent age-group in terms of child enrollments and teacher hiring. Results in Panel A reveal that the enactment of any group size regulation increases the demand for bachelor's degrees among assistant teachers. Indeed, the coefficient in column (5) implies that the likelihood of requiring such a degree increases by nearly seven percentage points. However, increasing the regulatory strictness at the intensive margin (for group sizes and child-to-staff ratios) does not appear to alter the demand for bachelor's degreed assistant teachers, suggesting that the rise in demand for these more educated child care teachers is driven by the extensive margin (i.e., providers required to comply with newly-enacted group size regulations).

Turning to Panels B (all lead teachers) and C (lead preschool-age teachers), we find that states' newly-enacted

group size regulations encourages child care providers to reduce their demand for bachelor's degreed lead teachers, particularly in the labor market for lead preschool-age teachers. Indeed, the coefficient in column (5) of Panel C implies that the likelihood of requiring such a degree declines by 6.7 percentage points. Conversely, there is some evidence to suggest that increasing the stringency of already-enacted group size regulations may encourage education-based upskilling by increasing the demand for bachelor's degreed lead teachers. However, increasing the stringency of child-to-staff ratios has the opposite effect, lowering the odds that job postings require bachelor's degrees, particularly for lead preschool-age teachers.

In sum, these results yield some important insights about the ways in which regulations alter the demand for child care labor. Providers that are required to comply with a newly-enacted group size regulation respond by decreasing their demand for labor (i.e., posting fewer teacher advertisements). However, when they do recruit teachers, they are more likely to hire lead teachers, as opposed to assistant teachers. This finding makes intuitive sense, because, at a minimum, a lead teacher is required to run a child care classroom. Furthermore, the adoption of a group size regulation is associated with an increased number of postings that require a bachelor's degree, conditional on posting for an assistant teacher, but a decreased number of such postings for lead teachers. This suggests that child care regulations lead to a substitution away from higher-skilled lead teacher jobs towards higher-skilled assistant teacher jobs. In addition, such downskilling may occur in order to offset the increased cost of compliance with a (newly-enacted) regulation aimed a reducing classroom group sizes.

On the other hand, we find little response from providers located in states that increase the stringency of preexisting group size regulations. There is no change in labor demand, nor is there a change in the demand for lead teachers. If anything, we uncover some evidence of lead teacher upskilling (i..e., lead teacher advertisements are more likely to require a bachelor's degree) as the group size regulations become tougher. Finally, our results suggest that increasing the stringency of preexisting child-to-staff ratios have important effects on providers' hiring behavior. In particular, providers are induced to decrease their overall labor demand, reduce the demand for lead teachers, and downskill their workforce by becoming less likely to require lead teachers to have a bachelor's degree. Again, such results indicate that increasing the strictness of child-to-staff ratios is sufficiently costly that providers respond by substituting away from higher-skilled labor in order to comply with the requirements.

Finally, the effects on input substitution are roughly as large as, if not larger than, the magnitudes we find on

child care job postings overall. For example, the introduction of any group size regulation is associated with a 6.9% increase in assistant teacher job postings with a BA+, compared with a 5.5% decline in child care job postings overall. In this sense, the decline in overall job postings was coupled with a fundamental shift in the demand for different types of skills in the market for child care. Together, these findings suggest that providers respond to regulations in ways that may unintentionally reduce classroom quality.

6 Extensions and Robustness

The results presented so far highlight the adverse consequences of child care regulations on the demand for child care labor and the composition of the labor force. In this section, we examine an additional unintended consequence of regulations via their impact on compliance with other state regulations. We then conduct an auxiliary analysis of maternal employment. Finally, we end with a discussion of robustness checks.

6.1 Non-compliance with State Regulations

For each job posting, we construct an indicator variable for whether the advertised education requirement meets the corresponding state education requirement for lead teachers. We then estimate models that relate compliance with the measures of group sizes and child-to-staff ratios, exploiting variation within the same state over time. The goal of this analysis is to test whether providers are less likely to comply some regulations as others become increasingly strict. Table 6 presents results from this exercise, estimating a version of Equation 2.

Looking at column (5) of Panel A, which focuses on all lead teacher job postings, we find that the enactment of any group size regulation reduces the likelihood of complying with states' teacher education requirements by 3.7 percentage points, although the coefficient is not statistically significant at conventional levels. We also see that increasing the stringency of already-enacted group size regulations is associated with increases in the probability of meeting the state requirements, while increasing the stringency of child-to-staff ratios reduces the probability of meeting the requirements. When the sample is restricted to lead preschool-age job postings, as is done in Panel B, we see even larger and more statistically significant declines in the probability of meeting the state education requirements as the group size and ratio regulations become tougher. These results, together with those presented in

Table 5 underscore the potential unintended consequences associated with supply-side regulations: in an endeavor to comply with tougher regulations, providers may be encouraged to violate other standards to mitigate the cost of compliance. Furthermore, enacting tougher regulations may induce more violations if states' enforcement efforts are weak.

6.2 Implications for Maternal Employment

To the extent that regulations affect the demand for child care labor, then we should also see effects on the labor market outcomes of the families who are exposed to them. In Equation 3, we focus on maternal labor force participation and weekly hours of work, conducting a difference-in-differences analysis in which we compare mothers with children ages 0 and 10 with those with children ages 11 and 17, isolating variation within the same state and age-group over time.

Table 7 documents these results. Starting with column (1), we explore the impact of enacting a group size regulation on labor force participation, controlling for state and month fixed effects and mothers' demographic characteristics. Not surprisingly, we find that mothers whose youngest child is ages 0 and 10 are 5.3 percentage points less likely to participate in the labor force. More importantly, enacting a group size regulation leads to a statistically significant 2.0 percentage point decline in the labor force participation rate among mothers whose youngest child is ages 0 to 10, but a statistically insignificant for mothers whose youngest child is ages 11 to 17.

Are our results contaminated by time-varying unobserved geographic shocks or to mothers with younger children? We gauge these concerns in three ways. First, in column (2), we introduce region $\times$ month and income bin fixed effects, which control for all shocks that are common within each of the nine Census regions in a given month and among individuals in the same income bracket. We take a semi-parametric approach, placing 16 bins on the distribution of family income.[11] This allows us to compare families that generally earn similar amounts per year, mitigating concerns about selection effects and skill differences among mothers. Here, we see a slight increase in our point estimate on the interaction effect to a 2.0 percentage point reduction in labor force participation among with mother with children ages 0 to 10.

[11] Our bins on the distribution of family income are indicators for whether the family earns: less than $5,000 per year, $5,000-7,499, $7,500-9,999, $10,000-12,499, $12,500-14,999, $15,000-19,999, $20,000-24,999, $25,000-29,999, $30,000-34,999, $35,000-39,999, $40,000-49,999, $50,000-59,999, $60,000-74,999, $75,000-99,999, $100,000-149,999, and $150,000 and over.

Second, in column (3), we introduce a control for monthly state employment growth to purge variation in the local labor market that might adversely affect maternal employment. Again, our results are robust to the inclusion of this control. Finally, in column (4), we introduce income × month fixed effects, which isolates variation within narrowly defined skill brackets of families (as measured by income) over the pandemic. Here, the adoption of a group size regulation leads to a 2.0 percentage point decline in labor force participation rates for mothers with a youngest child between ages 0 and 10, while the direct effect for mothers with a youngest child between ages 11 and 17 becomes statistically insignificant and smaller in magnitude.

We also explore whether child care regulations affect the intensive margin of labor supply. Columns (5) to (8) in Table 7 document these results. We see no statistically or economically significant results. In additional results, which we omit for brevity, we also examine the marginal effect of changes in group sizes and child-to-staff ratios on labor force participation rates and hours worked, but we find no significant effects. In sum, these results suggest that child care regulations create fixed costs for families that affect the extensive margin of labor supply much more than the intensive margin. In particular, if employers for these mothers generally provide limited options for remote work, they may have little option of varying the amount of time that they spend at work.

We now the examine whether pre-trends in the difference-in-differences estimator might confound the results. Specifically, we adopt an event study design, regressing labor force participation on lags and leads separately for our treatment and comparison groups, normalized to the state × group cells that did not experience a change in their group size regulations. Figure 5 documents these results. Importantly, whereas there is a null association between group sizes and labor force participation in both the lags and leads among the mothers with a youngest child between ages 11 and 17, as one would expect, we see a statistically significant decline in labor force participation among mothers with a youngest child between ages 0 and 10 following the introduction of the regulation. These results provide more confidence that labor force participation rates of mothers with a youngest child between ages 0 and 10 and those with a youngest child between ages 11 and 17 would have trended similarly in the absence of these group size regulations.

6.3 Robustness Test

As a final robustness exercise, we now ask whether any of our results on child care labor demand could be driven by a key time-varying shock that coincided with the introduction and increased stringency of child care regulations. Specifically, many states fundamentally altered the health and safety standards for center-based child care programs in order to mitigate the transmission of the virus, and they did so contemporaneously with the reforms to group sizes and child-to-staff ratios. Specifically, states mandated face coverings and health screenings for staff and children, social distancing, the provision of sanitizing/disinfecting supplies, enhanced cleaning protocols, staggered arrival and departure times, no visitation, among other things. We code 10 such requirements in state x day cells over the period January 1 to September 30, and we use these data to answer two questions: do these policies have an independent effect on the child care labor demand outcomes studied earlier, and does their inclusion in the model alter the estimates on group sizes and child-to-staff ratios? The analyses implied by these questions serve as a final test of whether other time-varying policies that were enacted contemporaneously with changes to states' group sizes and child-to-staff ratios bias the estimates on those regulations.

Table 8 presents the results associated with regressions of the child care labor demand outcomes on a standardized index of 10 COVID-19 health and safety regulations. If our main results are not contaminated by the presence of time-varying omitted variables, then we should find statistically insignificant associations with the COVID-19 regulations. Fortunately, as shown in Panels A through E, the coefficient on the COVID-19 regulations is consistently small in magnitude and never statistically significant. Furthermore, in results not shown in the paper, inclusion of this index variable in the model does not alter the estimated effects of group sizes and child-to-staff ratios.

7 Conclusion

Over the last several decades, there has been an ongoing debate over the welfare effects of licensing and minimum quality standards. On the one hand, in the presence of information frictions, they can provide a much needed quality control, which is especially important in markets like child care, in which quality can influence early childhood health and development, as well as long-run adult outcomes. On the other hand, regulations can lead to

negative unintended consequences for both the quantity and quality of services provided.

In this paper, we combine unique data on online child care job postings with newly available information on child care regulations to study impact of regulations on the demand for child care labor. Our analysis exploits the substantial variation in states' regulations that arose during the COVID-19 pandemic. Indeed, during the first nine months of 2020, nearly all states enacted new regulations or expanded existing ones. Our identification strategy therefore exploits variation in regulatory stringency both within states over time and across children's age groups (within states and days) to estimate the causal effect of maximum classroom group sizes and child-to-staff ratios. Importantly, our variation across age groups within the same state allows us to introduce state $\times$ time fixed effects, thereby purging all variation in state containment policies during the pandemic that would otherwise induce a spurious correlation.

Our key findings can be summarized as follows. First, we show that the introduction and increased stringency of group sizes and child-to-staff ratios reduces the demand for child care labor. This is particularly true for providers located in states that are exposed to a newly-enacted group size requirement, which reduces the number of child care job postings by 5.5 to 8.4 percent. Second, our results indicate that such regulations distort the demand for specific workforce characteristics. Specifically, the enactment of a new regulation on group sizes increases the number of lead teacher postings by 3.6 percentage points, but reduces the probability that these postings require a bachelor's degree by 3.5 percentage points, while also reducing the probability that the education requirements comply with the corresponding state education regulations for lead teachers by 3.7 to 8.0 percentage points. Third, although increasing the stringency of group sizes in states already regulating this feature does not appear to influence the demand for child care teachers, we find that increasing the stringency of child-to-ratios has strong effects—leading to fewer job postings, fewer lead teacher and bachelor's degree postings, and more postings in violation of the state education regulations. Finally, we find that introducing a group size regulation has implications for the broader labor market, leading to lower labor force participation rates among mothers with children ages 0 to 10.

These results indicate that child care providers operating in states that did not regulate group sizes prior to the pandemic—but began regulating them for the first time after the pandemic—experienced significant challenges adjusting to the new regulatory environment. Such providers not only preferred to hire fewer teachers, but sought to downskill the teacher positions being advertised, at least as it relates to education. Conversely, providers in

states already regulating group sizes prior to the pandemic appear to have adapted well to the post-pandemic period, when these regulations became tougher. Indeed, increasing the strictness of group sizes altered virtually no aspect of providers' hiring behavior. However, changes to child-to-staff ratios are costly for providers, leading to lower demand for teachers and a decrease in the skill requirements for the job. Furthermore, we show that the implications of introducing tougher regulations extend beyond the child care labor market and into broader labor market for mothers with young children.

Our finding that regulations decrease labor demand in the child care market is consistent with a related line of work showing that regulations also reduce the number of center-based establishments (Gormley, 1991; Hotz and Xiao, 2011). Together, our work suggests that the supply of child care may decline through a contraction in the size of the workforce and a drop in the number of providers. In addition, our work shows that providers engage in input substitution in ways that may not increase quality, as intended. Specifically, as regulations become tougher, child care providers appear to trade-off some quality-related characteristics (i.e., by downgrading teachers' education requirements) in order to comply with regulations set in other domains. This result is consistent with those in Blau (2007), who finds similar evidence on input substitution as well as null effects of regulations on a measure of classroom quality. In sum, our paper suggests that regulations may not be the most effective policy tool for improving quality within the child care market, and that regulatory-effects may have spillovers to labor markets beyond just the child care labor market.

Our results leave several questions open for future research. First, how have these regulations affected child development? Given the decline in job postings in center-based child care market, the caregiving burden has shifted increasingly onto families. To what extent have these regulatory changes altered the mix of parental versus non-parental time with young children as well as the quality of those time investments? Second, how have different child care providers adapted to these regulations? Although the regulations are uniform in the same state and age group, some child care providers may have more margins to adjust than others. Third, how have the employees in the child care market fared, and have those who were laid off returned back to work in the child care market? These are just a sample of future research questions.

References

Ali, U., Herbst, C. M., and Makridis, C. A. (2021). The Impact of Covid-19 on the U.S. Child Care Market: Evidence from Stay-at-Home Orders. *Economics of Education Review*, 82.

Anderson, P. M. and Levine, P. B. (2000). Child care and mothers' employment decisions. In David, C. and Rebecca, B., editors, *Finding jobs: Work and welfare reform*. Russell Sage Foundation, New York.

Blau, D. and Hagy, A. (1998). The demand for quality in child care. *Journal of Political Economy*, 106:104–146.

Blau, D. M. (2001). *Child Care Problem: An Economic Analysis*. Russell Sage Foundation, New York.

Blau, D. M. (2003). Do Child Care Regulations Affect the Child Care and Labor Markets. *Journal of Policy Analysis & Management*, 22(3):443–465.

Blau, D. M. (2007). Unintended Consequences of Child Care Regulations. *Labour Economics*, 14(3):513–538.

Blau, D. M. and Currie, J. (2006). Preschool, Day Care and After-School Care: Who's Minding the Kids? *Handbook of the Economics of Education, New York: Elsevier*, 2:1163–1278.

Boyd-Swan, C. and Herbst, C. M. (2018). The Demand for Teacher Characteristics in the Market for Child Care: Evidence from a Field Experiment. *Journal of Public Economics*, 159:183–202.

Boyd-Swan, C. and Herbst, C. M. (2019). Racial and Ethnic Discrimination in the Labor Market for Child Care Teachers. *Educational Researcher*, 48:183–394–406.

Brown, J. H. and Herbst, C. M. (2021). Child Care over the Business Cycle. *IZA Discussion Paper No. 14048. Bonn, Germany: Institute on Labor Economics*.

Bryson, A. (2020). Coronavirus Florida: Over half of state's child care facilities are closed. News report. [Online; accessed 05-May-2021].

Carr, R. C. (2020). North carolina pre-k remote learning survey results: Covid-19 response. *North Carolina, Division of Child Development and Early Education*.

Chipty, T. (1995). Economic Effects of Quality Regulations in the Day-Care Industry. *American Economic Review*, 85(2):419–424.

Chipty, T. and Witte, A. D. (1999). An Empirical Investigation of Firms' Responses to Minimum Standards Regulations. *Children and Youth Services Review*, 21:111–146.

Currie, J. and Hotz, V. J. (2004). Accidents will happen?: Unintentional childhood injuries and the effects of child care regulations. *Journal of Health Economics*, 23:25–59.

Del Boca, D., Oggero, N., Profeta, P., and Rossi, M. (2020). Women's and Men's Work, Housework and Childcare, Before and During COVID-19. *Review of Economics of the Household*, 18:1001–1017.

Delap, S., Franko, M., Nicolaou, K., Silva-Padron, G., and Thornton, C. (2021). Measuring the impact of COVID-19 on Coloradoâs early care and learning sector. Early Milestones Colorado. [Online; accessed 09-June-2021].

Gormley, William T., J. (1991). State Regulations and the Availability of Child-Care Services. *Journal of Policy Analysis & Management*, 10(1):78–95.

Herbst, C. M. (2010). The labor supply effects of child care costs and wages in the presence of subsidies and the ETIC. *Review of Economics of the Household*, 8:199–230.

Hotz, V. J. and Kilburn, M. R. (1994). Regulating child care: The effects of state regulations on child care demand and its cost. Working Paper 9405, Harris Graduate School of Public Policy Studies, University of Chicago., Chicago, IL.

Hotz, V. J. and Xiao, M. (2011). The impact of regulations on the supply and quality of care in child care markets. *American Economic Review*, 101:1775–1805.

Leland, H. E. (1979). Quacks, Lemons, and Licensing: A Theory of Minimum Quality Standards. *Journal of Political Economy*, 87(6):1328–1346.

Raifman, J., Nocka, K., Jones, D., Bor, J., Lipson, S., Jay, J., and Galea, S. (2021). Covid-19 us state policy database. *Ann Arbor, MI: Inter-university Consortium for Political and Social Research*.

Rothwell, J., Makridis, C. A., Ramirez, C., and Desai, S. (2021). The effects of information on policy and behavioral beliefs during a pandemic. *SSRN working paper*.

Ruggles, S., Flood, S., Goeken, R., Grover, J., Meyer, E., Pacas, J., and Sobek, M. (2020). Integrated Public Use Microdata Series, Current Population Survey: version 7.0 [dataset]. *Minneapolis, MN: IPUMS*, 10:D030.

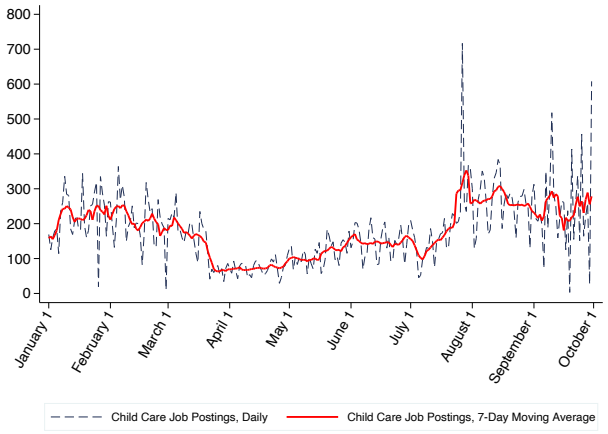
Shapiro, C. (1986). Investment, Moral Hazard, and Occupational Licensing. *Review of Economic Studies*, 53(5):843–862.

Sonnier-Netto, L., Cope, H., Falgoust, T., Oakey-Frost, R., and Lewis, R. (2020). The Impact of COVID-19 on Louisiana Child Care Providers. *Louisiana Policy Institute for Children*.

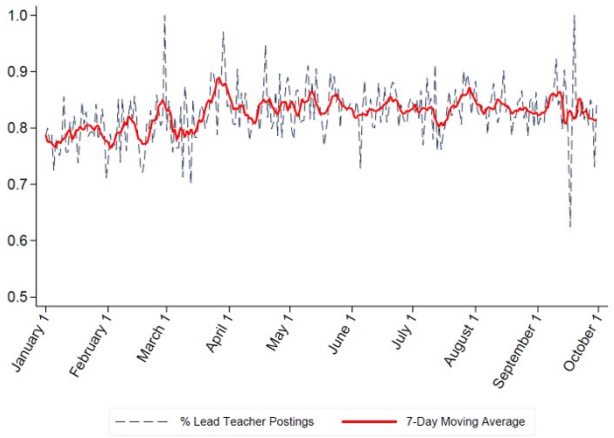
Figures and Tables

Figure 1: Characteristics of Child Care Job Postings

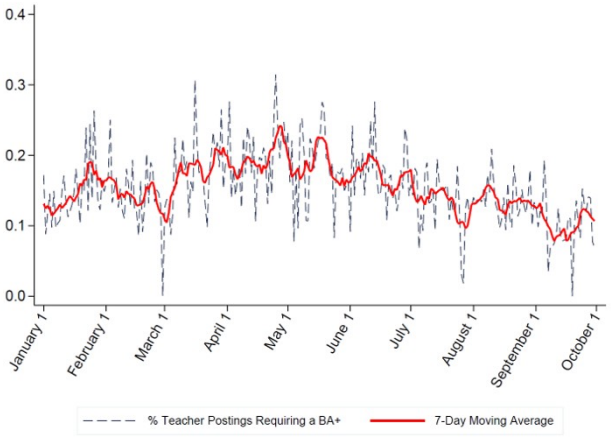
((a)) Panel A: Total Child Care Job Postings



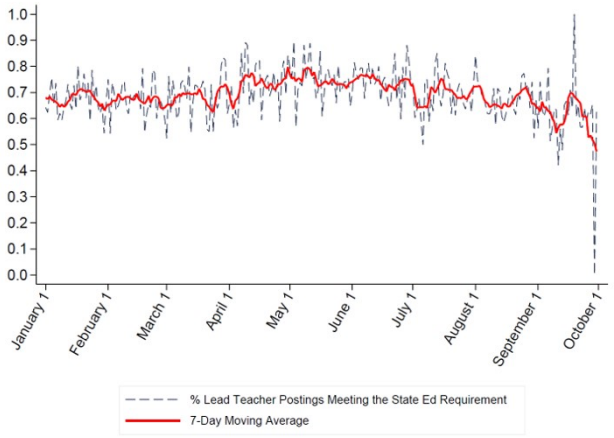
((b)) Panel B: % of Lead Teacher Job Postings



((c)) Panel C: % Teacher Postings Requiring a BA+

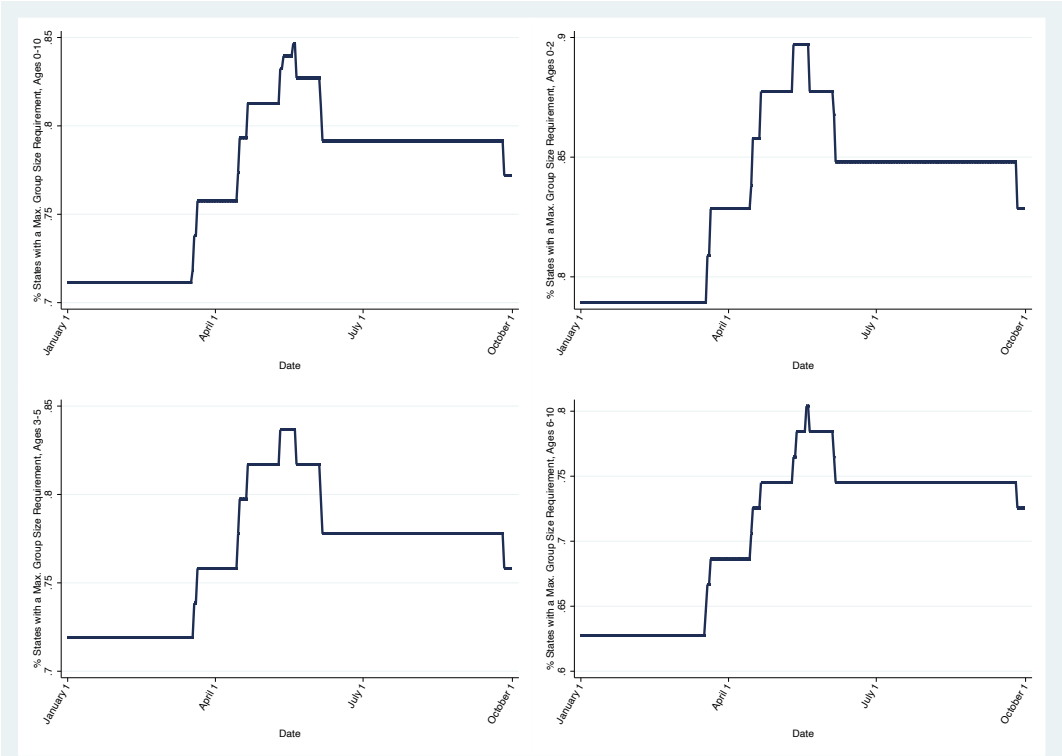


((d)) Panel D: % Postings Complying with State Regulations



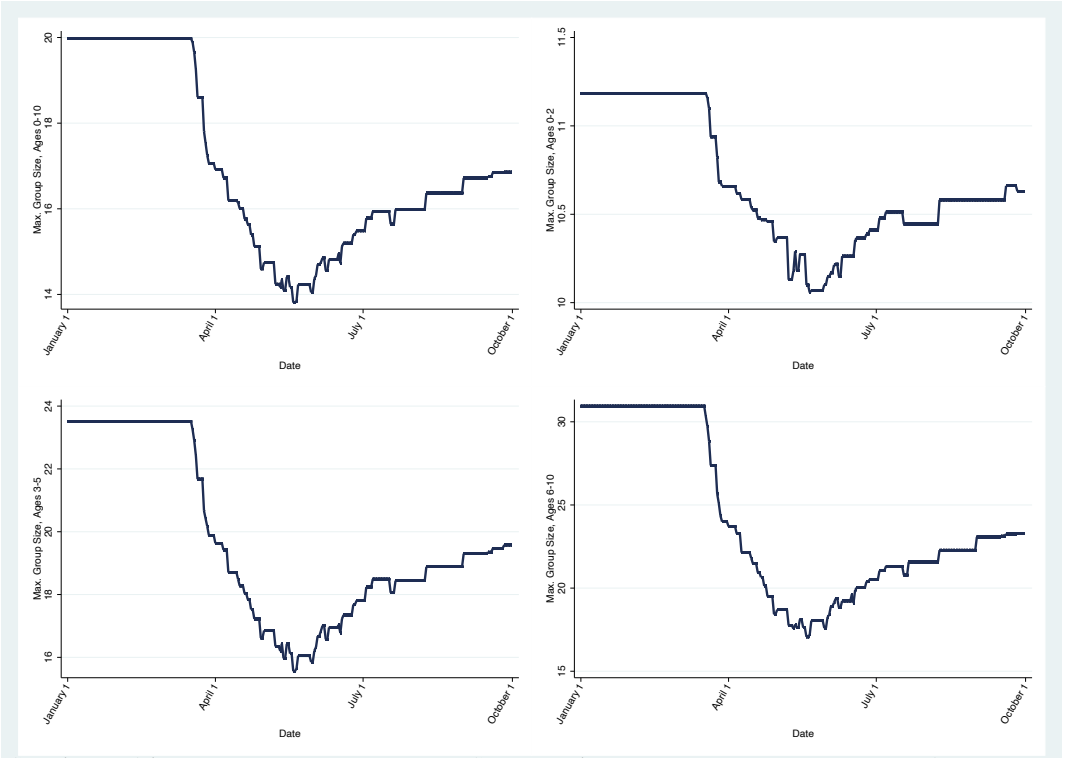
Source: Emsi, 2020. Panel A shows the daily (and 7-day moving average) number of child care job postings. Panel B shows the share of job postings that advertise for a lead teacher. Panel C shows the share of job postings that require a bachelor's degree. Panel D shows the share of job postings that comply with the state's teacher education regulatory requirements.

Figure 2: % States Regulating Maximum Classroom Group Size, by Age Group



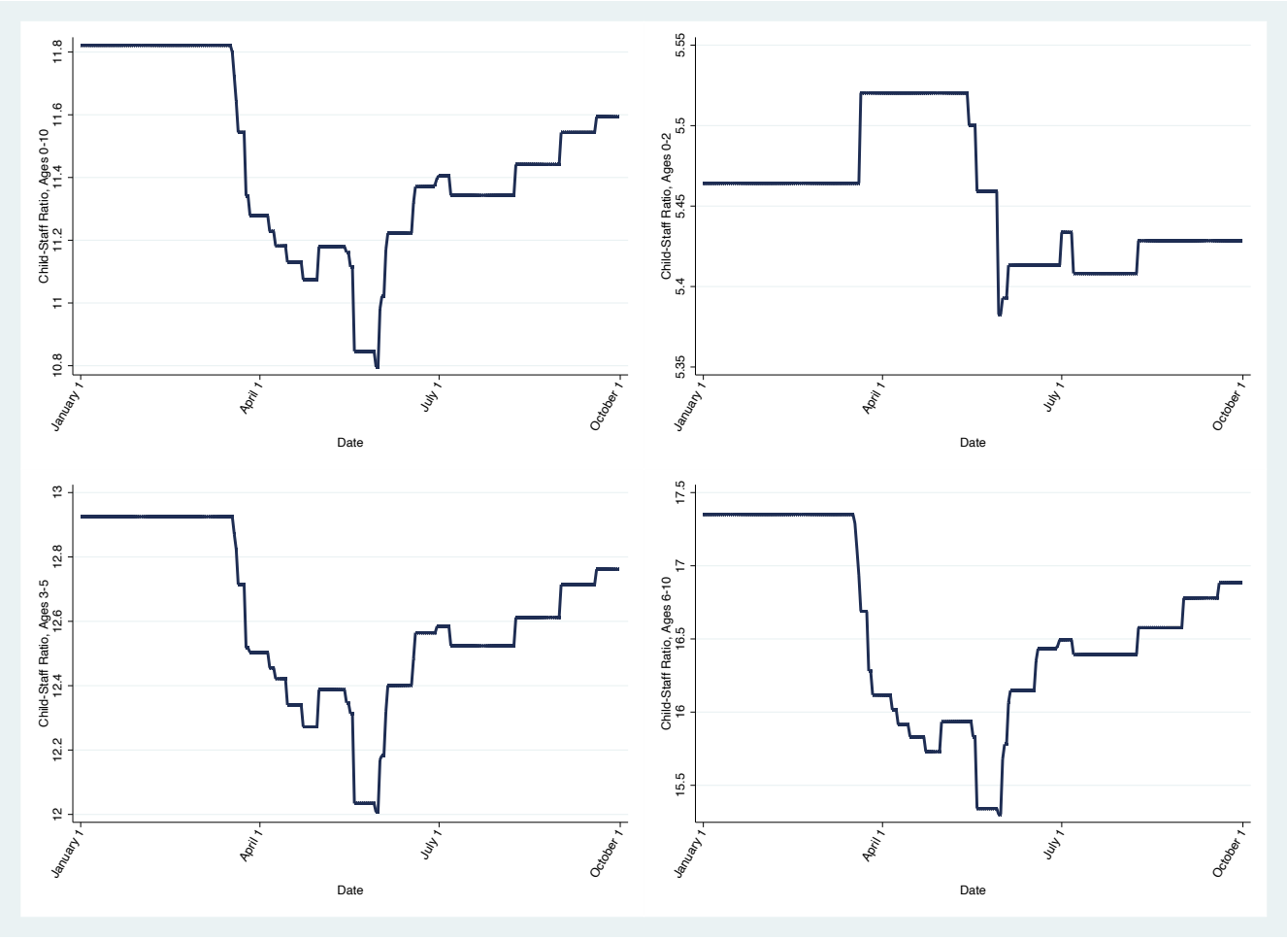
Source: Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites. The figure plots the share of states regulating center-based maximum classroom group sizes over time for each age-group.

Figure 3: Time Series in States' Maximum Classroom Group Size, by Age Group



Source: Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites. The figure plots the average value of the center-based maximum classroom group size regulation over time for each age-group.

Figure 4: Time Series in States' Child-to-Staff Ratio, by Age Group



Source: Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites. The figure plots the average value of the child-to-staff ratio regulation over time for each age-group.

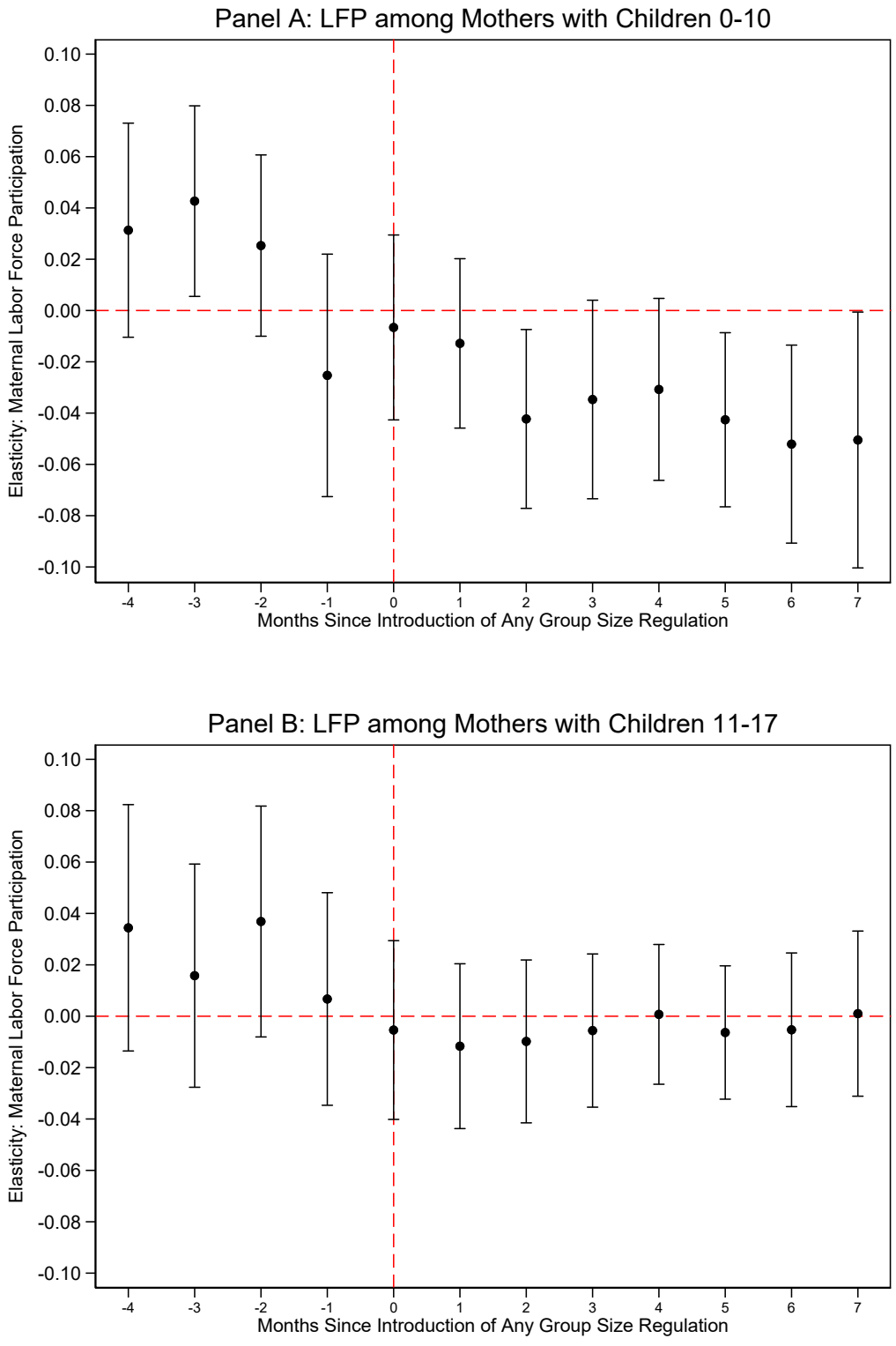


Figure 5: Evaluating Parallel Trends for Maternal Employment Outcomes

Source: Current Population Survey, Hunt Institute, National Governor's Association, and states' Department of Health websites. The figure plots the coefficients associated with regressions of an indicator for labor force participation (restricted to the set of females) on leads and lags of the child care regulation indicator, conditional on individual demographics and state policy controls and both state and month fixed effects, separately for mothers with a youngest child between age 0 and 10 and for those with a youngest child between age 11 and 17. Demographics include: a quadratic in age, marital status, race (White, Black, Asian), and education (less than high school, high school, some college, college, more than college). State policies include: state of emergency, stay-at-home order, school closure, business closure, reopenings, face mask requirements, and search intensity for child care from Google trends. Standard errors are clustered at the state-level.

Table 1: Summary of the Child Care Regulatory Environment

State	Group Size	Child to Staff Ratio	Minimum Staff Education Requirement		
			Assistant Teacher	Lead Teacher	Director
Alabama	–	8	8th grade	HSD	HSD & 8 semester hrs or CDA
Alaska	20	10	–	–	HSD & 12 semester hrs or CDA
Arizona	–	13	–	HSD	HSD & 6 credit hrs
Arkansas	24	12	HSD	HSD	CDA
California	–	12	HSD & 6 semester credits	HSD & 6 semester units or CDA	HSD & 15 semester units
Colorado	20	10	HSD & 1 ECE course	HSD & 12 semester hrs or CDA	HSD & 60 semester hrs or CDA
Connecticut	20	10	or HSD (ECE experience or HSD)	HSD & 12 credit hrs or CDA	HSD & 3 ECE credit hrs
Delaware	15	10	HSD & 6 credits	HSD & 9 credits or CDA	AA
District of Columbia	16	8	HSD	HSD & 48 credit hrs or CDA	HSD & 48 credit hrs
Florida	–	15	–	AA	HSD & 30 ECE credit hrs
Georgia	30	15	–	HSD & 15 semester hrs or CDA	HSD & 15 semester hrs or CDA
Hawaii	–	12	HSD & CDA or 60 credit hrs	HSD & 60 credit hrs or CDA	HSD & 60 credit hrs or CDA
Idaho	–	–	–	–	–
Illinois	20	10	HSD	HSD & 30 semester hrs or CDA	AA
Indiana	20	10	HSD	CDA	AA
Iowa	–	13	–	HSD	HSD
Kansas	24	8	–	–	Observation Hours or CDA
Kentucky	24	12	–	HSD	HSD
Louisiana	26	13	–	–	HSD & 6 credit hrs
Maine	22	9	–	–	HSD
Maryland	20	10	HSD	HSD & 6 semester hrs or CDA	HSD & 6 semester hrs or CDA
Massachusetts	20	10	HSD	HSD & 12 credit hrs or CDA	HSD & 16 credit hrs or CDA plus 4 credit hrs
Michigan	–	10	–	HSD & 6 semester hrs	HSD & 60 semester hrs or CDA plus 18 ECE semester hrs
Minnesota	20	10	HSD & 8 credit hrs	HSD & 16 credit hrs[1]	HSD & 6 credit hrs [1]
Mississippi	14	14	–	HSD	HSD & 24 ECE credit hrs or CDA
Missouri	–	10	–	–	HSD & 6 semester hrs or CDA
Montana	8	–	–	–	HSD
Nebraska	–	10	–	HSD	HSD & 6 credit hrs or CDA
Nevada	–	13	–	–	HSD & 15 semester hrs in ECE or CDA
New Hampshire	24	8	–	HSD & 18 ECE credit hrs or CDA	HSD & 60 credit hrs plus 6 credit hrs CD/Mngt [2]
New Jersey	20	10	CDA	BA	BA
New Mexico	–	12	–	–	HSD & 3 ECE courses or CDA
New York	18	7	or HSD	HSD & 9 college credits	CDA
North Carolina	25	15	HSD	HSD	HSD & 12 semester hrs (CD) or CDA
North Dakota	14	7	–	HSD	CDA
Ohio	24	12	HSD	HSD	HSD
Oklahoma	24	12	–	HSD & 6 ECE/CD credit hrs or CDA	HSD & 6 ECE/CD credit hrs or CDA
Oregon	20	10	–	HSD & 10 semester hrs or CDA	or HSD & 30 semester hrs or CDA
Pennsylvania	20	10	HSD	AA	AA
Rhode Island	18	9	HSD	HSD	BA
South Carolina	–	13	–	HSD	HSD
South Dakota	20	10	–	–	HSD & 32 credit hrs CD/Mngt or CDA
Tennessee	18	9	–	HSD	HSD
Texas	30	15	HSD	HSD	HSD & 18 credit hrs CD/Mngt
Utah	24	12	–	–	CDA
Vermont	20	10	HSD & 3 credit hrs	BA	HSD & 21 credit hrs
Virginia	–	10	–	HSD	HSD & CDA or 30 semester hrs
Washington	20	10	–	HSD	HSD & CDA or 6.66-30 credit hrs
West Virginia	20	10	HSD	HSD	HSD
Wisconsin	20	10	HSD	HSD & 2 non-credit ECE courses	HSD & 2 non-credit/for-credit ECE courses[3]
Wyoming	24	10	–	–	HSD

Source.—Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites
Notes.—The data presented in this table summarizes states' child care regulations as of January 1, 2020. [1] RN/LPN meets requirements for infants, [2] or CDA plus 6 credit hours in Child Development or Management, [3] 4 courses if the center has an enrollment of 51 or more

Table 2: Child Care Regulations: Summary Statistics

Panel A: Any Group Size Regulation Enacted (%)	
Ages 0-10	0.711
	(0.007)
Ages 0-2	0.789
	(0.397)
Ages 3-5	0.719
	(0.445)
Ages 6-10	0.627
	(0.484)
Panel B: Maximum Group Size (no.)	
Ages 0-10	20.0
	(5.4)
Ages 0-2	11.2
	(2.9)
Ages 3-5	23.5
	(4.9)
Ages 6-10	30.9
	(7.4)
Panel C: Child-to-Staff Ratio (no.)	
Ages 0-10	11.8
	(2.3)
Ages 0-2	5.5
	(1.0)
Ages 3-5	12.9
	(2.6)
Ages 6-10	17.4
	(3.8)

Source.—Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites..
Notes.—The table shows means and standard deviations for different child care regulations for respective age group over the Jan-Feb 2020, pre-pandemic period.

Table 3: Effects of Regulations on the Demand for Child Care Labor

	Dep Var: ln(number of job postings)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Child Care Job Postings					
Any Group Size Regulation	-0.055***		-0.053***		-0.055***
	[0.010]		[0.013]		[0.013]
(1/Group Size)		-0.012***	-0.001		0.002
		[0.003]	[0.004]		[0.005]
(1/Child-to-Staff Ratio)				-0.010**	-0.007
				[0.004]	[0.005]
Mean Daily No. of Job Postings	3.509	3.509	3.509	3.509	3.509
Observations	41,922	41,922	41,922	41,922	41,922
Age-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Robustness Check					
Any Group Size Regulation	-0.064***		-0.083***		-0.084***
	[0.012]		[0.015]		[0.015]
(1/Group Size)		-0.004	0.013**		0.016***
		[0.004]	[0.005]		[0.006]
(1/Child-to-Staff Ratio)				-0.009*	-0.009*
				[0.005]	[0.005]
Mean Daily No. of Job Postings	3.509	3.509	3.509	3.509	3.509
Observations	41,922	41,922	41,922	41,922	41,922
Age-Group Fixed Effects	Yes	Yes	Yes	Yes	Yes
State x Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel C: Falsification Test Using Head Start and Pre-K Job Postings					
Any Group Size Regulation	-0.004		-0.008		0.000
	[0.014]		[0.018]		[0.019]
(1/Group Size)		0.000	0.002		-0.003
		[0.004]	[0.006]		[0.006]
(1/Child-to-Staff Ratio)				0.013	0.017
				[0.011]	[0.013]
Mean Daily No. of Job Postings	0.594	0.594	0.594	0.594	0.594
Observations	27,948	27,948	27,948	27,948	27,948
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes

Source.—Emsi, 2020.

Notes.—Panel A in the table reports the coefficients associated with regressions of logged child care job postings on an indicator for whether there is any group size regulation in effect, the inverse of average group size, and the inverse of average child-to staff-ratio, controlling for the state-level covariates and child age group, state, and day fixed effects. Panel B introduces state × day fixed effects, isolating variation in child care regulation across group sizes in the same state. Panel C reports the results associated with Head Start and pre-k job postings as a placebo exercise. Standard errors are clustered at the state-day level and the observations are unweighted.

Table 4: Effects of Regulations on the Demand for Lead Teachers

	Dep Var: =1 if Job Posting is for a Lead Teacher				
	(1)	(2)	(3)	(4)	(5)
Any Group Size Regulation	0.032**		0.047***		0.036*
	[0.013]		[0.018]		[0.019]
(1/Group Size)		0.001	-0.007		0.000
		[0.004]	[0.005]		[0.007]
(1/Child-to-Staff Ratio)				-0.014**	-0.017*
				[0.007]	[0.009]
Dep Var Mean	0.792	0.792	0.792	0.792	0.792
Observations	49,045	49,045	49,045	49,045	49045
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes

Source.—Emsi, 2020.
Notes.—The table reports coefficients associated with regressions of a binary variable indicating if a child care job posting is for a lead or head teacher on an indicator for whether there is any group size regulation in effect, the inverse of average group size, and the inverse of average child-to staff-ratio, controlling for the state-level covariates and state and day fixed effects. Standard errors are clustered at the state-day level and the observations are unweighted.

Table 5: Effects of Regulations on the Demand for Teachers with a BA+

	Dep Var: =1 if Job Posting Requires a BA+				
	(1)	(2)	(3)	(4)	(5)
Panel A: Assistant Teacher Job Postings					
Any Group Size Regulation	0.046		0.062**		0.069**
	[0.029]		[0.031]		[0.032]
(1/Group Size)		0.001	-0.008		-0.012
		[0.007]	[0.006]		[0.008]
(1/Child-to-Staff Ratio)				-0.000	0.010
				[0.010]	[0.011]
Dep Var Mean	0.044	0.044	0.044	0.044	0.044
Observations	8,685	8,685	8,685	8,685	8,685
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Lead Teacher Job Postings					
Any Group Size Regulation	-0.021		-0.032*		-0.035*
	[0.013]		[0.019]		[0.021]
(1/Group Size)		-0.000	0.005		0.008
		[0.005]	[0.006]		[0.008]
(1/Child-to-Staff Ratio)				0.001	-0.005
				[0.008]	[0.011]
Dep Var Mean	0.173	0.173	0.173	0.173	0.173
Observations	40,360	40,360	40,360	40,360	40,360
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel C: Lead Preschool-Age Teacher Job Postings					
Any Group Size Regulation	-0.023		-0.058**		-0.067**
	[0.018]		[0.028]		[0.028]
(1/Group Size)		0.005	0.016*		0.028**
		[0.006]	[0.009]		[0.011]
(1/Child-to-Staff Ratio)				-0.007	-0.022**
				[0.007]	[0.011]
Dep Var Mean	0.161	0.161	0.161	0.161	0.161
Observations	13,090	13,090	13,090	13,090	13,090
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes

Source.—Emsi, 2020.
Notes. The table reports the coefficients associated with regressions of a binary variable indicating if a child care job posting requires at least a BA degree on an indicator for whether there is any group size regulation in effect, the inverse of average group size, and the inverse of average child-to staff-ratio, controlling for the state-level covariates and state and day fixed effects. Panel A is restricted to the sample of job postings for assistant teachers, Panel B is restricted to the sample of job postings for lead teachers, and Panel C is restricted to the sample of job postings for lead preschool-age teachers. Standard errors are clustered at the state-day level and the observations are unweighted.

Table 6: Estimating the Probability of Job Posting Compliance with State Regulations

	Dep Var: =1 if Job Posting Complies with the State Educ Regulation				
	(1)	(2)	(3)	(4)	(5)
Panel A: Lead Teacher Job Postings					
Any Group Size Regulation	0.002		-0.014		-0.037
	[0.018]		[0.023]		[0.027]
(1/Group Size)		0.006	0.008		0.022**
		[0.006]	[0.007]		[0.010]
(1/Child-to-Staff Ratio)				-0.013	-0.033***
				[0.009]	[0.012]
Dep Var Mean	0.667	0.667	0.667	0.667	0.667
Observations	20,296	20,296	20,296	20,296	20,296
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes
Panel B: Lead Preschool-Age Teacher Job Postings					
Any Group Size Regulation	-0.000		-0.057		-0.080**
	[0.029]		[0.036]		[0.040]
(1/Group Size)		0.019**	0.028**		0.049***
		[0.008]	[0.011]		[0.015]
(1/Child-to-Staff Ratio)				-0.007	-0.040***
				[0.009]	[0.013]
Dep Var Mean	0.684	0.684	0.684	0.684	0.684
Observations	6,948	6,948	6,948	6,948	6,948
State Fixed Effects	Yes	Yes	Yes	Yes	Yes
Day Fixed Effects	Yes	Yes	Yes	Yes	Yes

Source.—Emsi, 2020.

Notes.—The table reports the coefficients associated with regressions of a binary variable indicating if the education requirement in a job posting complies with the minimum educational requirement set by the state on an indicator for whether there is any group size regulation in effect, the inverse of average group size, and the inverse of average child-to staff-ratio, controlling for the state-level covariates and state and day fixed effects. Panel A is restricted to the sample of job postings for lead teachers, and Panel B is restricted to the sample of job postings for lead preschool-age teachers. Standard errors are clustered at the state-level and the observations are unweighted.

Table 7: Effects of Child Care Regulations on Maternal Labor Force Participation Rate and Hours Worked

	Dep Var =1 if Participating in the Labor Force				Dep Var: log(weekly hours of work)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Any Group Size Reg	-0.014	-0.019*	-0.019*	-0.012	-0.003	-0.009	-0.009	-0.003
	[0.010]	[0.011]	[0.011]	[0.010]	[0.012]	[0.013]	[0.013]	[0.012]
Yngst Child<=10	-0.034***	-0.032***	-0.032***	-0.032***	-0.046***	-0.046***	-0.046***	-0.045***
	[0.008]	[0.008]	[0.008]	[0.008]	[0.010]	[0.011]	[0.011]	[0.010]
Any Group Size Reg × Yngst Child<=10	-0.018**	-0.020**	-0.020**	-0.020**	-0.008	-0.009	-0.009	-0.009
	[0.009]	[0.009]	[0.009]	[0.009]	[0.011]	[0.012]	[0.012]	[0.011]
State Employment Growth			0.002**	0.001			-0.002	-0.001
			[0.001]	[0.001]			[0.002]	[0.002]
Observations	97,756	97,756	97,756	97,756	62,043	62,043	62,043	62,043
Individual Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Month Fixed Effects	Yes	No	No	No	Yes	No	No	No
Region x Month Fixed Effects	No	Yes	Yes	No	No	Yes	Yes	No
Income Bin Fixed Effects	No	Yes	Yes	No	No	Yes	Yes	No
Income Bin x Month Fixed Effects	No	No	No	Yes	No	No	No	Yes

Source.—Current Population Survey (CPS) from Ruggles et al. (2020), 2020.

Notes.—The table reports coefficients associated with regressions of various maternal labor force participation (1/0) and log weekly hours worked on an indicator for whether there is any group size regulation in effect (in the state × group × month), whether the youngest child in the family is aged 10 or below, and an indicator for interaction across any regulation in effect and families with youngest children aged 10 or below, controlling for time-varying individual and state-level covariates and state fixed effects. Columns (1) through (4) present estimates on labor force participation. Columns (1) includes month fixed effects. Column 2 includes region × month fixed effects and Income Bin fixed effects. Column (3) includes includes region × month fixed effects and Income Bin fixed effects, and adds state by month change in employment rates, while columns (4) adds income × month fixed effects to the set of controls from column (1). Our bins on the distribution of family income include indicators for whether the family earns: less than $5,000 per year, $5,000-7,499, $7,500-9,999, $10,000-12,499, $12,500-14,999, $15,000-19,999, $20,000-24,999, $25,000-29,999, $30,000-34,999, $35,000-39,999, $40,000-49,999, $50,000-59,999, $60,000-74,999, $75,000-99,999, $100,000-149,999, and $150,000+. Standard errors are clustered at the state-month level and the observations are weighted by the final household level weights assigned by CPS.

Table 8: Effects of COVID-19 Health and Safety Regulations on Child Care Labor Demand

Panel A: All Child Care Job Postings	
Dep Var: ln(number of job postings)	
Standardized Index of 10 COVID-19 Regulations	0.007
	[0.005]
Dep Var Mean	3.509
Observations	41,922
Panel B: Lead Teacher Job Postings	
Dep Var: =1 if Job Posting is for a Lead Teacher	
Standardized Index of 10 COVID-19 Regulations	-0.004
	[0.005]
Dep Var Mean	0.792
Observations	49,045
Panel C: Assistant Teacher Job Postings	
Dep Var: =1 if Job Posting Requires a BA+	
Standardized Index of 10 COVID-19 Regulations	-0.008
	[0.006]
Dep Var Mean	0.044
Observations	8,685
Panel D: Lead Teacher Job Postings	
Dep Var: =1 if Job Posting Requires a BA+	
Standardized Index of 10 COVID-19 Regulations	0.004
	[0.006]
Dep Var Mean	0.173
Observations	40,360
Panel E: Lead Teacher Job Postings	
Dep Var: =1 if Job Posting Complies with the State Education Regulations	
Standardized Index of 10 COVID-19 Regulations	-0.002
	[0.008]
Dep Var Mean	0.667
Observations	20,296

Source.—Emsi
Notes.—The table reports the coefficients associated with regressions of different measures of child care job postings on an index of 10 COVID-19 health and safety regulations. Standard errors are clustered at the state-day level and the observations are unweighted.