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RESEARCH ARTICLE

Minimum quality regulations and the demand for childcare labor

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[Corrections added on 18 May 2024 after first online publication: Three paragraphs have been added in the "Introduction" section.]

Abstract
Minimum quality regulations are often justified in the childcare 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' childcare 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 childcare 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 evidence that these regulations reduce the number of childcare job postings and encourage providers to substitute away from higher-skilled postings, thereby increasing the number of positions that are out-of-compliance with states' teacher education requirements. In sum, the results imply that childcare regulations may reduce the demand for childcare labor, while simultaneously altering the composition of the workforce.

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).[1] The key rationale for regulating the childcare market is to mitigate the negative consequences of informational frictions between parents and providers, in which the former are 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.

[1] See, for example, Kleiner (2006) for early evidence that licensing restrictions can raise quality in a market by establishing standards, and Kleiner and Krueger (2010) and Kleiner and Krueger (2013) for measurement on the incidence of these restrictions.

However, the benefits of childcare regulations must be weighed against their potential costs. Indeed, the imposition of minimum quality standards may reduce the quantity of childcare services available, distort providers' input decisions, and lead to higher prices without improving quality (Blau, 2001; Shapiro, 1986). Over the last few decades, a large empirical literature has assessed the predictions of the canonical model of regulations in the center-based childcare market.[2] 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 childcare 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 limited because changes to regulations are fairly infrequent and restricted to a subset of states.[3] 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 estimate dichotomous and continuous treatment difference-in-differences (DD) models to 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. We cover the period surrounding the onset of the COVID-19 pandemic, when nearly all states enacted dramatic changes to the regulatory environment in an attempt to mitigate the spread of the virus. Our study focuses on revisions to maximum classroom group sizes and child-to-staff ratios, arguably two of the most important labor-related regulations. During the first 9 months of 2020, which coincides with our study's time frame, 31 states reformed their group size regulations and 18 states reformed their child-to-staff ratios, with most of these states making multiple changes over this period. At the height of states' regulatory stringency (lasting from late May to early June), approximately 85% of states had a group size regulation in place (up from 70% prior to the pandemic), the average group size fell below 14 children (from 20), and the average child-to-staff ratio dropped to 10:1 (from 12:1).

Although we rely on within-state over-time changes in childcare regulations, this study exploits a largely unused source of policy variation: the differential regulatory stringency across children's age groups. Indeed, classrooms serving younger children in center-based settings are exposed to tougher standards than their older counterparts. For example, prior to the pandemic 79% of states regulated group sizes for infant/toddler classrooms, compared to 63% for school-age classrooms. Furthermore, maximum group sizes averaged 11 children for infants/toddlers, while those at the school-age level averaged 31 children. Together, these two sources of policy variation—changes over time within states as well as across children's age groups within states—provide us with the flexibility to test different assumptions about the cross-sectional and time series nature of the unobservables.[4]

Data on these regulations are matched to the universe of online childcare teacher job postings in state × day × child age group cells over the period January 1 to September 30, 2020. These data are provided by the labor analytics company EMSI, which scrapes and organizes job postings from all of the major online job banks (e.g., Indeed, Glassdoor, and LinkedIn). We conduct extensive keyword searches within the postings to classify each according to the sector in which the position is based (center-based child care, Head Start, or pre-K), the rank of the teacher (assistant or lead), the child

[2] 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).

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

[4] To our knowledge, the only other study to exploit variation in regulations across children's age groups is Blau (2007). However, it relied on data from only four states, and it did not exploit temporal variation in regulatory stringency (i.e., it is cross-sectional.)

age group to be served (infants/toddlers, preschool-age, or school-age), and the level of education required. Therefore, 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.

Although our study represents a unique opportunity to examine a period in which most states enacted meaningful changes to their regulatory environment, it is nevertheless difficult to isolate the causal effect of regulations in this context, given the large number of economic and pandemic-related factors that changed contemporaneously with the regulations. For example, states enacted a number of policies—ranging from stay-at-home orders to mandatory school and business closures—aimed at mitigating the spread of COVID-19. Recognizing that these policies, coupled with the recession-driven shock to the labor market, influenced the demand for childcare labor independent of any regulatory effects, we take a number of steps to mitigate the influence of these time-varying state confounders. First, in addition to incorporating two-way fixed effects for state, time, and child age groups, our baseline model controls for 25 state characteristics. These variables account for not only the severity of the pandemic and states' policy responses to it, but also changes in key childcare supply and demand, labor market, and political environment that may influence providers' hiring behavior. Second, our baseline model includes state specific time trends to control for any component of the unobservables that trends within states. Third, whenever possible we exploit the panel structure of the data (organized into state × day × age group cells) by incorporating more restrictive sets of two-way fixed effects, including a model with state × day effects, which leverages only between-age-group (i.e., within-state and -day) variation in regulatory stringency. Finally, we implement a falsification test in which job postings for childcare teachers are replaced with those for Head Start and pre-K positions. Since the regulatory changes we study are aimed at center-based childcare services, we would not expect them to influence hiring behavior at Head Start and pre-K programs, which are not exposed to these reforms.

Our results are robust to changes in the specification. In the most stringent model, in which we control 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 childcare job postings by 9.2% 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 teacher 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) leads to small or null effects on overall labor demand, as well as the demand for specific teacher characteristics. 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, encourages providers to hire fewer lead teachers and those with a bachelor's degree, and increases rates of non-compliance with states' teacher education regulations. In an encouraging sign for the credibility of our results, we show that none of the regulations are associated with labor demand in the market for Head Start and pre-K teachers, meaning that our measure is not simply a proxy for alternative regulations.

Together, these results indicate that regulations have heterogeneous effects on childcare providers. Those operating in states that enact a new group size regulation substantially alter their labor demand. Such providers not only hire fewer teachers, but also downskill the teacher positions being advertised, at least as it relates to education. Conversely, providers in states already regulating group sizes appear to adapt well when these regulations become tougher. Indeed, increasing the strictness of group sizes alters virtually no aspect of providers' hiring behavior. However, changes to existing child-to-staff ratios are costly for providers, leading to lower demand for teachers, a decrease in the skill requirements for the job, and an increase in noncompliance with other regulations. These patterns suggest that enacting a new group size regulation and increasing the stringency of existing child-to-staff ratios are likely to be binding on providers, who respond by hiring fewer teachers. In addition, we interpret the downskilling of advertised positions as evidence that providers are willing to reduce some costly quality investments in order to comply with regulations in other domains.

This paper makes several contributions to the regulations literature. First, we introduce a new data source—the universe of online job postings—to study how childcare 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 childcare regulations, but also whether providers trade off certain teacher characteristics as regulations become tougher. Second, our analysis period contains substantially more variation in regulatory policy than that exploited in previous studies. In addition, the magnitudes of the changes are sizable, so that our parameter estimates reflect meaningful, not marginal, policy shifts. Although the larger context and precipitating event for these policies—the COVID-19 pandemic—might raise concerns over the generalizability of our results, we argue that the advantages of using this period to examine childcare regulations outweigh the disadvantages. We nonetheless recognize that providers may respond differently to regulations during times of public health emergency versus their aftermath, an issue we address in a future section. Finally, our identification strategy exploits not just within-state over-time variation regulations, but also between child-age-group (within states and days) variation, allowing us to control for all time-varying shocks within states. This additional source of group variation is crucial for testing the robustness of our policy effects in an environment as complex as the recent pandemic.

Our paper also contributes to a literature on the effects of recessions generally and the COVID-19 pandemic specifically on the childcare market. For example, Brown and Herbst (2022) examined how the supply and quality of child care varies over the business cycle. Other papers have focused on the pandemic period, estimating changes in the supply of child care in specific states (e.g., Bryson, 2020; Sonnier-Netto et al., 2020). For example, a recent paper by Zhang et al. (2023) examined the impact of the pandemic on the supply and composition of providers in North Carolina. Other studies, such as that by Ali et al. (2021), have shown that states' pandemic containment policies, specifically stay-at-home orders, reduced the demand for childcare labor. Finally, a parallel body of work has assessed how the pandemic influenced administrator and teacher experiences, routines, and mental health (Bassok et al., 2000; Carr, 2020; Delap et al., 2021), 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. The section "The Childcare Regulatory Landscape" provides a summary of the regulatory landscape in the U.S. childcare market. Next, "Data and Management" introduces the data on childcare teacher job postings along with newly collected data on childcare regulations across age groups and states. The section "Empirical Strategy" describes the identification strategy, while "Main Results" presents the main results. "Extensions and Robustness" examines several dimensions of heterogeneity and robustness. We provide a detailed discussion and interpretation of the results in "Discussion," and conclude in "Conclusion."

THE CHILDCARE REGULATORY LANDSCAPE

Background on regulations

Ever since Kleiner (2006), there has been a general recognition that licensing requirements can raise quality in a market by establishing standards. Licenses cover nearly a third of the labor force (Kleiner & Krueger, 2010, 2013). Although there is some evidence of positive wage effects for incumbent workers (Kleiner & Krueger, 2010), many studies have shown that licensing restrictions can create unintended employment and career consequences. For example, Johnson and Kleiner (2020) found that individuals exposed to state-specific licensing exams have 36% lower migration rates than their peers in other occupations. Furthermore, Kleiner and Xu (2023) showed that licensing restrictions reduce labor market fluidity, namely the number of job changes and the propensity to become unemployed. Taking into account any possible effects on quality, Kleiner and Soltas (2023) found that the net effects are negative: a 12% decline in surplus where workers bear 70% of the losses and consumers bear 30%.

The literature on occupational licensing provides a theoretical backdrop for our paper, since child care in the U.S. is heavily regulated, 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; Herbst, 2023). Regulations require providers to be licensed and to meet a series of requirements related to the physical attributes of the setting. Specifically, regulations can be characterized as governing two broad areas of the childcare 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 3-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 varied 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 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.

Theoretical considerations

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 childcare providers engage in input substitution, whether the regulations are binding, and whether consumers are willing to pay 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.

TABLE 1 Summary of the child care regulatory environment.

			Minimum state education requirement		
State	**Group size**	**Child to staff ratio**	**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

(Continues)

TABLE 1 (Continued)

State	Group size	Child to staff ratio	Minimum state education requirement: Assistant teacher	Lead teacher	Director
Minnesota	20	10	HSD & 8 credit hrs	HSD & 16 credit hrs1	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

(Continues)

TABLE 1 (Continued)

State	Group size	Child to staff ratio	Minimum state education requirement: Assistant teacher	Lead teacher	Director
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

Sources: 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.

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 childcare 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 regulations will influence supply and prices within the market. Unfortunately, whether a regulation is binding has received only scant attention by researchers. Blau (2001) compared the observed child-to-staff ratios within center-based classrooms with the relevant state regulation and found that most providers exceed (i.e., perform better than) the state ratio requirement. Boyd-Swan and Herbst (2018) also compared the experience and education requirements posted in online childcare 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, which examines the period surrounding the COVID-19 pandemic, when states enacted unprecedented changes to their childcare 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 alter their hiring decisions more dramatically than in previous years.

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 childcare services and for quality are moderately sensitive to prices (Blau & Hagy, 1998), as are parental employment decisions (Anderson & 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 childcare environment, their ability to purchase such care during the pandemic—a period of rapid job loss—may have been adversely affected, making them more sensitive to price changes. Insofar as these hypotheses hold, the demand for and quality of childcare labor will fall as regulations become tougher.

DATA AND MEASUREMENT

Labor demand for child care

Data on the demand for and characteristics of childcare labor come from EMSI (now Lightcast), an analytics company that scrapes and unduplicates every job opening that is posted in several major online job banks (e.g., Indeed, Glassdoor, and LinkedIn).[5] 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.[6] All job postings in the EMSI database include detailed information on the characteristics of the position, such as its title, required skills and education level, and its salary structure. The data also include geographic identifiers for the city, county, and state of the job location, thereby allowing us to merge other data to the postings. Finally, the postings stipulate whether the job is classified as part- or full-time.

[5] Unfortunately, we are unable to gather more recent data beyond what was provided because of changes to the data sharing policy (EMSI was acquired by Burning Glass Technologies, which rebranded to Lightcast).

[6] 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.

Relying on information in each job posting, we employ keyword searches to classify all childcare 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 type of teacher position (assistant or lead teacher), and the child age group with which the teacher would 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. For example, we identify pre-K positions through the search terms "Pre-K," "Pre-Kindergarten," and "UPK" (among many others), while Head Start positions are found primarily by searching "Head Start" and "Early Head Start." Similarly, search terms such as "Infant," "1's," and "2yo" are used to identify infant/toddler teacher positions, while terms like "preschool," "3's," and "4 Year Old" are used to identify preschool-age positions.[7]

We use these job postings data to examine the impact of regulations on four key outcomes. We begin by studying the demand for childcare labor, defined as the number of new childcare jobs advertised each day. Specifically, we collapse the data into state × day × age group cells, counting the number of job postings in each cell. The data therefore consist of 41,922 observations (51 states × 274 days × 3 child age groups) over the period January 1, 2020 to September 30, 2020. One might be concerned that job postings (vacancies) are not a good proxy for actual employment levels. Ali et al. (2021) showed that there is a 0.91 correlation between log employment and log job posting levels, suggesting that the trends match each other. Motivated by that relationship, we delve deeper into the demand for childcare labor. While the composition of actual employees on the job can alter demand (e.g., endogenous turnover), we view job postings as a mechanism for influencing the composition of labor supply.

We then examine 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 childcare providers hire for similar roles, but alter the skill level required for the positions. To do so, we exploit information listing the minimum education level required for each position. We focus on whether a given childcare job posting lists a bachelor's degree (or more) as a job requirement, and again construct a binary indicator equal to one if a posting requires a bachelor's degree and zero otherwise.[8] The unit of analysis for these outcomes is the job posting, and the sample consists of a maximum of 49,045 observations, treating each posting as an individual observation.

Finally, we examine whether providers remain compliant with other regulations in response to increasingly strict group sizes and child-to-staff ratios. Specifically, we study whether job postings' teacher education requirements meet or exceed the corresponding state regulation for teachers' education. We begin by coding each state's center based minimum education requirement for lead teachers. Table 1 focuses on lead teachers because most states regulate their education levels, displaying substantial variation in these regulations. The lead teacher education requirements range from a high

[7] It is important to note a few other characteristics of the job postings. First, the postings data do not cover the home-based child care market, nor employment opportunities for au pairs and babysitters. Thus, the current study provides evidence on the formal, center-based child care market. Second, in a small number of cases, multiple positions are advertised within the same job posting (e.g., an infant/toddler teacher as well as a preschool-age teacher). In such cases, we code a given posting to be included in as many categories as is relevant, but we conduct a number of specification checks to ensure that our results are not sensitive to a particular decision about how to treat the posting. For example, although we code job postings for infant/toddler and preschool-age teachers in both age group categories, we conduct separate analyses that treat these postings as either for infant/toddler or preschool-age teachers (but not both), as included in both categories, and as excluded entirely from the analysis. Results reported here are based on analyses that treat these postings as appearing in multiple categories, although the results are not sensitive to the choice of categorization.

[8] The decision to study the demand for teachers with a bachelor's degree is driven by two considerations. First, a 4-year college degree is increasingly the norm among center-based child care teachers. Recent work by Boyd-Swan and Herbst (2018) showed that a plurality of lead teachers (42%) have at least a bachelor's degree. This is confirmed by another recent paper using different data (Herbst, 2023). Second, some previous work shows that having a bachelor's degree is associated with higher center-based classroom quality (Blau, 2000) and positive teacher behavior (Blau, 1997). Therefore, we believe this education level is the most relevant and important one to investigate.

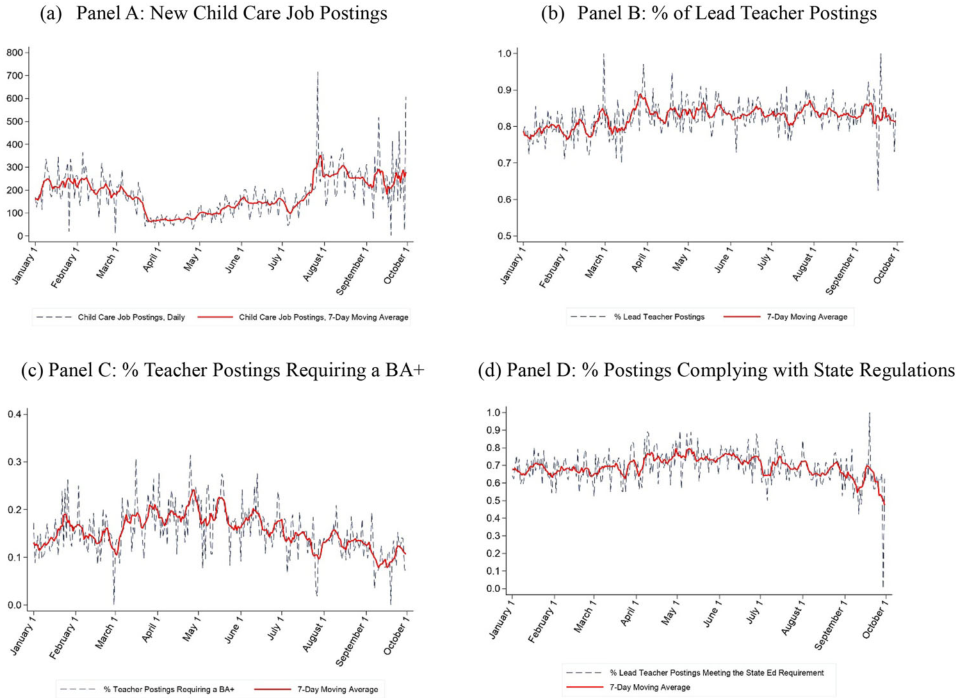

FIGURE 1 Characteristics of child care job postings.
[Color figure can be viewed at wileyonlinelibrary.com]
Source: Emsi.
Notes: Panel A shows the daily (and 7-day moving average) number of child care job postings. Panel B shows the share of job postings that advertise for a lead teacher. Panel C shows 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 lead teacher education requirements.

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 relevant 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 on the subset of lead teacher job postings, for which there is a total of 20,296 observations.

Figure 1 presents the daily time series for the four outcomes of interest over the study period: total number of childcare job postings (Panel A), share of postings that are for lead teachers (Panel B), share of postings requiring a bachelor's degree or more (Panel C), and share of lead teacher 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 childcare job postings each day, but which 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 an 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, eventually receding to its pre-pandemic levels. Finally, nearly 70% of lead teacher 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 its pre-pandemic levels by the end of the study period.[9]

[9] While a non-compliance rate of 30% appears to be high, it is in line with the existing evidence on child care providers' noncompliance with regulations. For example, Blau (2001) found that up to 20% of randomly selected rooms within the child care centers included in the Cost,

Childcare regulations

Our analysis examines the impact of two state-level childcare regulations: center-based maximum classroom group sizes and child-to-staff ratios.[10] 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).[11] Thus, we code these regulations in state × day × age-group cells over the period January 1 to September 30, 2020.[12] 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.[13]

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 if there is no such 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. 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 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. As will be shown, these variables allow for the estimation of regulatory effects along two policy-relevant margins: the average treatment effect of enacting a groups size regulation for the first time by many states during the pandemic, and the marginal effect of increasing the stringency of group sizes in states that had already enacted such requirements prior to the pandemic.

Our final measure of childcare regulations captures the stringency of center-based child-to-staff ratios. As with group sizes, child-to-staff ratios vary by single year of children's age, up to age 10. Thus, we calculate the average value of the ratio in the three age groups defined above, and allow it to vary within each state × day × age-group cell, again making this a continuous measure of the stringency of the ratio regulation. We impute a value of zero to cells without a ratio in effect, and we invert the variable so that its values indicate increasingly strict regulations. It is also standardized to have a mean of zero and a standard deviation of one. Given that nearly every state regulated

Quality, and Child Outcomes Study were out-of-compliance with the relevant state regulation on child-to-staff ratios. More relevant is recent work by (Boyd-Swan & Herbst, 2018), who, in a resume audit study, compared states' education regulations with providers' posted requirements in on-line job advertisements. The authors found that among providers located in states with an education requirement of an associate's degree for lead teachers, 30% of such providers advertised for teachers with no more than a high school diploma.

[10] We encountered a small number of instances where local governments in some states could enact their own regulations. Those states include California, Missouri, Nebraska, and New York. However, information on these local regulations was missing or vague, which precluded systematic data collection on how they evolved over time. Thus, our study focuses only on the state-enacted requirements.

[11] 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.

[12] That our data exploits states' child-age-specific variation in regulations is advantageous for two reasons. First, it provides 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 & Herbst, 2019; Hotz & Xiao, 2011). Second, the additional age-group variation reduces the correlation between the variables measuring group sizes and 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 & Herbst, 2019; Currie & Hotz, 20024; Hotz & Xiao, 2011).

[13] Child Care Aware data are available at https://www.childcareaware.org/coronavirus-hub/coronavirus-landing-page/state-policies-and-ratio-changes-during-covid-19/, NGA website resources are found at https://education.nga.org/#section-statetable, while the Hunt Institute's data summary can be seen at https://hunt-institute.org/covid-19-resources/. Our database of childcare regulations will be made available to researchers upon request.

TABLE 2 Summary statistics on the child care regulations.

Panel A: Any group size regulation	
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	
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	
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)

Sources: 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 (in parentheses) for the child care regulation variables by age group during the pre-pandemic period, defined as January and February of 2020. Panel A shows the share of states with any classroom group size regulation enacted for each listed age group. Panel B shows the average value of the group size regulation, while Panel C shows the average value of the child-to-staff ratio regulation for each listed age group.

child-to-staff ratios prior to the pandemic, and that no state changed its implementation status during the pandemic, our ratios capture only the marginal effect of a change in the toughness of a pre-existing standard.

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

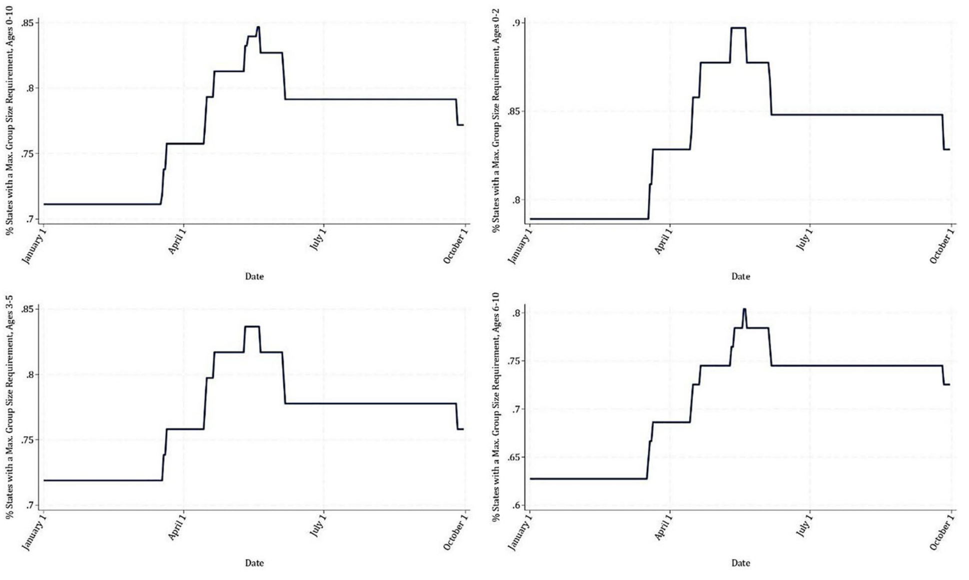

FIGURE 2 Share of states regulating maximum classroom group size, by age group.
[Color figure can be viewed at wileyonlinelibrary.com]
Sources: Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: Each figure plots the daily share of states regulating center-based maximum classroom group sizes between January 1 and September 30 (2020), separately for children ages 0 to 10, ages 0 to 2, ages 3 to 5, and ages 6 to 10.

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, average group sizes still remained 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, even though the ratios did not return to their pre-pandemic levels.[14]

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

[14] It is worth noting that child-to-staff ratios for children ages 0 to 2 follow a slightly different time path: they became more lenient in the early days of the pandemic, before growing more strict, as was the case for all other age groups.

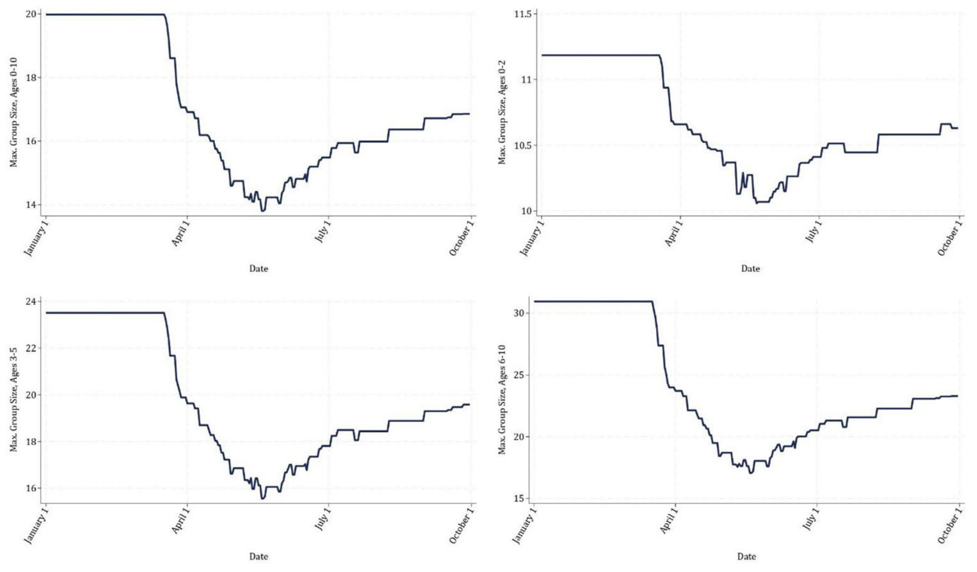

FIGURE 3 States' maximum classroom group size, by age group.
[Color figure can be viewed at wileyonlinelibrary.com]
Sources: Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: Each figure plots the daily average value of the center-based maximum classroom group size regulation between January 1 and September 30 (2020), separately for children ages 0 to 10, ages 0 to 2, ages 3 to 5, and ages 6 to 10.

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 the average state making over 18 changes to its age-group-specific standards. Similarly, 18 states revised their child-to-staff ratios, and these states made an average of 14 changes to its age-group-specific standards. We exploit this policy variation within and across states and age groups in the empirical models, as described in the next section.

EMPIRICAL STRATEGY

We begin by studying the impact of childcare regulations on the demand for childcare labor. We then turn our attention to analyzing the demand for teacher characteristics, such as preferences for lead teachers and those with 4-year college degrees. Finally, we assess whether states' group size and ratio regulations have implications for providers' compliance with other labor-related regulations. Our specifications contain elements of binary and continuous treatment DD designs, capitalizing on variation in treatment intensity from states that enacted new childcare regulations or made further changes to existing ones. Specifically, this policy variation is driven primarily by within-state over-time changes in regulatory stringency as well as between child-age-group differences in exposure to regulatory stringency.

Demand for childcare labor

To understand the relationship between regulations and the demand for childcare labor, we start by estimating regressions of the following form:

$$Y_{gstm} = \gamma r^{e}_{gst} + \varphi r^{i}_{gst} + X'_{st} + \zeta_g + \xi_s + \eta_t + Y'_{st} * \theta_m + \xi_s * f(time)_t + \varepsilon_{gstm}, \quad (1)$$

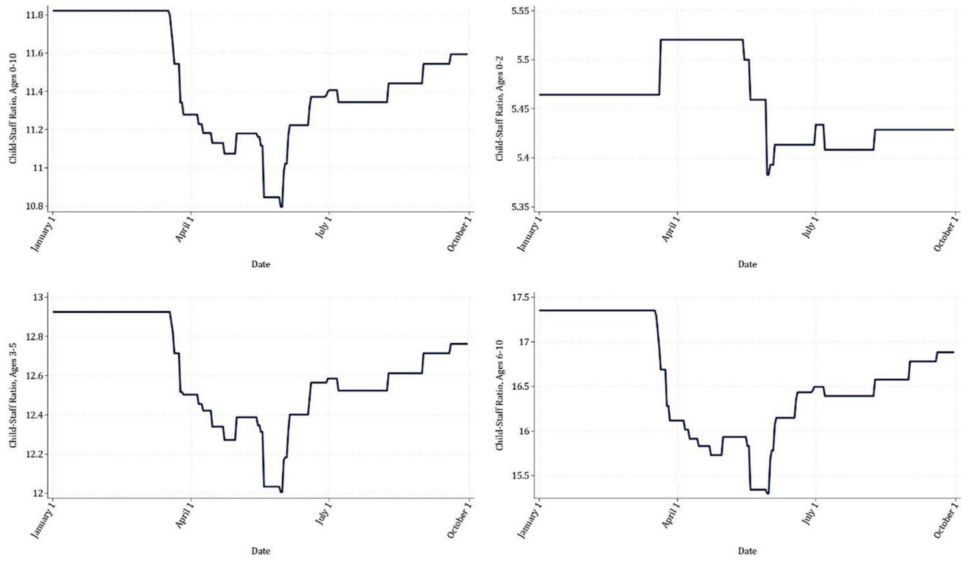

FIGURE 4 States' child-to-staff ratio, by age group.
[Color figure can be viewed at wileyonlinelibrary.com]
Sources: Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: Each figure plots the daily average value of the center-based child-to-staff ratio regulation between January 1 and September 30 (2020), separately for children ages 0 to 10, ages 0 to 2, ages 3 to 5, and ages 6 to 10.

where Y_{gstm} denotes the log number of childcare job postings in child age group g, state s, day of the year t, and month m. The key variables of interest are r^e, which denotes an indicator for whether the state has any group size regulation in place, and r^i, which denotes a vector of standardized measures of group sizes and child-to-staff ratios within a given state × day × age group cell. 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, allowing us to distinguish between provider responses to newly-enacted regulations (i.e., those implemented for the first time during the pandemic) versus responses to incrementally increasing the stringency of existing regulations. Therefore, the coefficient γ represents the percent change in the number of childcare job postings among providers in states that newly-enact a group size regulation for a given child age group, while the coefficient φ represents the percent change in the number of job postings for providers in states that reduce by one standard deviation the regulated group size and child-to-staff ratio. Our standard errors are adjusted for clustering at the state × day level.[15]

The baseline model includes a set of fixed effects for states, days, and child age groups. The state fixed effects, ξ, account for any time-invariant unobserved differences across states that may be correlated with decisions regarding childcare regulatory stringency. For example, states with tougher regulations may have other quality-related early education initiatives in place or include parents with stronger preferences for quality, both of which may influence providers' labor demand. The day-of-the-year fixed effects, η, control for any unobserved time-varying national shocks that influence states' regulatory decisions and providers' labor demand. Such controls are particularly important in this context, given the rapidly changing macroeconomic and pandemic-related conditions throughout our study period. Finally, child-age-group fixed effects, ζ, absorb any differences across children's

[15] In results not reported in the paper, we undertook a series of robustness tests intended to check the sensitivity of the standard errors to different approaches to clustering. The four alternative clustering methods are state × month, state × group, day × state, and state, and we apply these methods to the models in columns (6) and (7) of Table 3. We find that changing the structure of clustering does not produce large changes in the magnitude of the standard errors or in the statistical significance of the coefficients. Results from these tests are available upon request.

age groups that may explain the differential stringency of regulations across those age groups. For example, the importance of childcare quality might vary across children's ages, thereby leading to an age-specific component in the demand for regulated care (e.g., targeting younger children).

Given that the baseline model includes state and day fixed effects, the coefficients γ and φ represent the causal effect of childcare regulations as long as there are no time-varying differences within states that are correlated with the timing of the adoption of new regulatory policies within those states. Such an assumption is likely problematic in our context, given the large number of economic and pandemic-related factors that changed contemporaneously with the enactment of states' childcare regulations. For example, the new regulations might be a response to changing preferences for enhanced health and safety controls as well as supervision as the risk of COVID-19 transmission changed. In addition, states enacted a number of policies (e.g., state-at-home orders and mandatory business closures) aimed at mitigating the spread of COVID-19, all of which likely influenced the demand for childcare labor (Ali et al., 2021). Finally, there may be pre-pandemic differences across states in the functioning of the childcare market (i.e., supply and demand conditions) whose impact on labor demand during the pandemic evolved differently over time. Failure to control for these time-varying factors could bias the coefficients on regulations if they are correlated with childcare providers' hiring behavior.

We take a number of steps to mitigate the influence of these potential time-varying confounders. First, we control directly for the evolving severity of the pandemic in each state by including in the model the log number of COVID-19 cases in each state × day cell. In addition, we include a proxy for changes in household child care demand by controlling for Google Trends search intensity scores under the topic "child care," also measured in state × day cells. Second, states enacted several new health and safety requirements for center-based providers aimed at mitigating the spread of COVID-19. Therefore, the empirical model controls for whether programs were required to provide sanitizing and disinfecting supplies to children and staff on site, required to sanitize and disinfect facilities daily, precluded from allowing inter-group (i.e., between-classroom) mixing for all activities, and precluded from allowing visitors to enter the facility.[16] All four health and safety requirements are coded as binary indicators equal to one if a given requirement is enacted in each state × day cell.[17] Third, we include a variety of controls for states' COVID-19 containment policies that were enacted contemporaneously with the childcare regulations. These variables include binary indicators for the enactment of state-of-emergency declarations, stay-at-home orders, childcare program closure mandates, public school closures, business closures (and re-closures), and statewide indoor mask mandates.[18] All of these controls are included within the X' variable matrix.

Fourth, we attempt to further account for time-varying unobservables by including in the model an additional 12 state-level variables. In particular, each variable is collected for the year 2019—prior to the pandemic and thus before the policy treatments were enacted. Given that these variables are measured at a single point in time, they are interacted with a set of binary indicators for each month, as denoted by the term $Y'_{st} * \theta_m$. Therefore, the model allows the impact of these state characteristics to vary over time. The variables include the log population ages 0 to 4, Black share of the child population, marriage rate, share of the population ages 25 and over with a bachelor's degree, a binary indicator equal to one if the state's governor is a Republican, unemployment rate, median household income, log number of childcare establishments, log number of childcare industry employees, log weekly earnings for childcare employees, log number of children attending Head Start, and log per

[16] Several states enacted a requirement that only children and staff were allowed to enter a child care facility. Therefore, even parents and legal guardians were prevented from entering. As a result, programs organized pick-up and drop-off outside the facility, and staggered the arrival and departure times in an attempt to ensure a smooth transition of children from the provider to parents (and vice versa).

[17] Key resources used in the extraction of these data on health and safety regulations are relevant policy documents issued by state agencies, as outlined in the Child Care Aware of America COVID-19 Hub, the National Governors Association (NGA) state-action tracker, and the Hunt Institute database on State Child Care Actions in Response to COVID-19.

[18] These data were 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 on State Child Care Actions in Response to COVID-19.

child education spending.[19] These data are aimed at capturing potentially important childcare supply and demand, labor market, and political conditions that may influence within-state over-time changes in providers' hiring behavior. Furthermore, the model includes $\xi_s * f(time)_t$, which is a set of state-specific time trends, using a linear function of time. Such controls are important if any component of the unobservables is trending within states.

Once the results from the basic model are established, we fully exploit the panel structure of the data (organized into state × day × age group cells) to test additional assumptions about the nature of the unobservables. In particular, we experiment with more restrictive two-way fixed effects, beginning with a model that include state × child age group fixed effects as well as day × child age group fixed effects. The former assumes that any permanent state-specific unobservables have an age group component, while the latter assumes that any time-varying shocks have an age group component. We then estimate what is perhaps our most stringent specification, which includes state × day fixed effects. In this model, we use only within-state and -day (i.e., between-child-age-group) variation in the childcare regulations to identify their impact on labor demand. Thus, this specification controls for all within-state time-varying shocks, including changes to labor market and political conditions, the enactment of COVID-19 containment polices, and other pandemic-induced shifts in the childcare market.[20]

As a final robustness check to validate that the coefficients γ and φ are not picking up any state × day × age group shocks to the childcare market, we implement a falsification test in which the number of childcare job postings is replaced with the number of Head Start and pre-kindergarten job postings as the outcome. If γ and φ are to be interpreted as causal estimates, changes to childcare group sizes and child-to-staff ratios should not affect job postings for Head Start and pre-kindergarten teachers. One concern with this test is that regulatory changes in the center-based childcare market may create spillovers to the Head Start and pre-kindergarten labor market if teacher characteristics are substitutable across sectors. Fortunately, this is not likely to be the case, given that both sets of teachers face different education and training requirements and are exposed to different classroom group size and child-to-staff ratio regulations. Fully 72% of Head Start teachers have at least a bachelor's degree, while 33 out of 62 state-administered pre-kindergarten programs require all lead teachers to have such a degree (National Institute for Early Education Research [NIEER], 2016).[21] In contrast, only 27% of center-based child care teachers have a bachelor's degree (Herbst, 2023). Furthermore, a majority of pre-kindergarten programs require group sizes to be no higher than 20 (47 programs) and child-to-staff ratios to be no higher than 10:1 (50 programs; NIEER, 2023). These are significantly tougher standards than what preschool-age childcare classrooms must comply with, as shown in Table 2. Thus, changes to childcare regulations should not influence labor demand in these public early education sectors, given that the regulatory changes were directed at childcare providers and that it is unlikely that a large number of childcare workers have the skills to quickly transition to the Head Start or pre-kindergarten labor market.

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 childcare regulations. We estimate

[19] These data are drawn from the Annie E. Casey Kids Count Data Center, Bureau of Labor Statistics, and Quarterly Census of Employment and Wages (QCEW).

[20] Of course, this model does not include the time-varying state controls or the state-specific time trends, given that they are collinear with the state × day fixed effects. However, we incorporate the day × child age group fixed effects as well as interactions of the 2019 state characteristics with age group fixed effects to account for an unobserved heterogeneity that has an age group component.

[21] The Improving Head Start Act for School Readiness of 2007 increased teacher qualifications, requiring at least 50% of Head Start teachers to have a bachelor's degree or higher. There are 62 pre-kindergarten programs because several states operate multiple programs.

regressions for workforce characteristics as follows:

$$Y^k_{istm} = \gamma r^e_{st} + \varphi r^i_{st} + P'_{ist} + X'_{st} + \xi_s + \eta_t + Y'_{st} * \theta_m + \varepsilon_{gstm}, \tag{2}$$

where Y_{istm} denotes an indicator variable for whether a given childcare job posting i in state s, day-of-the-year t, and month m corresponds to a particular characteristic. Thus, the unit of analysis for these outcomes is the job posting, rather than the state × group × 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). The model includes a number of job posting characteristics, denoted by P', including a set of binary indicators for whether the posting is for an infant/toddler, preschool-age, or school-age teacher; a set of binary indicators for the education requirement of the position; a binary indicator for whether the position is part- or full-time; and a binary indicator for whether the position requires shift work. We also include X' and $Y'_{st} * \theta_m$, which denote the same set of time-varying state characteristics outlined in Equation 1. Finally, the model includes state (ξ_s) and day (η_t) fixed effects. Standard errors are clustered on state × day cells.

As outlined in the previous section, we study three outcomes using this specification, all of which are expressed as binary indicators. First, we differentiate across the level of each job posting i and create a variable denoting whether the posting corresponds to a lead teacher or an assistant teacher. The second outcome examines whether each job posting requires at least a bachelor's degree. 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 education requirement in the job posting meets the state education regulation. We rely on the full set of job postings for the first two outcomes, but limit the sample to only lead teacher job postings for the third outcome. We limit the sample to lead teachers because for most states the minimum education requirements for assistant teachers are either undefined or much more lenient.

MAIN RESULTS

The demand for childcare labor

We now present the main results for childcare labor demand in Table 3 associated with Equation 1. We present results from seven specifications, each one either enriching the set of control variables or making different assumptions about the nature of unobserved heterogeneity. Specifically, the results in column (1) come from a model that includes age group, state, and day fixed effects as well as the basic set of time-varying state covariates (i.e., X'). Column (2) includes the additional 12 state controls (separately interacted with month fixed effects and age group fixed effects), while column (3) adds the state-specific linear time trends. We then add the state × age group fixed effects to the model in column (4) and the day × age group fixed effects to the model in column (5). Both sets of fixed effects are included together in column (6). Finally, column (7) incorporates the state × day (along with day × age group) fixed effects, purging all unobserved shocks within a state and day.[22]

Looking at the results in Table 3, two observations are immediately apparent: the regulations have different effects on labor demand, and the estimates are quite similar across the various specifications. Generally speaking, the results indicate that the enactment of any group size regulation reduces the demand for childcare labor, as proxied by the number of job postings. Indeed, the estimate in column (1), which corresponds to the most sparsely controlled model, implies that enacting a group

[22] The model in column (4) also includes day fixed effects, while that in column (5) includes state fixed effects.

TABLE 3 Estimates of the impact of regulations on the demand for childcare labor.

	Dep var: ln(number of new job postings)						
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**
Any group size regulation	-0.075***	-0.086***	-0.088***	-0.066***	-0.083***	-0.055**	-0.092***
	(0.013)	(0.014)	(0.015)	(0.024)	(0.015)	(0.024)	(0.016)
(1/Group size)	0.010**	0.040***	0.046***	0.028***	0.046***	0.027***	0.061***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.006)	(0.007)	(0.007)
(1/Child-to-staff ratio)	-0.008	-0.014**	-0.015***	-0.018**	-0.017***	-0.022***	-0.018***
	(0.005)	(0.005)	(0.005)	(0.007)	(0.005)	(0.007)	(0.006)
Mean daily no. of job postings	3.509	3.509	3.509	3.509	3.509	3.509	3.509
Observations	41,922	41,922	41,922	41,922	41,922	41,922	41,922
State-level controls: Time-varying	Yes	Yes	Yes	Yes	Yes	Yes	No
State-level controls: Interactions	No	Yes	Yes	Yes	Yes	Yes	Yes
Age group fixed effects	Yes	Yes	Yes	No	No	No	No
State fixed effects	Yes	Yes	Yes	No	Yes	No	No
Day fixed effects	Yes	Yes	Yes	Yes	No	No	No
State-specific time trends	No	No	Yes	Yes	Yes	Yes	No
State x age group fixed effects	No	No	No	Yes	No	Yes	No
Day x age group fixed effects	No	No	No	No	Yes	Yes	Yes
State x day fixed effects	No	No	No	No	No	No	Yes

Sources: Emsi, Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: This table reports the coefficients associated with regressions of the log number of child care job postings on an indicator for whether there is any maximum classroom group size regulation in effect, the inverse of average classroom group sizes, and the inverse of average child-to staff-ratios. Standard errors are clustered at the state × day level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

size regulation is associated with a 7.5% reduction in the number of childcare job postings, while that in Column (7), which corresponds to the most richly controlled model, reveals a 9.2% reduction in the number of job postings.[23] Conversely, increasing the stringency of (already-existing) group size regulations appears to increase the demand for childcare teachers. The coefficient in column (1) suggests that a one standard deviation (SD) reduction in the group size is associated with a 1.0% increase in the number of job postings, an effect whose magnitude increases to 6.1% in column (7). Finally, our results suggest that increasing the stringency of (already-existing) child-to-staff ratios reduces the demand for childcare labor. Column (1) shows that a one SD reduction in the child-to-staff ratio is associated with a 0.8% drop in job postings, while that in column (7) implies a 1.8% drop.[24]

As an additional robustness check, we implement a falsification test, exploring whether center-based childcare regulations influence the number of Head Start and pre-kindergarten job postings. Such results are presented in Table 4, and the columns follow the same model progression as in Table 3. We

[23] A key observation is that, if anything, the magnitude of the coefficients in column (7) is consistently larger than their counterparts in columns (1) through (6), implying that the latter estimates may be biased toward finding no impact of regulations. Thus, the results in column (7) suggest that there are no time-varying state-specific sources of unobserved heterogeneity.

[24] Given that the outcome is a count variable, it is not surprising that there is a mass of data points at zero. Approximately two-thirds of the state × day × age group cells include zero job postings. Although the results discussed above measure the outcome variable as the log number of new job postings, we conduct a number of specification checks to ensure robustness. We first estimate the model in column (1) using an OLS regression on the (non-logged) number of postings, and find coefficients (and standard errors) of −0.431*** (0.041), 0.075*** (0.015), and −0.082*** (0.016) on any group size regulation in effect and the continuous group size and child-to-staff ratio regulations, respectively. We then estimate a negative binomial regression, which provides estimates of −0.138*** (0.051), 0.057*** (0.018), and −0.056*** (0.018). Therefore, results from these alternative models are consistent with those reported in the text.

TABLE 4 Estimates of the impact of regulations on the demand for Head Start and pre-K labor.

	Dep var: ln(number of new job postings)					
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Any group size regulation	-0.006	0.001	0.020	0.020	0.020	0.020
	(0.019)	(0.021)	(0.030)	(0.030)	(0.030)	(0.030)
(1/Group size)	-0.002	0.004	0.006	0.006	0.006	0.006
	(0.006)	(0.007)	(0.008)	(0.008)	(0.008)	(0.008)
(1/Child-to-staff ratio)	0.016	-0.004	-0.003	-0.003	-0.003	-0.003
	(0.013)	(0.014)	(0.016)	(0.016)	(0.016)	(0.016)
Observations	27,948	27,948	27,948	27,948	27,948	27,948
Mean daily no. of job postings	0.594	0.594	0.594	0.594	0.594	0.594
State-level controls: Time-varying	Yes	Yes	Yes	Yes	Yes	Yes
State-level controls: Interactions	No	Yes	Yes	Yes	Yes	Yes
Age group fixed effects	Yes	Yes	Yes	No	No	No
State fixed effects	Yes	Yes	Yes	No	Yes	No
Day fixed effects	Yes	Yes	Yes	Yes	No	No
State-specific time trends	No	No	Yes	Yes	Yes	Yes
State x age group fixed effects	No	No	No	Yes	No	Yes
Day x age group fixed effects	No	No	No	No	Yes	Yes

Sources: Emsi, Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: This table reports the coefficients associated with regressions of the log number of Head Start and pre-K job postings on an indicator for whether there is any maximum classroom group size regulation in effect, the inverse of average classroom group sizes, and the inverse of average child-to staff-ratios. Standard errors are clustered at the state × day level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

find consistently null associations: all of the coefficients are small in magnitude, inconsistently signed, and never statistically significant. If the results in Table 3 were simply an artifact of unobserved time-varying or age-group-specific shocks, we would expect to see an effect on labor demand in the Head Start and pre-K markets, which we do not. Overall, these results are consistent with those in Ali et al. (2021), who found that the decline in overall early care and education job postings throughout the pandemic was driven by the substantial reduction in the center-based childcare sector.

In results not reported in the paper, we undertake two final robustness checks. First, we remove the state characteristics interacted with month fixed effects and replace those controls with a set of interactions in the changes in state characteristics between 2015 and 2019 with linear time trends. These controls account for any pre-trends in states' characteristics that may drive changes in labor demand. Our results are robust to the inclusion of these controls. Second, we test for the symmetry of our results across periods in which the regulations became tougher and when they became more lenient. Recall from Figures 2 through 4 that the regulations grew tougher during the first part of our analysis period, peaking in late May to early June, after which they became more lenient. To test for symmetry, we estimate the model in column (7) of Table 3 separately for the period January 1 to June 30 and for July 1 to September 30. Our results reveal substantial symmetry: the impact of regulations during a period in which regulatory stringency was increasing is similar to their impact during a period in which regulatory stringency was decreasing.[25]

To put our results in perspective, consider that the daily average number of childcare job postings across states and age groups is 3.5. This implies that the enactment of any group size regulation leads

[25] The coefficients (and standard errors) on the three regulation variables are −0.079*** (0.019), 0.056*** (0.008), and −0.013* (0.007) for the period January 1 to June 30. The corresponding results are −0.131*** (0.035), 0.071*** (0.013), and −0.027** (0.013) for the period July 1 to September 30.

TABLE 5 Estimates of the impact of regulations on the demand for lead teachers.

	Dep var: = 1 if job posting is for a lead teacher		
	(1)	**(2)**	**(3)**
Any group size regulation	0.040**	0.049***	0.039**
	(0.019)	(0.019)	(0.019)
(1/Group size)	-0.001	-0.004	-0.003
	(0.007)	(0.006)	(0.006)
(1/Child-to-staff ratio)	-0.016*	-0.024**	-0.021**
	(0.009)	(0.010)	(0.010)
Dep var mean	0.792	0.792	0.792
Observations	49,045	49,045	49,045
State-level controls: Time-varying	Yes	Yes	Yes
State-level controls: Interactions	No	Yes	Yes
State fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Job posting characteristics	No	No	Yes

Sources: Emsi, Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: This table reports the coefficients associated with regressions of an indicator variable for whether a given job posting is for a lead teacher on an indicator for whether there is any maximum classroom group size regulation in effect, the inverse of average classroom group sizes, and the inverse of average child-to staff-ratios. Standard errors are clustered at the state × day level. $*p < 0.10$; $**p < 0.05$; $***p < 0.01$.

to roughly 0.32 fewer job postings each day, or nearly 10 fewer job postings each month. However, increasing the stringency of already-existing group size regulations (which corresponds to a one SD reduction classroom group sizes) would result in over six more job postings each month. Finally, increasing the stringency of already-existing child-to-staff ratios (which corresponds to a one SD reduction in ratios) would result in approximately two fewer job postings each month. Given that there were fewer 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 for labor demand are robust to the inclusion of a variety of controls for unobserved state, time, and age group heterogeneity. We find that childcare providers, when making decisions about labor demand, respond differently depending on the regulation. In particular, the enactment of any regulation on classroom group sizes as well as increasing the stringency of child-to-staff ratios reduce the demand for childcare labor, while increasing the stringency of group size regulations increases the demand for childcare labor. Thus, we uncover a strong negative effect of group size regulations on providers located in states that enacted such a regulation for the first time during the pandemic. On the other hand, it appears that making an already-existing group size regulation marginally tougher induces providers to slightly increase labor demand. However, as it relates to child-to-staff ratios, increasing the toughness of an already-existing ratio encourages providers to reduce labor demand. We discuss potential explanations for this pattern in the section "Discussion."

The characteristics of childcare labor

We now study the impact of childcare regulations on the characteristics of the job postings. In doing so, our goal is to understand whether childcare providers respond to tougher regulations by engaging in input substitution, or varying the skill composition of the workforce. As shown in Table 5, we begin by studying a binary indicator equal to one if a given job posting is for a lead teacher and zero if it is for an assistant teacher. Column (1) presents results from a model that includes the basic set of time-varying state covariates as well as the state and day fixed effects, while Column (2) adds the 12 additional state controls (each one interacted with month fixed effects). Finally, Column (3) adds the job posting characteristics.

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, which indicates an increased demand for such teachers relative to assistant teachers. Indeed, the estimate in Column (3) implies that having a group size regulation in place increases the odds of advertising for a lead teacher by 3.9 percentage points. Among providers located in states with a group size regulation already enacted, increasing the stringency of that regulation does not alter the demand for lead (versus assistant) teachers. However, Table 5 also shows that increasing stringency of already-enacted child-to-staff ratios reduces the demand for lead teachers. Specifically, the coefficient in Column (3) implies that a one SD decrease in the child-to-staff ratio reduces the probability of advertising for a lead teacher by 2.1 percentage points.

Table 6 further tests for input substitution by examining whether a given job posting requires at least a bachelor's degree.[26] 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.[27] Results in Panel A reveal that the enactment of any group size regulation may increase the demand for bachelor's degrees among assistant teachers. Although the coefficient is large and statistically significant in Column (1), its magnitude is reduced by about one-half and is statistically insignificant in Column (3). Furthermore, increasing the regulatory stringency at the intensive margin (for group sizes and child-to-staff ratios) does not appear to alter the education requirements for assistant teachers, suggesting that any rise in demand for these more educated childcare 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 childcare providers to reduce their demand for (4-year) college educated lead teachers, particularly in the labor market for lead preschool-age teachers. Indeed, the coefficient in column (3) of Panel C implies that the likelihood of requiring such a degree declines by 8.8 percentage points. Conversely, there is some evidence to suggest that increasing the stringency of an already-enacted group size regulation encourages education-based upskilling by increasing the demand for bachelor's degrees among 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.[28]

EXTENSIONS AND ROBUSTNESS

The results presented so far highlight the unintended consequences of childcare regulations for childcare labor demand and the composition of the workforce. In this section, we examine another

[26] The same model progression used in Table 5 applies to Tables 6 and 7.

[27] Indeed, data from the 2019 National Household Education Survey reveal that 67% of preschool-age children attend a non-parental arrangement, compared to 47% among infants/toddlers (authors' calculation). Furthermore, job postings for lead preschool-age teachers comprise a majority of all postings for lead teachers. These data, along with the possibility that preschool-age children receive more education-intensive services (and thus require teachers with better training), motivated our examination of this subset of lead teachers.

[28] It is important to note that not all job postings list an education requirement. For example, approximately 47% lead preschool-age teacher postings do not list such a requirement. All of the models described above are estimated on the full set of job postings. We do so because conditioning the analysis on the decision to list an education requirement might introduce a form of selectivity bias. Nevertheless, we do several things to ensure that the education results are not driven by our sampling choices. First, we test whether the propensity to include an education requirement changed over the course of the study period. We find that the share of job postings listing such a requirement remained constant over the 9-month study period. Second, we estimate the impact of the regulations on a binary indicator for whether a posting lists any education requirement. We find that the regulations are not correlated with this decision. Finally, we estimate the models again, this time conditioning the sample on job postings that list any education requirement. Our results are robust to this sample definition.

TABLE 6 Estimates of the impact of regulations on the demand for teachers with a BA.

	Dep Var: = 1 if a job posting requires a BA+		
	(1)	**(2)**	**(3)**
Panel A: Assistant teacher job postings			
Any group size regulation	0.068**	0.033	0.032
	(0.033)	(0.028)	(0.028)
(1/Group size)	-0.012	-0.009	-0.009
	(0.008)	(0.007)	(0.007)
(1/Child-to-staff ratio)	0.011	0.008	0.008
	(0.011)	(0.013)	(0.013)
Dep var mean	0.044	0.044	0.044
Observations	8,684	8,684	8,684
State-level controls: Time-varying	Yes	Yes	Yes
State-level controls: Interactions	No	Yes	Yes
State fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Job posting characteristics	No	No	Yes
Panel B: Lead teacher job postings			
Any group size regulation	-0.029	-0.040*	-0.042*
	(0.021)	(0.022)	(0.022)
(1/Group size)	0.006	0.003	0.003
	(0.008)	(0.008)	(0.008)
(1/Child-to-staff ratio)	-0.005	-0.001	-0.001
	(0.011)	(0.012)	(0.012)
Dep var mean	0.173	0.173	0.173
Observations	40,360	40,360	40,360
State-level controls: Time-varying	Yes	Yes	Yes
State-level controls: Interactions	No	Yes	Yes
State fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Job posting characteristics	No	No	Yes
Panel C: Lead preschool-age teacher job postings			
Any group size regulation	-0.069**	-0.088***	-0.088***
	(0.029)	(0.030)	(0.030)
(1/Group size)	0.027**	0.029**	0.029**
	(0.011)	(0.012)	(0.012)
(1/Child-to-staff ratio)	-0.022**	-0.026*	-0.026*
	(0.011)	(0.013)	(0.014)
Dep var mean	0.161	0.161	0.161
Observations	13,090	13,090	13,090

(Continues)

TABLE 6 (Continued)

	Dep Var: = 1 if a job posting requires a BA+		
	(1)	(2)	(3)
State-level controls: Time-varying	Yes	Yes	Yes
State-level controls: Interactions	No	Yes	Yes
State fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Job posting characteristics	No	No	Yes

Sources: Emsi, Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: This table reports the coefficients associated with regressions of an indicator variable for whether the minimum education requirement in a job posting is a bachelor's degree. Panel A restricts the analysis to assistant teacher postings, Panel B restricts the analysis to lead teacher postings, and Panel C restricts the analysis to lead preschool-age teacher postings. The regulation variables include an indicator for whether there is any maximum classroom group size regulation in effect, the inverse of average classroom group sizes, and the inverse of average child-to staff-ratios. Standard errors are clustered at the state × day level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

implication of regulations via their impact on compliance with other state regulations. We end with some additional robustness checks.

Non-compliance with state regulations

In order to comply with tougher regulations in some domains, it is possible that some providers reduce their regulatory compliance in other domains. Such a response may be particularly relevant if the new regulations are highly costly from a compliance perspective (e.g., because they require more staff) or if states' enforcement efforts are weak. To test this proposition, we construct for each job posting a binary indicator 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 states over time. Again, the goal of this exercise is to test whether providers are less likely to comply with some regulations as others become increasingly strict. Table 7 presents results from this analysis, with Panel A restricted to the subset of lead teachers and Panel B restricted to lead preschool-age teachers.

Looking at Column (3) of Panel A, we find that the enactment of any group size regulation reduces the likelihood that a job posting meets the state teacher education requirements by 5.1 percentage points. We also find that increasing the stringency of already-enacted group size regulations is associated with a small but statistically insignificant increase in the probability of meeting the state requirements, while increasing the stringency of child-to-staff ratios reduces the probability of meeting the requirements by 1.9 percentage points. When the sample is restricted to lead preschool-age job postings, we see larger and more statistically significant changes in the likelihood of meeting the state education requirements. Specifically, job postings originating in states with any group size regulation in place are 8.3 percentage points less likely to meet the corresponding state education requirement, while those exposed to tougher child-to-staff ratios are 2.7 percentage points less likely to be in compliance.

These results, together with those presented in Table 6, 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 offset the increased the cost of compliance. Furthermore, enacting tougher regulations may induce more violations if states' enforcement efforts are weak. As we discuss in the "Discussion section", one reason for non-compliance may stem from the severe staffing shortages that providers faced, changing hiring standards to fill major gaps in their labor supply.

TABLE 7 Estimates of the impact of regulations on compliance with state teacher education requirements.

	Dep var: = 1 if a job posting complies with the state educ regulation		
	(1)	**(2)**	**(3)**
Panel A: Assistant teacher job postings			
Any group size regulation	-0.025	-0.015	-0.051**
	(0.026)	(0.026)	(0.021)
(1/ Group size)	0.020**	0.015	0.011
	(0.010)	(0.009)	(0.007)
(1/Child-to-staff ratio)	-0.033***	-0.032***	-0.019*
	(0.012)	(0.012)	(0.011)
Dep var mean	0.667	0.667	0.667
Observations	20,295	20,295	20,295
State-level controls: Time-varying	Yes	Yes	Yes
State-level controls: Interactions	No	Yes	Yes
State fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Job posting characteristics	No	No	Yes
Panel B: Lead preschool-age teacher job postings			
Any group size regulation	-0.060	-0.088**	-0.083**
	(0.043)	(0.041)	(0.034)
(1/Group size)	0.045***	0.046***	0.023**
	(0.015)	(0.015)	(0.011)
(1/Child-to-staff ratio)	-0.039***	-0.066***	-0.027**
	(0.014)	(0.015)	(0.012)
Dep var mean	0.684	0.684	0.684
Observations	6,947	6,947	6,947
State-level controls: Time-varying	Yes	Yes	Yes
State-level controls: Interactions	No	Yes	Yes
State fixed effects	Yes	Yes	Yes
Day fixed effects	Yes	Yes	Yes
Job posting characteristics	No	No	Yes

Sources: Emsi, Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: This table reports the coefficients associated with regressions of an indicator variable for whether a given job posting complies with the state's education regulation for lead teachers on an indicator for whether there is any maximum classroom group size regulation in effect, the inverse of average classroom group sizes, and the inverse of average child-to staff-ratios. Panel A is restricted to lead teacher postings, and Panel B is restricted to lead preschool-age teacher postings. Standard errors are clustered at the state × day level. $^{*}p < 0.10$; $^{**}p < 0.05$; $^{***}p < 0.01$.

Robustness checks

We conduct a few additional robustness checks, beginning with an explicit test for pre-trends. Our event-study model defines the outcome variable as the log number of childcare job postings, while the main regulation variable is a binary indicator equal to one if a given state has a center-based group size regulation in place and zero otherwise. Collapsing the data into state × week × age group cells and relying on the staggered introduction of group size regulations, we first estimate a standard TWFE

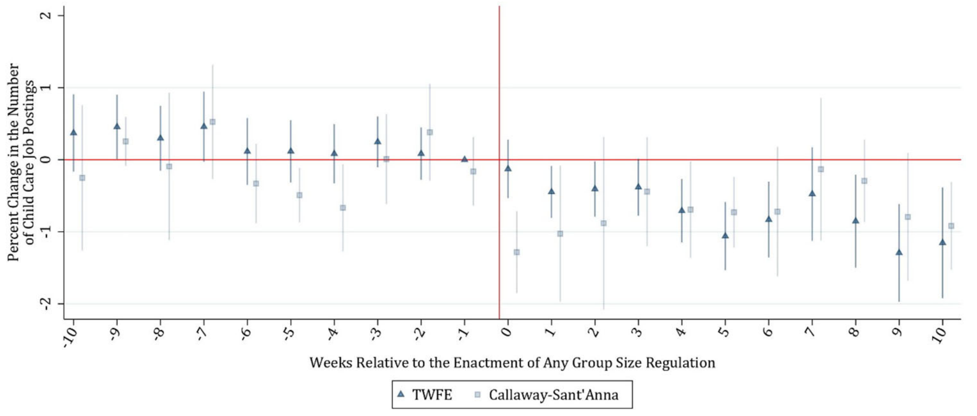

FIGURE 5 Event-study estimates of the impact of group size regulations on the demand for child care labor. [Color figure can be viewed at wileyonlinelibrary.com]

Sources: Emsi, Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
Notes: Using data collapsed into state × week × age group cells, the figure plots event-time coefficients of weeks relative to the enactment of any group size regulation from a model in which the outcome is the log number of child care job postings. All models include the state-level controls as well as state × age group fixed effects and week fixed effects. The event window is restricted to lags and leads of 10 weeks from the enactment of the regulation, with error bars representing 95% confidence intervals. Excluded are "always treated" states and observations after a newly treated state × group once again removes all group size regulations. Standard errors are clustered at the state × age group level, and observations are weighted by the state population ages 0 to 10.

event-study model.[29] This methodology is useful for examining whether childcare labor demand was already shifting in states prior to the implementation of this regulation. In particular, our event-study model takes the following form:

$$Y_{gstm} = \gamma r_{gst}^{any} + \sum_{k} \delta_k^{PRE} r_{g,s,t-k}^{any} + \sum_{k} \delta_k^{POST} r_{g,s,t+k}^{any} + X'_{st} + \zeta_{sg} + \eta_t + \varepsilon_{gstm}, \tag{3}$$

where the main difference from Equation 1 is that r_{gst}^{any} any denotes whether any group size regulation is enacted, $r_{g,s,t-k}^{any}$ and $r_{g,s,t+k}^{any}$ denote indicators for whether the observation period is k periods (i.e., weeks) before or after the treatment, respectively, δ_k^{PRE} and and δ_k^{POST} denote the coefficients on these indicators. The model includes the same state-level controls in X' as well as state × age group and week fixed effects. One concern with the standard event-study design is that the staggered adoption of the regulations could bias the results if there are dynamic treatment effects (Borusyak et al., 2021; Callaway & Sant'Anna, 2021; Goodman-Bacon, 2021; Sun & Abraham, 2021). Therefore, we also show results from the Callaway and Sant'Anna (2021) model by obtaining group × time average treatment effects—that is, groups of state × age pairings that are treated by r_{gst}^{any}.[30]

Figure 5 plots the resulting estimates. While the pre-regulation period shows no detectable time trend in childcare job postings, we uncover a sharp and economically meaningful reduction in job postings almost immediately upon the enactment of a group size regulation. The coefficients are initially slightly larger under the Callaway and Sant'Anna (2021) estimator—but not statistically different—than the standard TWFE estimator. Thus, the absence of any pre-trend in job postings, together with a

[29] As shown in Appendix Table A1, we estimate DD models that include all three regulation variables using the state × week × age group data structure. Our results are quite similar to those presented in Table 3. All appendices are available at the end of this article as it appears in JPAM online. Go to the publisher's website and use the search engine to locate the article at http://onlinelibrary.wiley.com.

[30] The models exclude states that are always treated. We also exclude from the TWFE model observations from newly treated state × group cells after after the regulation is removed from those groups. This accounts for the fact that newly treated state × group observations no longer remain a valid counterfactual.

marked reduction in postings throughout the post-enactment period, provide additional support for a causal interpretation of our results.

As a final robustness exercise, we ask whether any of our results could be driven by a key time-varying shock that coincided with the introduction and increased stringency of childcare regulations. Specifically, many states fundamentally altered the health and safety standards for center-based programs in order to mitigate the transmission of COVID-19, 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 and disinfecting supplies, enhanced cleaning protocols (e.g., daily facility sanitizing), staggered arrival and departure times, no between-age-group mixing, and no sharing of materials and toys across age groups or classrooms. We code 10 such requirements in state × 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 labor demand outcomes studied earlier, and does their inclusion in the model alter the estimates on group sizes and child-to-staff ratios?[31] The analyses serve as a final test of whether other time-varying policies 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 labor demand outcomes on a standardized index of 10 COVID-19 health and safety regulations. Interestingly, these regulations are not correlated with overall labor demand (Panel A), nor are they correlated with any dimension of the childcare workforce (Panels B through D) or with compliance rates (Panel E). Indeed, the coefficients are consistently small in magnitude and never statistically significant.[32] Furthermore, in results omitted for brevity, inclusion of this index variable in the model does not alter the estimated effects of group sizes and child-to-staff ratios. Together, results from these analyses suggest that our main estimates are not confounded by these health and safety standards, even though they were sometimes introduced by states alongside changes to group sizes and child-to-staff ratios. Such evidence therefore provides more confidence in the credibility of our results.

DISCUSSION

Summary and interpretation of main findings

In this paper, we combine online childcare job postings with newly available information on childcare regulations to study impact of regulations on the demand for childcare labor. We have three key findings. First, the introduction and increased stringency of group size and child-to-staff ratio regulations have different effects on the demand for childcare labor. For example, among providers located in states that are exposed to a newly-enacted group size requirement, the number of childcare job postings decreases between 5.5% and 9.2%. However, increasing the stringency of already-existing group size requirements leads to more postings. Second, our results indicate that such regulations distort the demand for workforce characteristics. Specifically, the enactment of a new regulation on group sizes increases the number of lead teacher postings by 3.9 percentage points, but reduces the probability that these postings require a bachelor's degree by 4.2 percentage points, while also reducing the probability that the postings' education requirements comply with the corresponding state education regulations

[31] Each health and safety regulation is coded as a binary indicator equal to one if a given regulation is in effect and zero otherwise. We then average and standardize the set of 10 regulations, with a mean of zero and a standard deviation of one. Thus, increasing values on the index imply more stringent health and safety standards are in place in a given state and day.

[32] One concern with combining the COVID-19 regulations into an index is that the coefficient on the index may reveal a mechanical null effect if the individual regulations influence labor demand in different ways. In results not reported in the text, we estimate the same model in Table 8, except that we enter each COVID-19 variable individually, for a total of 10 regressions. In nine of the regressions, the coefficient on the COVID-19 regulation is negatively signed in the model for job postings, which indicates that, when combined into an index, they are unlikely to produce null effects on labor demand because of conflicting and offsetting individual effects.

TABLE 8 Effects of COVID-19 health and safety regulations on childcare labor demand.

Panel A: Job postings	
Health and safety regulations	0.007
	(0.005)
Dep var mean	3.509
Observations	41,922
Panel B: Lead teacher	
Health and safety regulations	-0.004
	(0.005)
Dep var mean	0.792
Observations	49,045
Panel C: Requires a BA+ (assistant teacher)	
Health and safety regulations	-0.008
	(0.006)
Dep var mean	0.044
Observations	8,685
Panel D: Requires a BA+ (lead teacher)	
Health and safety regulations	0.004
	(0.006)
Dep var mean	0.173
Observations	40,360
Panel E: Complies with state education regulation	
Health and safety regulations	-0.002
	(0.008)
Dep var mean	0.667
Observations	20,296

Sources: Emsi, Child Care Aware of America, Hunt Institute, National Governor's Association, and states' Department of Health websites.
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. The outcome in Panel A is the log number of child care job postings. The outcome in Panel B is a binary indicator for a lead teacher job posting. The outcomes in Panels C and D are binary indicators for job postings that require a BA degree for assistant and lead teachers, respectively. The outcome in Panel E is a binary indicator for a lead teacher job posting that complies with the state teacher education requirements. Standard errors are clustered at the state × day level. * $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$.

by 5.1 percentage points. Third, although increasing the stringency of group sizes in states already regulating this feature appears to have weaker effects on the demand for childcare teachers, we find that increasing the stringency of child-to-staff ratios has strong effects—leading to fewer job postings, fewer lead teacher and bachelor's degree postings, and more postings out-of-compliance with the state education regulations.

These results yield important insights about the ways in which regulations alter the demand for childcare labor. Providers that are required to comply with a newly-enacted group size regulation respond by decreasing the demand for labor (i.e., posting fewer teacher advertisements). However, when they recruit teachers, they are more likely to seek out lead teachers. This is intuitive because, at a minimum, a lead teacher is required to operate a childcare classroom. Furthermore, the adoption of a group size regulation is associated with a decreased number of lead teacher postings that require a bachelor's degree. Such results suggest that regulations may impart high compliance costs on providers, thereby encouraging some to substitute away from higher-skilled (and therefore most costly) lead teacher jobs. In addition, such downskilling has the unintended consequence of reducing the likelihood that the job posting's education requirement is in compliance with the state education regulation.

In contrast, we find small or null effects on labor demand of increasing the stringency of preexisting group size regulations. Specifically, enacting tougher group size mandates leads to a small increase in overall labor demand, no change in the demand for lead teachers, and no change in the demand for lead teachers with a bachelor's degree. 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 encouraged 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.

These results indicate that childcare providers operating in states that previously did not regulate group sizes—but began regulating them sometime in early 2020—experienced significant challenges adjusting to the new regulatory environment. Conversely, providers in states already regulating group sizes adapted relatively well when these regulations became tougher. Such findings suggest that the newly-enacted regulations on group sizes were binding on providers that were previously not exposed to these requirements. Given that compliance with the new requirements was likely to be costly, providers responded by hiring fewer workers overall and downskilling the advertised positions. On the other hand, it appears that the tougher group size regulations were not binding on providers that were already exposed to such requirements. In other words, many providers may have already exceeded the new standards before they introduced during the pandemic. In such cases, as previously discussed, a non-binding regulation is not predicted to induce large changes by childcare providers. Indeed, results in this study seem to confirm this theoretical prediction, at least as it relates to providers' hiring behavior. That said, we also recognize the possibility that childcare providers may vary in their attentiveness during periods of public health emergency versus their aftermath.

While strengthening group size regulations did not produce large changes in providers' hiring behavior, increasing the stringency of child-to-staff ratios induced providers to make several important changes. One possible explanation for these results is that—similar to the discussion above—the new ratios were binding on childcare providers, leading to lower demand for teachers and a decrease in the skill requirements for the job in an effort to cut operating costs. Another explanation focuses on the level at which states established the new group size and ratio requirements during the pandemic. Prior to the pandemic, most states set different mandated levels for group sizes and ratios, such that the ratios were often half as large as the group sizes. For example, Maryland's center-based group size and child-to-staff ratio requirements for 5-year-olds were 30 and 15, respectively. To comply with both regulations, classrooms were required to have two teachers (assuming full classrooms of 30 children in attendance). However, after the pandemic, Maryland—perhaps strategically—lowered both regulations to 10, meaning that just one teacher was needed to comply with both requirements.[33] This practice—lowering ratios substantially more than group sizes, and setting them at the same level—made it easier for providers to comply with the new child-to-staff ratios because they required fewer workers. Such changes may therefore explain why providers responded by decreasing their demand for new teachers.

Another important question is whether the regulation-driven decline in job postings is indicative of an exodus of some childcare businesses from the market or a decline in labor demand among providers that remained open. Although we do not have conclusive evidence to support either explanation, indirect evidence from multiple sources suggests that both might be responsible. First, other studies have shown that increasing the stringency of group sizes and child-to-staff ratios reduce the

[33] Our review of the data suggests that this practice was fairly common.

number of childcare establishments (Hotz & Xiao, 2011). Second, the pandemic revealed just how sensitive childcare businesses are to negative shocks, with a recent analysis finding that 16,000 childcare programs closed between December 2019 and March 2021, representing a 9% drop in the number of programs (Child Care Aware of America, 2022). Another study found that the pandemic era's stay-at-home orders reduced labor demand by 16%, as measured by the volume of job postings (Ali et al., 2021). Third, the pandemic reduced childcare enrollments, which likely influenced providers independently of any business-specific shocks or policies. For example, one study of North Carolina found that enrollments declined 40% during the pandemic, with larger drops in high-income communities (Zhang et al., 2023). Finally, childcare providers generally operate under difficult conditions, earning profit margins of roughly 1% coupled with labor costs that account for 80% of expenses (Annie E. Casey Foundation, 2023; Brown & Herbst, 2022; National Association for the Education of Young Children, 2021). Such conditions make it difficult to increase the size of the workforce—or even retain workers—during periods of macroeconomic or policy uncertainty.[34] Together, this evidence suggests that the supply of child care is sensitive to a variety of factors—including regulatory stringency and other policies, changes in demand, and macroeconomic conditions—suggesting that the regulation effects uncovered in this study are likely driven by a combination of provider closures and workforce downsizing among programs that remained open.

A final issue that warrants discussion is the speed with which childcare providers responded to the new regulations after learning about them. Here, our event-study results are potentially illuminating. Based on the absence of pre-trends, as shown in Figure 5, it appears that providers were not aware of the new regulations before they were enacted, or at least did not respond to them before they took effect. Indeed, the reduction in labor demand occurred after the regulations were introduced. However, a close inspection of the TWFE results reveals that the effects were relatively small in the first three weeks of enactment, and grew larger in weeks 4 and 5. Such patterns suggest that childcare providers required several weeks to fully absorb the policy changes and implement a hiring plan that reflected the new regulatory environment.

Implications for childcare quality

Recall that one of our key findings is that childcare regulations encourage providers to reduce the use of inputs in some domains in order to comply with a potentially costly requirement in another domain. In particular, we find that while enacting new group size and child-to-staff ratio regulations reduce overall labor demand, they encourage providers (i.e., those looking to hire new staff) to downskill the education requirements of advertised teacher positions. This raises an important question about whether regulations—which are aimed at improving program quality—might instead generate (offsetting) reductions in quality.

Characteristics such as group sizes, child-to-staff ratios, and staff education levels are referred to as indicators of structural quality—or the static, easy-to-measure features of the childcare environment (Pianta et al., 2009). They are thought to be relatively static because once the level of each characteristic is established by a provider, they vary little across children, teachers, and classrooms within the provider. For these reasons, such characteristics are easier and less costly to observe, and they are typically among the key features regulated by states in the formal childcare sector.

In thinking about quality trade-offs, a key consideration is whether and how the structural features studied here affect program quality. On the one hand, it may be the case that characteristics such as group sizes and ratios mainly influence the safety of the childcare environment by reducing the incidence of child accidents and injuries, but have little effect on the dimensions of quality that are important for the classroom learning environment and child development. If this holds, our results

[34] Recent work by Brown and Herbst (2022) found that the childcare industry is highly sensitive to macroeconomic conditions, with a 1 percentage point increase in the unemployment rate associated with a 2% to 3% decrease in employment and a 1% decrease in the number of facilities.

imply a net-reduction in quality: increasing the stringency of group sizes and ratios would benefit only child safety, while the reduction in teachers' education levels might reduce quality in ways that are detrimental to child development (e.g., by reducing the quality of child-teacher interactions).

On the other hand, it is possible that structural characteristics like group sizes and ratios influence quality indirectly by creating an environment in which process quality can thrive. Process quality refers to children's contact and experiences with the people and objects in the childcare setting (Boyd-Swan & Herbst, 2018; Pianta et al., 2009). This dimension of quality involves both the types of activities in which children participate and way those activities are administered: the quantity and quality of interactions between children and teachers, and the intellectual and emotional support teachers provide. Importantly, there is some evidence to suggest that process quality is the primary mechanism through which child care influences child development, and that the structural features of the care setting—including group sizes and ratios—create the physical conditions for process quality to be successful (NICHD Early Child Care Research Network, 2002). If this holds, our results imply no net change in quality: lowering group sizes and ratios would improve the classroom learning environment, perhaps by increasing the frequency and quality of child-teacher interactions, while the reduction in teachers' education levels might neutralize some of the improvement in the classroom environment.

The discussion above is relevant largely to non-pandemic circumstances. Thus, it is also worth speculating on whether these quality trade-offs were present during the COVID-19 pandemic. States lowered group sizes and ratios in an effort to limit large gatherings and reduce the transmission of the virus. In this sense, despite the consequences we have documented, increasing the stringency of these regulations may have led to an improvement in program quality and child development by benefiting long-run child and teacher health. For example, by improving teacher health, reducing class sizes and ratios may have decreased rates of turnover and sickness-related absences, thereby allowing teachers to maintain developmentally important connections with children. Furthermore, if the teacher workforce remained healthy, local childcare providers could have been more likely to stay in business to serve future cohorts of children, who might benefit from being exposed to high-quality care. However, whether there were any such public health benefits is a separate question outside the scope of this paper.

External validity

A natural question is whether our results generalize beyond the COVID-19 era, which provides the setting for our analysis. There has long been a tradition in policy analysis to exploit large-scale economic, political, and social shocks to understand real economic behavior, with examples ranging from the 1918 flu (Barro et al., 2022) and the 1930s Dust Bowl (Hornbeck, 2012) to the New Deal (Cole & Ohanian, 2004) and World War II (Acemoglu et al., 2004; Herbst, 2017). The COVID-19 pandemic—through its consequent economic and social disruption as well as its policy innovation—offered a similar opportunity to study a range of important phenomena. Indeed, this period provided researchers and policymakers with evidence on school closure policy (Halloran et al., 2021), the role of social isolation in domestic violence (Leslie & Wilson, 2020), and the impact of unemployment insurance on income replacement (Larrimore et al., 2022), among other things. The pandemic similarly provided a unique setting in which to examine childcare regulatory policy because states experimented with a variety of changes to health and safety standards, visitation protocols, and staffing requirements. Therefore, by exploiting this pandemic-driven policy innovation, our study contributes to an established practice within the social sciences to use periods of major disruption to make progress on questions of longstanding importance.

Although our study's setting is unique, our key finding—that regulations decrease childcare labor demand—is consistent with a related line of work showing that regulations reduce the number of center-based workers and establishments (Gormley, 1991; Hotz & Xiao, 2011). In addition, our work shows that providers substitute between inputs as the regulations become tougher, trading-off some quality-related characteristics in order to comply with regulations set in other domains. This result is also consistent with the extant literature, in particular with Blau (2007), who found similar evidence of input substitution. That our results correspond with previous work should help to assuage any concerns about the ability to generalize beyond the COVID-19 pandemic.

While the policy variation exploited here is larger and more widespread than that available to previous researchers, our estimates are still informative about the underlying relationship between policy and childcare provider behavior. Indeed, there is broad recognition that key policy parameters require multi-faceted sources of variation to identify a robust microeconomic elasticity. In this sense, a silver lining in periods of crisis is that they provide invaluable variation to recover robust parameter estimates that are impossible to estimate during "normal times," but are still useful for guiding public policy and conducting benefit-cost analyses. Specifically, our results may be useful to policymakers in at least three ways. First, given that a number of states enacted a new group size regulation during the pandemic, our work offers lessons for policymakers who might wish to establish a similar requirement. It is uncommon for states to introduce new regulations, and we provide contemporary evidence on the impact of this important policy margin. Our work can also inform policymaking aimed at increasing the stringency of existing group size and ratio requirements. Making a regulation tougher might have different implications for the childcare market (as compared to introducing a new regulation), and our paper sheds light on both margins in a unified empirical framework. Finally, our paper provides insight into how providers respond to regulations beyond changes in supply or prices. In particular, we inform the discussion over whether regulations unambiguously increase quality, or whether providers make trade-offs between inputs in ways that could undermine quality.

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. Indeed, results in our paper suggest that regulations might undermine quality if providers respond to new regulations by shifting resources to less productive inputs in an attempt to comply with the standards. Therefore, the unintended consequences of regulations should be considered by policymakers when weighing alternative policies for improving program quality, including consumer subsidies and quality certification initiatives.

Our paper builds on an empirical literature in labor economics that studies the impact of regulations on the childcare and maternal labor markets. In particular, previous work focuses on childcare supply (e.g., Gormley, 1991; Hotz & Xiao, 2011) and quality (Blau, 2007; Boyd-Swan & Herbst, 2019; Hotz & Xiao, 2011), families' use of and expenditures on child care (Blau, 2003; Hotz & Kilburn, 1994), and parental employment (Blau, 2003). Far less attention has been given to how regulations influence the demand for and characteristics of childcare labor. In fact, Blau (2007) is the only paper to our knowledge that examines these outcomes. Thus, our paper's main contribution is to provide new evidence on these workforce adjustments.

Our results leave several questions open for future research. First, have these regulations affected child development? Given the decline in job postings in the center-based childcare market, the caregiving burden shifted 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 childcare providers may have more margins to adjust than others. Third, how have the employees in the childcare market fared, and have those who were laid off returned to work in the childcare market? Given recent empirical work on the allocation of time and remote work (Makridis, 2023), understanding how policy has shaped child care will help us identify and manage the long-run implications for childhood development.

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SUPPORTING INFORMATION

Additional supporting information can be found online in the Supporting Information section at the end of this article.

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