Unintended Consequences of Child Care Regulations

David M. Blau

University of North Carolina at Chapel Hill

January 2006

Thanks to Naci Mocan for providing access to the data used here, and for collaboration on previous work that led to the idea for this paper. Thanks also to Joe Hotz and Becky Kilburn for sharing data on regulations. Thanks to Koleman Strumpf and a referee for helpful comments and suggestions. The author is responsible for errors and opinions. Comments welcome at david_blau@unc.edu.

Unintended Consequences of Child Care Regulations

Abstract

The effects of regulations governing staff-child ratio, group size, and staff qualifications in child care centers are estimated, using data on a sample of centers. The data contain measures of staff characteristics and wages, price of the service, and the developmental quality of the child care provided. Regulations vary across states, but may be endogenous to these outcomes. Estimates with state fixed effects are feasible because regulations vary within states by age group of children and job title of staff. Estimates with state fixed effects show that tougher regulations have some impact on input use, but have little or no impact on price and quality. The most striking finding is that tougher regulations reduce staff wages, suggesting that the incidence of child care regulations is on employees of day care centers.

JEL Codes: J13, L51

Key words: child care, regulation, quality, day care, establishments

1. Introduction

A substantial proportion of child care in the United States is asserted to be of low developmental quality: it does not stimulate the cognitive, social, and emotional development of children (Helburn, 1995; Cryer et al., 1999; Whitebook, Howes and Phillips, 1990; Kontos et al., 1995). There is considerable interest among policy makers in finding ways to improve the quality of child care. The main form of government policy aimed at improving child care quality is regulation. Subsidies could be used to encourage use and provision of high-quality child care, but in practice most child care subsidies in the U.S. are unrestricted with respect to the quality of care. These subsidies can be used to purchase child care from any provider that complies with or is legally exempt from regulations (including relatives and babysitters). The exceptions are Head Start, Title I-A, and state pre-Kindergarten programs, which are generally thought of as early education programs rather than child care subsidies.

Child care is regulated by the states in an effort to reduce the risk of harm to children from exposure to child care. The risks to which regulations are addressed include developmental impairment, injury, and the spread of disease (Morgan and Azer, 1997). Regulations require child care providers to be licensed or registered and to meet minimum standards of safety, hygiene, and developmental appropriateness. Providers that fail to meet regulatory standards can be fined and denied a license to operate. Most states regulate the ratio of children to staff in a group, the education and training of the staff, building and equipment safety, sanitation, first aid, staff background checks, discipline practices, food safety, immunization, and other program features.

The rationale for child care regulations is easily understood in the context of economic models of markets with asymmetric information. Parents may be poorly informed about the quality of child care

received by their children, either because they do not know how to assess quality, or because they cannot closely monitor the child care provider (Walker, 1991). Under these circumstances, minimum quality standards can protect consumers by ensuring an "acceptable" level of quality. Regulations may accomplish this goal by driving out low-quality providers or inducing them to increase the quality of their services (Leland 1979, Shapiro 1986). This may or may not increase social welfare, since regulations can also affect the price of the service. If there are positive externalities from high quality child care, then even if consumers are fully informed about the quality of service, regulations may be desirable if they eliminate the lower end of the quality distribution from the market. High-quality child care might provide an external benefit if it results in more educated, productive individuals who are less prone to criminal behavior and welfare dependence.[1]

Large numbers of young children in the U.S. are cared for by someone other than a parent or relative while the parents work. Almost two thirds of mothers with children under age six are in the labor force, and the majority of their children are cared for by a non-relative in a center, family day care home, or the child's home (Smith, 2002). Developmental psychologists argue that low-quality child care is harmful to children (Love, Schochet, and Meckstroth, 1997; Lamb, 1998), and there is evidence that high-quality preschools can have lasting benefits for disadvantaged children (Karoly et al., 1998, Currie, 2001). Thus it is important to determine whether regulations have any impact on child care quality, and whether they affect price as well. Little is known about these issues. Previous studies

[1] An alternative to regulation in the case of asymmetric information is a government certification system, in which the quality of service provided by each firm is evaluated by an independent agency and made known to consumers. Shapiro (1986) discusses the conditions under which certification is superior to regulation as a means of improving consumer welfare.

of the effects of child care regulations have mainly analyzed effects on the aggregate supply and utilization of child care (Blau, 2003; Gormley, 1991; Lowenberg and Tinnin, 1992; Hofferth and Chaplin, 1998; Hotz and Kilburn, 1994; Hotz and Xiao, 2005; Rose-Ackerman, 1983). These studies generally find that stricter regulations governing day care centers are associated with the existence of fewer day care centers and less utilization of care in centers, and similarly for family day care homes. Studies of the effects of regulations on input use are rare, and effects of regulations on input prices, quality, and output price have not been analyzed.[2] States have been increasing the strictness of most of their child care regulations in recent years (Blau, 2003), so these issues are increasingly important.

This paper investigates the effects of child care regulations on input use, input price, and the quality and price of care in day care centers, using a rich data set. The analysis addresses a number of issues that have not been previously analyzed. First, to what extent are child care regulations binding? Non-binding regulations have no bite and would be unlikely to affect the child care market. Day care centers are very heterogeneous, so the real question is what proportion of centers face binding regulations? This question can be addressed because the data include measures of many of the items that are regulated, including group size, staff-child ratio, and staff qualifications. Second, to what extent are regulations violated? If compliance is low, perhaps because of low enforcement efforts, then regulations might have little impact on the market. Third, to what extent do firms substitute among inputs

[2]Blau (2003) and Hotz and Kilburn (1994) analyze the effect of child care regulations on household child care expenditure per hour, but this is conceptually distinct from price. Price is the fee charged by a provider for a given quality of care, while household expenditure depends on the quality of care selected by the household as well as the price for a given level of quality. Hotz and Xiao (2005) analyze the effect of child care regulations on an indirect indicator of quality: accreditation.

in response to regulations? For example, do firms facing regulations requiring use of highly trained teachers respond by using fewer teachers per group of children and larger groups of children? Fourth, how do input regulations affect price and quality? Child care regulations govern inputs to the production of quality, but do not directly regulate the quality of child care. If the regulated inputs are not very productive, or if the regulations are not binding or enforced, or if there is considerable input substitution in response to regulations, then regulations would have little effect on quality. If regulations do result in higher quality, then they should also affect price. An important strength of the data used here is that the developmental quality of care was assessed by trained observers using a quality-rating instrument with good psychometric properties. In a review of the occupational licensing literature, Kleiner (2000) notes that no studies have been able to directly examine the impact of regulations on quality. This is a major gap in the literature that is addressed in this paper. Fifth, how do child care regulations affect the price of the main input, labor? If regulations result in increased cost but consumer willingness to pay fails to increase by enough to cover marginal cost, then the incidence of regulations could be partly on staff wages. This issue has not been previously investigated.

Finally, the robustness of the empirical results to alternative identification strategies is examined. Previous studies of child care and other regulations have relied almost exclusively on variation in regulations across states for identification. This is a powerful source of variation because regulations vary substantially across states. But it may not yield unbiased estimates if unobserved state-level factors influence both the strictness of regulations and demand for quality in child care. Some regulations vary by the age of children in child care, and this can be exploited to achieve identification using variation across states in the age gradient of regulations rather than in the level of regulations. Other regulations

vary by the position of a staff member - director, teacher, assistant teacher. Differences in regulations by staff position within states can identify the effects of such regulations without relying on cross-state variation in the average level of regulation. These are not necessarily better sources of identification than cross-state variation, but they make it possible to determine the robustness of the results to alternative identification assumptions.[3]

The empirical results show that tougher regulations appear to be associated with higher quality and price, but that these effects are not robust. Controlling for state fixed effects eliminates the impact of regulations on price and quality. The absence of robust effects of regulations on price and quality appears to be a consequence of three factors. First, there is a significant amount of input substitution in response to regulations: a tougher regulation on one input affects the use of other inputs as well as the regulated input. For example, regulations that require higher staff qualifications cause centers to employ fewer staff members per child. Second, tougher regulations induce greater violation, indicating that enforcement is far from perfect. Third, other research suggests that many of the regulated inputs are in fact not very productive in improving quality. The only input that has been found to have robust positive effects on quality is recent staff training in early childhood development (Blau, 1997, 2000). The other important inputs to producing quality may be intangible factors that are not straightforward to measure and regulate (motivation, dedication, etc.). This finding is reminiscent of much of the school quality literature (Hanushek, 2002), though not all (Krueger, 2003).

---

[3]Variation in regulations over time within states is exploited for identification in Blau (2003), Currie and Hotz (2004), and Hotz and Xiao (2005). The data used in this paper are from a cross-section survey.

The most striking empirical finding is that tougher regulations result in lower wages for workers in day care centers. This is a robust finding, and suggests that tougher regulations increase cost. Given that price fails to rise in response to tougher regulations, the cost increase is absorbed by workers in the form of lower earnings. This finding suggests that the incidence of child care regulations is mainly on workers in the regulated day care center sector, an unintended consequence of child care regulations.

The following sections of the paper discuss the conceptual basis for the analysis, the econometric models, data, results, and conclusions.

2. Conceptual Framework

To provide a useful basis for empirical analysis of the effects of child care regulations, a theory of the child care market must account for two key features of the market. First, child care quality is not directly regulated. Rather, regulations govern inputs to the production of quality, such as group size, child-staff ratio, and teacher training. Leland's (1979) model of occupational licensing assumes that the quality of a service can be observed and regulated by a public agency. This may be reasonable in some industries, but not in child care.

Second, child care providers are very heterogenous. The data used here are limited to day care centers and preschools, but even within this type of child care the range of input levels and quality is very wide (Blau, 2001). Shapiro's (1986) model of licensing assumes that service providers are *ex ante* identical, and differ *ex post* only by the level of investment in training they choose. This might be a plausible description of informal child care, in which the provider is self-employed and typically has no employees. But day care centers hire workers to provide care, and can respond to incentives by hiring

staff with more or less training. A model in which heterogeneity is due solely to a one-time irreversible investment is not a good characterization of the day care center industry. A more plausible assumption is that firms (and potential firms) vary in "managerial ability" or some other factor that is given ex ante and affects productivity and decisions on inputs and quality.

The implications of the theory of the firm for the behavior of child care providers in response to regulations are sketched here. A firm that minimizes cost subject to a quality production function and given input prices would respond to a perfectly enforced and binding input regulation by increasing use of the regulated input to comply with the regulation, decreasing use of other inputs that are substitutes, and increasing use of complementary inputs (conditional on a given level of output). For example, a binding regulation on the staff-to-child ratio would cause a firm to increase its staff-to-child ratio compared to the unregulated optimum, but perhaps shift toward less-trained staff. The effect on quality is uncertain, as it depends on how the regulation affects both the marginal cost and the marginal revenue from improving quality. A regulation could reduce the marginal cost of improving quality, as in Shapiro (1986), if it forces low-quality providers to improve quality but has no direct effect on high-quality providers. But it would raise marginal cost if it distorts the input mix. A regulation could increase the marginal revenue associated with quality improvement by making consumers more confident that the child care they use is of acceptable quality. If all relevant input regulations are binding and enforced, then a firm has no control over inputs and would either increase them all or go out of business. Finally, a tougher regulation increases the cost of compliance. If enforcement is not perfect, then we would expect a decrease in compliance.

An additional possible effect of binding input regulations is a decline in the wages of day care

center employees. If the cost of entry is low in the day care market, then a zero-profit long run equilibrium is likely. In this case, a binding input regulation increases demand for the regulated input in the short run, tending to drive up the input price and quantity employed. Marginal cost increases, but if increased use of the regulated input does not result in higher quality of service, then consumers are unwilling to pay a higher price. In addition, competition from the large unregulated informal child care sector limits price increases. Hence, there is a profit squeeze and some firms are forced to leave the market. This reduces demand for the regulated input and drives down the input price until a zero-profit equilibrium with the pre-regulation price is restored. The remaining firms use more of the regulated input than in the pre-regulation equilibrium, but there are fewer firms in the market.[4] The incidence of the regulation is entirely on the input price in this scenario. This outcome would be most likely if the wage rate for child care labor is determined mainly in the child care market rather than in a broader labor market. This suggests that wage effects of regulations will be larger for workers with more day-care-specific skills, such as highly educated and trained teachers.

3. Econometric Issues

Two types of models are specified in order to estimate the impact of regulations on outcomes of interest. The first is a reduced form linear regression model for an outcome Y for observation i in unit j in center k and state s,

[4]The implications of regulations for entry and exit from the child care market cannot be analyzed with the cross section data used in this paper. See Hotz and Xiao (2005) for an innovative analysis of the effect of child care regulations on entry and exit from the child care market, using establishment-level data from the Census of Services.

$$Y_{ijks} = R_{js}\alpha + X_{ijks}\beta + \gamma_j + \eta_s + \epsilon_{ijks}$$

where R is a vector of regulation variables, X is a vector of control variables (specified below) assumed to be exogenous, γ_j is a unit fixed effect, η_s is a state fixed effect, and ϵ_{ijks} is an idiosyncratic error. The outcomes include inputs (group size, staff-child ratio, staff characteristics), quality, price, and staff wages. The unit of analysis is either a room in a center, in which case the unit refers to the age group of the children in the room; or an employee of the center, in which case the unit refers to the employee's job title: director, teacher, or assistant teacher. The role of the fixed effects is discussed below.

The second type of model is a reduced form discrete choice model in which the choices are (1) violate the regulation, (2) comply exactly with the regulation, and (3) exceed the regulation. These models have the same regressors as the linear models, and are specified as logits:

$$\Pr(Y_{ijks} = m) = \exp\{B_{ijksm}\}/\Sigma_n \exp\{B_{ijksn}\},$$

where $B_{ijksm} = R_{js}\alpha_m + X_{ijks}\beta_m + \gamma_{jm} + \eta_{sm}$, and m, $n = 1,2,3$. The logit models are useful for analyzing compliance and the degree to which regulations are binding.

A key issue is how to identify the effects of regulations. The most obvious source of variation in child care regulations is across states. Table 1 shows the regulations that were in effect at the time the data were collected in the states represented in the sample used here.[5] There is substantial variation

[5]Several states do not have an education requirement for assistant teachers, and there are two cases in which there is no minimum age requirement. Using zeros in the regression analysis for these cases may distort the results if there are implicit minimum values of age and education. As indicated in Table 1, I replaced these literal values of zero with what I believe to be reasonable implicit values. In the case of education, I use 10 years, based on the compulsory schooling age of 16 that was in effect in these states in 1993. For age, I base the implicit values on the associated education regulation: assistant teachers in California are required to have a minimum of 12 years of schooling, so I assume that the implicit minimum age is 18. For directors in Colorado the minimum education requirement is 14,

across states, and it is straightforward to statistically analyze the association between cross-state variation in regulations and cross-state variation in child care market outcomes. This strategy may yield biased estimates, however, if there are other differences across states that are correlated with both regulations and child care market outcomes.[6] For example, residents of Connecticut may on average have stronger preferences for high-quality child care than do residents of North Carolina. Such differences in preferences could be the reason why Connecticut has more stringent regulations than North Carolina, *and* the reason why child care quality is higher on average in Connecticut than in North Carolina (as documented below). In this scenario the more stringent regulations in Connecticut do not cause the higher quality child care (or are not the only cause); rather, residents of Connecticut are willing to pay for high-quality care and would be willing to do so even if regulations were less stringent. Similarly, the relatively lax regulations in North Carolina do not cause the relatively low quality of care; both the lax regulations and the low quality of care result from the lack of consumer interest in high-quality care. Imposing tough regulations in North Carolina would, in this scenario, lead to widespread non-compliance and/or withdrawal of many providers from the market. If this scenario is at all realistic, then relying on cross-state variation in regulations would lead to biased estimates of the effects of regulations.

One approach to dealing with unobserved state-level heterogeneity is to include observable

---

corresponding to an implicit minimum age of 20. I re-estimated all of the regression reported below using the literal values of zero instead of the values shown in Table 1. The results were not very sensitive to these changes: the coefficient estimates change by a lot in some cases, but all of the hypothesis tests yield the same findings.

[6]This is a general concern in analysis of the effects of regulations: see Besley and Case (2000) for a discussion.

state characteristics in the analysis. However, the sample used here includes only four states, so this limits the possibilities for including state characteristics as controls. There are two additional sources of variation in child care regulations that might be exploited to deal with the problem of endogenous regulations. Group size and child-staff ratio regulations are typically child-age-specific. Table 1 shows that the *difference* in regulations by child age varies across states, fairly dramatically in some cases. For example, the child-staff ratio regulations for children ages one and two are 4 and 12 in California, while in Connecticut they are 4 and 4. This makes it possible to control for unobserved differences across states using state fixed effects, and rely only on variation across states in *differences* in regulations by child age for identification. A second additional source of variation is that staff regulations typically differ by the position of the staff member. As Table 1 illustrates, regulations governing directors, teachers, and assistant teachers often differ within states, and the differences vary across states. Thus it is possible to include state fixed effects and rely only on variation in within-state differences in regulations by staff position to identify the effects of staff-qualification regulations.[7] In both cases, fixed effects for child age or staff position are included as well, since it is likely that the outcomes of interest differ by child age and staff position for reasons that have little to do with regulations.

These fixed effect methods may yield biased estimates if the *differences* in regulations by child age and staff position are due in part to unobserved heterogeneity across states. This raises the question

[7]There are many other child care regulations, but they do not vary by child age or staff position, so their effects cannot be estimated in a state fixed effect specification with cross section data. These other regulations generally cover inputs that are less relevant for the developmental quality of care and more relevant for health and safety. See Blau (2003) and Currie and Hotz (2004) for estimates of the impact of other child care regulations on a different set of outcomes than those examined here, using repeated cross sections.

of why the child-age and job-title gradients in regulations vary across states. One possibility is that this variation reflects differences in preferences for or opinions about child development by age. For example, taking care of very young children may be viewed as "child care" in some states, and as "early preschool" in other states. Tougher development-oriented regulations may be considered more appropriate in the latter case, but less important than health-and-safety-oriented regulations in the former case. Along the same lines, assistant teachers may be considered "workers" in some states, and "educators" in other states. A state in which assistant teachers are thought of as influencing child development through their interactions with children is more likely to impose tougher regulations on assistant teachers than is a state in which they are viewed as performing menial labor such as cleaning up after children and changing diapers. In these scenarios, state fixed effect estimates would yield biased estimates. Another scenario in which state fixed effect estimates would be biased is analogous to the "endogenous program placement" problem, where tougher regulations for certain age groups of children or staff positions are a response to perceived quality problems specific to those age groups or staff types.

Alternatively, variation in regulation gradients across states could reflect differences in outcomes of the political process or in interpretations of findings in the child development literature that are independent of the disturbances in the outcome equations. While there is no direct evidence to support this interpretation, specification checks discussed below do not provide any strong evidence against the validity of the proposed state-fixed-effects identification strategy.[8]

---

[8]Another concern with the state fixed effects approach is that the regulations in effect at the time of the survey may have been in force for varying amounts of time across states. If it takes time for firms

4. Data

The data are from a sample of day care centers surveyed in California, Colorado, Connecticut, and North Carolina in 1993 as part of the Cost, Quality, and Outcomes Study (CQOS). A random sample of 50 for-profit and 50 non-profit day care centers providing full-time year-round care was selected from licensing lists in specified regions within each state.[9] Interviewers visited each center and gathered detailed information on costs, fees, quality, staff characteristics, and wages. Two rooms at each center were randomly chosen to be directly observed: one preschool and one infant-toddler room if the center served both age groups.[10] Trained observers spent three hours observing the rooms. The Early Childhood Environment Rating Scale (ECERS) and the Infant-Toddler Environment Rating Scale (ITERS) were used to measure the quality of care provided in the selected rooms. These instruments

---

to respond to changes in regulations, then the state fixed effects will capture in part the fact that states are at different points on the way toward long run equilibrium. As it happens, almost all of the regulations analyzed here had been in effect for at least four years, and most for at least 10 years. The only exceptions are the experience requirement for teachers and directors in Connecticut, which were changed in 1993.

[9] The regions were Los Angeles County; the "Front Range" area of Colorado Springs, Denver, Boulder, Fort Collins, and Greeley; the Hartford-New Haven corridor; and the "Triad" area of Winston-Salem, Greensboro, and Burlington. Response rates were 44 percent in California, 67 percent in Colorado and Connecticut, and 41 percent in North Carolina. A short screener was administered to all centers to determine eligibility. Comparisons of centers that participated with those that refused reveal no significant differences in characteristics except in California, where for profit centers, smaller centers, and centers not serving infants were more likely to refuse. As shown below, a substantial share of centers are of low quality, and some violate regulations. One might wonder why such centers agree to participate in the survey, and whether non-respondents provide lower quality care than respondents. Unfortunately, there is no specific evidence on these points.

[10] Infant-toddler rooms were defined as those where the majority of children were less than two-and-a-half years old. Preschool classrooms were defined as those where the majority of children were at least two-and-a-half years old, but not yet in kindergarten. No school age or kindergarten classrooms were directly observed.

contain around 35 items characterizing personal care routines, furnishings, language-reasoning experience, fine and gross motor activities, creative activities, and social development. Each item is scored on a seven point scale with a score of one representing inadequate and a score of seven representing excellent. These are widely used instruments, and have good psychometric properties.[11] The average score across the items is the measure of quality.

The income elasticity of demand for quality as measured by this instrument has been estimated to be very small (Blau, 2001, chapter 4). This suggests that consumers might be unaware of the quality of care their children receive, or perhaps place little value on quality. The former interpretation is supported by the fact that parents significantly overestimate the quality of care their children receive (Cryer and Burchinal, 1995) and that parents tend to incorrectly associate some characteristics of centers (such as clean reception areas) with quality, and fail to use other more relevant signals of quality (Mocan, 2001). Despite the fact that parents do not appear to place much value on quality as measured by the ECERS-ITERS instrument, it is an appropriate measure to use in an analysis of regulations. Regulations are intended to improve the developmental quality of child care, and that is precisely what the ECERS-ITERS score measures. The effect of regulations on price, discussed below, can provide indirect evidence on whether regulations affect the quality of care as perceived by parents.

The center director provided information on the number of children enrolled in each room in the center (by age), and the number of staff assigned to each room (by position title), as well as the number

---

[11] See Harms and Clifford (1980) and Harms, Cryer, and Clifford (1990) for description of the instruments. Inter-rater reliability at each site and between sites was very high for these instruments (Helburn, 1995). See Blau (2001, chapter 7) and Vandell and Wolfe (2000) for reviews of the evidence on the association between these measures and child development.

of children and staff in each room who were present on the day of the interview. This information is used to compute measures of "enrolled" and "present today" group size and staff-child ratio for every room in the center. Measures of group size and staff-child ratio also are available for the two rooms per center that were visited by observers. The number of children and staff present in these two rooms were recorded at 30 minute intervals during the three hour morning observation period. Both the average of the recorded group size and staff-child ratio during the observation period, as well as the 11:00 a.m. observation, referred to as the "prime time" measure, are used in the analysis. The center director provided a roster of all workers in the center, including data on the hourly wage, years of education and experience, tenure at the center, type of training in early childhood education, age, race, gender, the age group of children served, and the worker's job title.

Means of the outcomes analyzed here are shown by state in Table 2. Price is measured by the age-group-specific normal monthly fee, converted to an hourly fee by dividing by monthly hours of care provided. There is substantial variation across states in price, quality, group size, child-staff ratio, and many of the staff characteristics. Average quality differs across states by as much as a standard deviation (the standard deviation of the quality measure is 1.0). The number of children per group present on the day of the interview is about two fewer than the number enrolled, on average, but average group size in the observed rooms is closer to the enrolled average than the present average. Day care center workers are relatively well educated on average, but rather poorly paid.[12] Comparing

[12]Average hourly earnings in 1993 of women who were not child care workers was $10.58, and the average level of education of such women was 13.4 years (computed from the March 1994 Current Population Survey).

staff by the type of position (not shown in the table), directors have more human capital and higher wages than teachers, and teachers have more human capital and higher wages than assistant teachers. Comparing rooms by the age group of children (not shown in the table), the fee declines with age, group size and child-staff-ratio rise with age, and quality increases with age.

Table 3 provides an alternative perspective on the data, classifying each outcome into one of three categories: exceeds, violates, or complies exactly with the regulation. The great majority of rooms exceed the group size and child-staff ratio regulations. 71-72 percent of rooms exceed the regulations based on the enrolled measures, and 80-83 percent based on the other measures. This indicates that the regulations are not binding on the great majority of centers. Nevertheless, there is considerable variation across states, age groups of children, and staff position in the extent to which regulations bind, and this provides the leverage needed for analysis of regulatory effects. Of the rooms that do not exceed the regulation, the majority are in violation for most outcomes. Fewer than 10 percent of rooms are in exact compliance with regulations, with the exception of the education regulation, for which 23 percent of staff are in exact compliance and 7 percent in violation. Violation rates are *lower* in the two states with tougher regulations - California and Connecticut - than in the other two states. This highlights the potential for unobserved state-level heterogeneity, and the need to control for it with state fixed effects. Infant-toddler rooms have tougher regulations than preschool rooms, and the former are substantially more likely to be in violation than the latter.[13]

---

[13]Exact compliance might not be an optimal choice for a firm if inputs such as staff and group size are indivisible. A looser definition of compliance, in which a room that is within one unit on either side of the group size or child-staff ratio regulation is counted as complying, yields compliance rates of up to 26 percent for the enrolled measures and 19 percent for the other measures.

In addition to regulation variables, all models include as control variables (X) the percentage of students in the center who are white, total center enrollment, indicators for whether the center is for-profit, part of a national chain, and church-affiliated, the age of the center, and the local unemployment rate. Descriptive statistics for these variables are shown in the Appendix. Models of staff characteristics also include dummies for Black, Hispanic, other race, and gender. Room-level models include fixed effects for the age group of children, and staff-level models include fixed effects for staff position.

4. Empirical results

Staff-Child Ratio

Table 4 shows regression results for the impact of regulations on staff-child ratio. In order to make the results more easily interpretable, the group size and child-staff ratio regulations were inverted so that higher values represent tougher regulations.[14] The upper panel shows results without state fixed effects (SFE) and the lower panel shows results with SFE. The first row of each panel show results from models in which the only regulation included is the staff-child ratio regulation, and the remaining rows show results from specifications in which five regulation variables were included.[15] The staff-child

[14]Another advantage of inverting the group size regulation is that states with no group size regulation can be included in a natural way. Absence of a group size regulation can be interpreted as a regulation of infinity, which when inverted becomes zero. Hence, cases with no group size regulation are included with a value of zero. To convert the coefficient estimates to the uninverted effects, the coefficient β_1 in the model $Y = \beta_1 X + ...$ can be estimated by $\alpha_1 Y^2/X^2$ using an estimate of α_1 from the model $(1/Y) = \alpha_1(1/X) + ...$ Coefficient estimates for variables other than the regulations are not shown, and are available on request.

[15]In this table, the age, education, and experience regulations are weighted averages of the position-specific regulations. There was not enough variation in the training regulations to include them in these models, but they are included in the staff characteristic models reported below.

ratio regulation has positive effects on all measures of the staff-child ratio, significantly different from zero at conventional levels in most cases.[16] The effect sizes are smaller in most cases when SFE are controlled, and are somewhat smaller in several cases when other regulations are included. Excluding the regulation variables is strongly rejected by F-tests, as shown in the table, and excluding the SFE is also rejected at the five percent level of significance in three out of four models. Hence, there is robust evidence that SCR regulations have an impact on actual SCR. This is similar to the finding of Chipty (1995) using data from a sample of households. The largest effects in the SFE models that control for other regulations are on the average observed and prime time SCR.

A coefficient of one on the SCR regulation implies that the conditional expectation of staff-child ratio increases by the same amount as the change in the regulation. The hypothesis that the SCR regulation coefficient equals one in the SFE models cannot be rejected in 15 out 16 cases in Table 4. This raises an important question: if the majority of centers exceed the SCR regulation, as shown in Table 3, why does the SCR regulation have such large positive effects on actual SCR, especially after controlling for SFE? One possibility is that even after controlling for SFE there is unobserved heterogeneity across states *within* age groups that is correlated with the age gradient of the SCR regulation. Another possibility is suggested by a game-theoretic model proposed by Ronnen (1991), in

[16]The standard errors reported in all of the tables are adjusted to account for multiple observations from each center, using the "cluster" option in *stata*. This increased the standard errors substantially. The regulation variables do not vary within unit-state groups, and Moulton (1986) has shown that standard error estimates that do not account for this can be seriously biased. The regression models were re-estimated using unit-state groups as the cluster variable. This resulted in much *smaller* standard errors than those reported here, so it seems more important in practice to adjust for clustering on centers than on unit-state groups.

which firms compete by differentiating their product along the quality dimension. If regulations force low-quality firms to improve quality, then in this scenario higher-quality firms also improve quality in order to maintain the quality differential. See Hotz and Xiao (2005) for an application of this framework to the child care case. One reason to be skeptical about this interpretation is that the evidence linking staff-child ratio to child care quality is weak (Blau, 1997, 2000).

An interesting feature of the results is that tougher regulations on inputs other than SCR are associated with lower SCR. Thus, tougher GS, education, and experience regulations have consistently negative effects on SCR, many of which are significantly different from zero. This implies that firms engage in substitution among inputs in response to regulations, as suggested by the discussion in Section 2. The SFE estimates imply that a one year increase in the education regulation would lead to a decrease in enrolled SCR of about .02, for example from 1:10 to 1:12.

Inverse Group Size

Estimates for inverse group size are shown in Table 5. As noted above, both the dependent variable and the group size regulation were inverted to make the results easier to interpret. The results for inverse group size are quite different from those for SCR. None of the 16 coefficient estimates on the inverse GS regulation are positive and significantly different from zero. Three are negative and significantly different from zero. The absence of positive effects of GS regulations is robust to SFE and controls for other regulations. In most of the specifications with controls for other regulations, F-tests do not reject excluding the entire set of regulations. The most consistent and robust result for the other regulations is a positive impact of a tougher education regulation. The estimates for the education regulation are significantly different from zero in several cases, and imply that a one year increase in the

education requirement would cause enrolled inverse GS to increase from 1:25 to 1:21. The results are not very sensitive to controls for SFE, and specification tests fail to reject excluding the SFE in most cases.[17]

It is not obvious why GS regulations matter less than SCR regulations, and why GS generally is less response to regulations than SCR. One possibility is that there are fixed costs associated with changing group size. For example, it may be cheaper to provide care of a given quality for groups of children who are homogeneous in age rather than of mixed ages. Changing GS may result in more mixed-age groups, while changing SCR by shifting assistant teachers from one room to another may be less costly.

Staff Characteristics

Table 6 shows regulation coefficient estimates on staff characteristics, in the same format as Tables 4 and 5. The age regulation never has a positive and significant coefficient estimate in the age equation, and similarly for the experience regulation in the experience equation. The education regulation has a positive and significant effect on education in the multiple-regulation model without SFE, but the effect vanishes in the SFE model (and excluding the SFE is strongly rejected in the education model). One of the training regulations has a positive and significant impact on actual training when other regulations are excluded, but not when the other regulations are included. Specification tests

[17]As noted above, California and Colorado have no group size regulation, and these states are included in the regressions with an inverse group size regulation equal to zero. As a check on the robustness of the results, the group size models were re-estimated excluding centers from these two states. The main conclusion from Table 5 - lack of evidence that group size regulations affect group size - is robust. Of the 16 coefficient estimates on the inverse GS regulation, only one is positive and significantly different from zero with these two states excluded.

reject excluding the full set of regulation variables, as well as the SFE. Focusing on the results with SFE and the full set of regulation variables, there are several cases of significant substitution effects of regulations. Tougher training and experience requirements result in firms employing workers with fewer years of education, although there is no evidence of symmetry in this case: a tougher education regulation reduces experience and training but the effects are small and insignificantly different from zero. There are also some cases in which tougher regulations of one input result in increases in other inputs; for example, a positive effect of the education regulation on age. The effects of SCR and GS regulations are mixed but significantly different from zero in only two cases in the lower panel: a tougher SCR regulation results in an increase in average staff age and less trained staff.

Staff Wages

Table 7 shows regulation effects on log wages. The results show negative effects of most regulations on wages, significantly different from zero in most cases. The only exception is a positive effect of the SCR regulation in the upper panel, but that effect becomes small and insignificantly different from zero in the lower panel with SFE. As discussed in Section 2, a negative impact of regulations on staff wage rates would be expected if firms face a zero-profit constraint and price fails to rise by enough to cover the higher cost associated with tougher regulations. Based on the SFE results in the first column, raising the age and education requirements by one year would result in wages falling by 5.5 and 9.0 percent respectively. Raising the hours of training required at the time of hire by 100 hours would result in a wage decline of 16 percent ($1-e^{-.18}$), while imposing any requirement for ongoing training reduces wages by 30 percent ($1-e^{-.36}$). Requiring an additional year of experience is estimated to reduce wages by 21 percent ($1-e^{-.24}$). Several of these effects seem surprisingly large, but the costs

associated with meeting these requirements might be large as well. These findings are robust to inclusion of SFE. They are also robust to inclusion of controls for observed human capital characteristics of staff in the wage equation. The results for the latter specification are shown in the second column, and are very similar to the results without human capital characteristics. This indicates that the regulation effects on wages do not operate mainly be influencing the human capital characteristics of the staff hired by centers, but rather by directly affecting market wages.[18]

It is worth emphasizing the fact that the effects on log wages reported in Table 6 are *not* rates of return to human capital characteristics. Rather, they are unintended consequences that arise because regulations appear to increase the cost of providing child care by more than they increase consumer willingness to pay. However, as noted above, these estimates do not account for the possibility that the regulation age and staff-position-gradients are endogenous as a result of unobserved heterogeneity or reverse causality. Specification tests reported below do not provide any strong evidence against a causal interpretation, but the tests are not definitive so some caution is warranted in interpreting the results in Table 7 as unintended causal effects of regulations.

Price and Quality

Table 8 shows the estimated effects of regulations on price and quality. Without SFE the regulation effects are jointly highly significant in both models, but when SFE are added the regulation

[18]The characteristics included in the second column are education, experience, job tenure, and dummies for 11 different kinds of training in early childhood education. The coefficient estimates on these variables are not reported in the table. They show positive but small returns to education, experience, job tenure, and a few forms of training. See Mocan and Viola (1997) and Mocan and Tekin (2003) for extensive analysis of wages of child care workers. The coefficients on the other variables included in the state fixed effect model (column 1) are shown in Table A-1.

effects as a group are not significantly different from zero. Note that in most cases addition of the SFE results in much smaller parameter estimates, but not much larger standard error estimates. The fact that the SFE are highly significant underscores the importance of unobserved state-level heterogeneity. As noted in the previous section, price and quality of child care are higher in states with tougher regulations, but within states there is apparently little systematic relationship across age groups of children or staff positions between regulations on the one hand and price and quality on the other hand. Thus, input regulation does not guarantee higher quality or an increase in price of sufficient magnitude to cover the increased cost generated by the regulations.[19] If regulations had a positive effect on the developmental quality of care and parents valued the increased quality by at least as much as its marginal cost, then we would expect to see a price increase in response to tougher regulations. However, given the finding that tougher regulations fail to increase quality, we cannot infer anything about parental preferences for quality from the lack of a price increase.

Compliance

One possible explanation for why regulations do not appear to affect the developmental quality of child care is that they are not effectively enforced. Table 9 reports results derived from multinomial logit models explaining the choice between violating a regulation, complying with it exactly, and exceeding it. Instead of reporting the coefficient estimates, which are not easily interpretable, the table

[19]The ECERS-ITERS quality measure is an average of about 35 individual items. Regressions like those in Table 7 that use each of the individual item scores instead of the average score generally confirm the findings reported in the table: in models without SFE, the regulations have effects that are significantly different from zero as a group in 87% of the models estimated, but in only 19% when SFE are included. There is no systematic pattern to the type of item that is affected by regulations in the SFE models.

reports simulations of the impact of changing regulations, along with F tests of the statistical significance of the regulations. The results are mixed, with no clear pattern to the effects. Focusing on the results with multiple regulations and state fixed effects, in some cases tougher regulations increase the probability of violation (e.g., experience, training at the hire date), and in other cases reduce it (e.g. "present" staff-child ratio and education).

Information on resources devoted by states to enforcement of child care regulations is limited, but the available data indicate that enforcement is weak on average. The U.S. General Accounting Office (2000) reports that in 1992 nine states inspected centers less than once per year, 29 states inspected once per year, and 13 inspected more than once per year. Enforcement efforts had increased significantly by 1999, as measured by budgets, staff, and the number of inspections. But even with a (weighted) average number of inspections of 1.8 per year in 1999, it seems that firms have considerable scope for non-compliance.

Interpreting the estimates

The regression analysis indicates that child care regulations affect the input choices of firms, but have little impact on price and quality. Thus child care input regulations appear to be ineffective at accomplishing the goal of increasing the quality of care, perhaps because of limited enforcement, input substitution, and low productivity of the regulated inputs. Regulations do appear to increase the cost of providing child care, as suggested by the negative impact of tougher regulations on staff wages.[20] If

[20]It would be useful to demonstrate the cost-increasing effect of regulations directly, using cost data. But the cost data are center-specific and do not vary across rooms or staff, so a state fixed effects analysis is not feasible. The average cost of care is higher in the states with tougher regulations, but this could be due to cross-state differences other than regulations. See Blau and Mocan (2002) for an

state fixed effects do not adequately control for the possibility that regulations are endogenous to the outcomes studied here, then the estimates could be biased and this interpretation would not necessarily be correct. As it happens, many of the implications of the estimates are similar whether state fixed effects are included or not, lending some support to the robustness of the results. In cases in which adding state fixed effects substantially changes the magnitudes of the estimates, it is almost always in the direction of smaller effects of regulations. This is consistent with the most plausible story discussed above about why regulations might be endogenous, namely that they reflect unobserved consumer preferences for child care quality that cause both tougher regulations and higher demand for quality.

However, as discussed in Section 3, alternative interpretations of the results are possible, and it is useful to consider whether there is any evidence that can distinguish the interpretation proposed here from alternatives. As noted in Section 2, a negative effect of regulations on staff wages is more likely if day care center wages are determined mainly in the day care center labor market rather than in a broader labor market. This is most likely to be the case for workers with substantial industry-specific human capital, for example teachers and directors rather than assistant teachers and aides. When the wage regressions are estimated separately by staff position, the negative effect of the education regulation appears only for directors and teachers (coefficients -.18 (.06) and -.16 (.02)) and not for aides (coefficient .024 (.025). This supports the interpretation described above. Comparisons for other staff qualification regulations are not possible because the regulations do not vary across states for all three positions.

---

analysis of cost using these data.

A key identifying assumption is that differences across states in the child-age-gradient in regulations is not associated with unobserved differences across states in factors that affect price, quality, and wages. One way to examine this assumption is to analyze the association between regulation age-gradients and observed age-gradients in child and family characteristics. If regulation gradients are associated with gradients in family income, education, and other child and family characteristics, this would suggest that differences across states in attitudes toward child care for infants and toddlers relative to preschoolers could be driving both the regulation gradients and observed outcomes. Parents of children in the observed rooms in each center were given a short questionnaire, from which measures of the room-average of parents' age, income, education, mother's hours of work and wage rate, hours of child care, fee and financial assistance were derived.[21] Regressions like those reported in Table 8 were estimated with each child and family characteristic as dependent variables. The regulations as a group had effects that were significantly different from zero in 12 out of 21 regressions without SFE, but in only 2 out of 21 regressions with SFE (fee and financial assistance). This suggests that after controlling for state fixed effects, observed child and family characteristics are not associated with regulations. The most useful piece of evidence from these regressions is probably the absence of any association between the age gradient in regulations and the age gradient in hours of child care. If states differ in their attitudes toward child development by age of children, this would likely be reflected in correlation between differences in regulations and hours of child care by age. The

[21]The response rate was relatively low, so these data were not used to construct control variables to include in the main regression analyses, since there would have been a significant drop in sample size.

absence of such an association suggests that unobserved heterogeneity is not driving the results in this case. Of course, these findings do not rule out the possibility that *unobserved* factors could be driving both the age gradient in regulations and the age gradient in child care outcomes, but they do not suggest any obvious violation of the identifying assumption.

The staff members in each of the observed room were also given a short questionnaire, providing measures of marital status, race, income, hours worked and income from other jobs, and enrollment and hours of their own children at the center. In regressions like those reported above, regulations as a group had significant effects on these outcomes in 14 out of 21 cases without SFE, and in 2 out of 21 cases with SFE. This does not provide any strong evidence against the identifying assumption, but again does not rule out the possibility that *unobserved* factors could be associated with regulations.

Another key identifying assumption is that differences across states in the job-title-gradient in regulations do not reflect unobserved differences across states in the human capital of day care workers. For example, in a state with low education levels, a tough experience regulation could be used to compensate for the difficulty of finding well-educated staff. One way to analyze this possibility is to examine whether the states are similar in staff characteristics by job title. For example, if staff in North Carolina are consistently lower in education than other states *within* job title classifications, this would suggest that low education is not a response to regulations, but rather is a characteristic of the NC population that influences the determination of staff regulations in NC. I estimated regressions like those reported in Table 6 separately by job title, although there was not enough variation to identify state fixed effects for directors. For teachers and aides, I find that state fixed effects have significant effects in

two out of eight cases at the 5% level of significance (education and experience of teachers). Hence there is some evidence that there are underlying differences in staff characteristics across states that are not explained by regulations, but the evidence is not strong.

Finally, there is the puzzling finding that regulations do not appear to be binding on most day care centers, yet there are clear effects of regulations on wages. One way to get some insight into this puzzle is to analyze whether regulations are more likely to have large wage effects in the types of centers for which regulations are more likely to be binding. To examine this issue, the logit results described in Table 9 were used to predict the probability that a given regulation is binding, where binding is defined as either meeting the regulation exactly or violating it. The predicted probability of a binding regulation was tabulated by various characteristics included in the logit models: type of center (for-profit chain, for profit independent, non-profit church-affiliated, non-profit independent); race, ethnicity, education, and experience of the staff; and quartiles of the racial composition of the children, enrollment, and years in operation. Wage regressions like those reported in Table 7 were re-estimated separately by these classifications, and the results were used to assess whether characteristics associated with an increased likelihood of facing a binding regulation were also associated with larger wage effects. The answer generally is no. Of the large number of pairwise comparisons examined, only about one quarter showed that factors that were associated with greater likelihood of facing a binding regulation were also associated with larger wage effects of regulations. Hence the apparently strong wage effects of regulation remains somewhat puzzling in view of the fact that relatively few centers are constrained by the regulations examined here.

Implications of the estimates

To illustrate the magnitude of the cost effect of regulations, the impact of regulations on wages is simulated, using each state's regulations in turn. Labor accounts for about 70 percent of total cost in day care centers (Helburn, 1995), so using wage effects to infer cost effects is reasonable. The simulations use the SFE results in the first column of Table 7 to predict the log wage of each observation, assigning each state's regulations in turn to every observation, and averaging the predictions over all observations. In order to avoid mixing up age group and staff position composition effects with regulation effects, the simulations assign regulations for teachers in preschool rooms to all observations. The results are shown in Table 10. The regulations used in the simulations are shown in the lower panel of the table. The first row shows the results of assigning each observation all of the regulations for a given state. This yields mean log wages of 1.65 for California, 1.42 for Colorado, 2.00 for Connecticut, and 1.85 for North Carolina. Thus regulations are estimated to result in wage gaps of 16 percent ($e^{.15}$-1) in North Carolina, 42 percent ($e^{.35}$-1) in California, and 79 percent ($e^{.58}$-1) in Colorado, compared to Connecticut. The next six rows show the results of changing one regulation at a time. The large differences across states in SCR and GS regulations make no difference at all, because these regulations have little impact on wages (see Table 7). The tougher teacher education regulation in Colorado relative to the other states results in a wage gap of 18 log points. The relatively tough teacher experience regulation in North Carolina causes a wage gap of 15 points relative to Connecticut. The biggest cost results from the 180 hour child development training requirement for teachers, which was imposed by California and Colorado but not by Connecticut and North Carolina. This results in a wage gap of 32 log points.

The middle panel of Table 10 show simulated effects of regulations on price and quality, using

the SFE results from Table 8. These simulations show that Connecticut's regulations yield the highest quality and the second highest price compared to those of the other states. However, none of the simulated effects on price and quality is significantly different from the others.

In order to translate the wage effects into aggregate cost estimates, an estimate is used from the 1997 Census of Services that there were about 629,000 employees in day care centers in 1997 (Blau, 2001, p. 39). The average wage in the CQOS sample was $6.61 and average hours of work per week was 32.9. Assuming a 52 week work year, total earnings of day care center employees are estimated to have been $7.1 billion in 1993. This figure is used as a base to which the percentage effects of regulations on wages calculated above are applied. If all states were to adopt North Carolina's regulations, the total cost would be $1.1 billion (16 percent of $7.1 billion) compared to all states adopting Connecticut's regulations. The corresponding cost estimates of adopting California and Colorado regulations versus Connecticut's are $3.0 billion and $5.6 billion, respectively, measured in 1993 dollars. The benefits of these regulation strategies in terms of higher quality are estimated to be nil.

5. Conclusions

Many states have imposed tougher child care regulations in recent years, and child care advocates continue to encourage states to adopt tougher regulations (Kagan and Cohen, 1996). The results presented here raise questions about why states impose such regulations. They appear to be ineffective at improving the average quality of child care, and the higher costs they create are absorbed largely by the staff of day care centers. Kleiner (2000, p. 198) notes that occupational licensing is becoming more common throughout the U.S. economy. Child care regulations are not the same as

occupational licensing, but there are enough similarities to suggest that the results of this study may have implications beyond the child care sector. Even if tougher regulation or licensing results in quality improvement, limited willingness to pay by consumers for higher quality may not allow firms to fully recover the higher costs associated with regulation. The incidence of regulations could fall largely on employees of regulated firms, rather than on firms and consumers.

More generally, the results of this study show that regulating inputs does not guarantee higher quality of output. Without any quality increase, the incidence of regulations could be largely on employees. This unintended consequence of regulation in the child care sector suggests a potentially fruitful avenue for research on the effects of regulations and occupational licensing in other sectors. The availability of a quality measure for child care made it possible to show explicitly that regulations had little impact on quality, and that as a result the cost of regulations was absorbed by employees in the form of lower wages. In other sectors in which quality measures are not readily available, estimating wage impacts of regulations would make it possible to determine whether consumers are willing to pay for the quality improvement (if any) induced by tougher regulations.

Policy tools other than regulation that might be used to try to improve the quality of child care include certification and subsidies. Certification is in use in several states. For example, North Carolina uses a certification system based on issuing "stars" to each licensed center, with the number of stars earned by each center listed in an on line database. Stars are awarded on the basis of regulated characteristics such as teacher training and group size, and based on the center's history of inspection results. Subsidies could be structured so that they have a higher value to consumers if used to purchase child care of higher quality. Together with independent certification of quality, such a system could

increase consumer willingness to pay for higher quality child care. See Blau (2001, chapter 10) for a proposal along these lines. Most child care subsidies currently do not discriminate on the basis of quality. Given the findings presented in this paper, exploring alternatives to regulation as a means of improving child care quality would be desirable.

Finally, several caveats to the findings and their implications should be noted. First, the sample used here includes only four states. There is no particular reason to suspect that the results lack broader applicability, but analysis with a larger sample of states would be desirable. Second, the sample is a cross section, so the effect of regulation on exit from the market could not be analyzed. See Hotz and Xiao (2005) for an analysis of the impact of regulations on exit in future work. Third, most of the estimates show relatively small effects of regulations, but the estimated effects on staff-child ratio are surprisingly large, especially in view of the fact that this regulation is apparently not binding on many centers. This is a puzzle and warrants further investigation. Last, the identification strategy used here is novel, but largely untested. Variation in regulations within states may provide a useful way to control for the possibility that regulations are endogenous, but further analysis with alternative sources of data is needed to determine how successful this strategy is.

References

Besley, T., and A. Case, 2000. Unnatural Experiments? Estimating the Incidence of Endogenous Policies, Economic Journal 110, F672-94.

Blau, D. M., 1997. The Production of Quality in Child Care Centers, Journal of Human Resources 32, 354-387.

Blau, D. M.., 2000. The Production of Quality in Child Care Centers: Another Look, Applied Developmental Science 4, 136-148.

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

Blau, D. M.., 2003. Do Child Care Regulations Affect the Child Care and Labor Markets? Journal of Policy Analysis and Management 22, 443-465.

Blau, D. M. and H. N. Mocan, 2002. The Supply of Quality in Child Care Centers, Review of Economics and Statistics 84, 483-496.

Chipty, T, 1995. Economic Effects of Quality Regulation in the Day Care Industry, American Economic Review 85, 419-424.

Cryer, D., and M. Burchinal, 1995. Parents as Child Care Consumers, in S. W. Helburn (Ed.) Cost, Quality and Child Outcomes in Child Care Centers, Technical Report, Department of Economics, University of Colorado at Denver, 203-219.

Cryer, D., W. Tietze, M. Burchinal, T. Leal, and J. Palacios, 1999. Predicting Process Quality From Structural Quality in Preschool Programs: A Cross-Country Comparison, Early Childhood Research Quarterly 14, 339-361.

Currie, J., 2001. Early Childhood Intervention Programs, Journal of Economic Perspectives 15, 213-238.

Currie, J., and V. J. Hotz, 2004. Accidents Will Happen? Unintentional Injuries and the Effects of Child Care Regulations, Journal of Health Economics 23, 25-59.

Gormley, W. T., 1991. State Regulations and the Availability of Child Care Services, Journal of Policy Analysis and Management 10, 78-95.

Hanushek, E. A., 2002. Publically Provided Education, in A. Auerbach and M. Feldstein (Eds.) Handbook of Public Economics Amsterdam, North Holland Press, 2054-2141.

Harms, T., and R. Clifford, 1980. Early Childhood Environment Rating Scale, Teacher's College Press, New York.

Harms, T., D. Cryer, and R. Clifford, 1990. Infant-Toddler Environment Rating Scale, Teacher's College Press, New York.

Helburn, S. W. (Ed.), 1995. Cost, Quality and Child Outcomes in Child Care Centers, Technical Report, Department of Economics, University of Colorado at Denver.

Hofferth, S. L. and D. D. Chaplin, 1998. State Regulations and Child Care Choice, Population Research and Policy Review 17, 111-140.

Hotz, V. J., and M. R. Kilburn, 1994. Regulating Child Care: The Effects of State Regulations on Child Care Demand and Its Costs, Working Paper, RAND, Santa Monica, CA.

Hotz, V. J., and M. Xiao, 2005. The Impact of Minimum Quality Standards on Firm Entry, Exit, and Product Quality: The Case of the Child Care Market, Working Paper, UCLA, Los Angeles, CA.

Kagan, S. L. and N. Cohen, 1996. A Vision for a Quality Early Care and Education System, in S.

Kagan and N. Cohen (Eds.), Reinventing Early Care and Education: A Vision for a Quality System, Jossey-Bass, San Francisco.

Karoly, L. A., P. W. Greenwood, S. S. Everingham, J. Houbé, M. R. Kilburn, C. P. Rydell, M. Sanders, and J. Chiesa, 1998. Investing In Our Children: What We Know and Don't Know About the Costs and Benefits of Early Childhood Interventions, Santa Monica CA, RAND Report MR-898-TCWF.

Kleiner, M.M., 2000. Occupational Licensing, Journal of Economic Perspectives 14, 189-202.

Kontos, S. C. Howes, M. Shinn, and E. Galinsky, 1995. Quality in Family Child Care and Relative Care, Teacher's College Press, New York.

Krueger, A., 2003. Economic Considerations and Class Size, Economic Journal 113, F34-63.

Lamb, M. E., 1998. Nonparental Child Care: Context, Quality, Correlates, and Consequences, I. Sigel and K. Renninger (Eds.) Child Psychology in Practice, Handbook of Child Psychology (Fifth ed.), W. Damon, (Series Ed.) Wiley, New York.

Leland, H., 1979. Quacks, Lemons, and Licensing: A Theory of Minimum Quality Standards, Journal of Political Economy 87, 1328-1346.

Love, J. M., P. Z. Schochet, and A. L. Meckstroth, 1996. Are They in Any Real Danger? What Research Does - And Doesn't - Tell Us About Child Care Quality and Children's Well-Being, Mathematica Policy Research, Princeton NJ.

Lowenberg, A.D., and T.D. Tinnin, 1992. Professional Versus Consumer Interests in Regulation: The Case of the U.S. Child Care Industry, Applied Economics, 24, 571-580.

Mocan, H. N., 2001. Can Consumers Detect Lemons? Information Asymmetry in the Market for Child

Care, National Bureau of Economic Research, Working paper 8291.

Mocan, H. N., and Deborah Viola, 1997. The Determinants of Child Care Workers' Wages and Compensation: Sectoral Difference, Human Capital, Race, Insiders and Outsiders, National Bureau of Economic Research, Working paper 6328.

Mocan, H. N., and E. Tekin, 2003. Non-Profit Sector and Part-Time Work: An Analysis of Employer-Employee Matched Data on Child Care Workers, Review of Economics and Statistics 85, 38-50.

Morgan, G., and S. Azer, 1997. A Primer of Child Care Licensing 1997: Its Role in Public Policy, Wheelock College, Massachusetts.

Moulton, B. R., 1986. Random Group Effects and the Precision of Regression Estimates, Journal of Econometrics 32, 385-397.

Ronnen, U., 1991. Minimum Quality Standards, Fixed Costs, and Competition, RAND Journal of Economics 22, 490-504.

Rose-Ackerman, S., 1983. Unintended Consequences: Regulating the Quality of Subsidized Day Care, Journal of Policy Analysis and Management 3, 14-30.

Shapiro, C., 1986. Investment, Moral Hazard, and Occupational Licensing, Review of Economics Studies 53, 843-862.

Smith, K., 2002. Who's Minding the Kids? Child Care Arrangements, Spring 1997, U.S. Census Bureau, Current Population Reports, P70-86.

U.S. General Accounting Office, 2000. Child Care: State Efforts to Enforce Safety and Health Requirements, Report GAO/HEHS-00-28, Washington D.C.

Vandell, D. L. and B. Wolfe, 2000. Child Care Quality: Does It Matter and Does It Need to be Improved? Institute for Research on Poverty, University of Wisconsin-Madison, http://aspe.hhs.gov/hsp/ccquality00/ccqual.htm.

Walker, J. R., 1991. Public Policy and the Supply of Child Care Services, D. Blau (Ed.) The Economics of Child Care, The Russell Sage Foundation, New York, 51-78.

Whitebook, M., C. Howes and D. Phillips, 1990. Who Cares? Child Care Teachers and the Quality of Care in America. Final Report of the National Care Staffing Study, Child Care Employee Project, Oakland, California.

Table 1: Selected Regulations in the Cost, Quality, and Outcomes Study States, 1993

	California	Colorado	Connecticut	North Carolina
Age group of children		Maximum Child-Staff Ratio		
0	4	5	4	5
1	4	5	4	6
2	12	8	4	10
3	12	10	10	15
4	12	12	10	20
5+	12	15	10	25
Age group of children			Maximum Group Size	
0			8	10
1			8	12
2			8	20
3			20	25
4			20	25
5+			20	25
			Minimum Staff Age	
Director	18	20[a]	20	21
Teacher	18	19	18	18
Assistant	18[a]	21	16	16
			Minimum Years of Education	
Director	12	14	12	14
Teacher	12	14	12	12
Assistant	12	10[a]	10[a]	10[a]
			Minimum Years of Child Care Experience at Date of Hire	
Director	4	1	.75	1
Teacher	.5	.5	.375	1
Assistant	0	1	0	0
			Minimum Hours of Child Care or Development Training at Date of Hire	
Director	225	360	180	180
Teacher	180	180	0	0
Assistant	0	0	0	0
			Ongoing Training is Required (1=yes)	
Director	0	1	1	1
Teacher	1	1	1	1
Assistant	1	1	1	1

Source: J. Hotz and R. Kilburn; National Child Care Information Center (http://nccic.org/statepro.html); Helburn (1995). Notes: For group size, an empty cell indicates no regulation. For staff regulations, 0 indicates no regulation. Some states report the number of hours per year of ongoing training required, but most states do not.

Note a: The figure shown is an "implicit regulation;" the literal regulation is zero. See footnote 5 for explanation of why implicit regulations are used in place of the zeros, and how the implicit values were chosen.

Table 2: Sample Means of Outcomes by State

	California	Colorado	Connecticut	North Carolina
Price per hour	2.31	1.97	3.09	1.62
Room characteristics:				
Quality	4.36	3.94	4.24	3.44
Enrolled Group Size (GS)	15.6	14.8	11.1	14.6
Present GS	13.6	12.5	9.6	12.3
Average observed GS	15.2	13.4	11.6	12.3
Prime time observed GS	13.6	12.1	11.3	13.2
Enrolled Child-Staff Ratio (CSR)	8.4	7.4	5.6	11.1
Present CSR	7.4	6.1	5.0	8.8
Average CSR	7.5	6.6	5.4	8.3
Prime time CSR	7.5	6.4	5.6	8.2
Staff characteristics:				
Title: director	.059	.075	.063	.058
Title: teacher	.606	.539	.471	.646
Title: assistant teacher	.335	.386	.466	.296
Age	34.8	31.0	33.4	31.7
Education	13.7	13.9	14.1	13.3
Any training in early childhood education	.943	.805	.947	.972
Experience in child care (years)	3.3	3.4	3.3	2.6
Average hourly earnings	7.83	5.79	7.62	5.53

Note: Quality is measured by the ECERS-ITERS score described in the text, which has a range of 1-7 and a standard deviation in this sample of about one. Sample size varies by item. The total sample size is around 600 for the observed rooms, 1,600 for all rooms, and 4,000 for staff characteristics and wages.

Table 3: Percent of Rooms and Staff that Exceed, Comply with, and Violate Regulations

	Child-Staff Ratio Regulation			Group Size Regulation		
	Exceed	Comply	Violate	Exceed	Comply	Violate
Enrolled	72	9	19	71	9	20
Present	83	5	11	80	6	15
Average Observed	83	2	15	82	3	15
Prime Time	81	7	12	83	6	12
Prime Time, by State						
California	85	7	7			
Colorado	81	4	15			
Connecticut	86	8	6	82	6	11
North Carolina	73	7	20	83	5	12
Prime Time, by Age						
Infant-Toddler	57	18	25	62	17	22
Preschool	89	3	8	92	1	7
	Staff Age Regulation			Staff Education Regulation		
	Exceed	Comply	Violate	Exceed	Comply	Violate
All	94	2	5	71	23	7
California	99	1	0	65	34	1
Colorado	81	4	16	67	14	19
Connecticut	99	1	0	89	10	0
North Carolina	99	1	0	66	31	4
Director	99	1	0	70	17	13
Teacher	99	1	0	62	29	9
Assistant	85	3	12	84	14	1
	Staff Experience Regulation			Staff Training Regulation		
	Exceed	Comply	Violate	Exceed	Comply	Violate
All	89	8	3		94	6
California	95	2	3		96	4
Colorado	90	7	3		85	15
Connecticut	100	0	0		98	2
North Carolina	74	23	4		99	1
Director	86	7	7		99	1
Teacher	91	7	1		97	3
Assistant	82	12	6		88	12

Notes: Enrolled and Present measures are derived from room rosters. Average Observed and Prime Time measures are based on direct observation of selected rooms. The training regulation is a binary indicator of whether any ongoing training is required, so a staff member either complies with or violates the regulation.

Table 4: Effects of Regulations on Staff-Child Ratio

	Enrolled	Present	Average observed	Prime Time
No state FE		One regulation		
Staff-Child Ratio regulation	1.59 (.16)	1.93 (.25)	1.19 (.25)	1.46 (.33)
		Multiple regulations		
SCR reg.	0.74 (.25)	.93 (.33)	1.07 (.43)	1.65 (.59)
Inverse GS regulation	-.001 (.15)	.11 (.24)	-.35 (.22)	-.56 (.28)
Age regulation/100	1.8 (.59)	2.6 (.80)	.29 (.87)	.39 (1.4)
Education regulation/100	-1.8 (.33)	-2.2 (.47)	-1.3 (.44)	-2.2 (1.4)
Exper. regulation/100	-9.8 (2.0)	-11.6 (2.7)	-2.7 (3.1)	2.9 (4.3)
Test of regulations (p)	.000	.000	.000	.000
With state FE		One regulation		
SCR regulation	.79 (.25)	.91 (.34)	.81 (.46)	1.55 (.64)
		Multiple regulations		
SCR regulation	.76 (.30)	.85 (.37)	1.25 (.53)	2.13 (.45)
Inverse GS regulation	-.08 (.22)	.01 (.35)	-.90 (.35)	-1.23 (.45)
Age regulation/100	-.61 (1.5)	-1.9 (3.1)	3.9 (1.7)	2.5 (2.2)
Education regulation/100	-2.1 (.39)	-2.7 (.69)	-.77 (.49)	-1.8 (1.4)
Exper. regulation/100	-3.6 (4.9)	1.1 (8.2)	-11.7 (4.9)	-4.5 (5.6)
Test of regulations (p)	.000	.000	.001	.021
Test of state FE (p)	.301	.000	.035	.035
Sample size	1600	1533	584	578
R^2 (mult. regs & SFE)	.51	.39	.47	.30

Notes: In the one-regulation specifications, only the SCR regulation is included. See the Appendix for the other covariates included in each model. Standard errors are in parentheses. The rows containing test results report the p-value from F-tests of the joint hypothesis that all regulations have zero coefficients or that all state dummies have zero coefficients.

Table 5: Effects of Regulations on Inverse Group Size

	Enrolled	Present	Average Observed	Prime Time
No state FE		One regulation		
Inverse Group Size (GS) regulation	.064 (.066)	.044 (.101)	-.08 (.07)	-.20 (.08)
		Multiple regulations		
Inverse GS regulation	.05 (.11)	.15 (.17)	-.09 (.12)	-.18 (.15)
SCR regulation	.33 (.23)	.45 (.26)	.19 (.24)	.21 (.28)
Age regulation/100	-.26 (.48)	.12 (.60)	-.28 (.48)	-.45 (.60)
Education regulation/100	.44 (.30)	.75 (.35)	.19 (.22)	.62 (.35)
Exper. regulation/100	-.25 (1.7)	.34 (.19)	1.1 (1.8)	1.8 (2.2)
Test of regulations (p)	.108	.061	.631	.047
With state FE		One regulation		
Inverse GS regulation	-.143 (.153)	-.006 (.231)	-.49 (.16)	-.37 (.20)
		Multiple regulations		
Inverse GS regulation	-.12 (.17)	-.02 (.25)	-.52 (.19)	-.41 (.24)
SCR regulation	.35 (.23)	.28 (.28)	.19 (.29)	.23 (.35)
Age regulation	1.8 (1.3)	1.8 (1.7)	-.01 (.79)	-.95 (.86)
Education regulation	.73 (.32)	1.1 (.42)	.39 (.22)	.64 (.33)
Exper. regulation/100	-5.1 (5.0)	-2.4 (4.8)	1.2 (2.5)	3.3 (2.9)
Test of regulations (p)	.097	.057	.023	.112
Test of state FE (p)	.175	.081	.000	.287
sample size	1812	1735	584	586
R^2 (mult. regs & SFE)	.18	.17	.39	.23

Notes: In the one-regulation specifications, only the inverse GS regulation is included. See the Appendix for the other covariates included in each model. The sample sizes are larger in this table than in Table 4 because computing the staff-child ratio requires data on both group size and the number of staff. Cases in which the number of staff is missing but group size is available can be used in this table but not in Table 4. Standard errors are in parentheses. The rows containing test results report the p-value from F-tests of the joint hypothesis that all regulations have zero coefficients or that all state dummies have zero coefficients.

Table 6: Effects of Regulations on Staff Characteristics

No state FE	Age	Education	Experience	Training
One regulation	-.82 (.18)	.17 (.05)	-.56 (.21)	-.014 (.009) -.035 (.019)
Multiple regulations:				
Age regulation	-.91 (.27)	.16 (.05)	.07 (.10)	-.035 (.010)
Education regulation	.42 (.34)	.14(.06)	.10 (.16)	-.030 (.010)
Experience regulation	1.15 (1.53)	-1.31 (.22)	-.76 (.62)	-.053 (.027)
Hours of training at hire date regulation/100	.65 (.65)	-.15 (.11)	.40 (.30)	-.005 (.015)
Ongoing training regulation (0/1)	3.3 (4.8)	-4.3 (.75)	-2.9 (2.0)	-.13 (.09)
Staff-Child Ratio regulation	31.4 (7.8)	2.1 (1.2)	4.6 (3.1)	-.34 (.20)
Inverse Group Size regulation	7.5 (14.4)	-2.7 (2.3)	2.1 (6.1)	.10 (.41)
Test of regulations (p value)	.000	.000	.000	.000
With state FE				
One regulation	-.89 (.23)	.13 (.05)	-.48 (.21)	.073 (.016) -.073 (.032)
Multiple regulations:				
Age regulation	-.33 (.33)	-.07 (.07)	-.20 (.18)	-.012 (.007)
Education regulation	.98 (.54)	-.13 (.10)	-.18 (.24)	-.006(.012)
Experience regulation	1.0 (2.5)	-1.7 (.37)	-.79 (.84)	-.04 (.04)
Hours of training at hire date regulation/100	.97 (.54)	-.73 (.25)	-.03 (.61)	.034 (.030)
Ongoing training regulation (0/1)	2.2 (6.3)	-4.3 (0.9)	-2.1 (2.2)	-.16(.10)
Staff-Child Ratio regulation	25.7 (8.1)	-.77 (1.2)	1.8 (3.5)	-.41 (.22)
Inverse Group Size regulation	18.7 (16.3)	.11 (2.5)	2.8 (7.0)	.30 (.43)
Test of regulations (p value)	.000	.000	.014	.000
Test of state FE (p)	.185	.000	.235	.024
Sample size	3623	3644	3547	3645
R^2 (mult. regulations & SFE)	.10	.25	.09	.12

Notes: In the specifications with one regulation, the regulation included is the one that corresponds to the outcome under consideration. Training is measured by a binary indicator of whether the individual has any training. In the "one regulation" specification for training, both the hire date and ongoing training regulations are included. Standard errors are in parentheses. The rows containing test results report the p-value from F-tests of the joint hypothesis that all regulations have zero coefficients or that all state dummies have zero coefficients.

Table 7: Effects of Regulations on Log Wages

No state FE	Excluding human capital	Including human capital
Age regulation	.007 (.010)	.000 (.009)
Education regulation	-.077 (.010)	-.072 (.009)
Experience regulation	-.31 (.04)	-.24 (.04)
Hours of training at hire date reg./100	-.040 (.018)	-.034 (.017)
Ongoing training regulation (0/1)	-.99 (.15)	-.71 (.13)
SCR regulation	1.82 (.28)	1.55 (.22)
Inverse GS regulation	-1.72 (.28)	-1.54 (.31)
Test of regs (p value)	.000	.000
With state FE		
Age regulation	-.055 (.028)	-.048 (.028)
Education regulation	-.090 (.017)	-.080 (.016)
Experience regulation	-.24 (.05)	-.18 (.04)
Hours of training at hire date reg./100	-.18 (.06)	-.14 (.06)
Ongoing training regulation (0/1)	-.36 (.16)	-.21 (.16)
SCR regulation	.26 (.27)	.23 (.22)
Inverse GS regulation	-.05 (.39)	-.07 (.32)
Test of regs (p value)	.000	.000
Test of state FE (p)	.000	.000
Sample size	3444	3444
R^2 (with SFE)	.55	.66

Notes: Human capital is represented by the individual's years of education, experience, and job tenure, and dummies for 11 different kinds of training in early childhood education. Standard errors are in parentheses. The rows containing test results report the p-value from F-tests of the joint hypothesis that all regulations have zero coefficients or that all state dummies have zero coefficients.

Table 8: Effects of Regulations on Price and Quality

	Price/hour	Quality
Regulation	**No state FE**	
SCR	.05 (.60)	7.7 (3.0)
Inverse GS	1.5 (1.5)	-5.5 (1.6)
Age	.11 (.05)	-.034 (.066)
Education	.016 (.068)	-.081 (.047)
Experience	-2.04 (.19)	-.65 (.26)
test of regulations (p value)	.000	.000
	With state FE	
SCR	-.39 (.54)	1.2 (3.3)
Inverse GS	-.50 (1.5)	1.6 (2.5)
Age	.50 (.26)	-.02 (.23)
Education	.067 (.068)	-.09 (.05)
Experience	-1.47 (.64)	-.41 (.68)
test of regulations (p value)	.230	.253
test of state FE (p)	.000	.000
sample size	794	641
R^2 (with state FE)	.41	.26

Notes: Quality is measured by the ECERS-ITERS score described in the text. Standard errors are in parentheses. The rows containing test results report the p-value from F-tests of the joint hypothesis that all regulations have zero coefficients or that all state dummies have zero coefficients.

Table 9: Simulated Effects of Tougher Regulations on Compliance

	Staff-Child Ratio		Group Size		Age	Education	Experience	Training
No state FE	Present	Prime	Present	Prime				
					One regulation			
ΔPr(meet)	.005	.025	.200	.077	.008	.074	.100	
ΔPr(violate)	-.067	-.078	-.067	.551	-.020	-.410	-.135	-.084; -.135
test of reg. (p)	.197	.197	.056	.068	.000	.000	.005	.000
					Multiple regulations			
ΔPr(meet)	-.021	-.022	-.021	.283	.002	.196	.263	
ΔPr(violate)	-.105	.119	.034	-.030	.013	-.452	-.307	-.038; -.092
test of regs. (p)	.000	.584	.004	.000	.000	.000	.000	.000
With state FE					One regulation			
ΔPr(meet)	-.031	-.064	-.013	-.260	.016	.205	.064	
ΔPr(violate)	.143	-.004	-.276	.096	-.028	.234	-.094	.041; -.039
test of reg. (p)	.018	.738	.016	.997	.000	.000	.000	.000
test of state FE (p)	.000	.333	.007	.000	.000	.000	.000	.000
					Multiple regulations			
ΔPr(meet)	-.006	.060	.026		.001	.223	.463	
ΔPr(violate)	-.178	.034	.009		.014	-.507	.343	.364; -.050
test of regs. (p)	.000	.773	.000	.437	.000	.000	.000	.000
test of state FE (p)	.004	.519	.000	.000	.000	.000	.000	.000
sample size	1533	578	835	281	4145	4162	2239	4036

Notes: The simulations show the impact of changing SCR and GS regulations from 1:16 to 1:8, increasing the age regulation from 18 to 19, the education regulation from 12 to 14, the experience regulation from zero to one, the training regulation at the hire date from zero to 180 hours, and the ongoing training regulation from none (0) to some (1). In the specifications with multiple regulations, the only regulation that is varied in a given simulation is the regulation that pertains to the outcome under consideration. In the training model there are two pertinent regulations, and the simulation results are reported for both, with each simulated while the other is held constant. The first entry in each cell for the training simulations is for the training regulation at the hire date, and the second is for the ongoing training regulation. Note that the training outcome is binary, so the simulation shows the impact on the probability of any training. Simulations for enrolled and averaged observed SCR and GS are not shown, but were similar to those reported in the table for present and prime time. The SCR regulation was excluded from the age, education, experience, and training models, because there were many cases in which a given staff member cares for multiple age groups of children, making assignment of a specific SCR regulation value arbitrary. The rows containing test results report the p-value from F-tests of the joint hypothesis that all regulations have zero coefficients or that all state dummies have zero coefficients.

Table 10: Simulated Impact of Regulations on Log Wages, Quality, and Price

	California	Colorado	Connecticut	North Carolina
Log Wage	All regulations changed at once			
	1.65 (.11)	1.42 (.14)	2.00 (.10)	1.85 (.10)
Regulation:	One regulation changed at a time			
Staff-Child Ratio	1.83 (.04)	1.83 (.04)	1.83 (.04)	1.82 (.04)
Group Size	1.84 (.04)	1.84 (.04)	1.84 (.04)	1.84 (.04)
Education	1.82 (.04)	1.64 (.06)	1.82 (.04)	1.82 (.04)
Experience	1.86 (.04)	1.86 (.04)	1.89 (.04)	1.74 (.05)
Age	1.85 (.05)	1.79 (.05)	1.85 (.05)	1.85 (.05)
Child development training at date of hire	1.64 (.09)	1.64 (.09)	1.96 (.07)	1.96 (.07)
	All regulations changed at once			
Quality	3.92 (.32)	3.75 (.42)	4.08 (.33)	3.76 (.47)
Price	2.35 (.27)	2.98 (.43)	2.50 (.28)	1.64 (.36)
	Regulation values used in the simulations			
Staff-Child Ratio	12	10	10	15
Group Size	0	0	20	25
Education	12	14	12	12
Experience	.5	.5	.375	1
Age	18	19	18	18
Child development training at date of hire	180	180	0	0

Note: The figures in a given column show the average predicted value of the outcome when all observations in all states are assigned the regulation for the state listed in the column heading. The ongoing training regulation for teachers in preschool classrooms is the same for all states, so its impact could not be simulated. Standard error of the prediction is in parentheses.

Table A-1: Descriptive statistics on the control variables included in the regression models, and estimated effects of the control variables on the log wage rate with all regulations and state fixed effects

Variable	Mean (standard deviation)	Coefficient (standard error) in log wage model
Preschool age children	.57 (.49)	.076 (.026)
Kindergarten-school age children	.24 (.42)	.098 (.034)
Full-time equivalent center enrollment	90.0 (55.7)	.00068 (.00026)
For profit center	.50 (.50)	-.17 (.03)
Part of a national chain	.16 (.36)	-.09 (.02)
Church-affiliated	.20 (.40)	-.11 (.03)
Percentage of students who are white	70.1 (29.4)	.00060 (.00043)
Age of the center (years)	13.2 (12.7)	.0005 (.0010)
Unemployment rate	6.9 (2.1)	.0003 (.0066)
Location: Colorado	.28 (.45)	-.07 (.07)
Connecticut	.21 (.40)	-.34 (.11)
North Carolina	.27 (.44)	-.57 (.10)
Staff member is a teacher	.57 (.50)	-.79 (.17)
Staff member is an assistant teacher	.37 (.48)	-1.43 (.27)
Staff member is Black	.15 (.36)	-.006 (.016)
Staff member is other race	.04 (.19)	-.036 (.027)
Staff member is Hispanic	.11 (.31)	-.040 (.014)
Staff member is Male	.03 (.17)	-.032 (.027)

Notes: The last six variables are included only in the staff characteristic and wage models. The omitted category for child age group is infant-toddler, for states is California, for center type is non-profit, non-church affiliated, and for staff position is director. The coefficient estimates in the second column correspond to the model in the first column of Table 7, lower panel. The sample size for the descriptive statistics in column 1 is 4,351.