Licensing Enforcement and the Supply of Childcare

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Abstract

Licensing authorities enforce regulations through inspections, which can worsen supply restrictions caused by licensing but may improve quality. We study the equilibrium impacts of licensing enforcement in the context of early childhood education. Using the childcare licensing program analysts' stringency as an instrument for violations, we study the causal impact of violations on facility closure. We find that violations lead to an increase of 4 percentage points in the probability of facility closure. Closures are not driven by involuntary administrative penalties like license revocation, but instead result from equilibrium shifts in both supply and demand. Overall, closure is more likely to result from administrative violations, and have greater impact on home daycares and underserved areas. Our results suggest that low quality facilities are more likely to exit after a violation, but that facilities in low supply areas are more likely to exit due to regulatory stringency. This implies licensing authorities facing a tradeoff between quality and adequacy of supply should increase stringency in detecting care-related, rather than administrative, violations.

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1 Introduction

Licensing regulation restricts entry into key markets, like childcare, and ensures that entrants provide high quality service. More stringent licensing creates a tradeoff between quality and access, since enforcing higher requirements can decrease supply of services. Research has shown that the tradeoff has real consequences for families. Approximately half of the families with children live in a childcare desert in the U.S. (Center for American Progress, 2018) and in the case of California, more than 65% of the children under 5 years old live in areas with inadequate or zero childcare coverage (Faundez and Padi, 2025). Lack of childcare is associated with lower labor supply and emotional distress for parents. Yet, children have only been shown to benefit from high quality facilites, with the largest long term impacts on disadvantaged children(Duncan et al., 2023).

Licensing authorities therefore have the power to impact both the quality and supply of childcare by changing the stringency of enforcement. Little is known, however, about how stringency in licensing enforcement impacts childcare supply, and how it may change the composition of childcare facilities. In this article, we fill this gap using an examiner instrumental variables (IV) approach to estimate how a shift in regulatory stringency impacts childcare supply. We use novel data on childcare facility inspections in California between 2020 and 2025, which includes detailed information on licensed facilities and inspections. We augment this data with Census variables and estimate demographics such as race, ethnicity, and gender of childcare providers. Our empirical strategy relies on the quasi-random assignment of licensing program analysts (LPAs) to childcare facilities and uses the variation in their stringency as a shifter of the probability that a violation is detected. We measure LPA stringency using a leave-out, residualized measure based on all other inspections that the LPA handled in a given year. This stringency measure is predictive of violations, but uncorrelated with inspection and facility characteristics.

Our baseline results show that facilities that are cited with any type of violation as a result of being assigned a more stringent LPA are 4 percentage points more likely to close than facilities without violations. This increase in closure is unlikely to be driven by the licensing division's ability to force facilities to stop providing care as we find no significant causal effect of violations on license suspension or revocation in the full sample. The most likely channel by which violations increase closure is by affecting facility's profitability, either by increasing operational costs or by decreasing revenues, or both. We use enrollment as a proxy for demand, which shifts revenues. We find that violations lead to a decrease of 2.5 percentage points in the proportion of the approved facility capacity that is being used, which roughly translates into 1 less child enrolled and a decrease of 6% in revenues for the average facility.

The impacts of additional stringency are not symmetric across different types of violations. More serious issues, labeled type A violations, are likely to come with significant penalties and must be disclosed to parents of enrolled children. LPAs who are more stringent in detecting type A violations increase closure rates by more than 9%, and increase suspensions and revocations by 3.5%. Enrollments in facilities that remain open decrease by 5%. In contrast, less serious type B violations increase closure by 4% and lower enrollment by 2%, with no impact on suspensions and revocations. These results are consistent with type A violations imposing costs that are nearly twice as high on facilities.

In addition, we find evidence that administrative violations, which are less related to child welfare and are costly to remedy, lead to significantly larger increases in the probability of closing without

causing significantly different effects on enrollment. In contrast, care-related violations, which directly impact children but can also be remedied more easily, reduce closure with lower magnitudes and do not decrease enrollment. This suggests that violations also affect closure by imposing higher operational costs to childcare providers. To test that closure is driven by LPA stringency, we show that type A violations and administrative violations cause significant increases in closure within one year of the LPA's visit.

We then separate the data into subgroups to assess which populations drive the results. Family daycares are primarily responsive to administrative violations, while childcare centers are more significantly impacted by care-related violations. Facilities in underserved cities with low childcare supply are also more sensitive to LPA stringency. Non-white providers are relatively less likely to exit in response to violations, while Hispanic, and male providers are more responsive to some violation types and face larger likelihood of suspension or revocation. These results do not seem to be driven by language barriers. Finally, lower quality facilities are more likely to close due to a violation, with childcare centers exiting voluntarily while family daycares face greater rates of suspension and revocation as well as lower enrollment.

Taken together, our results shed light on how market equilibria shift in response to examiner stringency, and provide guidance to licensing authorities on the tradeoffs induced by increased stringency, as well as on where LPAs should concentrate. Overall, increased stringency in detecting care-related violations induces fewer closures while increasing quality. Jurisdictions with low childcare supply, including "childcare deserts," should consider decreasing stringency to increase the supply of childcare. In areas with adequate childcare supply, policymakers may successfully increase quality by requiring more stringent enforcement by LPAs, but they must be aware that Hispanic and male providers may be disproportionately likely to exit in response.

This work contributes to three strands of literature.

First, we contribute to the literature on regulating childcare markets. Regulations usually focus on imposing standards for the inputs to the production of childcare services believed to affect quality rather than regulating quality itself (Hotz and Xiao, 2011). The problem with this approach is that such measures do not necessarily translate into better quality of care. Research shows that while regulations such as group size and staff-child ratio usually improve the quality of care provided by childcare centers, teacher qualification requirements do not necessarily improve the quality of care (Blau, 2000). These regulations tend to induce providers to engage in significant input substitution, which diminishes and possibly eliminates quality gains (Blau, 2007). Additionally, these regulations can have unintended consequences in the childcare market. Research has found that while imposing regulations can improve childcare quality, it can lead to a decrease in the number of childcare centers, especially in lower income areas, which increases the socioeconomic gaps in access to childcare and the quality of care (Hotz and Xiao, 2011). We contribute to this literature by introducing a rich new dataset on how facilities are impacted by childcare regulation, including detailed information on different rules and types of violations. We also show causal evidence of a direct tradeoff between quality and access to care.

Second, we contribute to a long line of research on licensing as a barrier to entry and the effect of licensing stringency on market supply and quality. This literature shows mixed impacts of licensing stringency on supply and quality of goods and services. Among recent examples, Farronato et al., 2024 show that licensing decreases the supply of goods and services and loosens competition without improving consumer outcomes, suggesting no net benefits from licensing. In contrast, Larsen et al.,

2020 show that more stringent requirements for public school teachers result in better outcomes for struggling students and Anderson et al., 2020 show better maternal and infant health outcomes after midwives began to be licensed. Our contribution to this literature is to move away from studying the effect of initial barriers to entry, such as licensing exams or education requirements, and towards ongoing inspection regimes and their impact on exit.

Third, we contribute to the large and growing literature that uses quasi-random assignment to examiner or judge to assess the causal impact of regulatory stringency. Our instrumental variable strategy is similar to those using a judge leniency tendency measure (Judge IV)[1] and those using examiners or investigators stringency propensities (Examiner IV).[2] A comparable strategy has been used to study hospital performance by taking advantage of the random assignment of patients to ambulance companies within a zip code (Doyle et al., 2012). We contribute to this literature by applying the examiner IV approach in a new context, childcare, where responses to examiner stringency can arise on both demand and supply sides of the market.

The remainder of this article is structured as follows. Section 2 provides institutional details about the childcare market and its regulations in California and presents a simple model of supply and demand to illustrate the effects of licensing violations. Section 3 describes how we created the dataset and selected the sample used for the analysis and provides summary statistics for our sample. Section 4 explains our empirical research strategy and provides evidence supporting our main identifying assumptions. Sections 5 and 6 present the results of our empirical analysis and discusses their implications for public policy. Finally, Section 7 summarizes the main conclusions of our analysis.

2 Institutional Background and Model

Childcare providers need a license to operate when they are not babysitting or nannying in the child's home and when they take care of children from multiple families. In California, there are two paths to becoming a licensed childcare business. Family daycares, which are further subdivided into small and large, provide group childcare in a home setting. A small family daycare is licensed to care for up to six to eight children, while large family child care homes, also based in a residence, may care for up to twelve children, or up to fourteen when an assistant is present. Daycare centers are based in non-home facilities, including commercial property, churches, or schools, and can care for many more children than a home-based facility. Each type of license requires applicants to satisfy different conditions. Locations must satisfy health and safety requirements including zoning and fire code compliance, emergency preparedness, and access to certain amenities. Personnel requirements include a background check for all inhabitants of family daycare, even those that

[1] The Judge IV strategy has been used to estimate the effects of incarceration (Aizer and Doyle, 2015; Bhuller et al., 2020; Green and Winik, 2010; Kling, 2006; Loeffler, 2013, Norris et al., 2021), the impact of pretrial detention (Arnold et al., 2018; Dobbie et al., 2018; Stevenson, 2018), the impact of electronic monitoring (Di Tella and Schargrodsky, 2013), the effects of bankruptcy (Dobbie and Song, 2015; Dobbie et al., 2017), the effects of eviction (Collinson et al., 2024), and the effects of judicial eminent domain decisions (Belloni et al., 2012).

[2] Examples of Examiner or Investigator IV include those using the disability examiners' propensity to approve disability claims (Autor et al., 2019; Dahl et al., 2014; French and Song, 2014; Maestas et al., 2013), the case workers' propensity to place children in foster care (Bald et al., 2022, Doyle, 2007; Doyle, 2008), the patent examiners' propensity to grant patents (Sampat and Williams, 2019), and the assistant district attorneys' propensity to prosecute nonviolent misdemeanor offenses (Agan et al., 2023).

do not provide care, and formal early childhood education for daycare center licensees. Before licensing, all facilities must submit completed applications and pass a physical inspection.

Once licensed, each facility is monitored through a combination of routine inspections and unannounced visits, plus targeted reviews. The primary liaison between the California Department of Social Services (CDSS) and daycare facilities are Licensing Program Analysts (LPAs). LPAs are the field staff charged with carrying out regular inspections, evaluating compliance with laws and regulations, and documenting deficiencies. They are full time government employees who use standardized inspection tools to guide and record inspections, and conduct investigations into reported complaints and incidents. LPAs are managed by the Licensing Program Managers (LPMs) and Regional Managers (RMs) who allocate caseloads and provide support. Most offices assign LPAs to facilities based on a specific geographic area, such as a set of zip codes that one LPA covers. LPAs can also move across offices and locations over time. Issues that require court orders or legal counsel can be escalated when necessary to the Legal Division.

Routine inspections are required every three years, though there is a backlog of inspections generated by a pause during the COVID-19 pandemic. There are primarily two types of non-routine inspections. First are complaint investigations, which stem from a parent, staff, neighbor or third party filing a complaint through CCLD's hotline, email, or online complaint portal. Second are incidents reported by the licensee or a worker on site, often due to regulatory requirements like an outbreak of communicable disease. Each of these reports are followed up by LPAs, with priority given to those alleging immediate risk, such as abuse, serious injury, death, and fire hazards. After intake, LPAs investigate by interviewing staff and parents, reviewing records, and visiting the facility. Providers must allow LPAs to enter and inspect the facility, and denying entry can lead to citation. Investigations determine whether there is a deficiency and what category of corrective action is required.

When an inspection or investigation finds a violation, the LPA documents deficiencies and typically works with the licensee to create a Plan of Correction (PoC). Not every deficiency leads to the same outcome. Type A deficiencies are those that "if not corrected, represent an immediate risk to the health, safety or personal rights of children in care." This is the most serious classification and result in a notice being placed in the facility in addition to a copy of the report being given to all parents of children currently enrolled and to each new enrollee for the next 12 months as a way to make them aware of the issue. Examples include physical abuse, children left unsupervised, unlocked access to toxic chemicals, and staff on duty without required criminal record clearances. Type B deficiencies create a potential risk to children's health, safety, or personal rights that are less immediately dangerous than Type A but still material. LPAs treat these as needing prompt correction and result in documentation found online in public records. Examples include missing or incomplete immunization records, incomplete meal menus, overall facility deterioration that could become hazardous if not fixed, and insufficient but not totally absent supervision. Type C deficiencies are technical violations or minor paperwork/maintenance problems that do not present an immediate or potential threat to child safety (for example, small recordkeeping omissions).

LPAs communicate deficiencies to licensees using citation forms, and some citations are accompanied by civil penalties. Moreover, facilities that do not comply with their LPA's PoC within the 30 day time limit will likely receive additional citations and/or increasing civil penalties. Continued or severe noncompliance can lead to stronger administrative actions, such as temporary suspension, emergency removal orders, or revocation of the license. CDSS follows administrative hearing

procedures when it seeks to suspend or revoke. In response, the licensee has appeal rights.

2.1 Equilibrium Effects of Licensing Violations

A simple model of supply and demand helps illuminate the potential impact of licensing violations on outcomes in the childcare context. Supply of childcare is highly regulated, with the number of children allowed in a location being fixed by center type and number of staff. Starting the business has significant fixed costs including sourcing a location, completing training, hiring staff, and purchasing physical equipment, as well as the licensing application process. Once operational, however, marginal costs are minimal and non-increasing once staff have been hired and the daycare is not exceeding its capacity limit.

The simplest type is small family daycares, where supply can be modeled as a piecewise function. Quantity must be high enough that revenues are greater than fixed cost of operation F for supply to be positive. After that point, any quantity below the maximum daycare size of $\bar{Q}$ can be supplied at variable cost v. From the perspective of a small individual center, market prices are largely fixed and are denoted m, meaning that the firm will shutdown if $q < \frac{F}{m-v}$. As long as $m > v$ and market-clearing quantity $q \in [\frac{F}{m-v}, \bar{Q}]$, the daycare will stay in business. Large family daycares and centers face similar cost functions, except that they can increase quantity past $\bar{Q}$ by hiring additional teachers and expanding to larger locations for centers. We assume a standard downward-facing demand curve intersects the supply curve, fixing the quantity of children enrolled in each daycare at the market clearing price.

Violations can impact equilibrium in two ways. The direct effect would increase costs the daycare provider faces. The indirect effect would occur by shifting demand for the daycare. Figures 1 and 2 demonstrate these in turn. An increase in fixed cost F, or of variable cost v would lead to a contraction in the supply curve, increasing the minimum quantity required to break even and stay in business. As Figure 1 shows, a small increase in cost would move supply from S to S', with no equilibrium impact on either price or quality. But, a large increase in cost would move supply to S'', which no longer intersects with demand. Quantity demanded is too low to overcome the cost of operation, and the daycare shuts down.

Similarly, Figure 2 shows that a significant decrease in demand for childcare, shown by the shift from D to D'', would lead to the facility shutting down. In contrast, however, a small decrease in demand can lower enrollment while the facility remains open, meaning that a larger part of the daycare's capacity would remain unutilized. We take this differential impact of supply and demand to the data to separate two channels by which licensing violations impact equilibrium.

PROPOSITION 1 *Violations that increase the probability of closure may be driven by an increase in costs that shift supply, or by a drop in demand due to reputation consequences.*

PROPOSITION 2 *Violations that decrease enrollment must shift demand.*

Therefore, we measure the impact of violations on two key outcomes - closure and enrollment. Violations that impact closure could be shifting both supply and demand, or just supply or demand. Violations that decrease enrollment are driven by pure demand-side effects. So, violations which shift closure but not enrollment are likely driven by supply side shifts, such as increased fixed costs.

3 Data

3.1 Data Sources and Sample Selection

We created a novel dataset that contains all available reports for visits conducted by the childcare licensing staff from the California Department of Social Services (CDSS) between 2020 and 2025. We began by downloading from CDSS website spreadsheets with information for licensed childcare facilities in the state of California. CDSS only provides information for childcare centers and large family daycare facilities. Information about small family daycare facilities is not provided due to privacy concerns. To get around this issue, we scraped from Upwards website (formerly Weecare) information for small family daycare facilities in California. We collected the facility name, license number, and location, among others. Then, we aggregated these data with the data obtained from CDSS to create a nearly comprehensive dataset of all licensed childcare facilities in California.

Later, using the license numbers, we scraped from CDSS website all reports available for each licensed facility. CDSS only posts online the reports for the last 5 years; hence, we were able to gather reports from 2020 to 2025. These reports include two main types: facility evaluation reports and complaint investigation reports. A facility evaluation report is generated after a routine inspection, a pre-licensing inspection, a case management visit, or an office visit. A complaint investigation report is created after a visit triggered by the department receiving a complaint against a facility. We collected more than 129,000 reports for the entire period, with over 88% being facility evaluation reports. These reports include over 39,000 different childcare facilities and 665 LPAs.

As the purpose of this study is to use LPA stringency when determining whether a facility meets the quality standards required by CDSS, we excluded from the analysis sample reports that do not reflect either LPA stringency or quality of care provided at the facility. The excluded reports include pre-licensing inspections, office visits, and other visits which main purpose was not to evaluate the level of care provided by the facility. Additionally, we excluded reports from 2025 since our outcomes are measured after the visit[3] and we expect that any effect would take at least a few months to take place. We further restricted the sample to reports from LPAs who had at least 30 visits during the period, which is an average of 6 visits per year. Our final analysis sample is comprised of 88,504 reports that span from 2020 to 2024, including 34,476 childcare facilities and 486 LPAs.

Our key independent variables include type A deficiency, type B deficiency, any deficiency, care-related violation, administrative violation, and other violations. Type A deficiency is a dummy variable equal to one if the LPA has cited a Type A deficiency during the inspection, zero otherwise. Type B deficiency is a dummy variable equal to one if the LPA has cited a Type B deficiency during the inspection, zero otherwise. Any deficiency is a dummy variable equal to one if the LPA has cited either a Type A or Type B deficiency during the inspection, zero otherwise. Care-related violation is a dummy variable equal to one if the LPA has cited a part of the code related to level of care, neglect, or abuse during the inspection, zero otherwise. Administrative violation is a dummy variable equal to one if the LPA has cited a part of the code related to record keeping, reporting, display of legal notices, qualifications, fire clearance, criminal record clearance, immunizations, false statements, or financial issues during the inspection, zero otherwise. Finally, other violation is a dummy equal to one if the violations cited during the inspection do not include any care-related

[3]The file from which we obtained closure date is from August 2025; hence, at least 8 months would have elapsed after the inspection for the most recent reports in our analysis sample.

or administrative violation, zero otherwise. While the other violation category includes everything that is not care-related or administrative, the majority of these violations are related to operational issues, the premises, food, and medications. In addition, we retrieved information about the issuance of civil penalties and their amount from the narrative of the reports.[4]

Our outcomes include closure within one year after the inspection, closure at any time after the inspection, having the childcare license suspended or revoked within one year after the inspection, having the license suspended or revoked at any time after the inspection, and change in used capacity. We extract the closure date from the facility information files downloaded from CDSS (childcare centers and large family daycare only) and from information scrapped from the CDSS website for small family daycare facilities. Then, we create a dummy variable equal to one if the facility closed within one year after the inspection, zero otherwise, and another dummy variable equal to one if the facility closed after the visit, regardless of the date, zero otherwise.

In order to determine whether the CDSS legal department has taken any administrative action against a childcare facility such as license suspension and/or revocation, we scanned the reports' narrative in search of key terms that would allow us to identify such actions. Specifically, to determine a license suspension, we searched for the term temporary suspension order. To determine a license revocation, we searched for license revocation, license revoked, intent to revoke, stay of revocation, and different variations of those terms. Additionally, we included probationary licenses in this category of actions taken by CDSS legal department, as it is common that during the license revocation appeal process, facilities are granted a probationary license for up to a couple of years. Then, we determined the date of the first occurrence of these administrative actions and used that date as the date of license suspension, revocation, and/or probation. Finally, we created a dummy variable equal to one if the aforementioned administrative action took place within one year after the inspection, zero otherwise, and another dummy variable equal to one if the administrative action took place any time after the inspection, zero otherwise.

Ideally, we would like to study how violations affect enrollment as a measure of demand sensitivity to quality. The closest proxy for enrollment is the "census" variable, the number of children observed in each visit to proxy enrollment. We acknowledge the challenges of using census as an enrollment proxy. Census only approximates enrollment, and it is affected by external factors such as children's illness, adverse weather conditions, planned and unplanned temporary closures, and even the time of the day the LPA visited the facility. We address some of these issues by first controlling for the time of the day the inspection took place (8 am to noon, noon to 5 pm, other time) and second by imputing missing values and cases reported as zero census that are unlikely to be due to zero enrollment. Many LPAs include in their reports narrative the census they observed during the visit. We use that information to corroborate whether a zero census value is due to zero enrollment and to update missing census values. Zero values that are not due to zero enrollment are set to missing to be imputed using the method described below.

Our census outcome is defined as change in used capacity after the inspection. We defined used capacity as the ratio of census over approved capacity. We calculate this ratio for every report and for those that we are unable to calculate it due to missing census values, we impute it using the average used capacity for that year in the city the facility is located. To calculate the used capacity ratio after the visit, we use all future visits for that facility. We impute missing values using the average used capacity ratio in that city in all future years (eg. the imputed future used capacity

[4]We were unable to obtain the penalty amount for approximately 35% of the civil penalties issued.

ratio for 2020 reports uses the city averages from 2021 to 2025, while the imputed future value for 2024 visits only uses the city average in 2025). Finally, we calculate the change in used capacity ratio as future used capacity minus current used capacity. We include in the regressions for this outcome a dummy variable equal to one if the variable was constructed using any imputed value.

Our analysis also controls for facility characteristics and zip code level socioeconomic characteristics. The facility controls include type of facility (family daycare, infant center, school age center, ill center, daycare center, and single licensed childcare), capacity, years operating, and total number of inspections during the entire sample period. The zip code level controls are derived from the 2020 census and include total population, employment indicators (LFP, unemployment rate, female LFP, female unemployment, fraction self-employed, fraction of households with two earners), racial composition, fraction below poverty line, homeownership rate, median house value, average income by sex, and fraction of rural population. Additionally, we noticed that in some inspections, the visit included not only the LPA listed in the report but also additional LPAs, a manager (LPM) and sometimes even the regional manager (RM).[5] For this reason, we included controls for these "group visits" in all specifications and we also removed that variation when we created our instruments.

Finally, we use names and locations to infer providers' estimated race, ethnicity and gender using Bayesian Improved Surname Geocoding (BISG). To do so, we hand-cleaned the names of facility representatives who met with LPAs in each report. We then geolocated the facility's address and assigned it to a Census tract, which in turn corresponds to a specific distribution of race and ethnicity. Based on the geographic probabilities as a prior, we use BISG to update the probability using name information. Gender inferences are made using name only. Finally, we use the text of the report to infer whether the daycare provider was an English speaker or not, based on whether a translator was requested or in attendance at the meeting. Spanish language interactions were documented as such in the reports.

3.2 Descriptive Statistics

Table 1 presents the summary statistics for our sample. We show summary statistics for inspections without violations, inspections with any type of violation, and for inspections with Type A, Type B, care-related, and administrative violations.

Panel A of Table 1 provides a breakdown of the type of violations cited during inspections, as well as civil penalties assessed during those inspections. In our analysis sample, approximately 30.2% of the inspections had at least one violation of any type cited. Among those with a violation cited, 30.8% had at least one Type A violation and 80.2% had at least one Type B violation. These figures mean that approximately 11% of inspections with any violation have both types of violations cited during the visit. Care-related violations are more common than administrative violations (34.4% versus 17.9%, respectively). Only 3.7% of inspections with a violation of any type also had a civil penalty assessed for an average amount of $468. Regarding the type of violation, almost 36% of inspections with Type A violations also had Type B violations, and 33.6% of these deficiencies were due to care-related violations and 23.6% due to administrative violations. Among inspections with Type B violations, 13.8% also had Type A violations, and 37.4% of these deficiencies were due to care-related violations and 16.7% due to administrative violations. Inspections with Type A violations

[5] In our sample, almost 19% of the inspections had more than one LPA present, 1.6% had an LPM present, and 2.1% had the regional manager present.

are significantly more likely to have a civil penalty assessed during the visit than inspections with Type B violations, 10.1% versus 2% respectively. The average amount of civil penalties also differs by type of violation; while it is close to $490 for inspections with Type A violations, it is only $412 for inspections with Type B violations.

Panel B of Table 1 presents a summary of the facility outcomes by type of violation cited during inspections. Closure rates, both within one year after the inspection and any time after the inspection, are significantly higher among facilities that had a violation cited during the inspection, regardless of the type of violation. In 4.6% of the cases without a violation cited during the inspection in our sample, the childcare facility closed within one year after the inspection, and 10.8% closed any time after the inspection. Among inspections with at least one violation cited during the visit, in 6.7% of the cases the facility closed within one year after the inspection, which is 46.6% higher than inspections without a violation, and 14.8% closed any time after the inspection, which is 37% higher than inspections without violations. Facilities with Type A violations are the most likely to close: 9.7% closed within one year after the inspection, which more than doubles the closure rate of facilities without violations, and 19.3% closed any time after the inspection, which is 78.7% higher than the closure rate of facilities without violations. Similarly, the rate at which facilities had an administrative action such as suspension or revocation taken against them by the licensing office legal department is significantly higher among those that had a violation cited during inspections. License suspension/revocation rates are the highest among facilities that had a Type A violation cited during inspections, and they can be as high as 8 times the rate of facilities without violations. Administrative violations do not lead to significantly higher license suspension/revocation rates compared to facilities without those violations. Lastly, while facilities without violations saw a minor increase in their used capacity after the inspection of approximately 0.5 percentage points, facilities with at least one violation experienced a decrease of 1.8 percentage points in their used capacity ratio. Facilities with Type A violations and care-related violations experienced greater decreases in used capacity, 4.2 percentage points and 2.4 percentage points, respectively.

Panel C of Table 1 presents some characteristics of the facilities in our sample. The average capacity of facilities with violations is not statistically different from the average of facilities without violations and it is approximately 36 children. However, there are significant differences by type of violation. Facilities with Type A violations and with administrative violations are significantly larger (39 and 58 children, respectively), while facilities with care-related violations are significantly smaller than facilities without violations (average capacity of 22 children). These differences are due to the fact that childcare centers are more likely to have Type A and administrative violations than family daycare facilities, while the latter are more likely to have care-related violations. Facilities with violations have a larger enrollment compared to their capacity than facilities without violations. The used capacity ratio is almost 2 percentage points higher for facilities with at least one violation than for facilities without violations, and this ratio is the highest among facilities with Type A violations (0.53). The average childcare facility in our sample has been operating for more than 12 years. Facilities with violations are on average half a year younger than facilities without violations. Facilities with Type A and care-related violations have been in operation for the shortest time, 11.9 and 11.5 years, respectively. Facilities with violations had one additional inspection during the sample period compared to facilities without violations (5.7 versus 4.7 visits). Facilities with Type A and care-related violations had the largest number of inspections during the sample period, more than 7 visits or approximately 1.5 visits per year.

Panel D shows descriptive statistics about the inferred race, ethnicity, gender, and language of

daycare providers. About 66% of all providers are white, whether or not a violation is detected. White providers are slightly underrepresented among care-related violations, and overrepresented among administrative violations. Nearly 40% of providers are Hispanic across all violation types, but Hispanic providers are slightly overrepresented among care-related violations nad underrepresented among administrative violations. The vast majority of providers are female, with just over 5% of providers being male. However, male providers are over-represented among any violations and among administrative violations. Finally, more than 90% of providers are English speakers. Non-English speakers generally, and Spanish speakers in particular, are overrepresented among Type B and care-related violations and underrepresented among administrative violations.

In Appendix Table A1 we present detailed summary statistics by type of childcare facility. Panel A of Appendix Table A1 provides a summary of the violations cited and civil penalties assessed during inspections for family daycare facilities and childcare centers. The figures show that while both types of facilities are cited with violations at similar rates (approximately 30% of inspections had a violation), the type of violation cited varies significantly by facility type. Family daycare facilities are more likely to be cited with Type B deficiencies and care-related violations and childcare centers are more likely to be cited with Type A deficiencies and administrative violations. Similarly, childcare centers are 31% more likely to have a civil penalty assessed than family daycare facilities, and they are assessed higher penalty amounts ($82 higher or 18% higher). Panel B of Appendix Table A1 shows that closure rates, both in the short term and medium term, are not statistically different by facility type. However, family daycare facilities are more than twice as likely to have their license suspended or revoked as childcare centers. In terms of change in the used capacity, the figures show diverging paths. While childcare centers experienced an increase of 0.3 percentage points in their used capacity ratio, family daycare facilities saw a decrease of 0.7 percentage points. This exacerbates the difference in baseline used capacity ratio of 1.3 percentage points in favor of childcare centers, as shown in Panel C of Appendix Table A1. Childcare centers had 2.5 more inspections during the period than family daycare facilities and the average childcare center has been in operation for 6 years longer than the average family daycare facility.

Appendix Table A2 presents additional descriptive statistics for the sample according the level of childcare coverage in the city the facilities are located. We use the categorization established in Faundez and Padi, 2025. There are few significant differences by city-level childcare coverage. While childcare providers in underserved areas are more likely to have Type B and care-related violations, providers in adequately served areas are more likely to have Type A violations. Closure rates are approximately 0.8 percentage points higher in adequately served areas. Underserved areas have a larger proportion of family daycare providers, which makes them have an average capacity of almost 8 fewer children per facility than adequately served areas. Additionally, the used capacity ratio is almost 2.7 percentage points lower in underserved areas.

4 Empirical Strategy

The LPA assessment about the quality of care provided at a childcare facility can significantly impact the facility's ability to stay in business. Consider a model that relates outcomes such as closure to an indicator of whether the facility was found to be in violation of a norm during an inspection:

$$Y_{ijt} = \beta_0 + \beta_1 Violation_{ijt} + \beta_2 X_{ijt} + \xi_{ijt} \tag{1}$$

where Y_{ijt} is the outcome of interest for facility i after inspection j in year t, $Violation_{ijt}$ is an indicator for whether the LPA cited facility i with a deficiency during inspection j in year t, X_{ijt} is a vector of inspection- and facility-level control variables, and ξ_{ijt} is an error term. The main issue with inference using OLS is that estimates of Equation 1 will likely be biased due to the correlation between violations and unobserved facility characteristics that are also correlated with the outcomes. For example, if high quality facilities are more likely to comply and charge higher tuition and higher tuition also means higher margins and lower probability of closing, then OLS regressions that omit tuition data would underestimate the true effect of a violation being detected.

We address the omitted variable bias issue by estimating the causal effect of violations using a measure of the tendency of a quasi-randomly assigned LPA to cite a deficiency during inspections as an instrument for violations. This method allows us to interpret the differences in outcomes between facilities assigned to a more or less stringent LPA as the causal effect of the change in the probability of identifying a violation associated with LPA assignment. This instrumental variable design identifies a local average treatment effect (LATE), that is, the causal effect of identifying a violation for facilities on the margin of being caught not complying with the rules.

We follow Dahl et al., 2014 and Dobbie et al., 2018 to create our instruments using a residualized, leave-out LPA stringency measure that accounts for potential case selection. Since LPA assignment to inspections is not truly random as in other settings, potential selection could affect our estimates if we use a simple leave-out measure of stringency. For example, some types of inspections are more likely to have more than one LPA present during the visit or even to have an LPM present, which we call a group visit. If certain LPAs or certain offices are more likely to engage in group visits, then a simple leave-out measure would be biased. Our residualized measure of LPA stringency accounts for this type of potential case selection. Additionally, our approach controls for differences across regional offices in both facility characteristics and LPA stringency.

We can define the residual decision to cite a violation after removing the effect of the regional office fixed effects and group visits as:

$$Violation^{*}_{ijt} = Violation_{ijt} - \gamma X_{ijt} = Z_{ilt} + \xi_{ijt} \tag{2}$$

where X_{ijt} includes the regional office fixed effects and the group visit controls. The residual decision to cite a violation, $Violation^{*}_{ijt}$, is composed of our LPA stringency measure Z_{ilt} and an idiosyncratic facility level variation ξ_{ijt}.

For each inspection, we use the residual decisions to cite a violation to construct the leave-out average decision of the assigned LPA within a year:

$$Z_{ilt} = (\frac{1}{n_{lt} - n_{ilt}})(\sum_{k=0}^{n_{lt}}(Violation^{*}_{ikt}) - \sum_{j=0}^{n_{ilt}}(Violation^{*}_{ijt})) \tag{3}$$

where n_{lt} is the number of inspections conducted by LPA l in year t and n_{ilt} is the number of inspections of facility i conducted by LPA l in year t. This approach removes the residualized decisions to cite a violation of all inspections of a facility conducted by LPA l in each year.

The leave-out LPA measure described in Equation 3 is the violation issuance rate for the assigned LPA after accounting for the regional office fixed effects and group visits. The importance of this measure for our analysis lies in the fact that regressing outcomes for facility i on the LPA stringency

measure without leaving out the data for facility i would introduce the same estimation errors on both sides of the regression and generate biased estimates of the causal effect of being cited with a violation. We use the predicted LPA stringency measure Z_{ilt} as an instrumental variable for whether the facility was cited with a violation during the inspection.

Similarly to Dobbie et al., 2018, we allow our instruments to vary across years as we would expect LPA's decisions to evolve over time as they become more experienced. In robustness analysis, we show results that use a single LPA stringency measure for the entire period.

Although the Childcare Licensing Division of the California Department of Social Services is organized in 21 regional offices, for our analysis we grouped a few offices resulting in 14 regional offices. Larger urban areas have their geographical area of influence split into two or more regional offices.[6] In most cases, two regional offices share the same premises, and while each regional office has its own regional manager and licensing program managers (LPMs), the assignment of LPAs to each office is less clear. Our analysis of the data showed that several LPAs conducted inspections for both regional offices located in the same premises. While in some cases most of the inspections were concentrated in one of the offices, in other cases they were almost equally split between both offices. Hence, it is not clear that the official regional office is the adequate level at which the quasi-random assignment of LPAs is performed. For this reason, we decided to consider regional offices that share premises as one regional office and use this classification to create our LPA stringency measures.

Our sample includes 485 LPAs across 14 childcare licensing regional offices in California. The median number of inspections per LPA is 151 during the 2020-2024 period included in our sample. Figure 3 shows the distribution of our residualized LPA stringency measure for citing any type of violation at the LPA-by-year level. This figure shows that moving from one of the most lenient LPAs to one of the most stringent LPAs increases the probability of being cited with a violation by more than 50 percentage points.

During inspections, an LPA can cite different types of violations which will depend on the underlying rule the facility is not complying with and the severity of the issue. In practice, as explained in Section 2, LPAs can cite Type A and Type B deficiencies, being Type A for more severe violations. Each type of citation might have different costs associated with its correction, as well as a different form in which parents are informed about the deficiency. It is possible that due to those differences, each type of violation could impact outcomes differentially. Also, those differences can help to disentangle supply side from demand side effects and help us understand the mechanisms through which violations impact business viability. Additionally, we could expect that the underlying rules that are broken could have differential effects on the outcomes. For example, parents might be more concerned if the facility is not providing adequate care to their children than if the facility is not complying with reporting requirements. Similarly, the cost of ensuring that staff have the required qualifications can be significantly different from the cost of changing care-related practices.

For our main analysis, we created a composite violation measure that groups Type A and Type B deficiencies into a single binary variable, as this measure captures a particularly policy relevant margin. Nonetheless, we also explore the effects of each type of deficiency (A and B) and the underlying category of rules the facility is not complying with (care-related and administrative). For each type of violation, we created an instrument following the procedure described above.

[6] These areas include Sacramento, Fresno, Oakland, El Segundo, Monterey Park, Riverside, and San Diego.

Figure 4 depicts the distribution of each of these residualized LPA stringency measures for citing each type of violation at the LPA-by-year level. Similarly to our composite violation measure, the figure shows that for each LPA stringency measure, the probability of being cited with that type of violation monotonically increases as LPA stringency increases.

We use the variation in LPA stringency for each violation measure described above to instrument for being cited with a violation to identify the causal effect of violations using two-stage least squares regressions. We can interpret the estimates from these regressions as causal if the following conditions are met: (1) LPA assignment is associated with the probability of being cited with a violation, (2) LPA assignment only impacts facility outcomes through the probability of being cited with a violation, and (3) facilities cited with a violation by a strict LPA would have also been cited with a violation by a lenient LPA. While some of these conditions are fundamentally untestable, we examine next whether they are likely to hold.

We examine condition (1), the relationship between LPA stringency and whether the facility is cited with a violation ($Violation^{*}_{ijlt}$), by estimating the following first-stage equation for facility i and inspection j, assigned to LPA l in year t:

$$Violation_{ijlt} = \alpha_0 + \alpha_1 Z_{jlt} + \alpha_2 X_{ijt} + \xi_{ijt} \tag{4}$$

where the vector X_{ijt} includes the regional office fixed effects and the group visit controls. Each Z_{jlt} is a leave-out measure of LPA stringency, which is allowed to vary across years. We follow Cameron and Miller, 2015 methodology to get robust standard errors that are two-way clustered at the facility and LPA level. Figures 3 and 4 show graphical representations of the first-stage relationships between each LPA stringency measure and the probability of being cited with each type of violation after controlling for group visits and regional office fixed effects. These graphs represent a flexible analog to Equation 4 by plotting a local linear regression of violations cited during an inspection against each LPA stringency measure. Each violation rate increases monotonically and approximately linearly in the core part of our LPA stringency measures. We present formal first-stage results for each instrument in the results section below.

Next, we help confirm that condition (2) holds, meaning LPA assignment only affects facility outcomes through the probability of being cited with a violation. Next, we verify whether the assignment of LPAs to inspections is as good as random conditional on regional office fixed effects. Table 2 displays the results of our randomization test. In Column 1 of Table 2, we use a linear regression to test whether facility and inspection characteristics predict being cited with a violation. We include regional office fixed effects and year fixed effects, and the standard errors are two-way clustered at the facility and LPA level. The estimates show that the type of facility is a significant predictor of being cited with a violation. While single licensed childcare centers and infant centers are 12 and 3 percentage points more likely to be cited with a violation than family daycare centers, respectively, school age centers and ill centers are 6 and 33 percentage points less likely to be cited with a violation than family daycare centers, respectively. Each additional year of operation reduces the probability of being cited with a violation by approximately 0.1 percentage points. Additionally, inspections with multiple LPAs and with an LPM present are 12 and 19 percentage points more likely to result in a violation being cited compared to inspections with a single LPA, respectively. In column 2 we assess whether the same facility and inspection characteristics are predictive of our LPA stringency measure using the same specification. The results provide evidence that LPA stringency is not associated with facility characteristics, in other words, LPA assignment to inspections is as good as random after we account for regional office fixed effects.

Finally, we test whether condition (3) seems to hold, namely that the effect of LPA assignment on the probability of being cited with a violation is monotonic across facilities. In practice, this monotonicity assumption requires that facilities cited with a violation by a strict LPA would also be cited with a violation by a lenient LPA. If this assumption is violated, we could not interpret our estimates as a well-defined LATE, since the estimates would be a weighted average of marginal treatment effects, but the weights would not sum to one (Angrist et al., 1996; Heckman and Vytlacil, 2005). The bias caused by this assumption violation would be an increasing function of the number of facilities for which the monotonicity assumption would not hold and the difference in the marginal treatment effects between facilities for which the monotonicity would and would not hold (Dobbie et al., 2018). Additionally, the bias amount would be a decreasing function of the first-stage relationship described above (Angrist et al., 1996).

This monotonicity assumption implies that the first-stage estimates should be non-negative for any subsample (Dobbie et al., 2018). In Appendix Table A3 we present first-stage estimates for the sample split by type of facility, years in operation, and average zip code income. The estimates are consistently positive and remarkably similar for all subsamples, thus providing strong support for the validity of the monotonicity assumption.

5 Results

In this section, we explore the effects of being cited with a violation using the instrumental variable strategy described earlier. We begin by studying the effects of having a violation on facility closure and then we examine the potential channels through which violations impact closure. We attempt to disentangle supply side from demand side effects by examining the effects of different types of violations. Finally, we check the robustness of our results by using alternative instrument specifications and we study how the effects vary for different subsamples.

5.1 The Causal Effect of Violations

In Section 3.2, we report that closure rates are significantly higher among childcare facilities that have been cited with deficiencies compared to facilities without deficiencies. Now, we proceed to examine whether there is a causal effect of these violations on facility closure by using the LPA IV strategy described in Section 4. Table 3 presents the results of such analysis along with OLS regression results. Columns 1 and 2 report OLS estimates and Columns 3 and 4 report 2SLS estimates. Regressions in Columns 1 and 3 include regional office fixed effects and year fixed effects and regressions in Columns 2 and 4 add facility- and zip-code-level controls. Additionally, we present graphical representations of the relationship between our instrument, LPA stringency, and closure rates.

Figure 5 displays the relationship between LPA stringency vigintiles and raw closure rates. The figure shows that there is a positive relationship between LPA stringency and closure. Facilities inspected by stricter LPAs close at higher rates than facilities inspected by lenient LPAs.

OLS results in Columns 1 and 2 of Table 3 show that there is a positive and significant association between being cited with a violation and the probability of closing, conditional on fixed effects and controls. Estimates in Columns 1 and 2 are remarkably similar, implying that facility controls as well as zip code level socioeconomic characteristics are only weakly associated with the probability

of closing. The point estimates suggest an increase of 3.6 percentage points in the probability of closing, or one third increase compared to the average closure rate of facilities without violations.

The 2SLS estimates in Columns 3 and 4 of Table 3 make use of plausibly exogenous variation in being cited with a deficiency arising from the quasi-random assignment of LPAs to facilities. These estimates confirm that facilities that are cited with a violation are more likely to close after they get the citation compared to facilities that do not get cited. The most saturated specification in Column 4 shows that violations increase the probability of closing any time after the inspection by 4.2 percentage points (39% increase), which is a larger effect than what OLS finds. We can interpret these 2SLS estimates as the causal effect of violations (LATE) since there is a significant first-stage relationship between between our instrument (LPA stringency) and the probability of being cited with a violation, as shown by the estimates in Columns 3 and 4 in the bottom panel of Table 3.

Next, we explore the potential mechanisms through which violations drive closure. The natural first mechanism is the CDSS Licensing Division ability to force facilities to stop providing childcare services by either suspending or revoking their licenses. We are able to directly study this potential mechanism and we include probation in this mechanism because many facilities that have had their license revoked are issued a probationary license for up to a couple of years. The second row of Table 3 reports OLS and 2SLS results for suspension, revocation, and probation. OLS results in Columns 1 and 2 show that facilities cited with violations are more likely to have their license suspended or revoked compared to facilities without violations. The most saturated specification in Column 2 suggests an increase of 0.5 percentage points in the probability of license suspension or revocation. However, 2SLS estimates in Column 4 show only a marginally significant effect of approximately 0.8 percentage points. These results show that it is unlikely that closures are being forced by CDSS; hence, there must be other mechanisms through which violations are driving childcare facilities out of business.

Violations can increase costs in several ways. There could be direct monetary costs associated to violations in the form of civil penalties and costs associated to correcting a deficiency (eg. providing training to staff or hiring additional staff to comply with staff ratios). Another option is that violations can affect demand. Parents might perceive a childcare facility as low quality if the facility is cited with violations and they might respond by switching their children to a better quality facility. Unfortunately, given the nature of our data we are not able to directly explore supply side mechanisms (eg. costs), but we are able to proxy the main demand side mechanism, enrollment. Figure 6 displays the relationship between LPA stringency vigintiles and change in used capacity, our enrollment proxy metric. The figure portrays a negative relationship between LPA stringency and our enrollment proxy. While facilities inspected by lenient LPAs experienced minimal to no change in their used capacity ratio, facilities inspected by strict LPAs suffered a decrease in their used capacity ratio. The third row of Table 3 presents formal OLS and 2SLS estimates for the change in used capacity. OLS estimates in Columns 1 and 2 show that facilities with violations experience a decrease in their used capacity of approximately 2 percentage points compared to facilities without violations. 2SLS estimates in Columns 3 and 4 show that the causal effect is slightly larger, approximately 2.5 percentage points. These effects, while relatively sizable, are unlikely to fully explain the increase in closure probability. Next, we take advantage of the unique characteristics of each type of violation to provide a better assessment of potential mechanisms.

5.2 Assessing Mechanisms

The intrinsic differences between Type A and Type B deficiencies, as well as those between care-related and administrative violations, can help shed light on the potential mechanisms through which violations drive facility closure. For example, while all inspection reports must be posted in a visible place in each facility, only reports containing a Type A violation must be given to parents of all enrolled children and any new enrolled children for 12 months. Hence, we could expect Type A violations to provide a stronger signal to parents about the quality of care provided by a facility than Type B violations. Therefore, Type A violations could have larger effects on enrollment and possibly closure. Similarly, we could expect parents to care more about violations that are related to the care provided by the facility than violations related to administrative issues. We also expect the compliance cost to vary significantly by the underlying violation, with facilities getting cited for administrative violations facing the highest costs.

We begin this part of the analysis by graphically examining the relationship between the instrument for each type of violation and our main outcomes. Figure 7 displays the relationship between each instrument and closure any time after the inspection. The graph shows that this relationship is positive for Type A violations and Type B violations, with a steeper slope for Type A violations. The fitted line shows that while facilities inspected by the 10% most lenient LPAs, according to their Type A stringency tendency, have an average closure rate of approximately 11%, facilities inspected by the strictest 10% LPAs have an average closure rate of approximately 13%. The difference in closure rate between the top 10% and the bottom 10% of the Type B LPA stringency distribution is less than 1 percentage point. On the other hand, the graph shows a negative relationship for care-related violations and administrative violations. Facilities inspected by the bottom 10% LPAs of the care-related stringency distribution have an average closure rate approximately 3 percentage points higher than those inspected by the top 10% of the LPA stringency distribution. The difference in closure rate between the bottom 10% and the top 10% of the administrative violation stringency distribution is minimal, less than half a percentage point.

Table 4 presents OLS and 2SLS estimates of the effects of Type A and Type B violations. OLS results in the first row show that facilities with Type A and Type B violations are more likely to close than facilities without those violations. As expected, the largest increase in the closure probability is among facilities with Type A deficiencies, 6.9 pp versus 1.9 pp for Type B. 2SLS results show a similar story. Estimates in Column 2 of Table 4 show that the causal effect (LATE) of getting a Type A citation is 36% larger than what OLS finds. Having a Type A violation increases the probability of closing after receiving the citation by 9.4 percentage points. On the other hand, Type B citations lead to a large increase of 4.1 percentage points in the probability of closing after the inspection.

The OLS results in the second row of Table 4 show that only facilities with Type A violations are more likely to have their license suspended or revoked after being cited with a violation. However, the 2SLS estimate in Column 2 shows only a marginally significant effect of 3.5 percentage points of Type A violations on suspension or revocations after the inspection. The estimate in Column 4 confirms that there is no effect of Type B violations on suspensions or revocations. The third row of Table 4 presents the results for our enrollment proxy. Both OLS and 2SLS estimates show that facilities with violations experience a decrease in enrollment, measured as the change in their used capacity ratio, compared to facilities without violations. The causal effect is larger than what OLS finds, although only marginally significant. The effect on enrollment of Type A violations is

more than twice the effect of Type B violations (5.1 pp versus 2.2 pp). Finally, the bottom panel of Table 4 shows the existence of a strong first stage for both Type A and Type B instruments, which allows us to interpret our 2SLS estimates as the LATE of each type of violation.

Table 5 displays OLS and 2SLS estimates of the effects of care-related, administrative, and other violations. Similarly to Type A and Type B violations, OLS estimates in the first row of Table 5 show that facilities with violations of any type are more likely to close after being caught violating a rule compared to facilities without violations. Estimates show that administrative and other violations are associated with increases of over 3 percentage points in the probability of closing, while care-related violations are associated with increases of 2 percentage points in the probability of closure. 2SLS estimates show that the causal effects are significantly larger than what OLS finds for care-related and administrative violations, while there is no meaningful effect of other violations. The estimate in Column 2 shows a large effect of almost 8.6 percentage points of care-related violations on closure after the inspection. Similarly, the 2SLS estimate in Column 4 shows even larger effects of administrative violations on closure. We find that facilities with administrative violations are 21.7 percentage points more likely to close after the inspection.

The estimates in the second row of Table 5 show that the increase in closure rates induced by care-related and administrative violations is not driven by an increase in the probability of the facilities having their license suspended or revoked. Coefficients estimated by OLS regressions are only statistically significant for care-related and other violations, while all 2SLS estimates are not statistically significant. The effects of these types of violations on our enrollment proxy are less clear, as shown in the third row of Table 5. While OLS estimates show that facilities with violations are more likely to see a decrease in their used capacity ratio of at least 1 percentage point, the 2SLS estimates only show a statistically significant decrease of 4.6 percentage points for other violations. However, it is important to keep in mind that the point estimate for administrative violations is relatively large (5.5 percentage points) but imprecisely estimated. For each of these three instruments, there is also a strong first stage, as demonstrated by the estimates in the lower panel of Table 5.

While most estimates show no meaningful effect of violations on license suspension and/or revocation, we cannot rule them out as a potential mechanism of closure that could conflate with other mechanisms. We conduct additional analysis of the effect of violations on closure but we exclude from the sample facilities that had their license suspended and/or revoked after the inspection to better isolate other mechanisms such as costs and demand change. We focus on closure within one year after the inspection. Table 6 presents the results of this analysis. OLS results in Column 1 show that having a violation is associated with an increase of 1.8 percentage points in the probability of closing within one year after the inspection. Every type of violation is associated with increased closure probability, with Type A violations having the largest increase (4.2 percentage points). On the other hand, 2SLS estimates show that violations only have a marginally significant effect of 1.7 percentage points on short term closure. This increase in the probability of closing is driven only by Type A and administrative violations.

5.3 Robustness Checks

We explore the sensitivity of our main results to alternative instrument specifications. Table 7 presents the results for those alternative specifications. Column 1 uses a leave-out measure of LPA stringency that is not allowed to vary by year. Columns 2 and 3 assume that the quasi-random

assignment of LPAs happens at the office-year level instead of just office level; hence, the leave-out stringency measure is residualized of office-by-year variation. Column 2 does not allow LPA stringency to vary by year but Column 3 does. Results across all specifications are qualitatively similar to our preferred specification in Table 3. LPA stringency measures that do not vary by year produce larger point estimates, especially for closure any time after visit. Although the first stage remains relevant in all alternative specifications, they are not as strong as in our preferred specification.

6 Heterogeneity Analysis

In this section, we analyze whether the effects of violations on closure and on our enrollment proxy differ by facility type, by the city-level childcare availability classification defined in Faundez and Padi, 2025, and by demographic characteristics. We also assess the impact of violations on provider quality.

6.1 Assessing Treatment Effects by Facility Type

Table 8 presents 2SLS estimates of the effects of violations on closure and our enrollment proxy for family daycare facilities and childcare centers. It is important to note that by splitting the sample into nearly two halves, we lose statistical power, making our estimates less precise. We find that the overall effect of violations on closure does not significantly differ by facility type. While violations increase the probability of closing after the inspection by 3 percentage points among family daycare facilities, there is a not statistically significant increase of approximately 5 percentage points among childcare centers.

On the other hand, we find significant differences in the effects of most types of violation on closure. While Type B and care-related violations increase the probability of closing after the inspection among childcare centers by 6.4 and 65.6 percentage points, respectively, there is no statistically significant effect among family daycare facilities. Type A violations lead to non statistically significant increases in the probability of closing after the inspection of 7 percentage points among family daycare facilities and 10 percentage points among childcare centers. Finally, administrative violations only have statistically significant effects among family daycare facilities.

Enrollment seems to be more sensitive to violations among family daycare facilities than among childcare centers. We find that the used capacity ratio decreases by 3.5 percentage points among family daycare facilities with violations, while there is no significant effect among childcare centers. The effects of Type B violations are similar to the overall effect of violations for both types of facilities. Our results indicate that Type A violations have similar effects among both types of facilities, finding non statistically significant decreases ranging from 4 to 5 percentage points. Care-related violations seem to have a larger effect among childcare centers, 13 percentage points versus 3.6 percentage points among family daycare facilities; however, none of the coefficients is statistically significant. Finally, our estimates suggest a possible large decrease in enrollment of 88 percentage points among family daycare facilities, although the estimate is very imprecise.

Overall, family daycares seem to be most responsive to LPA stringency when administrative violations are detected, while centers have a more significant response to care-related violations. Family daycares appear to experience larger demand-side shifts due to LPA stringency, large enough to

explain much of the closure margin. These results are consistent with the business differences across facility types — family daycares have a low cost of capital because they operate out of the licensee's home, but they have limited flexibility when facing personnel or other issues.

6.2 Does City-Level Childcare Coverage Matter?

Our results in Table 9 show that, depending on the city-level childcare coverage, violations can have different effects on closure. Violations only significantly increase the probability of closing among facilities located in underserved areas. The increase is 4.7 percentage points for any type of violation and Type B violations, 7.8 percentage points for care-related violations, and 32 percentage points for administrative violations. The increases in the closure probability are usually accompanied by decreases in the used capacity ratio of at least 3.4 percentage points; however, administrative violations do not lead to significant changes in the used capacity. While the point estimates suggest increases in the probability of closing of up to 8 percentage points among facilities in adequately served areas, all coefficients are imprecisely estimated, making inference difficult.

Overall, these results suggest that for most outcomes, higher LPA stringency can make access to childcare more difficult in areas that already have low supply of childcare. The impact seems to arise from both demand- and supply-side impacts of strict licensing enforcement.

6.3 Heterogeneity in Responses by Demographics

Our data allows us to infer several demographic characteristics of the facility representative meeting with the LPA during an inspection. Based on our estimates of race, ethnicity, language, and gender, we separate the sample of inspections by these characteristics to assess whether each group is differentially impacted by assignment to a stringent LPA.

Race results are shown in Table 7. An increased probability of a violation being detected, shifted by LPA stringency, has no impact on the probability of closure when the provider is estimated to be non-white. The non-white category includes Black, Native American, Asian, and Pacific Islander, as well as "other" races. White providers have a large and significant response, with a 6.4% higher probability of closure after a violation was detected by a strict LPA. Column 4 shows that the same population experiences a 1.1% increase in suspensions and revocations, while non-white providers are unaffected. White providers also experience a 4.2% drop in enrollment. Taken together, these suggest that the both voluntary and involuntary closure resulting from a violation being detected is concentrated among white childcare providers.

The subsequent rows in Table 7 confirm that story. White providers experience an increase of nearly 17% in closure probability after a type A violation is detected, out of which 4.9% may be driven by suspension and revocation. Type A violations also decrease enrollement by 6.6%. Non-white providers do not experience any of these impacts. Type B violations shift closure and enrollment with smaller magnitudes but still significantly for white providers, but not for non-white providers. Care-related violations drive significant voluntary closures for white providers, as well as significant enrollment drops, both of which are not observed in non-white providers. Finally, administrative violations generate the largest change in probability of closure, with a 27% increase in closure for white providers. This drop appears to be driven by compliance costs, since it it not accompanied by a change in enrollment or in suspensions or revocations. Non-white providers do not respond in a statistically significant way to LPA stringency.

The differential impact of violations by hispanic ethnicity tells a more complex story, as shown in Table 7. Similar to the results on race, violations are more likely to lead to closure and drops in enrollment among non-Hispanic providers, relative to Hispanic providers. However, suspensions and revocations result from violations most often among Hispanic providers. Type A and Type B violations show similar patterns, with non-Hispanic providers being most responsive to violations. Care-related violations result in closures among all ethnicities, but the magnitude of the effect is nearly twice as large for non-Hispanic providers. For administrative violations, however, Hispanic providers seem much more likely to close and more likely to be assessed with a suspension or revocation.

To better understand the Hispanic ethnicity results and to delve deeper into how demographics can impact outcomes, we turn to the language in which the visit was conducted. The results are shown in Table 7. Most of the impacts we observe appear to be driven by inspections conducted in English, for closure, suspension/revocation, and enrollment. Non-English visits by more stringent LPAs actually lead to fewer suspensions and revocations, relative to English-speaking visits.

Finally, we study whether provider gender generates differential responses, with results shown in Table 7. The baseline results are largely driven by female providers, who comprise the vast majority of providers. However, male providers close facilities and get suspensions or revocations more often in response to a type A violation. Enrollment decreases more substantially when men are found to have a care-related violation.

Our results on demographic differences in response add nuance to previous work. Licensing has historically be utilized to exclude minority populations from lucrative professions. Our results suggest that LPA stringency does not lead to systematic exit of providers with non-white race. The results on ethnicity tell a different story — Hispanic providers do seem to experience disproportionately high suspensions and revocations after a violation is detected, and are more likely to exit after an administrative violation is found. The analysis on language suggests that the differential impacts on Hispanic providers is not driven by language barriers, since the evidence shows that non-English speakers have lower rates of escalation to suspension or revocation. Finally, we have a unique opportunity to observe how male providers are treated in an industry where they are the minority gender. Male providers are disproportionately likely to close or receive a suspension or revocation after a type A violation is detected, and appear to lose more enrollment after a care-related violation is detected. These impacts are consistent with minority providers being judged more harshly for receiving certain types of violations.

6.4 How Does LPA Stringency Impact Quality?

Although we do not observe the quality of a facility directly, we can proxy for quality based on consumer complaints. Given the relatively short time frame in our data, relatively few facilities receive any complaints. Therefore, we call a facility "low quality" if it receives one or more complaints during our time period. We then separately estimate the LPA IV regression for low and high quality facilities.

The results are shown in Table 7. Low quality facilities are much more likely to close voluntarily in response to a violation. On the other hand, high quality facilities have a significant, but economically small, increase in the probability of suspension or revocation as a result of LPA stringency. Enrollment drops as a result of violations in both high and low quality facilities, but the magnitude

of the drop is larger for low quality facilities.

We then further subdivide facilities into family daycares and centers. Centers, which tend to be larger, drive closures of low quality facilities in response to LPA stringency. Low quality family daycares, in contrast, do not close voluntarily but do experience a much higher rate of suspension and revocation. Finally, drops in enrollment are only observed at family daycares, not at centers, for both high and low quality facilities. Enrollment drops at low quality family daycares are the largest.

These results suggest that more stringent LPAs are successful in inducing closure by detecting violations in lower quality facilities. The disproportionate exit of childcare centers of lower quality in response to LPA stringency may tell a positive or a negative story. Centers are often the largest facilities, meaning that closure decreases availability most significantly. At the same time, centers are likely to maintain higher ratios of children to adults, meaning that children may not benefit significantly from access. Low quality family daycares respond less often by closing and more often by facing suspension and revocation and drops in enrollment. This is consistent with the cost of capital being lower to family daycares, who operate from the licensee's residence. LPA stringency does negatively impact high quality daycares as well, however, by decreasing enrollment. Higher LPA stringency does seem to successfully improve quality, with some spillover costs on the demand side onto high quality family daycares.

6.5 Discussion

Our results indicate that have a violation detected by licensing authorities can bring dire consequences to childcare providers. Facilities that are cited with a violation are 4 percentage points more likely to close after receiving the citation than facilities without violations. However, it seems unlikely that the increased closure probability is driven by the licensing division forcing facilities to stop providing childcare services by suspending or revoking their licenses. Rather, violations affect business profitability, mainly by decreasing enrollment. We find that facilities with violations experience a decrease in their used capacity of 2.5 percentage points compared to facilities without violations. Considering that the average facility has a capacity of 36 children and uses approximately 48% of it, our estimate implies a decrease in enrollment of 1 child. Assuming that tuition is the same for every child, our estimate implies a decrease of 5.9% in revenues for the average facility.

The childcare business is generally considered a low profit margin business. Reports suggest profit margins as low as 1%, with potentially higher margins of around 15% for larger for-profit chains (Lynch and Su, 2024). Hence, a 6% decrease in revenues could significantly reduce profits, potentially eliminating them altogether for smaller facilities operating with low margins. Additionally, considering that 60% to 70% of the costs of childcare businesses are labor costs and the rest mostly fixed costs (Grunewald and Davies, 2011), it seems unlikely that providers can decrease costs in response to the reduction in revenues as the number of required staff is highly regulated.

While the drop in revenues could be enough to drive some providers out of business, we cannot rule out that violations also increase operational costs, reducing profits even further. There could be direct costs attached to the violations in the form of civil penalties. Earlier we reported that approximately 3.7% of reports with a violation also include a civil penalty for an average amount of almost $470. We created an instrument to study the effects of civil penalties on our outcomes, but unfortunately the instrument was weak. Nevertheless, 2SLS results as well as OLS results are

reported in Appendix Table A5. The weak instrument does not allow for robust inference using 2SLS, but OLS results show that civil penalties are associated with large increases in the probability of closing of up to 10.6 percentage points, which is almost three times the coefficient of any violation and almost 55% larger than the coefficient for Type A violations. However, OLS suggest weaker associations of civil penalties with enrollment than those of Type A violations. We interpret these estimates as showing that the direct cost of civil penalties is enough to drive additional providers out of business. To have an idea of the magnitude of a potential civil penalty, we compare the average civil penalty amount to the median tuition for toddlers in California.[7] The typical civil penalty amount ranges from 25% to 62% of the median monthly tuition in a childcare center, with an average of 46%. In the case of family daycare facilities, this figure ranges from 29% to 60% of the median monthly tuition, with a mean of approximately 45%.

Although we cannot quantify the magnitude of the costs required to fix the issues that caused a violation, we can have a sense of the relative costs between different types of violations. While Type A and Type B violations differ by their severity, it is not clear that there are meaningful differences in the costs imposed by them; however, there are clear cost differences between care-related and administrative violations. On one hand, care-related violations are related to norms regarding the level of care provided by facilities. Examples of this type of violation include those involving neglect, lack of supervision, and abuse. Fixing these issues usually requires creating plans to ensure that children will be supervised at all times, including during napping time, and making sure that no items that could be dangerous to children are within their reach. Hence, the costs imposed by these violations are relatively low. On the other hand, administrative violations include issues such as obtaining criminal record clearance, record keeping, staff qualifications, and immunizations. Some of these issues can be solved inexpensively, especially if they are related solely to record keeping; however, most of these issues can bring significant costs to the provider. For example, anyone without a criminal record clearance is not allowed to provide care to children; hence, the provider must find someone already cleared to replace this person until they get the clearance or potentially adjust the enrollment to comply with staff-children ratios in case replacement is not feasible. This issue can be particularly burdensome and costly for family daycare facilities if the person requiring criminal record clearance also intends to live in the residence. Similarly, we expect that compliance with staff qualification and immunization requirements to impose significant costs on providers, thus making administrative violations significantly more costly than care-related violations. Additionally, it is easier to verify compliance with the requirements imposed by administrative violations than care-related violations.

Our results show that the effect on closure of administrative violations is 1.5 times greater than the effect of care-related violations, while there are not significant differences in their effects on enrollment. We interpret these results as mostly reflecting that the difference in costs imposed by each type of violation is driving the difference in the effect on closure. The type of violation with the highest cost of compliance leads to the greatest increase in the probability of closing. This conclusion is reinforced by analysis that excludes from the sample facilities that had their license suspended and/or revoked and focuses on the first year after being cited with a violation. Our estimate points to an increase in closure of over 15 percentage points due to administrative violation with no significant effect of care-related violations. This effect within the first year after the inspection accounts for approximately 71% of the total effect of administrative violations reported in Table 5.

[7] We use county-level annual childcare cost data for 2022 gathered by KidsData.org.

Policymakers considering the optimal stringency of licensing enforcement face some tradeoffs in deciding how hard LPAs should work to detect violations, and which types of violations LPAs should prioritize. Our results show that more stringent enforcement causes decreases in childcare supply, but that it also increases quality by encouraging low quality facilities to close. A policymaker who prioritizes an increase in childcare supply should encourage LPAs to decrease stringency, especially with respect to administrative violations which drive a large fraction of closures. In contrast, a policymaker who is focused on increasing childcare quality should require LPAs to increase stringency in care-related violations, which drive fewer closures. If a policymaker wishes to prioritize family daycares, which have lower child to adult ratios but may be less professional, LPAs should be more stringent in detecting care related violations. LPAs should also be careful in their treatment of Hispanic and/or male providers, the minority groups that bear disproportionate costs of added stringency.

7 Conclusions

Licensing violations can improve quality by enforcing state requirements for service providers, but they can impose costs that shift market equilibria. We show that an increase in stringency of licensing program analysts, which shifts the probability of a daycare being found to violate regulations, is associated with closure and lower enrollment in daycares. The results are not driven by suspension or revocation of licenses by regulatory authorities. Instead, severe violations appear to shift demand because they are disclosed to parents, worsening the reputation of the daycare, and decreasing enrollment. Severe violations also lead to some closures. Less serious violations are not as easily observed by parents, and impose fixed costs on daycare providers. The largest costs come from complying with administrative requirements, rather than care-related violations, suggesting that facilities with higher quality of care may exit if they cannot shoulder administrative burdens. Family daycares and daycares located in cities with low childcare supply are more sensitive to violations than centers or daycares in cities with competitive markets. Policymakers should consider the needs of each community when deciding how stringently to enforce licensing regulation through the violations process, since lowering the probability of a violation being found will likely increase supply.

References

Agan, A., Doleac, J. L., & Harvey, A. (2023). Misdemeanor Prosecution. *The Quarterly Journal of Economics*, *138*(3), 1453–1505.

Aizer, A., & Doyle, J. J. (2015). Juvenile Incarceration, Human Capital, and Future Crime: Evidence from Randomly Assigned Judges. *The Quarterly Journal of Economics*, *139*(2), 759–803.

Anderson, D. M., Brown, R., Charles, K. K., & Rees, D. I. (2020). Occupational Licensing and Maternal Health: Evidence from Early Midwifery Laws [Publisher: The University of Chicago Press]. *Journal of Political Economy*, *128*(11), 4337–4383. https://doi.org/10.1086/710555

Angrist, J. D., Imbens, G. W., & Rubin, D. B. (1996). Identification of Causal Effects Using Instrumental Variables. *Journal of the American Statistical Association*, *91*(434), 444–455.

Arnold, D., Dobbie, W., & Yang, C. S. (2018). Racial Bias in Bail Decisions. *The Quarterly Journal of Economics*, *133*(4), 1885–1932.

Autor, D., Kostøl, A., Mogstad, M., & Setzler, B. (2019). Disability Benefits, Consumption Insurance, and Household Labor Supply. *American Economic Review*, *109*(7), 2613–2654.

Bald, A., Chyn, E., Hastings, J., & Machelett, M. (2022). The Causal Impact of Removing Children from Abusive and Neglectful Homes. *Journal of Political Economy*, *130*(7), 1919–1962.

Belloni, A., Chen, D., Chernozhukov, V., & Hansen, C. (2012). Sparse Models and Methods for Optimal Instruments with an Application to Eminent Domain. *Econometrica*, *80*(6), 2369–2429.

Bhuller, M., Dahl, G. B., Løken, K. V., & Mogstad, M. (2020). Incarceration, Recidivism, and Employment. *Journal of Political Economy*, *128*(4), 1269–1324.

Blau, D. M. (2000). The Production of Quality in Child-Care Centers: Another Look. *Applied Developmental Science*, *4*(3), 136–148.

Blau, D. M. (2007). Unintended consequences of child care regulations. *Labour Economics*, *14*(3), 513–538.

Cameron, A. C., & Miller, D. L. (2015). A Practitioner's Guide to Cluster-Robust Inference. *Journal of Human Resources*, *50*(2), 317–372.

Center for American Progress. (2018). *America's Child Care Deserts in 2018*. https://www.americanprogress.org/article/americas-child-care-deserts-2018/

Collinson, R., Humphries, J. E., Mader, N., Reed, D., Tannenbaum, D., & van Dijk, W. (2024). Eviction and Poverty in American Cities. *The Quarterly Journal of Economics*, *139*(1), 57–120.

Dahl, G. B., Kostøl, A. R., & Mogstad, M. (2014). Family Welfare Cultures. *The Quarterly Journal of Economics*, *129*(4), 1711–1752.

Di Tella, R., & Schargrodsky, E. (2013). Criminal Recidivism after Prison and Electronic Monitoring. *Journal of Political Economy*, *121*(1), 28–73.

Dobbie, W., Goldin, J., & Yang, C. S. (2018). The Effects of Pretrial Detention on Conviction, Future Crime, and Employment: Evidence from Randomly Assigned Judges. *American Economic Review*, *108*(2), 201–240.

Dobbie, W., Goldsmith-Pinkham, P., & Yang, C. S. (2017). Consumer Bankruptcy and Financial Health. *The Review of Economics and Statistics*, *99*(5), 853–869.

Dobbie, W., & Song, J. (2015). Debt Relief and Debtor Outcomes: Measuring the Effects of Consumer Bankruptcy Protection. *American Economic Review*, *105*(3), 1272–1311.

Doyle, J. J. (2007). Child Protection and Child Outcomes: Measuring the Effects of Foster Care. *American Economic Review*, *97*(5), 1583–1610.

Doyle, J. J. (2008). Child Protection and Adult Crime: Using Investigator Assignment to Estimate Causal Effects of Foster Care. *Journal of Political Economy*, *116*(4), 746–770.

Doyle, J. J., Graves, J. A., Gruber, J., & Kleiner, S. (2012). *Do High-Cost Hospitals Deliver Better Care? Evidence from Ambulance Referral Patterns* [Working Paper no. 17936, NBER, Cambridge, MA.].

Duncan, G., Kalil, A., Mogstad, M., & Rege, M. (2023, January). Investing in early childhood development in preschool and at home [ISSN: 1574-0692]. In *Handbook of the Economics of Education* (pp. 1–91, Vol. 6). Elsevier. https://doi.org/10.1016/bs.hesedu.2022.11.005

Farronato, C., Fradkin, A., Larsen, B. J., & Brynjolfsson, E. (2024). Consumer Protection in an Online World: An Analysis of Occupational Licensing. *American Economic Journal: Applied Economics*, *16*(3), 549–579. https://doi.org/10.1257/app.20210716

Faundez, L., & Padi, M. (2025). The Missing Labor Infrastructure of Effective Industrial Policy. *New York University Law Review*, *100*, 111–160.

French, E., & Song, J. (2014). The Effect of Disability Insurance Receipt on Labor Supply. *American Economic Journal: Economic Policy*, *6*(2), 291–337.

Green, D. P., & Winik, D. (2010). Using Random Judge Assignments to Estimate the Effects of Incarceration and Probation on Recidivism among Drug Offenders. *Criminology*, *48*(2), 357–387.

Grunewald, R., & Davies, P. (2011). *Hardly child's play*. Federal Reserve Bank of Minneapolis. https://www.minneapolisfed.org/article/2011/hardly-childs-play

Heckman, J. J., & Vytlacil, E. (2005). Structural Equations, Treatment Effects, and Econometric Policy Evaluation. *Econometrica*, *73*(3), 669–738.

Hotz, V. J., & Xiao, M. (2011). The Impact of Regulations on the Supply and Quality of Care in Child Care Markets. *American Economic Review*, *101*(5), 1775–1805.

Kling, J. R. (2006). Incarceration Length, Employment, and Earnings. *American Economic Review*, *96*(3), 863–876.

Larsen, B., Ju, Z., Kapor, A., & Yu, C. (2020, December). The Effect of Occupational Licensing Stringency on the Teacher Quality Distribution. https://doi.org/10.3386/w28158

Loeffler, C. E. (2013). Does Imprisonment Alter the Life Course? Evidence on Crime and Employment from a Natural Experiment. *Criminology*, *51*(1), 137–166.

Lynch, K. E., & Su, E. (2024). *Private Equity Investments in Large For-Profit Child Care Organizations: In Brief*. Congressional Research Service. https://www.congress.gov/crs-product/R48252

Maestas, N., Mullen, K. J., & Strand, A. (2013). Does Disability Insurance Receipt Discourage Work? Using Examiner Assignment to Estimate Causal Effects of SSDI Receipt. *American Economic Review*, *103*(5), 1797–1829.

Norris, S., Pecenco, M., & Weaver, J. (2021). The Effects of Parental and Sibling Incarceration: Evidence from Ohio. *American Economic Review*, *111*(9), 2926–2963.

Sampat, B., & Williams, H. L. (2019). How Do Patents Affect Follow-On Innovation? Evidence from the Human Genome. *American Economic Review*, *109*(1), 203–236.

Stevenson, M. T. (2018). Distortion of Justice: How the Inability to Pay Bail Affects Case Outcomes. *The Journal of Law, Economics, and Organization*, *34*(4), 511–542.

Figures and Tables

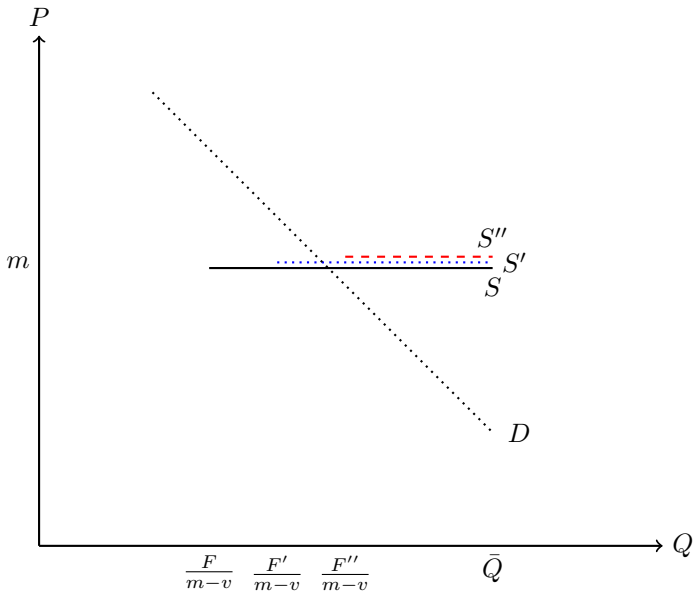


Figure 1: Shift in Supply Due to Fixed Cost

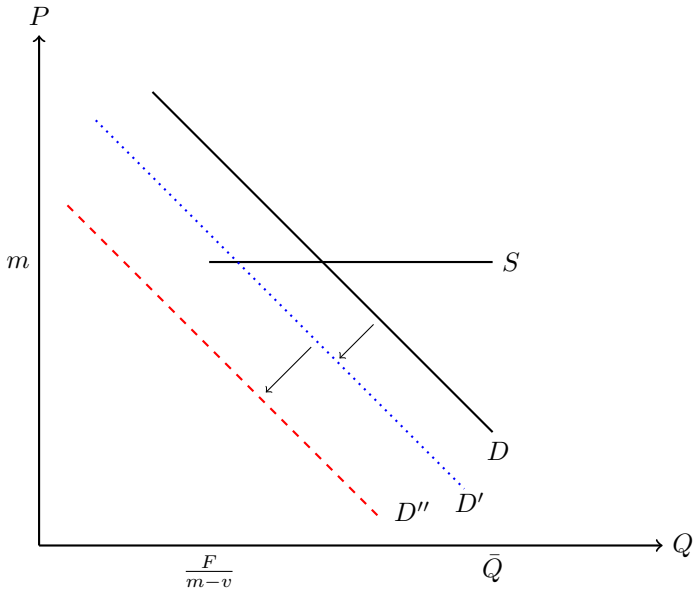


Figure 2: Shift in Demand

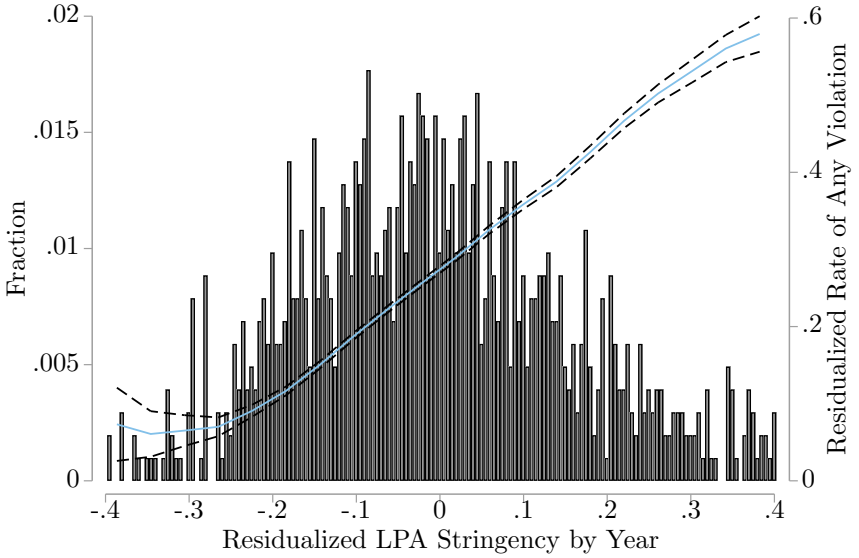


Figure 3: Distribution of LPA Stringency Measure and First Stage

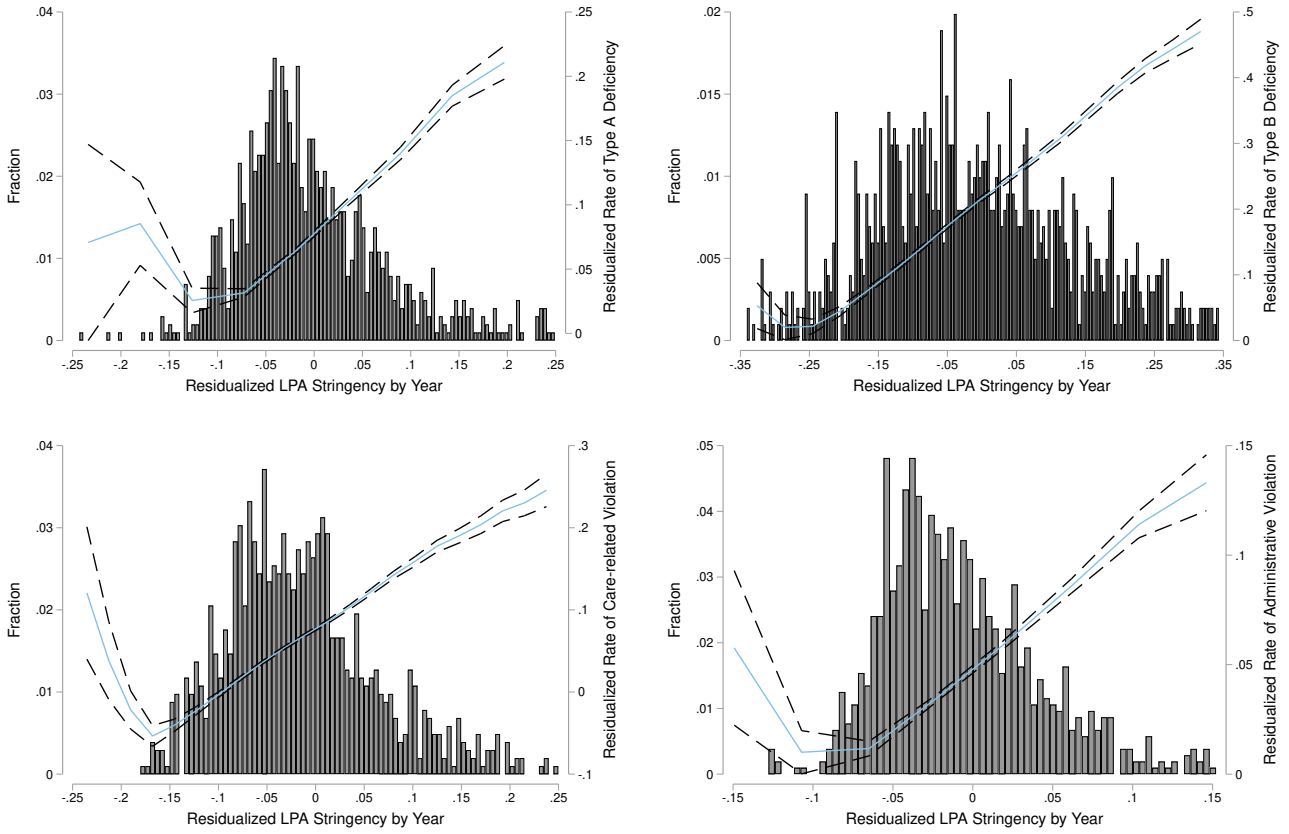


Figure 4: Distribution of LPA Stringency Measures and First Stages

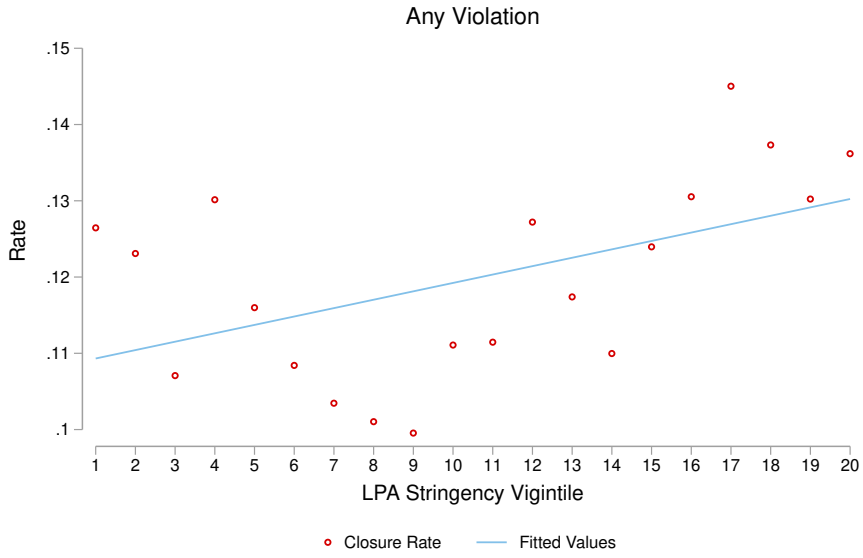


Figure 5: Closure Any Time after Inspection Rate by LPA Stringency Vigintile

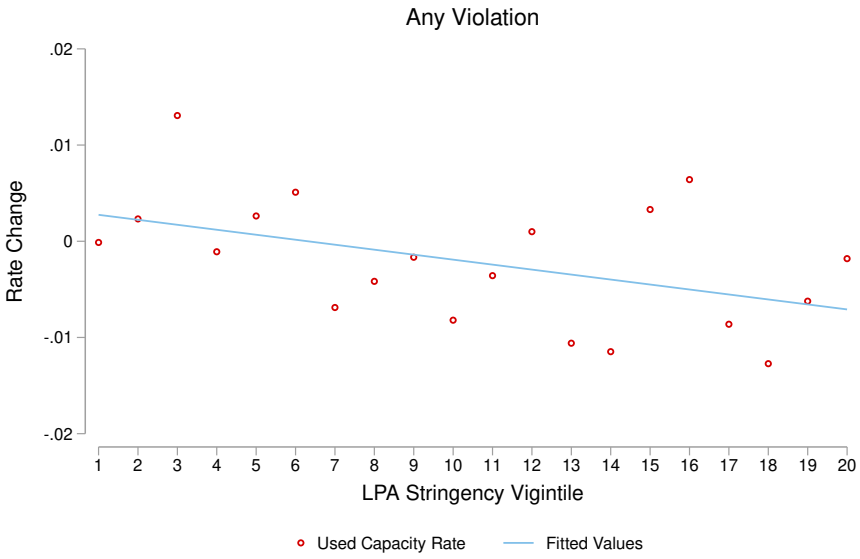


Figure 6: Change in Used Capacity by LPA Stringency Vigintile

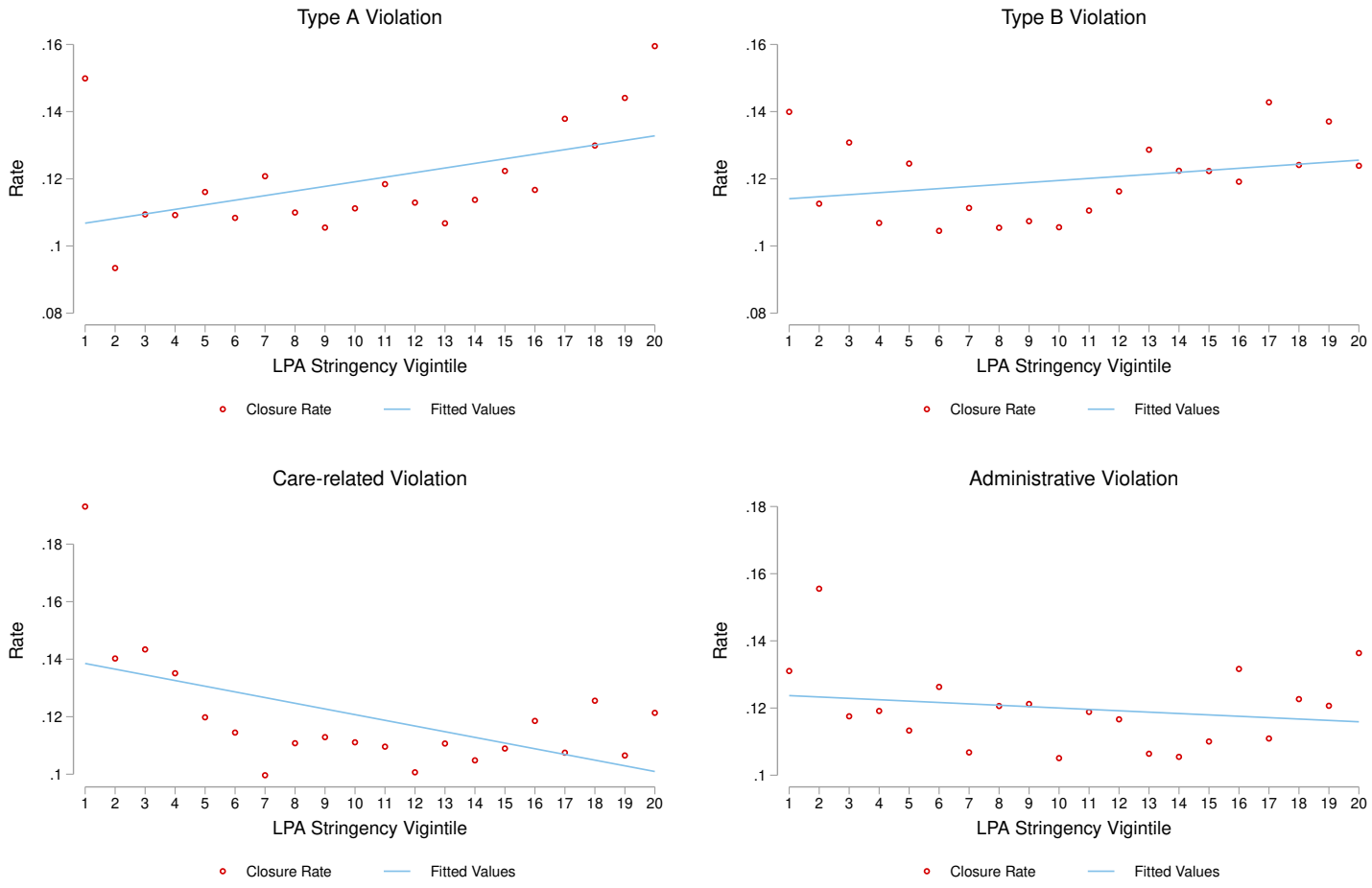


Figure 7: Closure Any Time after Inspection Rate by LPA Stringency Vigintile

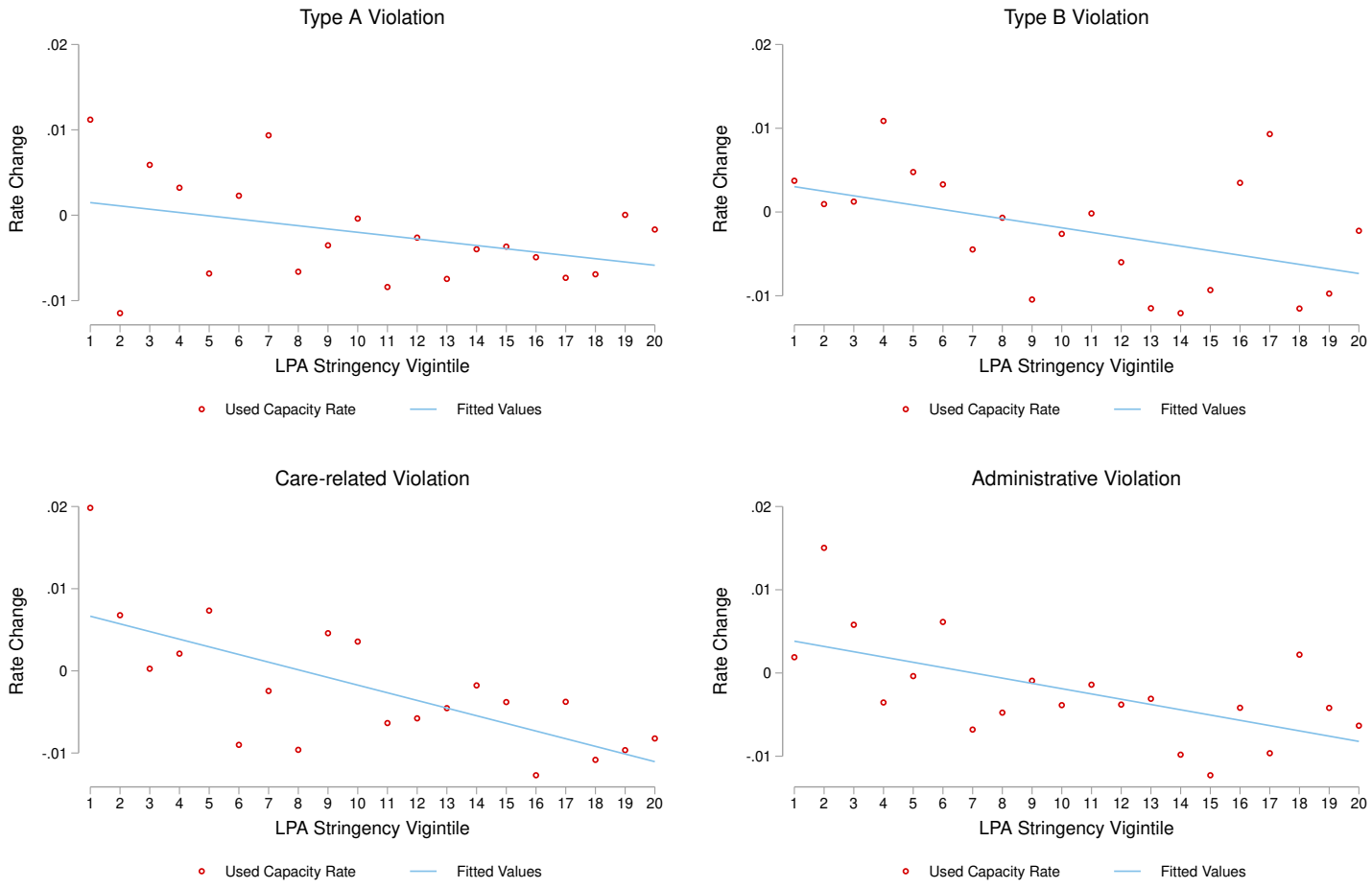


Figure 8: Change in Used Capacity by LPA Stringency Vigintile

Table 1: Descriptive Statistics

	No Violation	Any Violation	Type A	Type B	Care-related	Administrative
Panel A: Violation Type & Civil Penalties						
Type A Violation	-	0.308	1	0.138	0.328	0.359
Type B Violation	-	0.802	0.359	1	0.852	0.783
Care-related Violation	-	0.321	0.343	0.342	1	0.0837
Administrative Violation	-	0.194	0.226	0.189	0.0504	1
Civil Penalty Issued	-	0.0366	0.101	0.0198	0.0174	0.0170
Penalty Amount ($)	-	468.3	487.6	412.2	379.1	404.8
Panel B: Outcomes						
Closure within 1 Year	0.0457	0.0670*	0.0968*	0.0585*	0.0643*	0.0663*
Closure after Visit	0.108	0.148*	0.193*	0.135*	0.128*	0.148*
Suspension/Revocation/Probation within 1 Year	0.00209	0.00796*	0.0169*	0.00527*	0.00767*	0.00347
Suspension/Revocation/Probation after Visit	0.00390	0.0130*	0.0275*	0.00899*	0.0125*	0.00655
Change in Used Capacity	0.00484	-0.0182*	-0.0420*	-0.0142*	-0.0239*	-0.0116*
Panel C: Facility Characteristics						
Used Capacity	0.477	0.495*	0.530*	0.488	0.492*	0.494*
Capacity	36.1	35.8	39.2*	33.5*	19.0*	58.9*
Total Reports	4.7	5.7*	7.1*	5.2*	4.5*	7.0*
Years Operating	12.9	12.4*	11.9*	12.5*	11.0*	15.0*
Family Daycare	0.501	0.508	0.480*	0.536*	0.830*	0.0609*
Panel D: Demographic Characteristics						
White	0.659	0.661	0.668	0.653*	0.610*	0.714*
Non-White	0.341	0.339	0.332	0.347*	0.390*	0.286*
Hispanic	0.395	0.398	0.395	0.407*	0.448*	0.327*
Female	0.946	0.942*	0.938*	0.943	0.947	0.931*
Male	0.0539	0.0581*	0.0619*	0.0565	0.0525	0.0694*
English Speaker	0.924	0.907*	0.911*	0.898*	0.855*	0.975*
Non-English Speaker	0.0761	0.0933*	0.0888*	0.102*	0.145*	0.0254*
Spanish Speaker	0.0520	0.0608*	0.0529	0.0682*	0.0977*	0.0120*
Observations	61760	26744	8243	21461	8607	5188

* Mean is statistically different from mean of reports without this type of violation at the 95% confidence.

Table 2: Randomization Test

	(1) Any Violation	(2) LPA Stringency
Infant Center	0.0300**	-0.000463
	(0.00959)	(0.00545)
School Age	-0.0622***	-0.00565
	(0.0103)	(0.00634)
Ill Center	-0.338***	-0.0609
	(0.0311)	(0.0416)
Daycare Center	-0.0133	-0.00755
	(0.00850)	(0.00524)
Single Licensed Childcare	0.123*	0.0387
	(0.0623)	(0.0333)
Capacity	0.0000662	0.00000671
	(0.0000675)	(0.0000411)
Years Operating	-0.000790***	0.000187
	(0.000213)	(0.000104)
Multiple LPAs	0.118***	0.00339
	(0.00989)	(0.00598)
LPM	0.193***	0.00692
	(0.0169)	(0.0101)
RM	0.0325	-0.000985
	(0.0211)	(0.00908)
Observations	88490	88433
Joint F-test	[0.0000]	[0.158]

Each column reports reduced form results testing the random assignment of LPAs to facilities. Column 1 shows estimates from an OLS regression of being cited with a violation on the variables listed plus regional office fixed effects and year fixed effects. Column 2 shows estimates from an OLS regression of the LPA stringency on the variables listed plus regional office fixed effects and year fixed effects. Standard errors two-way clustered at the facility and LPA level are reported in parentheses. Row Joint F-test reports the p-value of an F-test of joint significance of the variables listed in the rows above.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: OLS and 2SLS Results for Effects of Any Violation

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Closure	0.0366***	0.0360***	0.0335*	0.0424**
	(0.00354)	(0.00321)	(0.0180)	(0.0171)
Suspension/Revocation/Probation	0.00799***	0.00531***	0.0118***	0.00796*
	(0.00124)	(0.00102)	(0.00455)	(0.00448)
Change in Used Capacity	-0.0223***	-0.0205***	-0.0285***	-0.0250**
	(0.00194)	(0.00194)	(0.0105)	(0.0106)
First Stage				
LPA Stringency			0.790***	0.773***
			(0.0140)	(0.0141)
F			3178.87	3005.73
Regional Office FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	88490	88490	88433	88433

Each coefficient is from a different OLS or 2SLS regression. The dependent variable is listed in each row. First stage results, including F statistics, are provided for 2SLS regressions. Standard errors two-way clustered at the facility and LPA level are reported in parentheses. Regressions for change in used capacity include 723 fewer observations and additional controls for time of visit and use of imputed values.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 4: OLS and 2SLS Results for Effects of Each Type of Violation Cited

	Type A		Type B	
	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)
Closure	0.0685***	0.0937*	0.0191***	0.0413**
	(0.00586)	(0.0516)	(0.00324)	(0.0187)
Suspension/Revocation/Probation	0.0157***	0.0348*	0.00120	0.00533
	(0.00273)	(0.0201)	(0.000922)	(0.00478)
Change in Used Capacity	-0.0421***	-0.0513*	-0.0129***	-0.0224*
	(0.00309)	(0.0283)	(0.00206)	(0.0116)
First Stage				
LPA Stringency		0.524***		0.772***
		(0.0302)		(0.0161)
F		300.76		2293.09
Regional Office FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes
Observations	88490	88433	88490	88433

Each coefficient is from a different OLS or 2SLS regression. The dependent variable is listed in each row. First stage results, including F statistics, are provided for 2SLS regressions. Standard errors two-way clustered at the facility and LPA level are reported in parentheses. Regressions for change in used capacity include 723 fewer observations and additional controls for time of visit and use of imputed values.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 5: OLS and 2SLS Results for Effects of Underlying Violation Cited

	Care-related		Administrative		Other	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Closure	0.0206***	0.0857**	0.0306***	0.217***	0.0331***	0.0358
	(0.00437)	(0.0421)	(0.00633)	(0.0975)	(0.00371)	(0.0328)
Suspension/Revocation/Probation	0.00387***	0.000979	-0.00114	0.0420	0.00661***	0.0155
	(0.00139)	(0.0101)	(0.00150)	(0.0267)	(0.00151)	(0.0108)
Change in Used Capacity	-0.0173***	-0.0372	-0.0125***	-0.0546	-0.0174***	-0.0458**
	(0.00310)	(0.0273)	(0.00325)	(0.0537)	(0.00234)	(0.0188)
First Stage						
LPA Stringency		0.653***		0.380***		0.615***
		(0.0284)		(0.0294)		(0.0226)
F		527.28		167.52		743.06
Regional Office FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88490	88433	88490	88433	88490	88433

Each coefficient is from a different OLS or 2SLS regression. The dependent variable is listed in each row. First stage results, including F statistics, are provided for 2SLS regressions. Standard errors two-way clustered at the facility and LPA level are reported in parentheses. Regressions for change in used capacity include 723 fewer observations and additional controls for time of visit and use of imputed values.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 6: OLS and 2SLS Results for Effects on Closure within 1 Year

	(1) OLS	(2) 2SLS
Any Violation	0.0184***	0.0169*
	(0.00200)	(0.00968)
Type A	0.0415***	0.0639**
	(0.00413)	(0.0302)
Type B	0.00723***	0.0119
	(0.00186)	(0.0104)
Care-related Violation	0.0136***	0.0259
	(0.00299)	(0.0235)
Administrative Violation	0.0156***	0.154**
	(0.00382)	(0.0642)
Other Violations	0.0151***	0.00734
	(0.00245)	(0.0193)
Regional Office FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
Observations	88148	88091

Each coefficient is from a different OLS or 2SLS regression. The independent variable is listed in each row. Standard errors two-way clustered at the facility and LPA level are reported in parentheses. All regressions exclude observations for facilities that has their license suspended or revoked within 1 year after the inspection.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 7: Robustness Checks for Closure

	(1)	(2)	(3)
Second Stage for Closure			
Any Time after Visit	0.0618***	0.0628***	0.0445**
	(0.0204)	(0.0207)	(0.0177)
Within 1 Year	0.0265**	0.0267**	0.0205**
	(0.0107)	(0.0107)	(0.00988)
First Stage			
LPA Stringency	0.641***	0.671***	0.763***
	(0.137)	(0.129)	(0.0151)
F	21.82	27.21	2555.59
Regional Office FE	Yes	No	No
Year FE	Yes	No	No
Regional Office by Year FE	No	Yes	Yes
Controls	Yes	Yes	Yes
Yearly Stringency	No	No	Yes
Observations	88488	88488	88433

Each coefficient is from a different 2SLS regression. The dependent variable is listed in each row. First stage results, including F statistics are provided. Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 8: 2SLS Results by Facility Type

	Closure		Change in Used Capacity	
	Family Daycare	Childcare Center	Family Daycare	Childcare Center
	(1)	(2)	(3)	(4)
Any Violation	0.0298*	0.0520	-0.0351**	-0.0129
	(0.0157)	(0.0324)	(0.0141)	(0.0147)
Type A Violation	0.0733	0.105	-0.0547	-0.0455
	(0.0509)	(0.0922)	(0.0401)	(0.0374)
Type B Violation	0.0222	0.0641*	-0.0353**	-0.00651
	(0.0166)	(0.0380)	(0.0152)	(0.0166)
Care-related Violation	0.0324	0.656*	-0.0364	-0.137
	(0.0232)	(0.343)	(0.0255)	(0.135)
Administrative Violation	2.417*	0.107	-0.882	-0.0189
	(1.259)	(0.0930)	(0.822)	(0.0437)
Observations	44484	43949	44204	43509

Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 9: 2SLS Results by City-Level Childcare Coverage

	Closure		Change in Used Capacity	
	Underserved	Adequately Served	Underserved	Adequately Served
	(1)	(2)	(3)	(4)
Any Violation	0.0473**	0.0253	-0.0340**	-0.0138
	(0.0224)	(0.0250)	(0.0142)	(0.0153)
Type A Violation	0.0810	0.0829	-0.0544	-0.0378
	(0.0718)	(0.0735)	(0.0430)	(0.0365)
Type B Violation	0.0469**	0.0236	-0.0357**	-0.00595
	(0.0231)	(0.0275)	(0.0155)	(0.0168)
Care-related Violation	0.0782*	0.0777	-0.0544	-0.0108
	(0.0455)	(0.0665)	(0.0407)	(0.0280)
Administrative Violation	0.324**	0.0848	-0.00239	-0.0969
	(0.141)	(0.125)	(0.0688)	(0.0863)
Observations	48628	39794	48176	39528

Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 10: 2SLS Results by Providers Race

	Closure after Visit		Suspension/Revocation		Change in Used Capacity	
	Non-White	White	Non-White	White	Non-White	White
	(1)	(2)	(3)	(4)	(5)	(6)
Any Violation	0.00547	0.0636***	0.00165	0.0114*	-0.00263	-0.0417***
	(0.0188)	(0.0238)	(0.00619)	(0.00584)	(0.0149)	(0.0133)
Type A Violation	-0.0365	0.168**	0.00375	0.0489*	-0.0439	-0.0655*
	(0.0670)	(0.0662)	(0.0262)	(0.0255)	(0.0406)	(0.0360)
Type B Violation	0.00594	0.0600**	-0.000598	0.00889	0.00497	-0.0417***
	(0.0201)	(0.0265)	(0.00626)	(0.00626)	(0.0163)	(0.0148)
Care-related Violation	0.0133	0.142**	-0.00523	0.00620	0.0119	-0.0783*
	(0.0350)	(0.0667)	(0.0105)	(0.0152)	(0.0280)	(0.0415)
Administrative Violation	0.0732	0.269**	0.0142	0.0524	0.0240	-0.0945
	(0.132)	(0.127)	(0.0318)	(0.0328)	(0.0986)	(0.0600)
Observations	30113	58302	30113	58302	30027	57668

Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 11: 2SLS Results by Providers Ethnicity

	Closure after Visit		Suspension/Revocation		Change in Used Capacity	
	Non-Hispanic	Hispanic	Non-Hispanic	Hispanic	Non-Hispanic	Hispanic
	(1)	(2)	(3)	(4)	(5)	(6)
Any Violation	0.0531**	0.0383	0.00266	0.0137**	-0.0282**	-0.0243
	(0.0210)	(0.0244)	(0.00630)	(0.00567)	(0.0118)	(0.0169)
Type A Violation	0.117*	0.105	0.0320	0.0378	-0.0737**	-0.0285
	(0.0679)	(0.0713)	(0.0317)	(0.0235)	(0.0327)	(0.0440)
Type B Violation	0.0534**	0.0350	0.000392	0.00984	-0.0211	-0.0285
	(0.0236)	(0.0247)	(0.00642)	(0.00609)	(0.0132)	(0.0188)
Care-related Violation	0.123*	0.0692*	0.00131	-0.000740	-0.0426	-0.0308
	(0.0634)	(0.0403)	(0.0195)	(0.0120)	(0.0293)	(0.0455)
Administrative Violation	0.0736	0.521**	0.00314	0.114**	-0.0682	-0.0334
	(0.105)	(0.203)	(0.0300)	(0.0546)	(0.0551)	(0.103)
Observations	53418	34997	53418	34997	52987	34708

Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 12: 2SLS Results by Visit Language

	Closure after Visit			Suspension/Revocation			Change in Used Capacity		
	English	Non-English	Spanish	English	Non-English	Spanish	English	Non-English	Spanish
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Any Violation	0.0417**	0.0422	-0.0105	0.0107**	-0.0274**	-0.00738	-0.0263**	-0.0362	-0.0287
	(0.0184)	(0.0394)	(0.0362)	(0.00482)	(0.0124)	(0.0126)	(0.0111)	(0.0249)	(0.0294)
Type A Violation	0.109*	-0.0247	0.00196	0.0435**	-0.0210	0.0465	-0.0595*	-0.0543	0.00487
	(0.0557)	(0.113)	(0.104)	(0.0207)	(0.0409)	(0.0429)	(0.0303)	(0.0816)	(0.0821)
Type B Violation	0.0372*	0.0616	-0.0254	0.00872*	-0.0390**	-0.0219	-0.0222*	-0.0443*	-0.0393
	(0.0200)	(0.0402)	(0.0349)	(0.00528)	(0.0155)	(0.0149)	(0.0123)	(0.0267)	(0.0323)
Care-related Violation	0.0874*	0.0335	-0.0171	0.00655	-0.0557**	-0.0161	-0.0409	-0.0356	-0.0347
	(0.0483)	(0.0685)	(0.0498)	(0.0110)	(0.0281)	(0.0228)	(0.0316)	(0.0419)	(0.0481)
Administrative Violation	0.170*	1.651*	1.175	0.0367	0.0473	0.345	-0.0649	-0.0455	-0.500
	(0.0964)	(0.854)	(0.932)	(0.0270)	(0.215)	(0.387)	(0.0544)	(0.336)	(0.604)
Observations	81236	7197	4839	81236	7197	4839	80589	7124	4773

Standard errors two-way clustered at the facility and LPA level are reported in parentheses.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table 13: 2SLS Results by Gender

	Closure after Visit		Suspension/Revocation		Change in Used Capacity	
	Male	Female	Male	Female	Male	Female
	(1)	(2)	(3)	(4)	(5)	(6)
Any Violation	0.0304	0.0437**	0.0203	0.00834*	-0.0469	-0.0277**
	(0.0502)	(0.0190)	(0.0155)	(0.00464)	(0.0314)	(0.0115)
Type A Violation	0.380**	0.0748	0.127**	0.0325	-0.141	-0.0539*
	(0.183)	(0.0575)	(0.0640)	(0.0221)	(0.0937)	(0.0313)
Type B Violation	0.00121	0.0429**	0.00376	0.00672	-0.0446	-0.0266**
	(0.0519)	(0.0206)	(0.0153)	(0.00489)	(0.0338)	(0.0127)
Care-related Violation	-0.0509	0.0866*	-0.00818	0.00640	-0.0999*	-0.0422
	(0.106)	(0.0447)	(0.0226)	(0.0108)	(0.0539)	(0.0301)
Administrative Violation	0.128	0.238**	0.0685	0.0372	-0.164	-0.0550
	(0.265)	(0.106)	(0.0807)	(0.0277)	(0.193)	(0.0571)
Observations	4398	75364	4398	75364	4373	74693

Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 14: 2SLS Results by Facility Quality Level

	(1) Lower Quality	(2) Higher Quality
Closure after Visit	0.0696*	0.0156
	(0.0360)	(0.0137)
Suspension/Revocation	0.0142	0.00315**
	(0.0104)	(0.00155)
Change in Used Capacity	-0.0385*	-0.0181*
	(0.0204)	(0.0110)
Observations	35542	52433

Each coefficient is from a different 2SLS regression. The dependent variable is listed in each row. The number of complaints is used as a quality proxy. Lower quality includes facilities with 1 or more complaints. Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

Table 15: 2SLS Results by Facility Type and Quality Level

	Family Daycare		Childcare Center	
	Lower	Higher	Lower	Higher
Closure after Visit	0.0292	0.0179	0.0923*	0.00317
	(0.0465)	(0.0153)	(0.0488)	(0.0270)
Suspension/Revocation	0.0369*	0.00316	-0.00182	0.00275
	(0.0214)	(0.00209)	(0.00907)	(0.00215)
Change in Used Capacity	-0.0827**	-0.0203*	-0.00936	-0.00958
	(0.0415)	(0.0115)	(0.0185)	(0.0204)
Observations	12511	31771	23031	20662

Each coefficient is from a different 2SLS regression. The dependent variable is listed in each row. The number of complaints is used as a quality proxy. Lower quality includes facilities with 1 or more complaints. Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$

A Appendix

Table A1: Descriptive Statistics by Type of Facility

	Family Daycare	Childcare Center	Difference
Panel A: Violations & Civil Penalties			
Any Violation	0.305	0.299	-0.00564
Type A Violation	0.0888	0.0975	0.00876*
Type B Violation	0.258	0.226	-0.0322*
Care-related Violation	0.161	0.0332	-0.127*
Administrative Violation	0.00710	0.111	0.104*
Civil Penalty Issued	0.0108	0.0142	0.00336*
Penalty Amount	451.7	533.7	82.03*
Panel B: Outcomes			
Closure within 1 Year	0.0525	0.0518	-0.000737
Closure after Visit	0.118	0.122	0.00349
Suspension/Revocation/Probation within 1 Year	0.00526	0.00246	-0.00280*
Suspension/Revocation/Probation after Visit	0.00896	0.00432	-0.00464*
Change in Used Capacity	-0.00717	0.00299	0.0102*
Panel C: Facility Characteristics			
Used Capacity	0.476	0.489	0.0131*
Capacity	11.84	60.42	48.57*
Total Reports	3.8	6.2	2.5*
Years Operating	9.7	15.9	6.1*
Observations	44524	43980	88504

* Difference is statistically different from zero at the 95% confidence.

Table A2: Descriptive Statistics by City-Level Childcare Coverage

	Underserved	Adequately Served	Difference
Panel A: Violations & Civil Penalties			
Type A Violation	0.0909	0.0959	-0.00501*
Type B Violation	0.254	0.228	0.0261*
Care-related Violation	0.105	0.0876	0.0176*
Administrative Violation	0.0578	0.0596	-0.00187
Civil Penalty Issued	0.0128	0.0121	0.000765
Penalty Amount	490.5	506.6	-16.06
Panel B: Outcomes			
Closure within 1 Year	0.0488	0.0563	-0.00753*
Closure after Visit	0.112	0.130	-0.0185*
Suspension/Revocation/Probation within 1 Year	0.00394	0.00377	0.000178
Suspension/Revocation/Probation after Visit	0.00694	0.00630	0.000641
Change in Used Capacity	-0.00302	-0.00107	-0.00195
Panel C: Facility Characteristics			
Used Capacity	0.471	0.497	-0.0266*
Capacity	32.86	39.80	-6.943*
Total Reports	4.995	4.994	0.00159
Years Operating	12.81	12.75	0.0669
Family Daycare	0.524	0.478	0.0465*
Observations	48674	39819	88493

* Difference is statistically different from zero at the 95% confidence.

Table A3: First Stage Results by Selected Facility Characteristics

	Facility Type		Years Operating		Zip Code Income	
	Family Daycare	Childcare Center	Below Median	Above Median	Below Median	Above Median
	(1)	(2)	(3)	(4)	(5)	(6)
LPA Stringency	0.841***	0.687***	0.784***	0.760***	0.771***	0.771***
	(0.0191)	(0.0232)	(0.0195)	(0.0208)	(0.0200)	(0.0205)
	[0.305]	[0.299]	[0.310]	[0.294]	[0.310]	[0.295]
Regional Office FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
N	44484	43949	44750	43683	44236	44197

Standard errors two-way clustered at the facility and LPA level are reported in parentheses. The mean of the dependent variable is reported in brackets.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table A4: First Stage Results by Facility Quality Level

	Quality Level	
	Lower	Higher
	(1)	(2)
LPA Stringency	0.603***	0.882***
	(0.0233)	(0.0148)
	[0.381]	[0.247]
Regional Office FE	Yes	Yes
Year FE	Yes	Yes
Controls	Yes	Yes
N	35542	52433

Standard errors two-way clustered at the facility and LPA level are reported in parentheses. The mean of the dependent variable is reported in brackets.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table A5: OLS and 2SLS Results for Effects of Civil Penalty

	(1) OLS	(2) OLS	(3) 2SLS	(4) 2SLS
Closure	0.109***	0.106***	-0.0790	-0.100
	(0.0162)	(0.0143)	(0.437)	(0.449)
Suspension/Revocation/Probation	0.0271***	0.0193***	-0.133	-0.156
	(0.00781)	(0.00681)	(0.0938)	(0.0979)
Change in Used Capacity	-0.0417***	-0.0388***	-0.177	-0.177
	(0.00808)	(0.00805)	(0.175)	(0.180)
First Stage				
LPA Stringency			0.231**	0.225**
			(0.0992)	(0.0976)
F			5.43	5.33
Regional Office FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Controls	No	Yes	No	Yes
Observations	88490	88490	88433	88433

Each coefficient is from a different OLS or 2SLS regression. The dependent variable is listed in each row. First stage results, including F statistics, are provided for 2SLS regressions. Standard errors two-way clustered at the facility and LPA level are reported in parentheses. Regressions for change in used capacity include 723 fewer observations and additional controls for time of visit and use of imputed values.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table A6: OLS and 2SLS Results for Effects of Underlying Type B Violation Cited

	Care-related		Administrative		Other	
	OLS	2SLS	OLS	2SLS	OLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Closure	0.00667	0.0795*	0.0244***	0.228**	0.0203***	0.0272
	(0.00449)	(0.0409)	(0.00720)	(0.108)	(0.00384)	(0.0364)
Suspension/Revocation/Probation	0.000102	-0.00285	-0.00231	0.0278	0.00275**	0.0131
	(0.00131)	(0.0111)	(0.00157)	(0.0289)	(0.00130)	(0.0104)
Change in Used Capacity	-0.0158***	-0.0378	-0.0106***	-0.0708	-0.00833***	-0.0306
	(0.00345)	(0.0290)	(0.00364)	(0.0585)	(0.00241)	(0.0223)
First Stage						
LPA Stringency		0.682***		0.405***		0.627***
		(0.0254)		(0.0324)		(0.0246)
F		721.25		155.57		648.31
Regional Office FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Observations	88490	88433	88490	88433	88490	88433

Each coefficient is from a different OLS or 2SLS regression. The dependent variable is listed in each row. First stage results, including F statistics, are provided for 2SLS regressions. Standard errors two-way clustered at the facility and LPA level are reported in parentheses. Regressions for change in used capacity include 723 fewer observations and additional controls for time of visit and use of imputed values.

* $p < .1$, ** $p < .05$, *** $p < .01$

Table A7: 2SLS Results by Meeting Language for Hispanics

	Closure after Visit		Suspension/Revocation		Change in Used Capacity	
	Non-Spanish	Spanish	Non-Spanish	Spanish	Non-Spanish	Spanish
	(1)	(2)	(3)	(4)	(5)	(6)
Any Violation	0.0449	0.00405	0.0165**	-0.00422	-0.0189	-0.0472
	(0.0281)	(0.0352)	(0.00670)	(0.0131)	(0.0172)	(0.0292)
Type A Violation	0.128	0.00960	0.0383	0.0563	-0.0279	-0.0465
	(0.0824)	(0.115)	(0.0254)	(0.0463)	(0.0457)	(0.0884)
Type B Violation	0.0434	-0.0112	0.0143*	-0.0173	-0.0204	-0.0576*
	(0.0290)	(0.0340)	(0.00736)	(0.0171)	(0.0195)	(0.0320)
Care-related Violation	0.101*	-0.0170	0.00202	-0.0204	-0.0167	-0.0699
	(0.0538)	(0.0522)	(0.0140)	(0.0263)	(0.0537)	(0.0442)
Administrative Violation	0.464**	1.663	0.110**	0.536	-0.0114	-1.120
	(0.209)	(1.248)	(0.0558)	(0.566)	(0.103)	(0.777)
Observations	30969	4028	30969	4028	30727	3981

Standard errors two-way clustered at the facility and LPA level are reported in parentheses.
* $p < .1$, ** $p < .05$, *** $p < .01$