AERA Open
October-December 2019, Vol. 5, No. 4, pp. 1–19
DOI: 10.1177/2332858419884540
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Child Care Subsidy Use and Children's Outcomes in Middle School

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This article examines associations between child care subsidy use in early childhood and children's middle school outcomes. Using a unique database linking administrative records of child care subsidy receipt with parental earnings, social assistance data, and students' public school outcomes, we generate quasi-experimental estimates of subsidy effects on children's reading and math test scores and school absences in third through eighth grades. Findings suggest that subsidies are associated with reduced absenteeism in seventh and eighth grades and with increased reading and math scores in third grade, but only for the subset of children whose subsidies were used to attend licensed center- or home-based care. Results provide initial evidence for longer term impacts of the child care subsidy program on children's school performance.

Keywords: *child care subsidies, middle school outcomes, low-income, quasi-experiment*

The federal child care subsidy program, the Child Care and Development Fund (CCDF; henceforth referred to as "child care subsidies"), is the largest public investment in early care and education for low-income children in the United States. In fiscal year (FY) 2015, federal and state governments spent nearly $8.5 billion on child care subsidies, serving approximately 1.5 million children each month (Office of Child Care, 2016, 2017). These figures are comparable to the $8.3 and $6.2 billion spent on the federal Head Start program and state-funded public pre-K in 2015, respectively (Barnett et al., 2015; Office of Head Start, 2015).

Despite the child care subsidy program's potential to affect millions of low-income children every month, the majority of published studies on the topic have focused on maternal employment outcomes rather than effects on children, possibly because the subsidy program was designed primarily to promote parental employment alongside the historic welfare reform legislation of 1996. Thus, the bulk of research evaluating the U.S. child care subsidy program has explored its potential to increase maternal employment, raise mothers' earnings, and/or reduce welfare participation (e.g., Blau & Tekin, 2007; Ha & Miller, 2015; Herbst & Tekin, 2011; Witte & Queralt, 2003; Zanoni & Weinberger, 2015).

Over the past decade, however, researchers have increasingly turned their attention to assessing direct impacts of subsidy receipt on children. This growing literature—nearly all of which has examined short-term effects of subsidies on child outcomes—has produced mixed conclusions: Some studies find negative or null impacts of subsidies on children's kindergarten skills (Hawkinson, Griffen, Dong, & Maynard, 2013; Johnson, Martin, & Brooks-Gunn, 2013), while others find negative effects of subsidies on children's kindergarten test scores (Herbst & Tekin, 2010a, 2010b) that fade out during first grade (Herbst & Tekin, 2016). Of the studies that have examined direct links from child care subsidies to children's outcomes, only one extended explorations to outcomes beyond kindergarten (to fifth grade; Herbst & Tekin, 2016). From a policy perspective, this is a glaring gap in the literature. Without knowing whether the nation's largest source of funding for low-income children's early care and education is contributing to positive, negative, or neutral longer term school outcomes, it is impossible to assess the full potential impact of such a substantial public investment.

Additionally, much of the subsidy literature—including recent evaluations (see Bernal & Keane, 2011; Fort, Ichino, & Zanella, 2016)—has focused disproportionately on cognitive test score outcomes, with few studies considering behavioral skills (e.g., Herbst & Tekin, 2016) despite the possibility that subsidy receipt would have positive effects on a range of later outcomes, from test scores to behavioral indicators. This hypothesis is grounded in the well-established literature that generally finds small to modest longer term effects of early childhood participation in Head Start (Deming, 2009; Gibbs, Ludwig, & Miller, 2011; Ludwig & Miller, 2007) and state pre-K (Gormley, Phillips, & Anderson, 2018; Hill, Gormley, & Adelstein, 2015) on cognitive and "noncognitive" outcomes, such as grade retention and enrollment in honors courses. In many cases, while the gains from program participation fade out by early elementary school, some "sleeper effects" of benefits primarily linked to gains in noncognitive skills resurface later in life (Barnett, Lamy, & Jung, 2005; Currie & Thomas, 1995; Garces, Thomas, & Currie, 2002; Heckman, Moon, Pinto, Savelyev, & Yavitz, 2010; Hustedt, Barnett, Jung, & Figueras-Daniel, 2009; Ludwig & Miller, 2007). If subsidies permit access to care that is on par with the care provided in Head Start and public pre-K, we might reasonably expect to see similar longer term effects of subsidies despite few, if any, positive short-term effects.

However, existing research comparing subsidized care to Head Start and pre-K suggests this is not the case: Head Start and public pre-K programs are consistently higher in quality than the "business as usual" care provided in community-based and home-based settings used by subsidy recipients (Forry, Davis, & Welti, 2013; Johnson, Ryan, & Brooks-Gunn, 2012). This is attributed to the fact that Head Start and pre-K are subject to relatively high-quality standards and regulations, including quality monitoring. Subsidies, on the other hand, can be used to purchase care in licensed center- and home-based settings or in unlicensed homes with care provided by family members, friends, or neighbors. Given that the broader field of child care research consistently finds licensed center- and home-based settings to be higher in quality than informal, unregulated home-based care (see Dowsett, Huston, Imes, & Gennetian, 2008; Li-Grining & Coley, 2006), if subsidy receipt leads to care in unlicensed settings, then subsidies are unlikely to have positive longer term effects on cognitive and behavioral skills. This could explain why a negative effect of subsidized care use in early childhood has predicted reductions in cognitive test score performance at age 6 only for children in unlicensed settings, while children in center-based care demonstrated no adverse effects (Bernal & Keane, 2011).

Conversely, subsidies may increase children's exposure to higher quality center-based or licensed/regulated home-based settings than they could afford without the subsidy (see Johnson & Ryan, 2015). While subsidies may not provide care that is on par with other public options like Head Start and pre-K that are more regulated, subsidized settings have been found to be higher in quality than available unsubsidized alternatives (Johnson et al., 2012). Could "business as usual" child care purchased with subsidies promote cognitive and behavioral skills enough to detect longer term effects? Evaluations of subsidy effects in the short term, as previously discussed, suggest that subsidies produce neutral or negative effects through the kindergarten year (Herbst & Tekin, 2016). Similarly, a study of children in universally subsidized day care in Bologna, Italy, suggests that exposure to subsidized care as opposed to maternal care in a child's earliest years (0–2 years of age) predicts lower IQ scores into middle childhood (ages 8–14 years). Yet in both studies, results were only significant for more affluent families: When the samples were limited to low–socioeconomic status children—who are the targets of the U.S. subsidy program—there were no negative effects of subsidized care (Fort et al., 2016).

One possible explanation for this phenomenon is the "foot-in-the-door" accrual of benefits process as articulated by Bailey, Duncan, Odgers, and Yu (2017), which suggests that experiences that shift children onto more adaptive trajectories during key developmental periods may not yield short-term impacts but could explain benefits that emerge later in the life cycle (i.e., "sleeper effects"). This may be especially true for low-income children, who are the target population in the United States for child care subsidies. If subsidies allow low-income parents to purchase better "business-as-usual" care than they could access without the subsidy, subsidies may provide early experiences that elevate children's developmental trajectories just enough such that no early impacts are detected but less adaptive early outcomes are avoided. This then paves the way for enhanced middle school achievement, particularly for gains in noncognitive skills that could impact important behavioral outcomes, such as school absences. Researchers have previously invoked the "foot-in-the-door" theory to help explain enduring impacts of "business as usual" community-based care on cognitive and social outcomes of children in the United States. Using multistate data from a U.S. sample of children, studies have found positive effects on cognitive, social, and behavioral outcomes into sixth grade, with cognitive effects lasting into adolescence (Belsky et al., 2007; Vandell, Belsky, Burchinal, Vandergrift, & Steinberg, 2010). Consistent with data previously discussed (Bernal & Keane, 2011), outcomes are typically more positive for children who experienced higher quality care and/or center-based care. Given the lack of existing literature, however, it is unknown whether subsidy receipt in the United States—where subsidies are means-tested and not universally available—gives low-income children a foot in the door to access sufficiently higher quality care and set them on more positive trajectories of development, or whether subsidies have neutral or even negative effects, as the short-term literature has found. To date, no studies have tested these possibilities, despite the vast number of children served and the substantial public investment it represents.

One final limitation of the existing subsidy evaluation literature—in addition to being largely focused on short-term, mostly cognitive outcomes if focused on child outcomes at all—is that extant studies have relied nearly entirely on survey data. This introduces some amount of imprecision into the key measure of subsidy receipt, as most surveys do not verify parents' reports of subsidy use with program records. Instead, researchers typically create measures of *likely* subsidy use based on parents' retrospective reported child care arrangements and funding (e.g., Hawkinson et al., 2013; Herbst & Tekin, 2010a, 2010b, 2016). Parents, however, may not be able to differentiate between sources of care subsidization or may not be able to recall the sources of child care assistance, which could lead to the misidentification of subsidy recipients. Indeed, parents have been found to underreport use of other public benefits, while overreporting use of subsidies specifically (Klerman, Ringel, & Roth, 2005; Krafft, Davis, & Tout, 2015; Meyer, Mok, & Sullivan, 2009). Attempts to verify parent report of subsidy status have involved testing for overlap with child care provider report (Johnson & Herbst, 2013). While child care provider report may be considered more accurate than parent report of subsidy status (Johnson & Herbst, 2013), it is still subject to some error given that most child care providers are not involved in center-level financial operations.

In light of these noted issues with misreporting of subsidy status, administrative data are widely considered to be the gold standard source of data for accurate measures of public benefit receipt, including subsidies. One study that compared parent-reported and administrative data–recorded subsidy receipt found substantial overreporting effects (Krafft et al., 2015). To address this concern, the current study uses high-fidelity administrative data to overcome potential misclassification of subsidy recipients. In so doing, we present the first quasi-experimental estimates of subsidy impacts on children's test score and school absence outcomes from third to eighth grades.

To summarize, the present study contributes to the extant literature in several important ways. First, this is the first study to test whether child care subsidy use is associated with outcomes of recipient children beyond elementary school. Second, by estimating effects on school absences alongside more traditional math and reading test scores, our study is able to test whether exposure to the subsidy program promotes or interferes with the development of important behavioral outcomes that predict life success (e.g., Allensworth, Gwynne, de la Torre, & Moore, 2014). Finally, we conduct these analyses using a unique data set that links administrative records across a variety of sources, generating the first-ever study of subsidy impacts on longer term outcomes using reliable indicators of subsidy receipt, where subsidy participation can be identified across settings and throughout the early childhood years with nearly zero measurement error. These data also contain rich information on baseline (i.e., presubsidy receipt) characteristics of parents and children that allow us to employ a variety of quasi-experimental matching methods designed to approximate a randomized controlled trial (under the assumption that selection into the subsidy program is based on observable characteristics—an admittedly untestable assumption).

With these data, we pursue the following primary research questions: first, "Is subsidy receipt in early childhood (infancy to age 5 years—before kindergarten entry) associated with increased reading and math test scores and reduced school absences in third through eighth grades?" Second, "Given prior literature finding differential effects of subsidized care exposure by care type, do these associations vary according to the type of child care setting in which the subsidy was used (center-based, licensed home-based, license-exempt home-based care provided by nonrelatives or relatives)?"

To address these questions, we compute estimates of the effects of subsidies, matching subsidy recipients with income-eligible nonrecipients using inverse probability weighting (IPW) methods. With respect to cognitive outcomes, we find that initially positive and significant average effects of child care subsidies on math test scores fade out by the eighth grade and reading scores are not associated with the use of child care subsidies in any grade. For school absences, we find reduced absenteeism among subsidy recipients in eighth grade. When we disaggregate these estimates according to the setting in which the subsidy was used, we find evidence of positive impacts of subsidies on reading and math and reduced school absences for children whose subsidies were used to purchase center-based care. The pattern of results is similar, though weaker, for children whose subsidies were used to purchase licensed home-based care.

Method

Data Source

The database that we employ in the current study consists of administrative records merged from multiple sources.[1] To create the database, we first used Chicago Public Schools' (CPS) administrative data. Each academic year (AY), CPS produces an enrollment database (called the "Master" database) that identifies students enrolled in the district and forms the core of a relational database system. Other subsidiary databases (with information about attendance, achievement test scores, disciplinary sanctions, GPA [grade point average], etc.) are then integrated with that core and complete a "tree"—a set of CPS records for a specific AY. However, not all the subsidiary databases are necessarily updated contemporaneously with the core databases. A new cross-sectional tree can be formed for each AY, and because each student has a unique identifier, students can be tracked longitudinally.

We were granted access to yearly CPS enrollment (core) databases from 1991 until the 2016–2017 school year. From those data, we selected the cohort of third-grade students in the AY 2008–2009 ($N \approx 32{,}000$) and followed them until the AY 2013–2014, when 27,000 of them remained active CPS students and most of them were in the eighth grade.[2] When we obtained permits to use the CPS data, the selected cohort of students was the only one with complete and consistent longitudinal records of absences and test scores that we could follow from third through eighth grades.

The second step in building the database consisted of merging the student records from CPS to records of participation in the Supplemental Nutrition Assistance Program (SNAP; formerly the Food Stamps programs), the Transfer

Aid for Needy Families (TANF; often referred to as the welfare program), and the CCDF program. In this stage, we identified a subset of those 27,000 students who (1) belonged to families who were receiving public assistance programs when the students were born and (2) had parents who had not received CCDF subsidies up until 2 years before the students were born. This subset consisted of 9,000 students who fulfilled these two criteria.

Because participation in TANF and SNAP is restricted to low-income families, the latter sampling choice limited the sample to students who were income eligible for CCDF. By linking the databases, we also recovered demographic and economic information about the parents, households, and neighborhoods associated with the student administrative data files available in the TANF and SNAP databases. Furthermore, by merging CPS to public assistance data, we recovered complete histories of participation in social assistance programs for all families in the database, including data spanning several years before and after the birth of the focal children.

Finally, given the importance of the employment information for CCDF selection (recall that the CCDF program's eligibility is conditional on employment), we identified the parents of the focal students in administrative records from the Unemployment Insurance program. This linkage allowed us to recover formal sector quarterly earnings and employment statuses of the parents in our sample.

Measures

Subsidy Receipt and Eligibility Period. To define a CCDF program participation variable, we used records of children's child care subsidy receipt from birth to age 5 years. Program participation was measured with a binary indicator equal to 1 if there were active CCDF payment records associated with a child in that age range. We further disaggregated subsidy receipt according to the type of care received by the child. In Illinois, subsidies can be used to purchase care in a child care center, a licensed home-based setting, or an informal or license-exempt home-based setting, which is typically care provided by a family member, friend, or neighbor in the provider's home or in the child's home (see Table 1 for a description of the state of Illinois' classifications of care types that can be purchased with CCDF). The type of care purchased with CCDF has changed over time (see Table 2). For instance, between 1998 and 2006, the predominant type of care purchased with subsidies shifted from informal, unlicensed (license-exempt) home-based care to licensed care in home- and center-based programs. The amount of the subsidy also varies by the type of care, with center-based child care programs (which are more expensive) receiving higher subsidy reimbursement amounts per child.[3]

Following Zanoni and Weinberger (2015), we defined an "eligibility period" as a time frame of reference that allows for analyzing the role of earnings, employment status, and participation in the TANF and SNAP programs in the choice of CCDF subsidies. An eligibility period was defined for both the CCDF program participants and nonparticipants. Among CCDF program participants, the eligibility period begins in the calendar quarter when a parent uses the subsidy for the focal child the first time and ends in the calendar quarter when the focal child turns 5 years old. Because nonrecipient parents do not have a CCDF program start time, we randomly assigned a number between 0 and 60 to each one of them that nominates an age of their focal child in months.[4] Notice that there is a calendar date associated with each one of those assigned ages. The eligibility period for children who do not receive CCDF benefits starts with the calendar date (the quarter) that corresponds with the calendar age randomly assigned to each nonrecipient child. Resembling CCDF recipients, the eligibility period for nonrecipients ends when the focal child turns 5 years old.

TABLE 1
Child Care Subsidy Take-Up by Type of Child Care Associated With the Subsidy Payment

Coded DHS value	Description
760	Center (licensed by DHS)
761	Center (exempt from licensing from DHS)
762	Licensed home (up to 8 kids)
763	Licensed group home (up to 12 kids)
764	Home exempt (up to 3 kids)
765	Provider is a relative at relative's home
766	Providers is a nonrelative at kid's home
767	Provider is a relative at kid's home

Note. There are eight original categories assigned by the Illinois Department of Human Services (DHS) for services that receive child care subsidy payments. These eight administrative categories were combined to form three new groups of providers: (1) licensed providers (comprising categories 760 to 764), (2) unlicensed nonrelative care (category 766), and (3) unlicensed relative care (categories 765 and 767).

By anchoring data on the eligibility period, we were able to retrospectively track quarterly earnings, employment status, and participation in the TANF and SNAP programs for all families. Defining an eligibility period as described enabled us to investigate the often overlooked role of key preprogram time-variant factors, particularly those related to labor supply decisions, on CCDF subsidy choices.

In our data, the parents of eligible nonrecipient children are those who did not use child care subsidies to pay for child care. As a consequence, the counterfactual state to subsidy receipt is *care utilized by low-income working parents*, which includes other publicly funded early care and education programming such as Head Start and state pre-K, as well as unsubsidized care (i.e., a heterogeneous mix of low- or no-cost care funded via scholarships or other mechanisms and unpaid care offered by family members, friends, and neighbors).[5] From the population of children aged 0 to 5 in Chicago during our study period, nearly 30% were enrolled

TABLE 2
Number of Children Ages 0 to 5 Using Child Care Subsidies in Illinois (1998–2006) by Type of Provider)

	Years								
Type of care	1998	1999	2000	2001	2002	2003	2004	2005	2006
Licensed	4,002	8,600	13,160	17,244	24,949	33,480	34,489	40,896	43,681
Unlicensed	5,910	16,532	26,975	34,263	37,072	42,418	36,906	35,137	30,228
Unlicensed care provided by relatives	3,600	10,195	16,980	21,600	23,188	26,013	21,570	19,530	16,466
Unlicensed care provided by nonrelatives	2,310	6,337	9,995	12,663	13,884	16,405	15,336	15,607	13,762
Total	9,912	25,132	40,135	51,507	62,021	75,898	71,395	76,033	73,909

in public pre-K programs in CPS, while approximately 13% participated in Head Start programs. The remainder experienced unsubsidized community-based care or home-based care. As discussed in the introduction, public pre-K and Head Start programs are typically higher in quality than subsidized settings (Johnson et al., 2012). Therefore, including participants of these programs in our comparison group is expected to downwardly bias estimates of effects of subsidy receipt on outcomes.

Outcomes. The outcomes of interest in the study include test scores in mathematics and reading between Grades 3 and 8, as well as school absences. Math and reading scores are pulled from the Illinois Standards Assessment Test (ISAT) data. School absences are tracked through a CPS database where teachers track student attendance.

Math and reading scores. Between 1999 and 2015, CPS administered the ISAT in mathematics and reading to all actively enrolled students in third to eighth grades. According to the Illinois State Board of Education, the test is designed to "measure individual student achievement relative to the Illinois Learning Standards. The results give parents, teachers, and schools one measure of student learning and school performance" (Illinois State Board of Education, 2014b; specific details about the content of the tests is provided in Illinois State Board of Education, 2014a). Our CPS data include scaled scores measuring students' performance in the math and reading ISAT tests (ranging from 120 to 400). Reliability data provided by CPS indicate that the items in the math and reading ISAT tests demonstrated high internal consistency ($\alpha > 0.90$; Illinois State Board of Education, 2014a). Among CPS students who were in third grade in AY 2008–2009 ($N = 27{,}000$), the mean ISAT scores in reading and math were 194 ($SD = 29$) and 202 ($SD = 30$). The scores in the eighth grade were 243 ($SD = 22$) and 269 ($SD = 32$), respectively.

School absences. Teachers in CPS schools use computers located in their classrooms to record whether students are present or absent for their classes. Based on daily teacher records, an automated system calculates the number of instructional minutes received and lost by every student and classifies them as absent for the day if they lose more than 150 minutes of class (the instructional time threshold is set by Illinois State law, from Chapter 122, para. 26-2a). Students can be absent for excused reasons if the absence has what CPS classifies as a valid cause, which includes illness, observance of a religious holiday, death in the immediate family, family emergency, and other situations determined by the district to be beyond the control of the student. In AY 2008–2009, third graders in CPS average 3.71 unexcused school absences ($SD = 5.71$) and 5% of students had 14 or more absences in that year. When those students were in eighth grade, their mean number of absences was 4.69 ($SD = 7.64$), with 5% having 16 or more unexcused absences. Considering that the CPS school year lasts for approximately 170 days, students who are in the 95th percentile of the unexcused absences distribution in third or eighth grades missed 8% of days during the school year.

Analytic Strategy

Our empirical strategy consisted of matching program participants to nonparticipants in two stages. In the first stage, we matched parents nonparametrically based on their preprogram employment and TANF participation histories. This is a form of "screening" on eligibility (as defined by Heckman, LaLonde, & Smith, 1999 and employed by Smith & Todd, 2005), the first step in a "matching in two stages" strategy where the research design first drops noneligible individuals, as those are considered poor matches with which to build counterfactual outcomes for program participants. In the absence of such screening, the data from several parents with no employment and/or TANF records (and consequently never employment or TANF eligible for CCDF) would have been used to answer the question on what would have happened to CCDF recipients in the absence of their participation in the program.

In this first stage, we subset the analytical database from 9,000 to 6,000 children born to families with eligible parents. Based on our definitions of CCDF subsidy receipt, 4,900 children received subsidies and 1,100 did not ($n = 430$ recipients in center-based child care, 590 in home based licensed child care, 1,460 in child care provided by nonrelatives (license-exempt), and 2,400 subsidy recipients received care in their own homes with relatives). Our analytic database included approximately 6,000 children (1) who were in the third grade in the CPS system in AY 2008–2009, (2) who continued in the CPS system until at least eighth grade in AY 2013–2014, (3) who were born to low-income households actively receiving public assistance (SNAP or TANF), (4) who could be identified as child care subsidy recipients or nonrecipients using CCDF data, and (5) whose families were deemed eligible for child care subsidies at the time of the focal child's birth, whether or not they received subsidies.

In the second stage of our matching strategy, we rely on a conditional independence assumption: holding several observable characteristics constant, differences in middle school test scores and school absences between children who did and did not receive child care subsidies in early childhood should be driven only by subsidy receipt. Based on this assumption, we estimate average treatment effects that match subsidy recipients to nonrecipients on observable characteristics, using IPW estimators (see Hirano, Imbens, & Ridder, 2003).

The IPW estimator employs a propensity score that models selection into the CCDF program and differences in the outcomes by treatment status as key inputs. We estimated the propensity score model with the dependent variable as an indicator of subsidy receipt (subsidy recipients are denoted as the "treated" group and coded with a value of 1, and eligible nonrecipients are denoted as the comparison group and coded with a value of 0). We also estimated four additional propensity score models where the treated groups varied according to the specific type of subsidized child care utilized (center-based, licensed homes, relatives, and nonrelatives), and the group of nonparticipants was always employed as the comparison group.

While selection into CCDF is conditioned on employment, the nature of the selection process most likely varies according to what type of care parents choose to purchase with the subsidy. For instance, in Illinois, a mother could use CCDF subsidies to help her pay for child care in a center-based program or for child care that her own mother (the grandmother of the focal child) could provide at home. In the former case, the subsidy is a transfer received by a private entity (i.e., a child care center). In the latter case, the CCDF subsidy is transferred to the grandmother providing care and, thus, could become a transfer that increases the income of the household of the focal child if the grandmother and the mother of the focal child share the same household budget. Because such distinct choices most likely impose quite distinct data-generating processes (and unobserved dynamics), we separately compute propensity score models from which to estimate the effects of the CCDF program within each type of care. In online Appendix A, we present a microeconomic model of choice to examine that rationale and its implications. The model suggests that factors driving the CCDF choices made by parents are quite distinct by type of care, and consequently, those choices need to be modeled independently and not jointly.[6]

Since the data from which to build the counterfactual outcomes are the same across all estimates (it always come from eligible nonparticipants), our design warrants that the estimated effects of the CCDF programs will be comparable across treatments (i.e., types of care).

Specifications of the Propensity Score Models. In choosing the specification of the propensity scores, we monitored changes in the proportion of correctly classified observations as we added covariates (see Smith, 2000; Smith & Todd, 2005). Jointly, the variables that we employ in this matching stage account for considerable heterogeneity in observable attributes that predict the choice of work and child care subsidies usage, the type of child care associated with those choices, and differences in children outcomes during school.

In online Appendix B, we present several graphs that show how the estimated probability of participation and the corresponding areas of common support vary across five model specifications, presented by type of care and across specifications. In Model 1, the most restricted version of the models, we included a battery of year-fixed effects to control for differences in overall economic conditions across the eligibility periods, as well as variable indicating if the family was drawn from an active SNAP case versus an active TANF case. Model 2 added a variable measuring household size; indicator variables for the focal child's gender, race, and ethnicity; and year of birth fixed effects. In addition, Model 2 controlled for the ages of the child (in months) and of the mother (in years) at the eligibility period. In Model 3, we augmented the specification to control for neighborhood characteristics, including the share of families that have children younger than 6 years, the median household income and its dispersion (standard deviation), and the proportion of female-headed households in the neighborhood. In Model 4, we added a variable counting the number of months in SNAP and TANF within 24 months before the eligibility period, and monthly indicator variables for TANF receipt up to 6 months before the eligibility period. In Model 5 (our preferred model and the one we will reference henceforth), propensity scores control employment status indicators and log of earnings (one per each quarter for the six quarters preceding CCDF participation), in addition to the variables described. Missing values in covariates were recoded to −1, and indicator variables to missingness were included in all models.

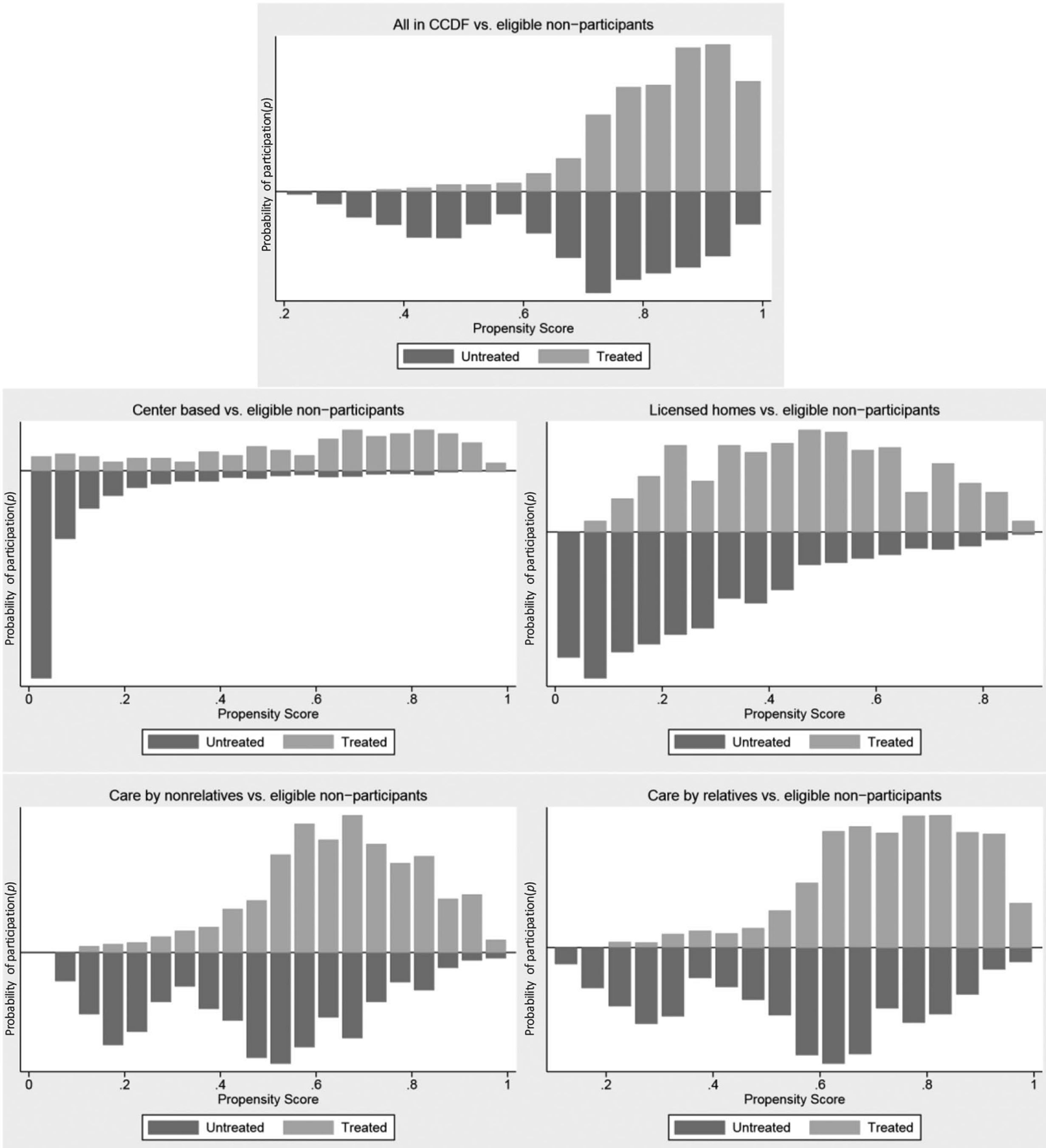

FIGURE 1. *Analysis of the area of common support. Estimates of the probability of subsidy participation p among treated (top) and untreated individuals (bottom), and estimates overall, and by type of care.*

Note. The vertical bars in the figure show the probability distribution function (PDF) of the probability of Child Care and Development Fund (CCDF) participation by treatment status as predicted by a propensity score model. Graphs are grouped with reference to all subsidy recipients, and conditional on subsidy receipt being used to purchase specific types of care—center-based, licensed homes, nonrelatives, and relatives. The top light gray bars in each graph plot the density among CCDF recipients. The dark gray bars below the horizontal dividing line are plotted over an inverted vertical axis, and as we move away from the origin, the bars portray increases in density among CCDF nonparticipants. All the propensity scores were estimated with reference to Model 5 described in the section "Specifications of the Propensity Score Models."

In Figure 1, we depict estimates of various propensity score functions (p) that were calculated overall and by type of care using the specification in Model 5. Those probabilities were computed by maximum likelihood with probit link functions (results are nearly identical to those generated with logit or linear probability models). Differentiating itself from the ordinary least square (OLS) estimator, the IPW does not impose a linear distribution function in the outcomes. Instead, IPW allows for a semiparametric distribution function in those outcomes, which makes it a more flexible method to account for nonlinearities than OLS (without weights). Additionally, our IPW estimates are computed over areas of common support (i.e., data with observations have similar probabilities of subsidy receipt, regardless of actual subsidy receipt status). Computing estimates over the areas of common support guarantees that estimated coefficients are not calculated by linear extrapolations over data segments where subsidy recipients and nonrecipients lack similarities in probability of participation and/or predicted outcomes. In online Appendix C, we provide results of balancing tests that show how the IPW weighting scheme contributed to balancing across the covariates in the analysis.[7] The data presented in online Appendix C suggest that, overall and by type of care, using IPW weights helps gain balance in most of the covariates. In online Appendix D, we present alternative sets of results using propensity score matching and OLS estimators.

Results

Descriptive Results

Covariates by Subsidy Receipt. Table 3 presents descriptive statistics for child and family demographics and neighborhood and economic characteristics by status of subsidy receipt overall and for subsidy recipients according to the type of setting in which the subsidy was used (center-based care, licensed home-based care, license-exempt care provided by either a non-relative and or a relative). Because formal and regulated settings are documented to have higher average quality than unlicensed alternatives (Bassok, Fitzpatrick, Greenberg, & Loeb, 2016; Dowsett et al., 2008), and child care quality is expected to affect child outcomes (e.g., Mashburn et al., 2008; Duncan & National Institute of Child Health and Human Development Early Child Care Research Network, 2003), we first describe how subsidy recipients who used their subsidy in a licensed child care setting (i.e., a center-based or licensed home-based setting; columns 2 and 3) differ in key attributes from those who used their subsidies in license-exempt settings (columns 4 and 5). Then, we compare all subsidy recipients with eligible nonrecipients (column 6).

In general, subsidy recipients who used licensed child care lived in less disadvantaged neighborhoods than those who used license-exempt care. Looking specifically at subsidy recipients in center-based care, the children tended to be older and were less likely to be African American and more likely to be Hispanic than were subsidy recipients in other care types. Compared with subsidy nonrecipients, subsidy recipients were again more likely to be older, while the mothers of subsidy recipients were on average younger than subsidy nonrecipients. Subsidy recipients were also more likely to be African Americans and less likely to be Hispanic than were eligible nonrecipients. Compared with subsidy nonrecipients, those using subsidies received SNAP or TANF benefits for fewer months in the 24 months leading up to the subsidy eligibility period. Subsidy recipients also resided in more disadvantaged neighborhoods, characterized by higher levels of income inequality, than the neighborhoods of subsidy nonrecipients.

As described in Zanoni and Weinberger (2015), CCDF participants exhibit a prototypical preprogram "Ashenfelter dip" in their earnings and employment status series (see Heckman & Smith, 1999, for the importance of accounting for this type of earnings patterns in the evaluation of social programs that affect employment outcomes). As in other social programs that affect employment, the existence of such a dip portrays temporary deviation from long-term earnings trajectories. In the presence of a preprogram earnings dip, researchers should opt for an identification strategy that addresses temporary differences in earnings when modeling selection. In this article, our approach to account for preprogram earnings differences between participants and nonparticipants was to parametrically control for the differences when modeling selection.

Variation in Outcomes by Subsidy Receipt Status. In Figures 2 to 4, we compare unconditional mean scores on the reading and math ISAT achievement tests and the number of school absences of the focal children by subsidy participation during Grades 3 through 8. The top portion of each figure shows differences in mean outcomes between all subsidy recipients and compares them with eligible nonrecipients. Subsequent graphs compare the outcomes of eligible nonrecipients with those of subsidy recipients by type of subsidized care (i.e., children in care in centers, licensed homes, and license-exempt relatives, or nonrelative providers).

In each graph in Figures 2 to 4, the top and bottom vertical markers reflect confidence intervals (1.96 standard errors for 95% confidence intervals) around the mean outcomes' values (the bolded dots along the lines). Inspecting the degree of overlap across those confidence intervals by subsidy receipt permits assessment of the statistical significance of the differences in the mean outcomes associated with each pair of data points for each outcome and school year combination. All the differences in means are statistically significant at 95% confidence or more.

In the top graphs of Figures 2 and 3, it is notable that while there seem to be no differences in math test scores by subsidy receipt in any grade, subsidy recipients perform better than other students in the reading assessment tests in Grades 3 and 5. However, as Figure 2 shows, these early differences in reading scores disappear in subsequent years, suggesting a fade-out effect of subsidized child care on reading test scores.

Figure 4 reveals that there are differences in the number of unexcused school absences between subsidy recipients and eligible nonrecipients in third through eighth grades.

TABLE 3
Descriptive Statistics of Selected Variables by Subsidy Receipt

	(1) All	(2) CB	(3) HB	(4) NRB	(5) RB	(6) ENP
Demographics						
Age of the child (months)[a]	15.94	32.61	15.99	13.94	14.18	12.61
	(14.74)	(14.71)	(13.76)	(13.61)	(13.74)	(12.04)
Age of the mother[b]	23.03	21.60	21.79	23.65	23.21	26.25
	(10.81)	(11.86)	(12.20)	(10.58)	(10.33)	(10.73)
Household size[b]	4.08	3.43	3.73	4.27	4.17	4.16
	(1.94)	(1.71)	(1.76)	(1.99)	(1.96)	(2.06)
Male	0.50	0.51	0.48	0.50	0.51	0.52
	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)	(0.50)
Black non-Hispanic	0.88	0.67	0.87	0.90	0.90	0.66
	(0.33)	(0.47)	(0.33)	(0.29)	(0.30)	(0.47)
Hispanic	0.11	0.28	0.11	0.08	0.09	0.29
	(0.31)	(0.45)	(0.31)	(0.28)	(0.28)	(0.45)
White non-Hispanic	0.01	0.03	0.01	0.01	0.01	0.03
	(0.09)	(0.17)	(0.08)	(0.07)	(0.08)	(0.17)
Neighborhood characteristics						
HHs with children age <6[c]	0.11	0.11	0.10	0.11	0.11	0.12
	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)
Female-headed HHs[c]	0.45	0.38	0.44	0.45	0.46	0.40
	(0.14)	(0.15)	(0.13)	(0.14)	(0.14)	(0.15)
Median income (U.S. dollars)	44,100	49,000	46,000	43,000	43,300	45,100
	(13502)	(14,890)	(12,074)	(13,213)	(13,521)	(12,327)
SD of median income	15,500	14,500	14,800	15,900	15,700	14,800
	(6,700)	(6,191)	(5,606)	(6,962)	(6,846)	(6,485)
CCDF in neighborhood[d]						
TANF recipients	55	41	51	56	57	43
	(40)	(40)	(37)	(39)	(39)	(35)
Black	82	86	79	81	83	60
	(66)	(80)	(63)	(64)	(66)	(54)
Number of CCDF cases	97	101	92	95	98	72
	(73)	(86)	(70)	(71)	(73)	(60)
SNAP and TANF[e]						
Months in SNAP	12.98	11.03	11.07	13.92	13.22	13.43
	(8.25)	(8.78)	(7.94)	(8.08)	(8.21)	(8.66)
Months in TANF	236.51	198.59	185.43	258.98	242.16	255.47
	(201.27)	(205.36)	(186.73)	(201.97)	(200.61)	(214.29)
N	4,872	426	591	1,459	2,396	1,071

Note. Table 3 cross-tabulates means and standard errors of selected variables (rows), distinguishing subsidy recipients from eligible nonrecipients (columns): (1) All subsidy recipients, (2) CB—Subsidy recipients in center-based care, (3) HB—Subsidy recipients in licensed home-based care, (4) NRB—Subsidy recipients in license-exempt home-based care provided by nonrelatives, (5) RB—Subsidy recipients license-exempt home-based care provided by relatives, and (6) ENP—Eligible nonrecipients. HHs = households; *SD* = standard deviation; CCDF = Child Care and Development Fund; TANF = Transfer Aid for Needy Families; SNAP = Supplemental Nutrition Assistance Program.
[a]In months at the eligibility period. [b]Measured when child was born. [c]Numbers are proportions. [d]Measured one quarter before eligibility. [e]Measured within 24 months prior to eligibility.

The pattern of those differences, however, shifts as children get older. In third grade, students who received subsidies in early childhood were *more* likely to be absent than other students, whereas this pattern is reversed in the eighth grade: Subsidy recipients showed *fewer* unexcused school absences than eligible nonrecipients, on average. This reversal may be largely explained by the fact that school absences in the third grade primarily reflect parental behavior in getting children to school when children are still typically dependent on parents for transportation, whereas school absences in the

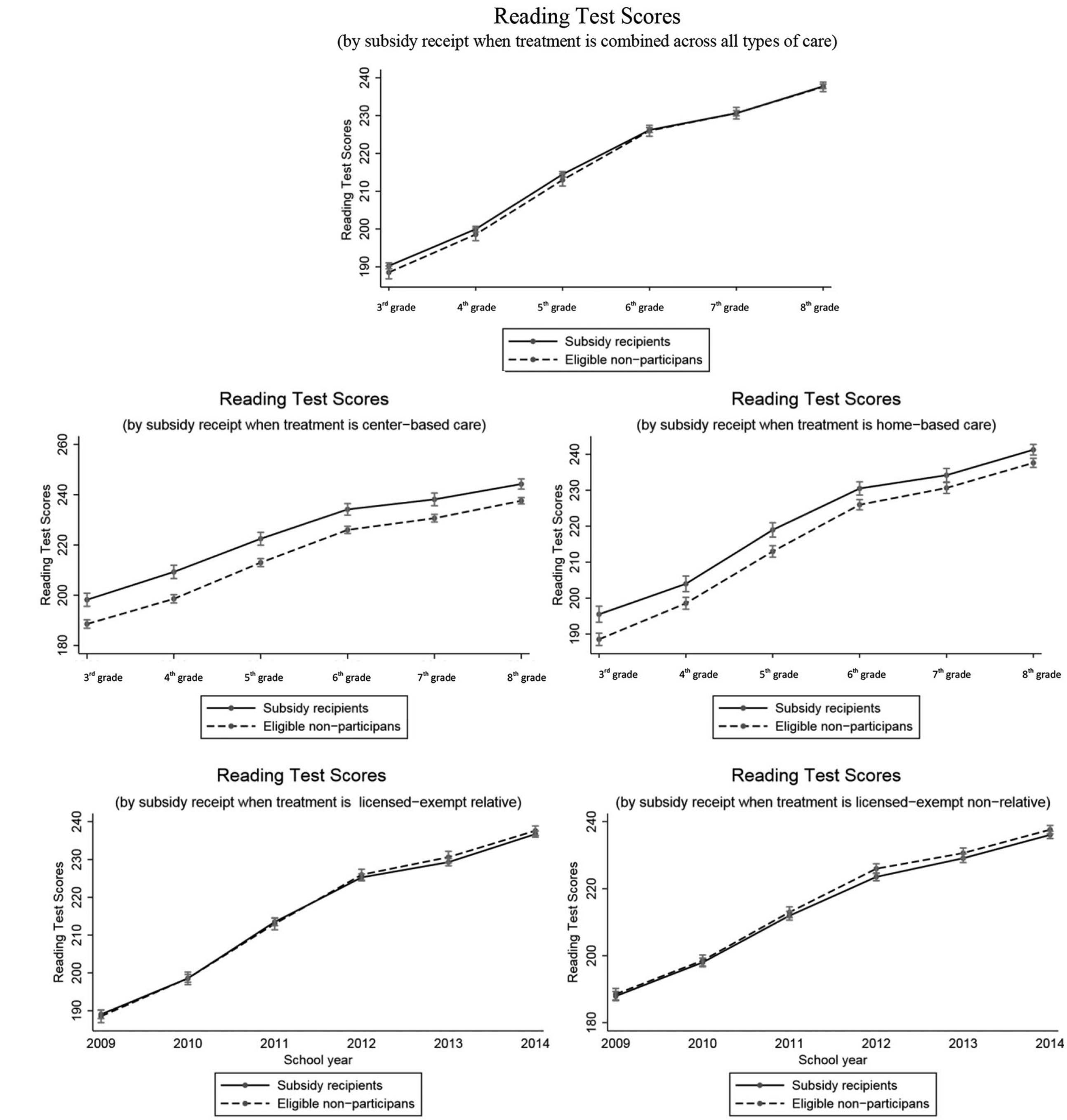

FIGURE 2. *Unconditional differences in ISAT reading scores in school years 2009 (when students were in the third grade) to 2014 (when students were in the eighth grade), by subsidy receipt.*
Note. The vertical markers spread 1.96 standard errors above and below the means. ISAT = Illinois Standards Assessment Test.

eighth grade primarily reflect student behavior as students are more independent and responsible for their own transportation and school attendance.

In Figures 2 and 3, we also highlight that whenever subsidized child care took place in either *center-based* or *home-based child care* programs, subsidy recipients outperformed eligible nonrecipients in their math and reading assessment tests in third through eighth grades. The magnitude of the differences, however, is bigger with reference to the reading than to the math test scores (all differences are statistically significant at the 5% level or smaller). Similarly, in any given year, the students who participated in child care subsidies and utilized home- or center-based child care programs always exhibit fewer absences than other students (see Figure 4). Across years, we did not observe significant differences in reading scores, math scores, and school absences

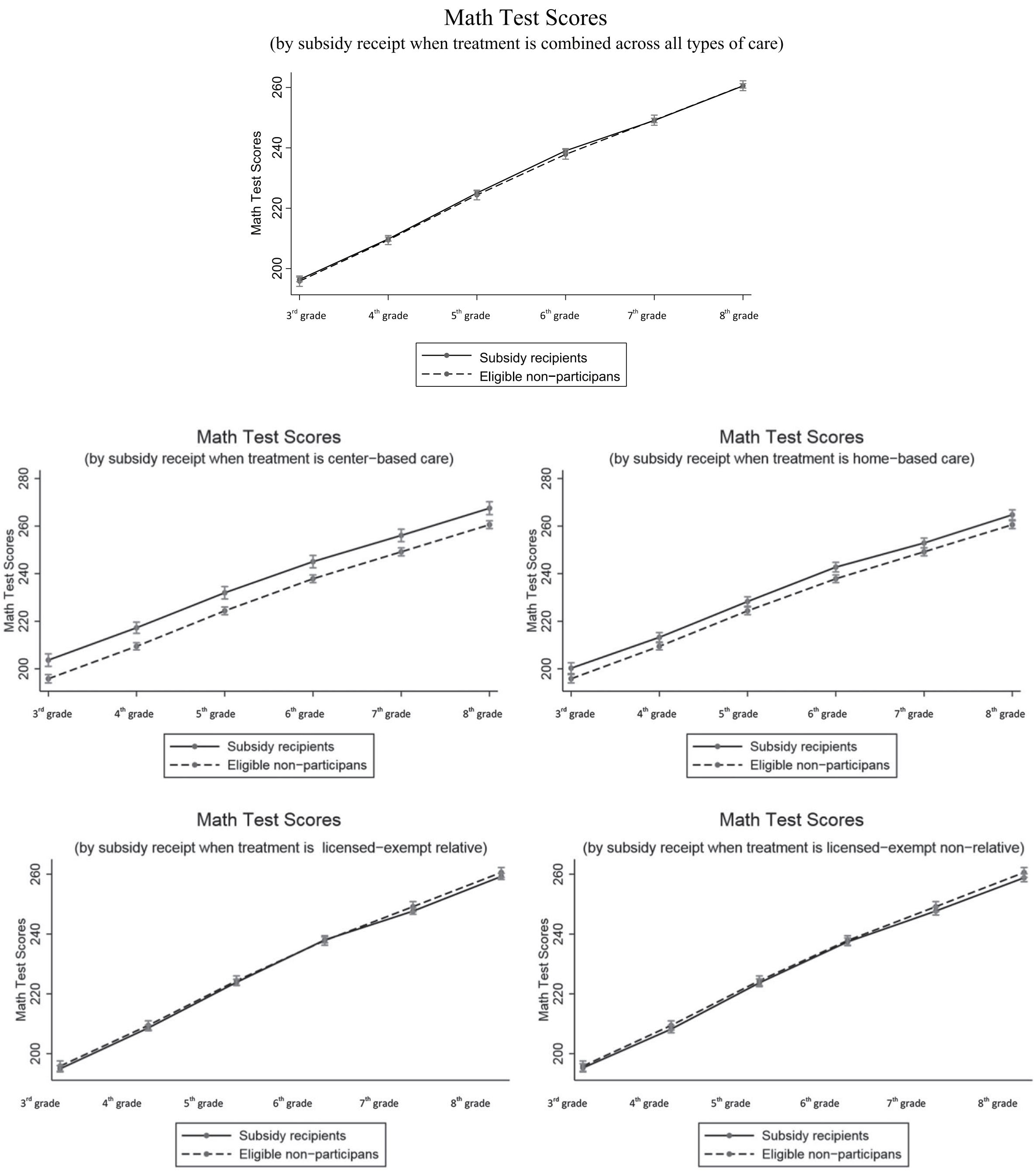

FIGURE 3. *Unconditional differences in ISAT math scores in school years 2009 (when students were in the third grade) to 2014 (when students were in the eighth grade).*
Note. The vertical markers spread 1.96 standard errors above and below the means. ISAT = Illinois Standards Assessment Test.

between eligible nonrecipients and children in license-exempt subsidized settings.

Impacts of Subsidies on Outcomes

Figures 5 to 7 summarize the main results of the article, presenting IPW estimates of the effects of subsidy participation on reading scores, math scores, and school absences, respectively, in Grades 3 through 8. The IPW estimates are weighted least squares regressions in which each comparison case outcome is weighted by a $[p/(1 - p)]$ factor, where p is the estimated probability of participation (or propensity score), and each treatment case is given a weight of one. The IPW specifications estimate robust standard errors that correct for heteroscedasticity and integrate over the area of common support.[8] As robustness checks, we also

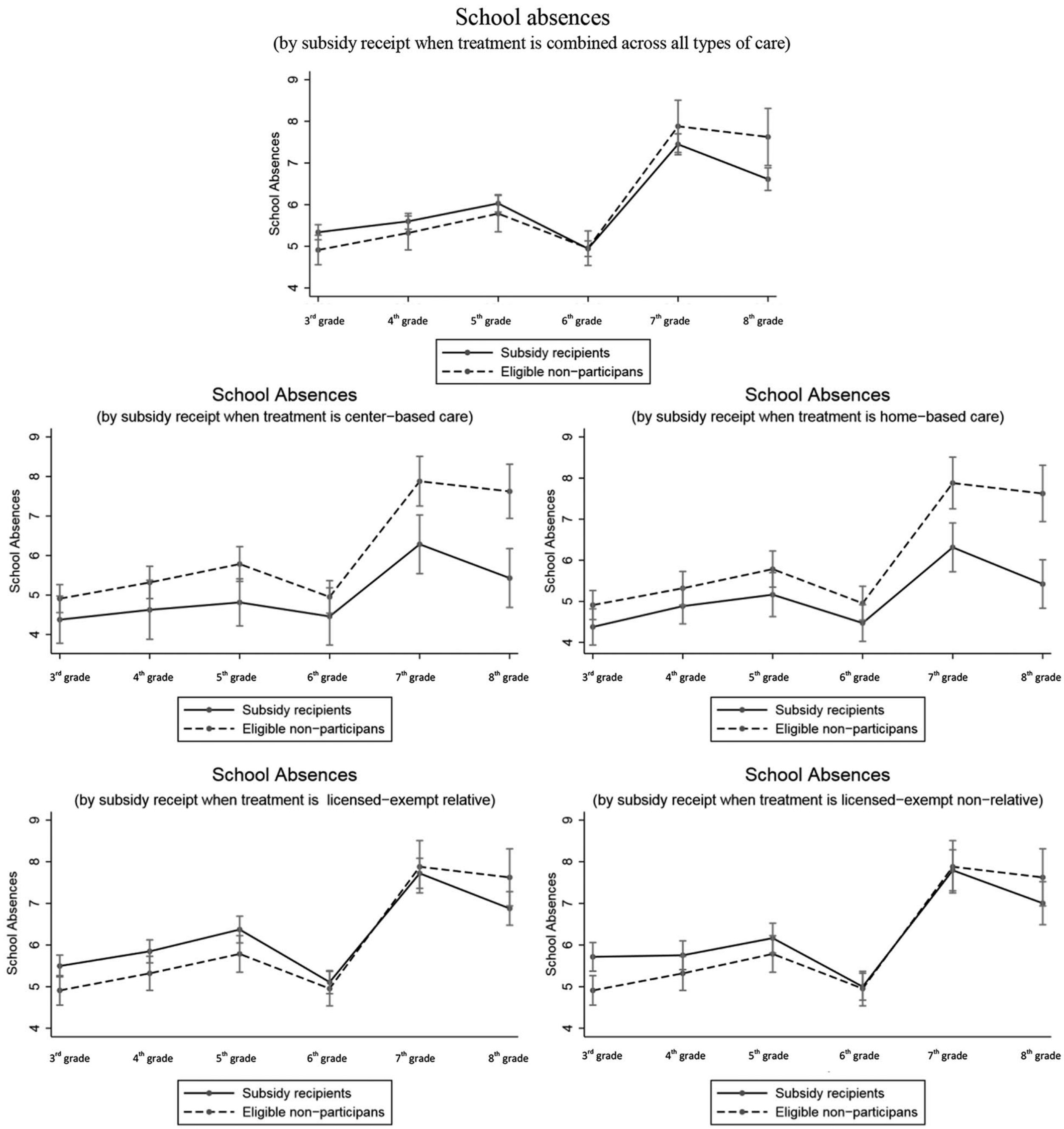

FIGURE 4. *Unconditional differences in school absences in school years 2009 (when students were in the third grade) to 2014 (when students were in the eighth grade).*
Note. The vertical markers spread 1.96 standard errors above and below the means.

computed propensity score matching (see Smith & Todd, 2005; Todd, 2008) and linear OLS estimates of the effects of using subsidized child care on student outcomes. Those estimates are presented in online Appendix D.

Each graph in Figures 5 to 7 presents the IPW-estimated impacts of subsidy receipt overall and for subsidy recipients in center-based care, licensed home-based care, license-exempt home-based care provided by nonrelatives, and license-exempt home-based care provided by relatives. We compare subsidy participants overall and in each care type with a comparison group of eligible nonrecipient children. Following conventional practices in education and developmental sciences, the distribution functions of the student outcomes were standardized so that estimated effects could be interpreted in terms of percentages of 1 standard deviation.

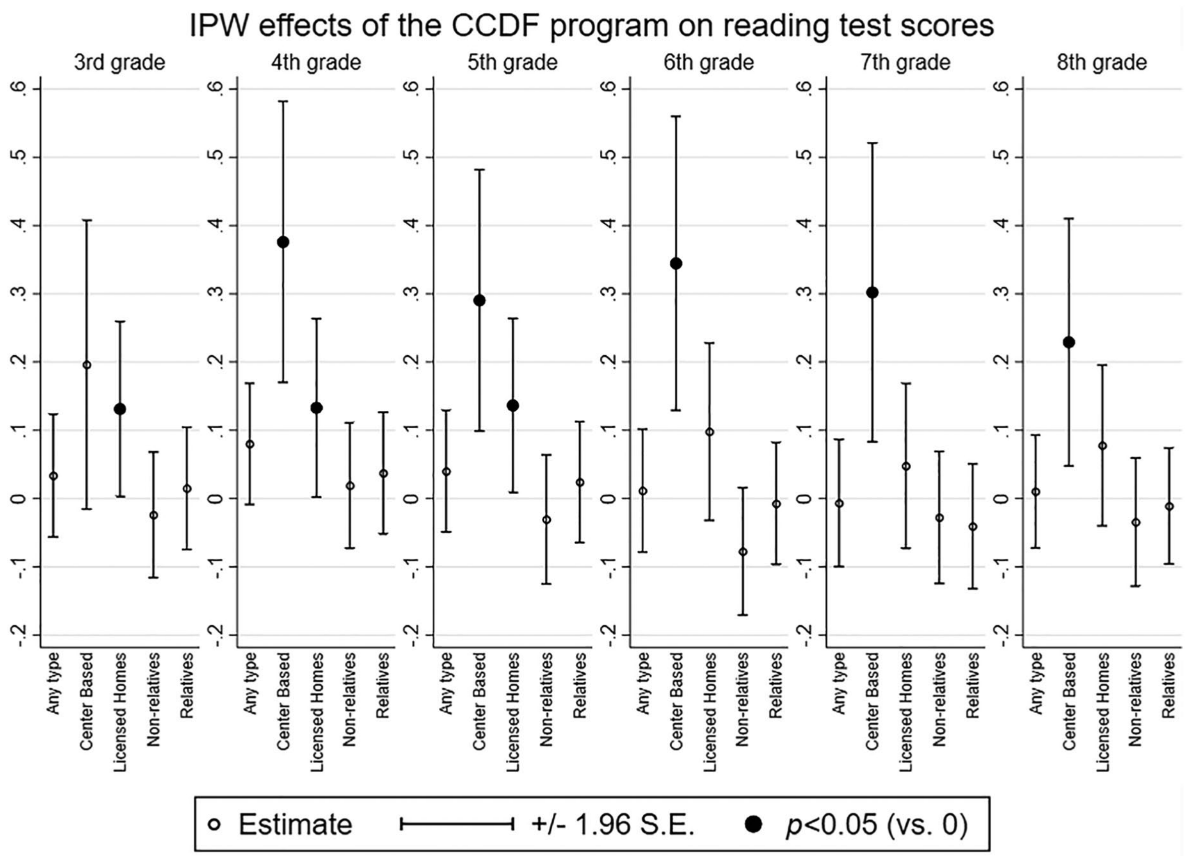

FIGURE 5. *IPW estimates of the effects of subsidies on ISAT reading scores, third to eighth grades.*
Note. The vertical markers spread 1.96 standard errors above and below the mean coefficient estimates. A solid dot at the top of each bar denotes statistical significance of the coefficient estimates at 10% of confidence level or less. The comparison group here is formed by all eligible nonrecipients. The labels "All," "CB," "Licensed HB," "Nonrelatives," and "Relatives," respectively, correspond to the impacts of subsidy participation on all subsidy recipients, subsidy recipients in center-based care, subsidy recipients in licensed home-based care, subsidy recipients in license-exempt home-based care provided by nonrelatives, and subsidy recipients in license-exempt home-based care provided by relatives. IPW = inverse probability weighting; ISAT = Illinois Standards Assessment Test.

Average Impacts of Subsidy Use on Middle School Outcomes. Figures 5 to 7 first present estimated impacts of subsidy participation on each outcome across all setting types. Figure 5, which presents the average effects of subsidy participation on ISAT reading test scores by grade, describes a nonsignificant impact of subsidy receipt in early childhood on reading scores in Grades 3 through 8 at the 5% level with the exception of fourth grade, where effects are statistically significant with an effect size of 0.08 standard deviations. Figure 6 communicates a similar pattern of results whereby the impacts of subsidy receipt in early childhood on ISAT math scores are generally not sustained over time. Although we observe positive and statistically significant effects of subsidy participation on math scores in the fourth and sixth grades, with an effect size of 0.08 standard deviations in both cases, the magnitude of these effects drops considerably in seventh and eighth grades and the effects do not remain statistically significant at the 5% level.

Figure 7 presents the average effect of subsidy participation on student absenteeism aggregated across setting types over the same span from third to eighth grades. Initially, in Grades 3 through 6, we do not observe statistically significant effects of subsidy receipt on unexcused absences in each school year, as estimates are close to zero and lack statistical significance at the 5% confidence level. However, the effects appear to be dynamically heterogeneous as statistically significant impacts first emerge in Grade 7 and sustain into Grade 8, with effect sizes of 0.14 standard deviations in both grades.

Impacts of Subsidy Use on Middle School Outcomes by Type of Care. As observed descriptively in Figures 2 to 4, there are nontrivial differences in the unconditional means of each outcome by type of care, and these trends are largely replicated in our main analyses that apply weights to reduce bias and more sensitively estimate the impacts of subsidy receipt on middle school outcomes by setting type. Estimates of the effects of subsidies on reading and math test scores and on school absences are presented in Figures 5 to 7, where a series of bar graphs show those estimates across outcomes,

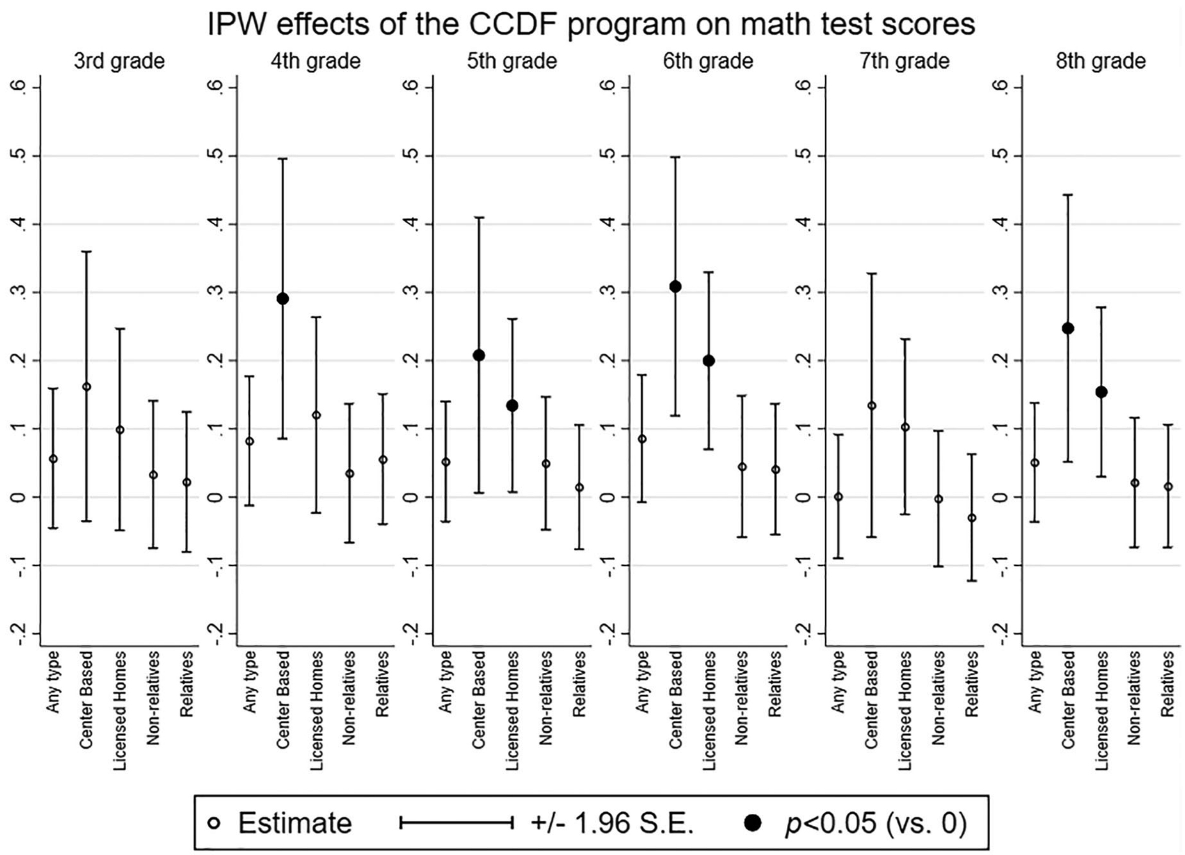

FIGURE 6. *IPW estimates of the effects of subsidies on ISAT math scores, third to eighth grades.*
Note. The vertical markers spread 1.96 standard errors above and below the mean coefficient estimates. A solid dot at the top of each bar denotes statistical significance of the coefficient estimates at 10% of confidence level or less. The comparison group here is formed by all eligible nonrecipients. The labels "All," "CB," "Licensed HB," "Nonrelatives," and "Relatives," respectively, correspond to the impacts of subsidy participation on all subsidy recipients, subsidy recipients in center-based care, subsidy recipients in licensed home-based care, subsidy recipients in license-exempt home-based care provided by nonrelatives, and subsidy recipients in license-exempt home-based care provided by relatives. IPW = inverse probability weighting; ISAT = Illinois Standards Assessment Test.

along grades and by type of care. In each bar, the vertical markers spread 1.96 standard errors above and below the mean coefficient estimates. Whenever relevant, a solid dot at the top of a bar denotes statistical significance of the coefficient estimates at the 5% level or less. The comparison group always joins all eligible nonrecipients.

As Figures 5 and 6 show, we found larger impacts of subsidy receipt on both reading and math scores for subgroups of children who attended center-based and licensed home-based arrangements relative to those who attended license-exempt care arrangements. Specifically, when child care occurred in center-based settings, the impact of subsidies on reading test scores is positive and statistically significant at every grade level, with effect sizes ranging from 0.20 to 0.38 standard deviations (Figure 5). For children who attended licensed home-based settings paid with subsidies, the effects of this program on reading test scores are positive and statistically significant in early grades (with effect sizes between 0.12 and 0.14 standard deviations) yet fade out in Grades 6 to 8.

When low-income parents use their subsidy to send their children to CCDF-subsidized center-based care arrangements, the impacts of that care on math test scores (Figure 6) are positive in Grades 4 through 6 and in Grade 8 (with effect sizes between 0.25 and 0.30 standard deviations). Similarly, for children who attended licensed home-based settings, we observe statistically significant positive, albeit muted, impacts of subsidy receipt on math scores in the same grades (effect sizes between 0.15 and 0.20 standard deviations). For both reading and math outcomes, the effects of subsidy receipt appear to be inconsequential for children in license-exempt relative or nonrelative care. In general, we do not observe statistically significant impacts for either outcome across grades for children in these setting types, and we estimate small negative impacts of subsidy receipt on reading scores in sixth grade for children in license-exempt nonrelative arrangements (with effects smaller than 0.10 standard deviations).

Figure 7 presents the impacts of subsidy use on unexcused school absences by type of care and highlights three

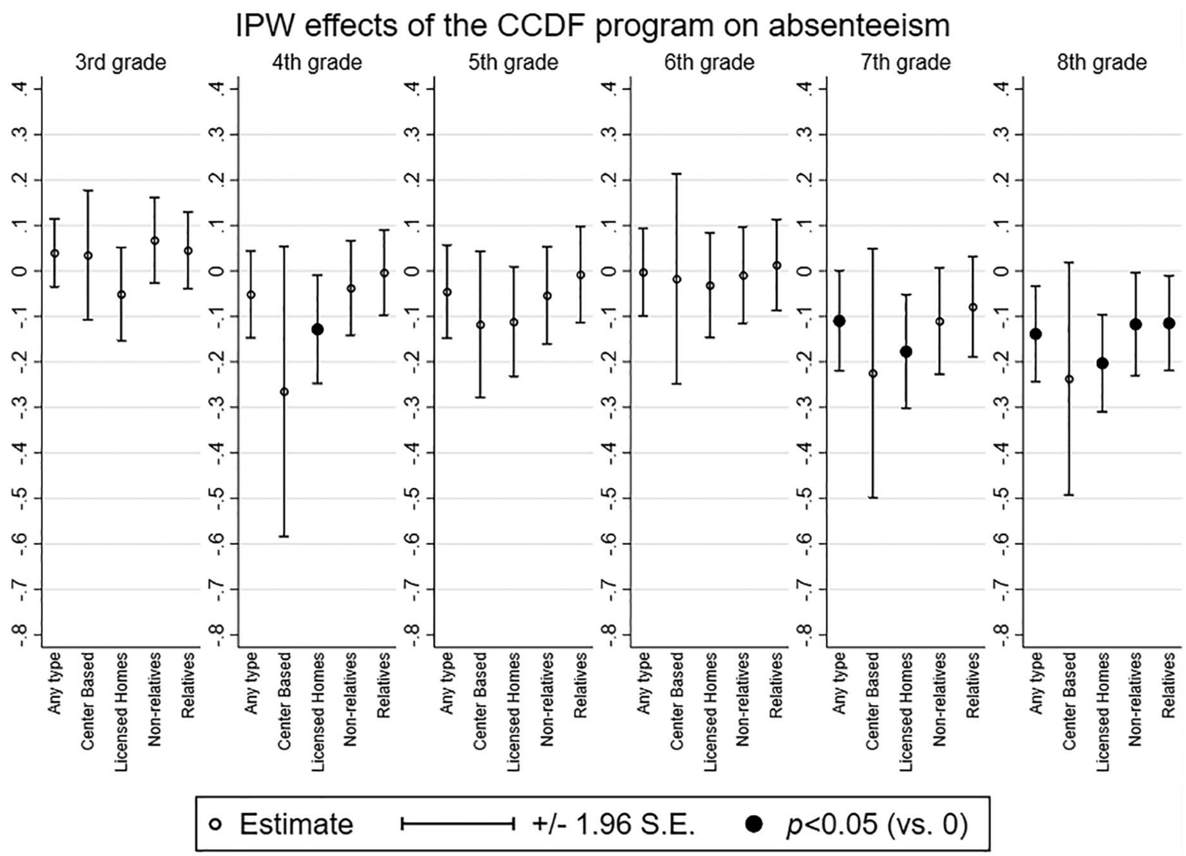

FIGURE 7. *IPW estimates of the effects of subsidies on absenteeism, third to eighth grades.*
Note. The vertical markers spread 1.96 standard errors above and below the mean coefficient estimates. A solid dot at the top of each bar denotes statistical significance of the coefficient estimates at 10% of confidence level or less. The comparison group here is formed by all eligible nonrecipients. The labels "All," "CB," "Licensed HB," "Nonrelatives," and "Relatives," respectively, correspond to the impacts of subsidy participation on all subsidy recipients, subsidy recipients in center-based care, subsidy recipients in licensed home-based care, subsidy recipients in license-exempt home-based care provided by nonrelatives, and subsidy recipients in license-exempt home-based care provided by relatives. IPW = inverse probability weighting.

distinctive patterns in the data. First, in most grades, the average treatment effects of subsidy use in center-based and licensed home-based child care programs trend in a negative direction, which suggest beneficial effects of subsidies on absenteeism across grades. Subsidy receipt significantly predicts decreased absenteeism for children in center-based care in Grades 4 and 8 (rounding to effect sizes of −0.12 standard deviations in each grade) and for children in licensed home-based care in Grades 4, 5, 7, and 8 (with effect sizes of −0.13 to −0.20 standard deviations). Second, consistent with the hypothesis of "sleeper" behavioral effects, we observe larger statistically significant effects in later grades rather than earlier grades. For example, the effect of subsidies in the center-based subgroup on absences in Grade 3 is nearly zero, while the effects by Grade 8 grow to 0.25 standard deviations. Furthermore, although exposure to subsidies used in license-exempt settings were not significantly associated with increased reading or math scores in any grade (see Figures 5 and 6), negative impacts of subsidy use on school absences materialized in these settings in the later grades (Grades 7 and 8). Finally, differing from the effects of subsidies on test scores, we do observe statistically significant effect of subsidies on absences for the average participant in the program in Grades 7 and 8, irrespective of the setting where care occurs.

False Discovery Rate Analysis. We studied the possibility that our results could have been driven by alpha inflation, as there are several *t* tests of statistical significance that compare conditional differences in means across grades, outcomes, and types of care. Of the 90 comparisons that we conducted, 23 were significantly different using traditional *t* tests and an alpha level of 0.05. The results from multiple hypothesis testing using the Benjamini-Hochberg procedure found that of the 23 originally statistically significant coefficients, 20 continued to be significant under more conservative alpha levels adjusted for multiple comparisons or potentially high false discovery rates (with a false discovery rate of 20%).

Discussion

Using a unique, linked administrative data set that provides high-fidelity information on child care subsidy eligibility, child care subsidy receipt, and children's middle school outcomes through eighth grade, the present study generated quasi-experimental estimates of impacts of subsidy receipt on children's test score and school absence data. We find that when comparing two groups of otherwise observationally equivalent children, child care subsidy receipt during early childhood does not produce different test score outcomes in eighth grade relative to nonreceipt of subsidies.

However, the average effects masked interesting variation by subgroup according to type of care purchased with the subsidy. Importantly, subsidy receipt used to purchase center-based child care in early childhood increased test scores relative to children who did not receive subsidies. With respect to math test scores, use of a subsidy to purchase care in a licensed home-based setting also produced positive effects such that the average math test scores of subsidy recipients who experienced licensed home-based care were higher than subsidy nonrecipients. Given that center-based care and licensed home-based care have been found to be higher in quality than available community-based alternatives (i.e., care that is *not* Head Start or public pre-K; Johnson et al., 2012), our results suggest that using subsidies to purchase child care in early childhood can be beneficial for children's achievement test scores but only when the care purchased is in a regulated (i.e., licensed) setting.

Turning to impacts on school absences—a consequential middle school outcome that has been ignored in prior subsidy evaluation research—our results suggest that children who attended care purchased with subsidies in early childhood experienced fewer absences in middle school than their peers who did not receive subsidies. These "sleeper effects" emerged in the later middle school years (e.g., seventh and eighth grades) when children have more control over their school attendance. As with test scores, the effects are considerably larger when subsidized care occurred in center-based programs. This is the first study to document that subsidy use has positive effects on low-income children's school-related behavior.

We emphasize that our results may actually *underestimate* the impact of subsidy receipt on low-income children's middle school test score and school absence outcomes, given that parents in our comparison group could have—and likely did—enroll their children in other early childhood programs, especially center-based child care. It is plausible that children in the comparison group attended Head Start or public pre-K—two public early childhood education programs that have been documented both to provide higher quality care than subsidized care (Johnson et al., 2012) and to produce positive short- and longer term child outcomes (Phillips, Gormley, & Anderson, 2016; Yoshikawa et al., 2013). Thus, our estimates may be considered a lower bound of the effect of the subsidy program on children's outcomes that would be obtained from a randomized controlled trial where the counterfactual implies parental care instead of child care. This is a limitation of our study, along with the fact that data on subsidy receipt were collected prior to the 2014 reauthorization of the Child Care and Development Block Grant, which implemented quality improvement measures and allocated substantial funding to achieve those improvements. Therefore, our results may not generalize to other states or localities and data sources, both prior to Child Care and Development Block Grant reauthorization or since. Another limitation of these data is that we are unable to get inside the "door" of the child care settings and elementary and middle school classrooms that these children attended. Identifying mediating mechanisms that could explain lasting impacts of subsidy receipt on children's later school outcomes should be a priority for future studies.

Given the high-fidelity nature of our measures drawn from administrative data, this evidence warrants attention during an era of increased quality improvement efforts to the subsidy program and child care subsidy expansion. Indeed, under the 2018 Omnibus Spending Bill, the parent legislation that funds child care subsidies received a record $2.4 billion dollars in additional spending (Consolidated Appropriations Act, 2018). If these funds are used to increase the number of children receiving child care subsidies, states may be well-advised to consider targeted efforts to link subsidy recipient parents with care provided in child care centers or licensed homes, increase efforts to incentivize licensing of existing providers, and to expand the number of children receiving subsidies relative to conditions of nonreceipt.

Acknowledgments

This research was funded by the federal Department of Health and Human Services, Administration for Children and Families Office of Planning Research and Evaluation (OPRE) Grant # 90YE0180-01-00. The authors are grateful to Chicago, Illinois IDES, CPS, and IDHS for data access and review; to Chris Herbst for his comments on an earlier version of the document; to David McQuown, Owen Schochet, and Anne Partika for research assistance and support with manuscript preparation; and to participants in the Association for Public Policy Analysis & Management (APPAM) and OPRE 2017 research conferences. Any opinions and/or errors belong solely to the authors.

Notes

1. The data set captures longitudinal enrollment data spanning the years from 1991 to 2017 ($N \approx 1.6$ million uniquely identified students).

2. This choice responds to how updated the "branch" or subsidiary databases containing absences and test scores data were when we obtained permits to use the data (2017). Notice also that we were constrained by the fact that absence records in CPS are consistently and homogeneously collected from 2008 on (when

a computerized attendance records system was extended to all schools in the district).

3. For instance, in 2009, the maximum reimbursement rates for full-time care of a 35-month-old child for licensed child care centers was US$741, for licensed child care homes and home groups, the amount was US$555, and for in-home child care providers (relatives and nonrelatives), the amount was US$276.

4. The described random assignment process was stratified by age ranges, so that the probability of a child who does not use subsidies was assigned a random age resembling the age distribution of children at the start of their eligibility period.

5. Estimates for 2009 and 2004 of the percentage of income included in child care costs (already accounting for subsidized options among poor families) place those costs between 19.6% and 28.2% of family income and 24.1% and 41.6% of personal income (Macartney & Laughlin, 2011). More recent estimates (2012) indicate that after accounting for subsidized options and provided parents pay some costs, the total income to child care costs ratio that characterizes households with income below 100% of the Federal Poverty Line face is 33%. Nationwide, around one in every six low-income households would have out-of-pocket costs of child care.

6. The model has several implications for the study of CCDF choices. For instance, a young mother could apply for the CCDF subsidy to pay to her own mother (who lives in the same household and owns the home) so that grandmother cares for the focal child while the mother works. The subsidy could increase the bargaining power of the mother of the focal child within the household, given that the grandmother of the focal child now would receive some income that she would have not received in the absence of the program. Another mother could opt for the CCDF subsidy to pay for a center for her child, so that the child can receive what she perceives is a better quality of care than what the grandmother was providing unpaid at home. These choices are not identical and need to be modeled separately. Moreover, given that the CCDF transfer implies an impact on budget size for low-income working families, the intrahousehold behavioral implications that result from the use of CCDF might not be minor. The dedicated study of joint choices of work and subsidized types of child care programs sponsored by CCDF is a fruitful area of research.

7. Covariate balance is neither a necessary nor a sufficient strategy for identification of IPW treatment effects when identification assumes matching on observables. Differing from randomized controlled trials, in matching methods, identification of treatment effects is based on an index sufficiency property, according to which the joint variability in all covariates in the propensity score (and not variability based on individual covariates) should fulfill the conditional independence assumption.

8. Across all estimates, fewer than 40 observations were outside the area of common support.

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