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OUT OF THE WOODWORK:
ENROLLMENT SPILLOVERS IN THE OREGON HEALTH INSURANCE EXPERIMENT

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ABSTRACT

We analyze the impact of expanded adult Medicaid eligibility on the Medicaid enrollment of already-eligible children. To do so, we exploit the 2008 Oregon Medicaid lottery, in which some low-income uninsured adults were randomly selected for the chance to apply for Medicaid. Children in these households were eligible for Medicaid irrespective of whether the household won the lottery. We estimate statistically significant but transitory impacts of adult lottery selection on children's Medicaid enrollment: for every 9 adults who enroll in Medicaid due to the lottery, one additional child also enrolls at the same time. Our results shed light on the existence, magnitude, and nature of so-called "woodwork effects".

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Additional information on the Oregon Health Insurance Experiment is available at
http://www.nber.org/oregon/1.home.html

1. Introduction

With the 2010 passage of the Affordable Care Act (ACA), the United States has moved closer to universal health insurance *eligibility*, but universal health insurance *enrollment* remains more elusive. Incomplete enrollment is particularly pronounced in the Medicaid population, where 14.3 percent of eligible adults and 7.2 percent of eligible children remain uninsured in spite of access to free or heavily subsidized coverage (Blumberg et al., 2018). To shed light on barriers to enrollment, we examine the impact of expanded Medicaid eligibility for adults on the Medicaid enrollment of their already-eligible children. Estimation of this so-called "woodwork" or "welcome-mat" effect also has implications for the total costs and benefits of expanded Medicaid eligibility; indeed, states cited potential woodwork effects to explain their reluctance to expand Medicaid under the ACA despite substantially enhanced federal subsidies, since the enhanced subsidies did not apply to the previously-eligible (Sommers and Epstein, 2011).

Credibly estimating woodwork effects, or any spillover effects of a policy, is challenging. Where the researcher may see a spillover effect from a policy change for group A on the behavior of group B, the skeptical seminar participant or referee may see a failed placebo test. Moreover, if one expects spillovers to be smaller than direct effects, plausible spillovers may be too small to be reliably detected. For good reason, therefore, the empirical bar for credibly identifying spillovers, or the lack thereof, is high.

Given these concerns, the 2008 Oregon Health Insurance Experiment provides an excellent opportunity to examine enrollment spillovers. A lottery randomly assigned some low-income adults and not others the ability to apply for Medicaid. The vast majority of children of these low-income adults were already eligible for Medicaid, and Medicaid eligibility for children did not depend on whether their parents won the lottery. The lottery only determined eligibility for adults.

We link existing Oregon Health Insurance Experiment data on the households that signed up for the lottery – including whether they were selected and whether and when they enrolled in Medicaid – to newly obtained data on Medicaid enrollment for all Oregon Medicaid beneficiaries. Prior work found that, in the year after random assignment, adults selected by the lottery to be able to apply for Medicaid were 25 percentage points more likely to enroll in Medicaid than adults who signed up for the lottery but were not selected (Finkelstein et al., 2012). Here, we use the lottery to study the impact of this expanded adult eligibility on the enrollment of their previously-eligible children.

Figures 1 and 2 summarize our key finding: a statistically significant impact of expanded adult Medicaid eligibility on children's Medicaid enrollment, with a spillover effect that is about an order of magnitude smaller than the direct effect. Specifically, we estimate that for every 9 adults who enroll in Medicaid due to the lottery, one additional child also enrolls. This impact of lottery selection on child enrollment occurs at the same time as the impact of lottery selection on adult enrollment. Both the direct effect of winning the lottery on adult enrollment and the spillover effect on child enrollment attenuate over time as some households not selected in the lottery gradually enroll in Medicaid through other mechanisms and some selected households that did enroll following the lottery do not re-enroll. As a result, one year after the lottery, the effect on child enrollment has declined from the initial, statistically significant increase of 0.024 children (compared to 0.22 adults) to a statistically insignificant increase of 0.008 children (compared to 0.14 adults). We estimate that the initial woodwork effect of 0.024 children newly enrolled represents about 5 percent of the total number of Medicaid-eligible children that could have enrolled in these households.

These results suggest that woodwork effects may be quantitatively less important than previously conjectured. Claims of potentially large woodwork effects – in excess of half of the direct effects – were prominent in discussions of the likely impact of the adult Medicaid expansion under the ACA (Murray, 2009; Norman and Ferguson, 2009). The existing literature is primarily based on difference-in-difference analyses of state Medicaid expansions in the 1990s and 2000s and of the ACA Medicaid expansions of the 2010s (Aizer and Grogger, 2003; Dubay and Kenney, 2003; Frean et al., 2017; Hamersma et al., 2019; Hudson and Moriya, 2017; Sommers et al., 2016; Sonier et al., 2013). Studies of pre-ACA adult Medicaid expansions have tended to find fairly large child enrollment spillovers; for example, Dubay and Kenney (2003) find that Massachusetts's adult Medicaid expansion raised child coverage rates by 15 percentage points. However, analyses of the ACA Medicaid expansions have tended to find more modest effects, with child Medicaid coverage rates rising by roughly 3 percentage points due to expanded parental eligibility (Hudson and Moriya, 2017; Sommers et al., 2016); this is roughly comparable to our estimate of an increase in 0.024 children enrolled per winning household relative to the average 0.85 children living in each household according to survey data. Of course, spillover effects may differ across contexts, and particularly between the large-scale expansions studied by most of the prior literature and a small-scale expansion such as the one we study in Oregon. The Medicaid enrollment of the children of adults participating in the Oregon lottery has also been the subject of prior study (DeVoe et al., 2015a), however the matching of children to parents was based on data that itself was directly affected by the lottery outcome, raising concerns about inference.[1]

More broadly, our findings contribute to the growing empirical literature on the pervasive phenomenon of incomplete take-up of social safety net programs. Commonly hypothesized barriers

[1] The cohort construction is described in Angier et. al. (2014); adults on the lottery list were matched to their children using data on adult and child Medicaid enrollment within the same household and also on adult and child use of the OCHIN community health center network. Adults were linked to their children if both adult and child enrolled in Medicaid and/or if both used a community health center in the network. Unfortunately, these family linkages were made using data from both pre (2002-2007) and post (2008-2010) lottery, which creates challenges for identifying the impact of winning the lottery on children's enrollment, since adult Medicaid enrollment and adult community health center use were significantly higher among lottery winners (DeVoe et al., 2015b; Finkelstein et al., 2012). Thus, for example, if children of lottery winners and losers were equally likely to enroll in Medicaid post lottery, children of winners might be more likely to be matched to their parents since the lottery increased the chance the parents themselves would be enrolled in Medicaid.

to take up include lack of information about eligibility, transaction costs associated with enrollment, or stigma from program participation (Currie, 2006). In the specific context of Medicaid, the ability of eligible individuals to wait and enroll when needed – so called conditional coverage – is another potential factor contributing to incomplete formal enrollment at any given point in time (Cutler and Gruber, 1996). Recent work has identified informational and transactional barriers to take up for Medicaid (Aizer, 2003; Wright et al., 2017), the Supplemental Nutrition Assistance Program (Finkelstein and Notowidigdo, 2019; Homonoff and Somerville, 2019), the Earned Income Tax Credit (Bhargava and Manoli, 2015), and Disability Insurance (Deshpande and Li, 2019). Our empirical finding of a contemporaneous increase in adult and child enrollment due to winning the lottery is likewise consistent with both limited information on eligibility and the transaction costs of enrolling as barriers to children's Medicaid take up.

Finally, our findings also contribute to the literature that has used the random assignment of adult Medicaid eligibility from the Oregon Health Insurance Experiment to study the impact of expanding Medicaid eligibility. Prior work has examined effects on adult health care use, health, financial outcomes, and voter participation over the first two years. (Baicker et al., 2014, 2013; Baicker and Finkelstein, 2019; Finkelstein et al., 2012, 2016; Taubman et al., 2014). It found that, for the adult lottery participants, Medicaid increased health care use across a wide range of settings, reduced out-of-pocket medical spending and the prevalence of unpaid medical debt, reduced depression and improved self-reported health, had no detectable impact on employment, earnings or several measures of physical health, and had a short-lived impact on increased voter turnout. The current paper expands the scope of the analysis of the Oregon Health Insurance Experiment to consider potential indirect effects on individuals not directly subject to the experiment, namely the children of participating adults.

The rest of the paper proceeds as follows. Section 2 describes the institutional setting and the possible mechanisms by which winning the lottery for adult Medicaid eligibility might affect already-eligible children's Medicaid enrollment. Section 3 describes the empirical framework and data. Section 4 presents the results. A final section concludes.

2. Setting

2.1 Medicaid in Oregon

Oregon's Medicaid program – the Oregon Health Plan (OHP) – consists of two distinct programs: OHP Plus and OHP Standard. The Oregon Health Insurance Experiment was a lottery for adults for coverage through OHP Standard; children of lottery participants were eligible for Medicaid coverage through OHP Plus and remained eligible regardless of whether their parents won.

At the time of the Oregon experiment, OHP Plus served the categorically eligible Medicaid population, including older adults, adults with disabilities, pregnant women, people eligible for TANF, and foster children, with coverage in each category available up to certain income limits. Children age 0-5 below 133% of the federal poverty line and children age 6-18 below 100% of the poverty line were eligible for OHP Plus; children between these limits and 185% of the federal poverty line were eligible for health coverage through the Children's Health Insurance Program or CHIP (Kaiser Family Foundation, 2019; National Academy for State Health Policy, n.d.).

OHP Standard, the program subject to the 2008 lottery, covered uninsured adults age 19-64 under the federal poverty line who did not otherwise qualify for OHP Plus. By construction therefore, the child of any adult eligible via lottery for OHP Standard (i.e. below 100% of the federal poverty line) would be eligible for OHP Plus. OHP Standard and Plus both provided comprehensive insurance benefit packages without cost-sharing, though OHP Plus's package was broader and had no premiums for children while OHP Standard charged a premium of up to $20 per month (Berkobien, 2008; Oregon Department of Human Services, 2008a).

2.2 Lotteried Eligibility for OHP Standard

Enrollment in OHP Plus was continuously open and so children of adults eligible for OHP Standard were continuously eligible to enroll in OHP Plus. However, enrollment in OHP Standard had been closed to new enrollment since 2004 due to limited state budgets. In 2008, with a budget sufficient to cover an estimated 10,000 additional individuals and anticipating significant excess demand if enrollment were re-opened without restriction, the state received permission from federal regulators to conduct a lottery.

For a five week period in January-February 2008, the state allowed anyone to sign up for the list from which lottery draws would be taken, which was called the reservation list. When individuals signed up for the lottery, they were told to list members of their household over the age of 19 whom they wanted to add to the reservation list, and all these individuals were included on the list. Extensive measures were taken to encourage sign-up: individuals could enroll by multiple means (telephone, fax, in-person, snail mail, and online) and the form was only one page long to simplify joining (see Appendix Figure A1). The state ran an intensive outreach campaign to solicit submissions, including mailing all recipients of state programs for low-income beneficiaries. No efforts were made to verify information contained in submissions, and 89,824 individuals joined the reservation list.

Following the sign-up period, the state began conducting lottery draws from the reservation list. Eight draws in total were conducted – roughly one a month – from the first draw on March 10, 2008 to the last draw on September 11, 2008. Although draws were conducted at the individual level, the state considered all adults in the individual's household to be selected by the lottery.

Ultimately, 35,169 individuals were selected in order to enroll 10,000 additional people in OHP Standard.

Lottery selection conferred eligibility to apply for OHP Standard. Upon selection, the state mailed the selected household an OHP enrollment form. From the date of mailing, the household had 45 days to submit the relevant documentation to the state. The state sought to encourage selected households to submit their forms by mailing them a reminder and calling them to offer assistance. Upon receipt of the OHP enrollment form, the state verified eligibility for an OHP plan and enrolled the participant with coverage retroactive to the weekday after the enrollment form was mailed. We call this date the “adult eligibility date”.

Among those selected, about 60% applied for coverage. The incomplete rate of applying could reflect inattention to the paperwork that was mailed, the burden of filling out the application and providing supporting documentation, and/or a realization that they were unlikely to be eligible. About half of those who applied were deemed eligible and enrolled in Medicaid. The main reason for a rejected application was failure to meet the income requirement, which required the last quarter’s income to correspond to an annual income below the poverty line.[2] For more details on the lottery and application process, see Finkelstein et al. (2012) and Finkelstein et al. (2010).

2.3 Enrolling in OHP Plus

At the time of the lottery, the state was continuously accepting new applications for OHP Plus. To initiate an application, anyone could make a request online, by phone, by mail, or in person. Those applying for OHP, whether they were selected off the reservation list or they requested an application from the state, were sent the same 46-page packet. At a minimum, applicants were required to fill out a 4-page section that requested information about themselves and their

[2] As noted, income limits for children extended higher, to 185% of the poverty line, mostly due to CHIP eligibility. Thus, spillovers could occur even for lottery list adults who were or would have been rejected due to high income. In practice, as discussed below, we found no evidence of spillovers onto CHIP enrollment.

household. Applicants were all also required to provide proof of address, citizenship (if they were U.S. citizens), and income. Depending on the household's circumstances vis-à-vis eligibility, an applicant could be required to fill out any of an additional nine sections in the packet, typically 1-2 pages each.

While all children of adults eligible for OHP Standard were eligible for OHP Plus regardless of the lottery outcome, a parent's winning the lottery might increase the chances of their children enrolling in OHP Plus by reducing the transaction costs of enrolling them or addressing information barriers about their eligibility. The OHP Standard application form asked the applicant to "list yourself and everyone living with you" and included a checkbox next to each name to request benefits for that person (see Appendix Figure A2). The form therefore gave parents an opportunity to request benefits even if they were not aware of the eligibility rules. In addition, staff who validated OHP Standard applications were instructed to "check to see if the applicant qualifie[d] for any other medical programs" (Oregon Department of Human Services, 2008b). Staff may have interpreted this directive as encouraging them to check on the eligibility of children in the same households as applicants. Finally, when participants applied in-person, case workers may have encouraged them to check the box on the application to enroll their children in coverage.

3. Empirical Framework and Data.

3.1. Empirical Framework

Our analytic framework closely follows the standard approach used in prior analyses of the Oregon Health Insurance Experiment (see e.g. Finkelstein et al., 2012). However, unlike the prior studies, our unit of analysis is the household rather than the individual. As we describe above, the household is the level of treatment (i.e. lottery selection conferred eligibility for all household adults). We compare Medicaid enrollment for households selected by the lottery (the treatment group) to households who signed up for the lottery but were not selected (the control group). We look separately at adult Medicaid enrollment (which in prior work was considered the "first stage" of the experiment) and children's Medicaid enrollment, the focus of our current analysis.

The basic estimating equation is:

$$y_h = \beta_0 + \beta_1 LOTTERY_h + X_h\beta_2 + V_h\beta_3 + \varepsilon_h \quad (1)$$

The outcomes (y_h) vary across analyses but are always some measure of household h's Medicaid enrollment. We examine Medicaid enrollment for children and adults separately and at various time periods after the lottery. Our main outcome variable is the number of children (or adults) enrolled at a given point in time relative to the adult eligibility date for the lottery draw – the weekday after the enrollment form was sent to winners of that lottery draw. We also examine indicator variables for whether any children (or any adults) in the household are enrolled, as well as the number of child (or adult) member-months enrolled over a given time period.

The indicator variable $LOTTERY_h$ takes the value of 1 if the household was selected by the lottery and 0 if the household was on the reservation list but not selected by the lottery. The key coefficient of interest is β_1, which measures the impact of the household's lottery selection on enrollment.

We denote by X_h the set of covariates that are correlated with treatment probability and thus must be controlled for so that β_1 produces an unbiased estimate of the impact of winning the lottery. Specifically, probability of treatment (i.e. winning the lottery) varied based on the number of adults in the household that were listed on the lottery sign-up form (hereafter "household size"). Although the state randomly sampled from individuals on the list, the entire household of any selected individual was considered selected and eligible to apply for insurance. As a result, selected (treatment) individuals are disproportionately drawn from households of larger household size. We therefore include indicator variables for the household size; 87% of households listed 1 member on the reservation list, 13% had 2 members, and less than 0.1% had 3 members. Lottery selection was random conditional on household size. For more detail on how the lottery was conducted – as well as verification that randomization was conducted as described – see Finkelstein et al. (2012).

We denote by V_h a second set of covariates that can be included to potentially raise statistical power because they are predictive of outcomes. These covariates are not needed for β_1 to give an unbiased causal estimate of the effect of lottery selection as they are independent of treatment status due to randomization, but they may improve the precision of the estimates. In our baseline analyses, we include indicators for lottery draw as well as four pre-lottery Medicaid enrollment measures (from January 15, 2008): number of reservation list adults enrolled, any reservation list adult enrolled, number of children enrolled, and any child enrolled. We show in robustness analyses below that results are similar but, as expected, less precise when pre-lottery enrollment measures are omitted.

For control households, we follow the approach of Finkelstein et al., (2012) and randomly assign each household a lottery draw, stratified by household size; specifically, for each household size, lottery draw assignment was randomly assigned to controls in proportion to the distribution of treatment households of that household size across lottery draws. This approach allows us to measure outcomes relative to each household's "lottery draw" adult eligibility date and to control for "lottery draw" for both treatment and control households.

3.2. Data sources and variable construction

We analyze two primary data sets, both of which we obtained from the State of Oregon. First, we use the state-provided reservation list, which includes the information each individual provided at sign-up, as well as whether they were selected by the lottery, and if so, in which lottery draw. The self-reported sign-up information consists of name, address, sex, and birthdate of the individual signing up as well as anyone else in the household 19 or older whom the individual wanted to add to the reservation list. All individuals on the reservation list are 19-64; there are no children on the reservation list. To test treatment-control balance, we additionally use pre-randomization measures of hospitalizations derived from a linkage to hospital discharge data (see Finkelstein et al. 2012 for more details).

Second, we use data on Medicaid enrollment for all Oregon Medicaid enrollees in 2008, 2009, and 2010. These are spell-level data which include the beginning and end date (if any) of the spell, the enrollee's name, date of birth and sex; the data also include address information with start and end dates for each location during the enrollment spell. We use these data to construct our outcome variables (Medicaid enrollment over particular periods of time). Our main analyses focus on enrollment within the first year post-lottery; in supplemental analyses, we show outcomes up to 720 days, the longest time period we can study before a new lottery for OHP Standard essentially treats the entire control group (see Finkelstein et al., 2016). The data contain both Medicaid and CHIP enrollment records. For our analysis, we count CHIP enrollment as a form of Medicaid enrollment.[3]

We use the address information to match the reservation list to the Medicaid enrollment data in order to measure the number of children and adults in each household who were enrolled in Medicaid at various points in time. Appendix A provides more detail on this matching exercise. Briefly, we use ArcGIS to geocode addresses in both data sets; this returns a latitude-longitude coordinate pair for each address (accurate to 1.1 meters). We are able to geocode 80 percent of all addresses on the reservation list (or 91 percent once we removed the 12 percent of addresses that listed a PO Box and therefore could not be geocoded) and 87 percent of the addresses in the

[3] Because everyone who was eligible for the OHP Standard expansion had family income below 100% FPL, we expect reservation list children of 'complier' adults (who gain, or would gain, coverage due to winning the lottery) to all be eligible for traditional Medicaid and not CHIP. And in practice, we did not detect changes in CHIP enrollment due to winning the lottery. However, we included CHIP in the analysis because the state did not verify eligibility of reservation list households unless they won the lottery and applied for coverage. Thus, higher income households could have entered and won the lottery; households may also have experienced income shocks between entering the lottery and winning. These households would not be able to enroll adults in OHP Standard, but could end up having children covered under OHP Plus or CHIP.

Medicaid enrollment data. We also extract and standardize apartment and unit numbers when they are available. We then match the geocoded addresses in the two data sets. For each reservation list household, we define the number of children enrolled in Medicaid as the number of individuals under age 19 enrolled at the address the household provided when signing up for the reservation list. We require that children be under 19 one year after the adult eligibility date for the last lottery draw (October 8, 2009) to ensure that they are children under Medicaid rules for the entire analysis period. We define the number of adults enrolled in Medicaid as the number of reservation list members in the household who were enrolled at the address; to count as a reservation list match, the record must have the same birthdate and sex in both datasets.

Addresses on the lottery list were self-reported by households at the time of lottery sign-up, while addresses in the Medicaid data reflect the most recent address that Medicaid has on file. These addresses may differ. A potential threat to our research design would occur if the addresses of previously enrolled children were updated as a result of their parents winning the lottery, enrolling in Medicaid, and updating the addresses on file for the entire family. This scenario could spuriously lead us to find more children enrolled in Medicaid among lottery winners than lottery losers even if there was no woodwork effect. To alleviate this concern, if a Medicaid enrollee has multiple addresses, we define the baseline address in the enrollment data as the first address on file starting from January 1, 2008, and only use this baseline address for matching the reservation list households to Medicaid enrollment. We later show in robustness analyses that our findings are similar if we instead use contemporaneous addresses.

We expect our outcome variables – counts of children and adults enrolled at reservation list households – to have measurement error arising from the imperfect matching of Medicaid enrollees to households on the reservation list using the address information in each data set. This measurement error may include both false positives (the reservation list household matches to enrollment of other households) and false negatives (the reservation list household has some members enrolled in Medicaid that we fail to match). Under the null hypothesis that winning the lottery has no spillover effect on child enrollment, false positives and false negatives are expected to be balanced between treatment and control households due to random assignment of treatment status. However, under the alternative hypothesis that Medicaid eligibility for adults does have (positive) spillover effects onto the enrollment of children, false negative matches will disproportionately occur in treatment households because we will fail to match some of the marginal enrollees. We thus expect attenuation bias in β_1, the estimated impact of lottery selection on enrollment, for our primary outcome, the number of children enrolled in Medicaid in the household.[4] Below, we use an alternative and arguably more precise measure of adult enrollment to estimate the extent of measurement error in our adult enrollment measures; under the assumption that the extent of mis-measurement is the same for children and adult enrollment, we show that adjusting for this measurement error has little quantitative impact.

3.3. Sample Definition and Summary Statistics.

We define our study sample based on households on the reservation list. Following Finkelstein et al. (2012), we exclude individuals and households that were not eligible for OHP Standard because they gave an address outside of Oregon, were not in the right age range, died prior to the lottery, had institutional addresses, were signed up by third parties, would have been eligible for Medicare by the end of our study period, or were inadvertently included on the original list multiple times by the state. This leaves us with the 74,922 individuals that formed the analysis sample of Finkelstein et al. (2012). These individuals represent 66,210 households, our unit of analysis.

[4] We study two other enrollment measures. The first is member-months of enrollment, where we expect attenuation bias under woodwork effects for the same reason as described above. The other is a binary indicator for any child enrollment; with this nonlinear transformation of the enrollment count, the bias in β_1 is of indeterminate sign.

We further restrict to the 53,147 (80.3%) of these households that have reservation list addresses that we successfully geocoded. Finally, to remove outlier observations for which enrollment is likely measured with substantial error, we exclude the 274 households above the 99th percentile of pre-lottery number of children enrolled in Medicaid (measured on January 15, 2008). The 99th percentile among households with a successfully geocoded address is five children enrolled. This exclusion is designed to alleviate the concern that a reservation list household inadvertently matched to a large number of children outside that household; for example, a household in an apartment complex that failed to provide a unit number on the reservation list would match to all children in the building without a unit number in their Medicaid addresses. We explore robustness to our handling of outliers below.

These criteria result in a final analysis sample size of 52,873 households. Table 2 shows descriptive statistics of variables measured pre-randomized for control group households, as well as treatment-control differences. Panel A shows variables derived from the self-reported information provided on the reservation list and Panel B shows four measures of baseline Medicaid enrollment (as of January 15, 2008). Column 1 indicates that in our analysis sample, the average age of the household member who signed up was 40, 58% were women, and 93% listed English as their preferred language; the median income in the household's ZIP code was, on average, $39,774. Prior to randomization, 22 percent of households in our sample had at least one child enrolled in Medicaid and, conditional on enrollment, 1.9 children were enrolled. Consistent with prior work (Finkelstein et al. 2012), only a small fraction (3%) of households had a reservation list adult enrolled before randomization. Columns 2 and 3 look at the treatment-control balance of these variables. Only one of the 11 measures – sex – is imbalanced between treatment and control (as it was in the sample analyzed in Finkelstein et al. 2012). The fact that baseline Medicaid enrollment is statistically indistinguishable between treatment and control (panel B) helps to verify that children gaining coverage did not receive it retroactive to before the date on which we measure baseline enrollment. This is consistent with documentation from the state that coverage for adults was retroactive to a later date – the weekday after the enrollment form was sent to the household, which we have called the adult eligibility date in this manuscript – and supports our use of these covariates to raise statistical power, although we will also show robustness to omitting them.[5]

Finally, to estimate the number of children "at risk" of gaining coverage through the woodwork effect, we draw on additional data from a mail survey administered around the time of the lottery drawings to a random 75 percent of our analysis subsample of 52,873 households; Section VC of Finkelstein et al. (2012) provides more detail on this survey. In our analysis subsample, the survey had a response rate of 46%. Among respondents, the average number of children per household was 0.85. Using the Medicaid enrollment data prior to the lottery, we estimate that on average, control group lottery participants had 0.42 children enrolled in Medicaid. While these numbers come from different sources (survey responses among the subsample of responders vs. matched administrative data for everyone)[6] and cover slightly different time periods, together they allow us to form a rough estimate of the size of the risk set: we estimate that there were about 0.4 children who could potentially have come out of the woodwork per lottery household.

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[5] The sample analyzed here differs from the one analyzed in Finkelstein et al. (2012) in two respects. First, it is limited to households with addresses we could geocode; this meant, in particular, that we omitted the 12% of households on the reservation list that provided P.O. boxes for their address because they could not be geocoded. Second, we analyze outcomes at the household level rather than the individual level. For completeness, Appendix Table A1 shows all of the variables in Table 1 – as well as pre-randomization measures of hospital utilization – for our household-level analysis sample (column 1), the full household-level analysis sample based on the analysis sample in Finkelstein et al. (2012) (column 2), and the individual-level analysis sample analyzed in Finkelstein et al. (2012) (column 3). Appendix Table A2 then shows balance tests for each of these three samples and for each of the three sets of variables (where feasible) as well as omnibus tests of balance across all the available sets of variables. We are unable to reject the null hypothesis that the covariates are balanced across treatment and control for all 10 of these tests.

[6] We suspect non-respondents have similar average numbers of children because, prior to the lottery, we estimate the average number of children enrolled in Medicaid to be 0.42 for control households who responded to the survey and 0.41 for control households who did not.

4. Results

4.1. Spillover estimates

Figures 1 and 2 illustrate the time path of effects of winning the lottery on children's enrollment and on adult enrollment. Both graphs plot treatment effects on the number of children or adults enrolled at varying times relative to the date of adult eligibility – the date that coverage would begin for adults who enrolled due to the lottery draw; the adult eligibility date is denoted with a dashed vertical line. We plot the estimated effects every 30 days, from 30 days prior to adult eligibility to 360 days after, which corresponds to our analysis period of 1 year post adult eligibility.

Figure 1 shows the impact of lottery selection on the enrollment of the household's children. As expected, the estimates of effects prior to the adult eligibility date are statistically insignificant. There is a large, concentrated increase in children's coverage immediately after adult eligibility. Figure 2 shows that the timing of the increase in children's enrollment mirrors the timing of the increase in enrollment for adults; this is consistent with children and adults applying for OHP together and the state enrolling them with roughly the same start dates. Both the child and adult enrollment effects peak around 90 days and decline after that.

Table 2 presents point estimates of the coverage effects measured at 90 days after adult eligibility. Winning the lottery increases the expected number of children enrolled by 0.024. This represents about one child for every 41 winning households, or about a 3 percentage point increase relative to the 0.85 children per household that we estimated from the survey data. We find a significant effect on the extensive margin of any child enrollment: winning the lottery increases the probability a household enrolls at least one child by 1.3 percentage points. We also consider member-months, i.e. the total months of enrollment for all children in the household during the 90 days following adult eligibility. Winning the lottery raises child member-months by 0.07. All of these effects are statistically significant at the <0.01% level.

We provide several ways to benchmark our baseline estimate of an increase in children's enrollment of 0.024 per winning household. One is to contrast it with the estimate in Table 2 of the 0.22 increase from winning the lottery on the number of enrolled adults. The ratio of the spillover effect on children to the direct effect on adults is 0.11, indicating that one child was enrolled in Medicaid for every 9 adults who took up coverage due to the lottery. Another informative benchmark is to note that the woodwork effect of 0.024 children gaining coverage represents only about 5 percent of the approximately 0.4 average number of children not enrolled in Medicaid pre-lottery in reservation list households – our estimate in Section 3.3 of the number that could potentially have gained coverage when adults applied. Thus the woodwork effect we estimate, while statistically significant, is only a fraction of its potential size.

The initial Medicaid coverage period for children (or adults) was the 6 months after enrollment began, excluding the first calendar month. To retain coverage past this point, the state required both adults and children to reapply and demonstrate that they were still eligible (Oregon Department of Human Services, 2008c). Figure 1 shows that a decline in the treatment effects on the number of children covered occurs roughly 180-210 days after adult eligibility. The timing suggests that some of the children who gained coverage through woodwork effects did not recertify their eligibility.

Table 3 quantifies how the woodwork and direct effects decline over time. At one year, woodwork effects are one-third the magnitude of the 90 day estimate and are no longer statistically significant. Effects for adults also decline, but at a somewhat slower rate. As a result, whereas at 90 days nine adults gain coverage for every child, at one year the ratio rises to 17 covered adults per covered child.

To better understand the sources of attenuating treatment effects, Figure 3 plots the predicted mean number of children enrolled in the treatment and control groups from the regression in equation (1) at various 30 day intervals from the adult eligibility date; for comparison, Figure 4 plots the analogous estimates for adult enrollment. For both groups, the figures show that two factors contribute to the attenuation of the treatment effects: a drop off in the enrollment of the treatment group when recertification is required (180-210 days from adult eligibility), and a secular increase in enrollment in the control group. For children (Figure 3), the latter effect appears quantitatively much more important, suggesting that the woodwork effect often acts to hasten the enrollment of eligible children who would otherwise have gained coverage within the year. For adults (Figure 4), the decline in treatment group enrollment around the recertification period appears to be the main driver of the attenuation; the only way control group adults (who lost the lottery) could enroll in Medicaid is if they became categorically eligible for OHP Plus.

In the appendix, we extend the analysis of the treatment effects out to 720 days for both children and adults (Appendix Figures A3 and A4). The estimates become somewhat noisier as they extend past the one year mark because we must increasingly up-weight a portion of the study population to adjust for a new lottery for OHP Standard that the state conducted beginning in fall 2009 (see Baicker et al., 2013 and Finkelstein et al., 2016 for more detail). Regardless, our finding of economically small and statistically insignificant woodwork effects at one year continues to hold over this longer horizon; adult enrollment effects continue to decline in this period.

4.2. Heterogeneity in spillover effects

Table 4 explores two dimensions of potential heterogeneity in spillover effects. Panel A examines the extent to which the spillover effects reflect previously unenrolled children gaining coverage rather than previously enrolled children being more likely to retain their coverage. Specifically, we redefine the outcome to either only count children who were not enrolled in Medicaid prior to randomization (left side) or to only count children who were enrolled previously (right side). Effects are statistically significant on both outcomes, but the gains are concentrated in previously unenrolled children, where the point estimate amounts to about three-fourths of the total enrollment effect. This result suggests that woodwork effects mostly operate by bringing new children into coverage, with smaller effects on the retention of the previously enrolled.

Panel B explores the extent to which the woodwork effect is concentrated in the three-quarters of households that did not already have a child enrolled in Medicaid as compared to the one quarter that had some *ex ante* child enrollment. For households without prior enrollment, effects are similar in magnitude to the full sample and highly statistically significant. Effects for households with prior enrollment are also similar in magnitude but are measured more imprecisely, at least partly reflecting the smaller sample. The estimates suggest that effects may be similar for both household types.

4.3. Sensitivity analysis

As noted earlier, mismeasurement of addresses – specifically false negatives – may attenuate our estimates of woodwork effects. To gauge the potential magnitude of this attention bias, we make use of an alternative – and arguably more accurate – measure of adult Medicaid enrollment produced by the state Division of Medical Assistance Programs (DMAP) and used in prior Oregon study analyses.[7] We estimate a "correction factor" (c) as the ratio of treatment effects on adult enrollment (i.e. β_1) estimated using the address-based measure of adult enrollment and the DMAP-based measure. Appendix Table A3 presents these two estimates as well as the correction factor (i.e. their ratio), which ranges from about 0.71 to 0.73 depending on the time frame; in other words, the address-based matching yields estimated treatment effects for adult enrollment that are 27 to 29

[7] To examine the two different measures of adult Medicaid enrollment, we studied their agreement for the 52,873 reservation list household heads in the analysis sample in December 2008. The results are consistent with a lower rate of false negatives for the DMAP measure. Specifically, both yielded the same enrollment status for the vast majority of adults (92%), but when they disagreed, it was largely because the DMAP measure detected enrollment when the address-based measure did not (7%) rather than vice versa (1%).

percent lower than the DMAP-based matching approach. Under the assumption that the rate at which we fail to capture Medicaid enrollment is the same for reservation list adults and for their children, we can then apply the same correction factor to the estimated treatment effects for children. The last column of Table A3 shows the results. The estimated impact on the number of children enrolled at 90 days increases from 0.024 to 0.034. Of course, to the extent that even the DMAP-based matching has measurement error, the correction factor (for both adults and children) may be itself an under-estimate.

Appendix Table A4 explores additional robustness exercises. Column 1 replicates the baseline results from Table 2. Subsequent columns show sensitivity to specific alternatives, with results that are generally similar to baseline. Column 2 omits controls for pre-randomization Medicaid enrollment – we control only for household size and lottery draw. As expected given the use of these controls to raise power, treatment effects are similar but measured more imprecisely. Column 3 uses contemporaneous addresses rather than the first observed address to match reservation list households to Medicaid enrollment data. Using contemporaneous addresses is appealing because it is possible that the initial addresses in the enrollment data could be out of date, leading to mis-measurement when we match the reservation list to enrollment. However, this approach could lead to upwardly biased estimates if, for example, the state updates children's addresses when their parents enroll in Medicaid. Compared to the baseline specification, effects are slightly larger using the contemporaneous address approach.

Columns 4 and 5 explore alternative approaches to handling outliers. In column 4, we take a more draconian approach, further omitting households above the 95th percentile (more than 3 enrolled children) rather than our baseline approach of omitting households above the 99th percentile (more than 5 enrolled children); the estimates are quite similar, showing that lesser outliers do not drive our findings. In column 5, we make no outlier exclusion, adding back the 275 outlier households representing just 0.5% of the overall sample. This change shrinks estimates of the effect on the number children enrolled by about 40 percent and more than doubles the standard error, so that the woodwork effect is no longer statistically significant. We suspect that results including outliers are substantially contaminated by measurement error: the outlier households have a median pre-randomization enrollment of 7 children and a mean of 11; some are (implausibly) matched to hundreds of enrolled children. Not surprisingly, the estimates of the woodwork effect on whether a household has any children enrolled are essentially unaffected by the treatment of outliers.

5. Conclusion

We use the 2008 randomized expansion of adult Medicaid eligibility in Oregon to better understand the magnitude and duration of woodwork, or spillover, effects of Medicaid eligibility expansions onto populations that were already Medicaid-eligible. We find clear evidence of woodwork effects: for every 9 adults who gained coverage from the expansion, so did one already-eligible child. While statistically significant, the increase in the number of eligible children who enrolled in Medicaid represents only about 5 percent of our estimated number of children of lottery list adults who could have enrolled. Both the direct effect on adult enrollment and the spillover effect on children's enrollment fade over the subsequent year. While the decline in direct effects is mostly driven by disenrollment of adults due to recertification rules, the decline in spillover effects is largely the result of children in control households enrolling in Medicaid; this pattern is consistent with adult Medicaid eligibility driving earlier enrollment of already-eligible children who otherwise would have enrolled soon thereafter.

In the last decade, the U.S. has moved closer to universal insurance eligibility by making both Medicaid and subsidized private health insurance available to a much broader population. Our findings, estimated from an earlier and smaller Medicaid eligibility expansion to a group similar to those covered by more recent Medicaid expansions, shed light on the determinants of incomplete take-up of Medicaid. The time pattern of the spillover effects – occurring contemporaneously with the direct enrollment effects – is consistent with both information frictions and application costs limiting take-up. That said, the magnitude of the effects we estimate cast some doubt on the potential for large spillovers from expanding Medicaid eligibility for adults on Medicaid enrollment of their already-eligible children. Taken together, the findings highlight the continuing challenges that policymakers will face in translating increases in Medicaid eligibility into increases in Medicaid enrollment.

References

Aizer, A., 2003. Low Take-Up in Medicaid: Does Outreach Matter and for Whom? American Economic Review 93, 238–241. https://doi.org/10.1257/000282803321947119

Aizer, A., Grogger, J., 2003. Parental Medicaid Expansions and Health Insurance Coverage (No. w9907). National Bureau of Economic Research, Cambridge, MA. https://doi.org/10.3386/w9907

Angier, H., Gold, R., Crawford, C., P. O'Malley, J., J. Tillotson, C., Marino, M., DeVoe, J.E., 2014. Linkage Methods for Connecting Children with Parents in Electronic Health Record and State Public Health Insurance Data. Matern Child Health J 18, 2025–2033. https://doi.org/10.1007/s10995-014-1453-8

Baicker, K., Finkelstein, A., 2019. The Impact of Medicaid Expansion on Voter Participation: Evidence from the Oregon Health Insurance Experiment 14, 383–400. https://doi.org/10.1561/100.00019026

Baicker, K., Finkelstein, A., Song, J., Taubman, S., 2014. The Impact of Medicaid on Labor Market Activity and Program Participation: Evidence from the Oregon Health Insurance Experiment. American Economic Review 104, 322–328. https://doi.org/10.1257/aer.104.5.322

Baicker, K., Taubman, S.L., Allen, H.L., Bernstein, M., Gruber, J.H., Newhouse, J.P., Schneider, E.C., Wright, B.J., Zaslavsky, A.M., Finkelstein, A.N., 2013. The Oregon Experiment — Effects of Medicaid on Clinical Outcomes. N Engl J Med 368, 1713–1722. https://doi.org/10.1056/NEJMsa1212321

Berkobien, R., 2008. Background Brief on Oregon Health Plan, Background Brief - Legislative Committee Services.

Bhargava, S., Manoli, D., 2015. Psychological Frictions and the Incomplete Take-Up of Social Benefits: Evidence from an IRS Field Experiment. American Economic Review 105, 3489–3529. https://doi.org/10.1257/aer.20121493

Blumberg, L.J., Holahan, J., Karpman, M., Elmendorf, C., 2018. Characteristics of the Remaining Uninsured: An Update, U.S. Health Reform—Monitoring and Impact.

Currie, J., 2006. The Take-Up of Social Benefits, in: Public Policy and the Income Distribution. Russell Sage Foundation, pp. 80–148.

Cutler, D.M., Gruber, J., 1996. Does Public Insurance Crowd out Private Insurance? The Quarterly Journal of Economics 111, 391–430. https://doi.org/10.2307/2946683

Deshpande, M., Li, Y., 2019. Who Is Screened Out? Application Costs and the Targeting of Disability Programs. American Economic Journal: Economic Policy.

DeVoe, J.E., Marino, M., Angier, H., O'Malley, J.P., Crawford, C., Nelson, C., Tillotson, C.J., Bailey, S.R., Gallia, C., Gold, R., 2015a. Effect of Expanding Medicaid for Parents on Children's Health Insurance Coverage: Lessons From the Oregon Experiment. JAMA Pediatr 169, e143145. https://doi.org/10.1001/jamapediatrics.2014.3145

DeVoe, J.E., Marino, M., Gold, R., Hoopes, M.J., Cowburn, S., O'Malley, J.P., Heintzman, J., Gallia, C., McConnell, K.J., Nelson, C.A., Huguet, N., Bailey, S.R., 2015b. Community Health Center Use After Oregon's Randomized Medicaid Experiment. The Annals of Family Medicine 13, 312–320. https://doi.org/10.1370/afm.1812

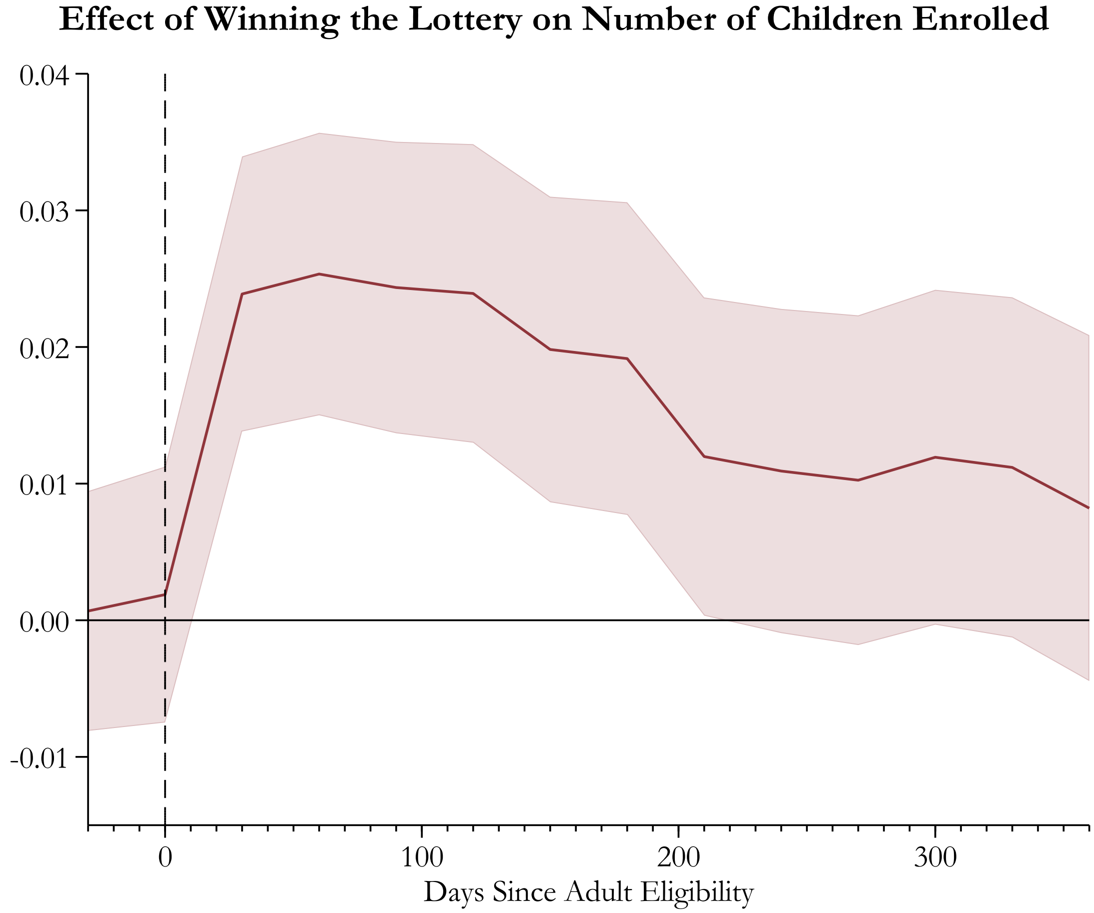
Dubay, L., Kenney, G., 2003. Expanding Public Health Insurance to Parents: Effects on Children's Coverage under Medicaid. Health Serv Res 38, 1283–1302. https://doi.org/10.1111/1475-6773.00177

Finkelstein, A., Notowidigdo, M., 2019. Take-up and Targeting: Experimental Evidence from SNAP. Quarterly Journal of Economics.

Finkelstein, A., Taubman, S., Allen, H., Gruber, J., Newhouse, J.P., Wright, B., Oregon Health Study Group, 2010. Oregon Health Insurance Experiment Analysis Plan: Evidence from the First Year.
Finkelstein, A., Taubman, S., Wright, B., Bernstein, M., Gruber, J., Newhouse, J.P., Allen, H., Baicker, K., Oregon Health Study Group, 2012. The Oregon Health Insurance Experiment: Evidence from the First Year*. The Quarterly Journal of Economics 127, 1057–1106. https://doi.org/10.1093/qje/qjs020
Finkelstein, A.N., Taubman, S.L., Allen, H.L., Wright, B.J., Baicker, K., 2016. Effect of Medicaid Coverage on ED Use — Further Evidence from Oregon's Experiment. N Engl J Med 375, 1505–1507. https://doi.org/10.1056/NEJMp1609533
Frean, M., Gruber, J., Sommers, B.D., 2017. Premium subsidies, the mandate, and Medicaid expansion: Coverage effects of the Affordable Care Act. Journal of Health Economics 53, 72–86. https://doi.org/10.1016/j.jhealeco.2017.02.004
Hamersma, S., Kim, M., Timpe, B., 2019. The Effect of Parental Medicaid Expansions on Children's Health Insurance Coverage: Parental Medicaid & Child Insurance. Contemp Econ Policy 37, 297–311. https://doi.org/10.1111/coep.12392
Homonoff, T., Somerville, J., 2019. Program Recertification Costs: Evidence from SNAP.
Hudson, J.L., Moriya, A.S., 2017. Medicaid Expansion For Adults Had Measurable 'Welcome Mat' Effects On Their Children. Health Affairs 36, 1643–1651. https://doi.org/10.1377/hlthaff.2017.0347
Kaiser Family Foundation, 2019. Trends in Medicaid Income Eligibility Limits [WWW Document]. URL https://www.kff.org/data-collection/trends-in-medicaid-income-eligibility-limits/ (accessed 8.12.19).
Murray, S., 2009. States Resist Medicaid Growth; Governors Fear For Their Budgets. The Washington Post A01.
National Academy for State Health Policy, n.d. State CHIP Fact Sheets—2008: Oregon.
Norman, J., Ferguson, E., 2009. Republican Governors Protest Medicaid "Unfunded Mandate" in Baucus Bill. Congressional Quarterly HealthBeat.
Oregon Department of Human Services, 2008a. Oregon Health Plan Annual Report.
Oregon Department of Human Services, 2008b. OHP Standard Reservation List: Application Progress Report (No. DMAP-IM-08-091).
Oregon Department of Human Services, 2008c. OHP Client FAQs, eligibility & enrollment [WWW Document]. URL https://web.archive.org/web/20081205123307/http://www.oregon.gov/DHS/healthplan/data_pubs/faqs/faqclientenroll.shtml#1 (accessed 9.11.19).
Sommers, B.D., Chua, K.-P., Kenney, G.M., Long, S.K., McMorrow, S., 2016. California's Early Coverage Expansion under the Affordable Care Act: A County-Level Analysis. Health Serv Res 51, 825–845. https://doi.org/10.1111/1475-6773.12397
Sommers, B.D., Epstein, A.M., 2011. Why States Are So Miffed about Medicaid — Economics, Politics, and the "Woodwork Effect." N Engl J Med 365, 100–102. https://doi.org/10.1056/NEJMp1104948
Sonier, J., Boudreaux, M.H., Blewett, L.A., 2013. Medicaid 'Welcome-Mat' Effect Of Affordable Care Act Implementation Could Be Substantial. Health Affairs 32, 1319–1325. https://doi.org/10.1377/hlthaff.2013.0360
Taubman, S.L., Allen, H.L., Wright, B.J., Baicker, K., Finkelstein, A.N., 2014. Medicaid Increases Emergency-Department Use: Evidence from Oregon's Health Insurance Experiment. Science 343, 263–268. https://doi.org/10.1126/science.1246183

Wright, B.J., Garcia-Alexander, G., Weller, M.A., Baicker, K., 2017. Low-Cost Behavioral Nudges Increase Medicaid Take-Up Among Eligible Residents Of Oregon. Health Affairs 36, 838–845. https://doi.org/10.1377/hlthaff.2016.1325

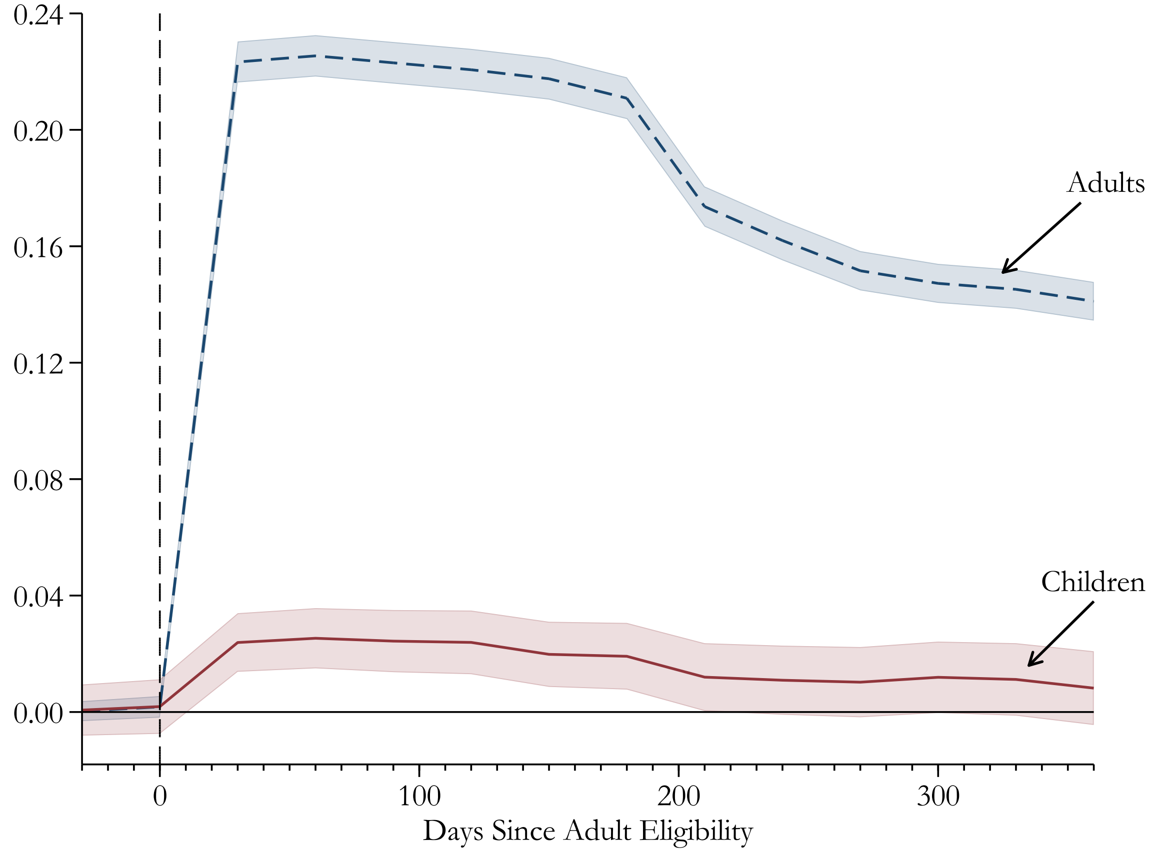
Figures



Notes: This figure presents estimates of the effect of a household winning the lottery on the number of children in the household enrolled in Medicaid. Specifically, it plots estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); the outcome variables are the number of children enrolled at different 30-day durations (from -30 to 360) relative to the adult eligibility date. All regressions also control for household size indicators, lottery draw indicators, and the measures of baseline Medicaid enrollment. The shaded area indicates the 95% confidence interval for the effect estimates, based on robust standard errors.

Figure 1

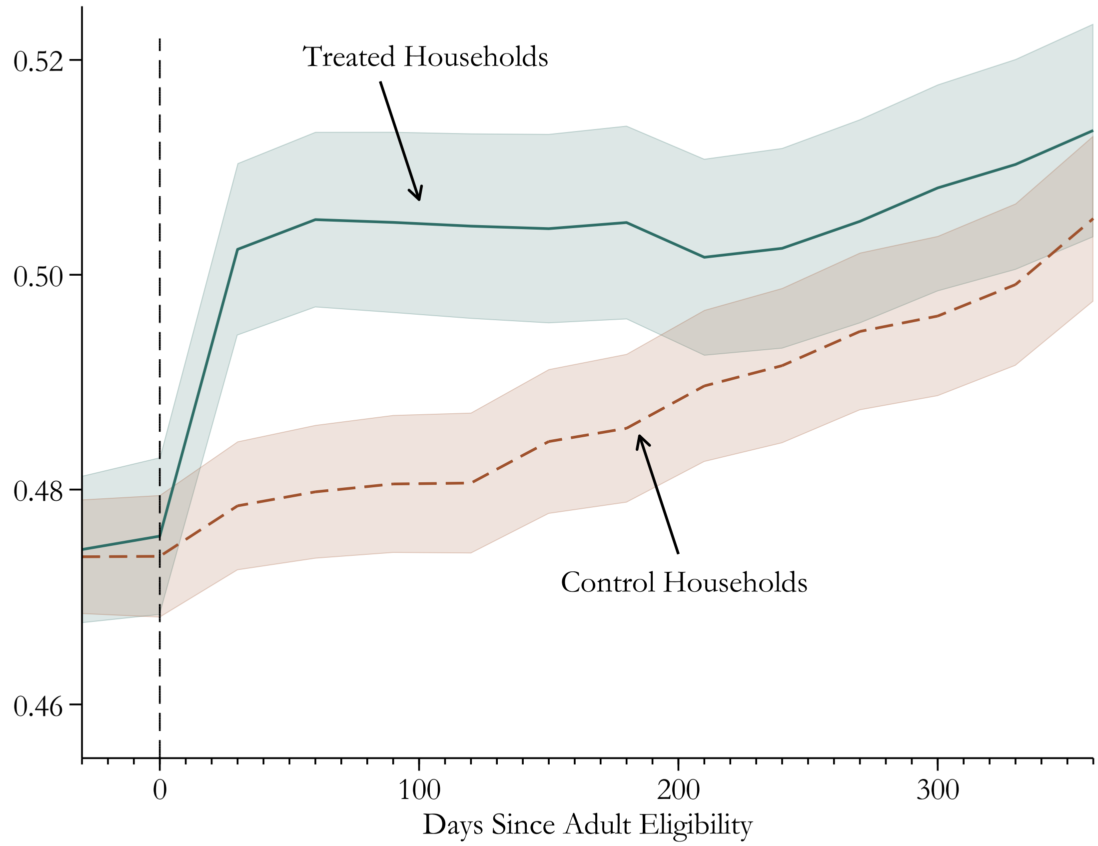
Effect of Winning the Lottery on Number of Adults and Children Enrolled



Notes: This figure presents estimates of the effect of a household winning the lottery on the number of reservation list adults in the household enrolled in Medicaid (blue dashed line), and the number of children in the household enrolled in Medicaid (maroon solid line). Specifically, it plots estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); the outcome variables are the number of children (or number of adults) enrolled at different 30-day durations (from -30 to 360) relative to the adult eligibility date. All regressions also control for household size indicators, lottery draw indicators, and the measures of baseline Medicaid enrollment. The shaded areas indicate the 95% confidence interval for the effect estimates, based on robust standard errors.

Figure 2

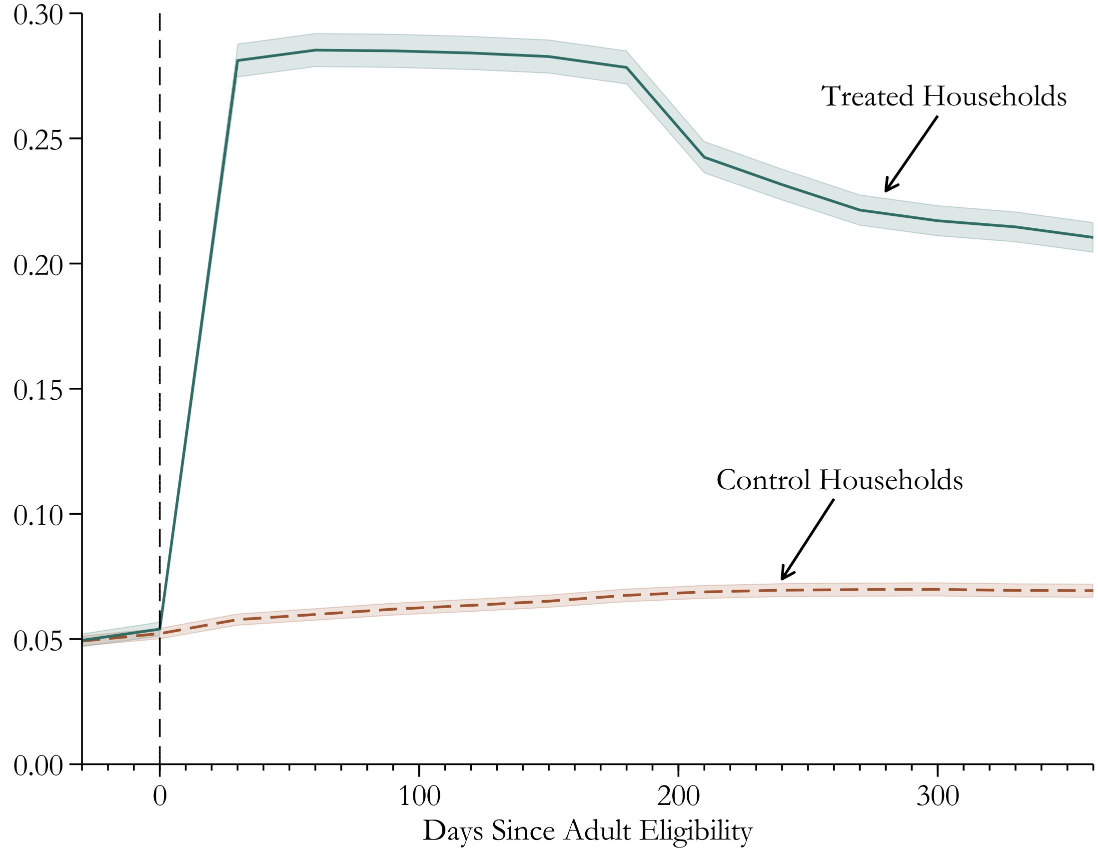
Expected Number of Children Enrolled in Treated and Control Households



Notes: This figure presents the predicted number of children in treatment households and the predicted number of children in control households who would be enrolled in Medicaid at different 30-day durations (from -30 to 360) relative to the adult eligibility date. The predictions are made using the estimates from equation (1). The 'treated households' prediction is made assuming all households in the analysis sample were treated while the 'control households' prediction is the prediction assuming all households were not treated. The shaded areas indicate 95% confidence intervals for the predictions.

Figure 3

Expected Number of Adults Enrolled in Treated and Control Households



Notes: This figure presents the predicted number of adults on the reservation list in treatment households and the predicted number of adults on the reservation list in control households who would be enrolled in Medicaid at different 30-day durations (from -30 to 360) relative to the adult eligibility date. The predictions are made using the estimates from equation (1). The 'treated households' prediction is made assuming all households in the analysis sample were treated while the 'control households' prediction is the prediction assuming all households were not treated. The shaded areas indicate 95% confidence intervals for the predictions.

Figure 4

Tables

Table 1. Treatment-Control Balance

Variable	(1) Control Mean	(2) Treat - Control Difference	(3) p-value
A. Lottery list variables			
Year of birth	1968.4	0.132 (0.112)	0.236
Female	0.577	-0.011 (0.004)	0.017
English as preferred language	0.927	0.001 (0.002)	0.599
Signed up first day of lottery	0.093	0.001 (0.003)	0.661
Gave phone number	0.863	-0.005 (0.003)	0.094
In MSA	0.821	-0.002 (0.004)	0.524
Zip code median household income	39,774.1	8.825 (77.785)	0.910
B. Baseline enrollment variables			
Number children enrolled	0.416	0.007 (0.009)	0.439
Any children enrolled	0.218	0.003 (0.004)	0.399
Number reservation list adults enrolled	0.027	0.001 (0.002)	0.491
Any reservation list adults enrolled	0.026	0.001 (0.002)	0.498

N=52,873. Notes: This table presents balance tests for two sets of variables. Specifically, we regress the given variable on an indicator for household lottery win as well as household size indicators and report estimates of the coefficient on the lottery win indicator. Robust standard errors in parentheses.

Column (1) reports the average control group outcome. Column (2) presents the estimated regression coefficient and its standard error, which is the treatment-control difference. Column (3) reports the p-value from the test that the regression coefficient equals zero.

Block A, which reports the lottery list variables, contains demographics of individuals who signed up for the lottery, which were provided by participants or could be derived from this information. Block B, which reports the baseline enrollment variables, contains the four measures of child and adult enrollment on January 15, 2008 at the household level derived from our linkage to Medicaid enrollment data. See Appendix Table A1 for balance tests for additional variables and comparisons to balance in prior work.

Table 2. Effects on Child and Adult Medicaid Enrollment at 90 Days

Outcome	(1) Control Mean (Children)	(2) Treatment Effect (Children)	(3) Treatment Effect (Adults)	(4) Effect Ratio Child:Adult
Number Enrolled	0.457	0.024	0.223	0.110
		(0.005)	(0.004)	
Any Enrolled	0.234	0.013	0.205	0.062
		(0.003)	(0.003)	
Member-Months	1.372	0.074	0.667	0.110
		(0.015)	(0.011)	

N=52,873. Notes: This table presents estimates of the effect of a household winning the lottery on child and reservation list adult Medicaid enrollment outcomes 90 days after the adult eligibility date. Specifically, it reports estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); all regressions also control for household size indicators, lottery draw indicators, and the measures of baseline Medicaid enrollment. Robust standard errors in parentheses. Column (1) reports the average control group child enrollment outcome. Columns (2) and (3) present treatment effect estimates on child and adult enrollment, respectively. Column (4) reports the ratio of child to adult treatment effects. The rows report results from three different dependent variables. "Number enrolled" is the count of members enrolled in Medicaid at 90 days after adult eligibility. "Any enrolled" is an indicator for number enrolled > 0. "Member-months" is the total months of enrollment at the household during the 90 day period following adult eligibility.

Table 3. Effects on Medicaid Enrollment at Varying Durations

Outcome: Number Enrolled	(1) Control Mean (Children)	(2) Treatment Effect (Children)	(3) Treatment Effect (Adults)	(4) Effect Ratio Child:Adult
30 days after adult eligibility	0.455	0.023 (0.005)	0.224 (0.004)	0.103
90 days after adult eligibility	0.457	0.024 (0.005)	0.223 (0.004)	0.110
180 days after adult eligibility	0.462	0.020 (0.006)	0.211 (0.004)	0.093
270 days after adult eligibility	0.472	0.010 (0.006)	0.152 (0.003)	0.068
365 days after adult eligibility	0.484	0.008 (0.006)	0.141 (0.003)	0.059

N=52,873. Notes: This table presents estimates of the effect of a household winning the lottery on child and reservation list adult Medicaid enrollment outcomes at varying durations after the adult eligibility date. Specifically, it reports estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); all regressions also control for household size indicators, lottery draw indicators, and the measures of baseline Medicaid enrollment. Robust standard errors in parentheses. Outcomes are the number of children or adults enrolled in Medicaid at the specified number of days after the adult eligibility date. Column (1) reports the average control group child enrollment outcome. Columns (2) and (3) present treatment effect estimates on child and adult enrollment, respectively. Column (4) reports the ratio of child to adult treatment effects.

Table 4. Heterogeneity in Effects on Child Enrollment

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Panel A: Outcome Measure Only Counts Children:				**Panel B:** Sample Restricted to Households with:			
	Not Enrolled *Ex Ante*		Enrolled *Ex Ante*		No Child Enrolled *Ex Ante*		≥1 Child Enrolled *Ex Ante*	
Outcome	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect
Number Enrolled	0.111	0.018	0.346	0.007	0.096	0.023	1.750	0.032
		(0.004)		(0.003)		(0.005)		(0.017)
Any Enrolled	0.073	0.012	0.185	0.002	0.059	0.014	0.859	0.010
		(0.002)		(0.002)		(0.003)		(0.006)
Member-Months	0.303	0.057	1.069	0.016	0.261	0.074	5.352	0.076
		(0.012)		(0.008)		(0.014)		(0.044)
N	52,873		52,873		40,856		12,017	

Notes: This table presents estimates of the effect of a household winning the lottery on child Medicaid enrollment outcomes 90 days after the adult eligibility date. Specifically, it reports estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); all regressions also control for household size indicators, lottery draw indicators, and the measures of baseline Medicaid enrollment. Robust standard errors in parentheses. The rows report results from three different dependent variables. "Number enrolled" is the count of members enrolled in Medicaid at 90 days after adult eligibility. "Any enrolled" is an indicator for number enrolled > 0. "Member-months" is the total months of enrollment at the household during the 90 day period following adult eligibility. In Panel A, the outcome measures are defined as in Table 2 but only count children who were not enrolled *ex ante* (on January 15, 2008) on the left side and only count children who were enrolled *ex ante* on the right side. In Panel B, the outcome measures are defined identically to those in Table 2 but the sample is split into households with no *ex ante* child enrollment (on January 15, 2008) on the left side and households with *ex ante* child enrollment on the right side.

Appendix A

In this appendix we describe in greater detail our processing of the Oregon reservation list data and the Medicaid enrollment data, including our approach to geocoding addresses in both files.

A.1. Processing addresses

Processing address data was performed on a secure, non-networked computer. We use ArcGIS software to convert text addresses to latitude-longitude pairs, a process called geocoding. Initially, we extracted all addresses from the reservation list as well as all addresses from the location spell records in the 2008, 2009, and 2010 Medicaid enrollment data. In the extremely rare case that a member had two overlapping address spells, we truncate the earlier address spell to end on the day before the later spell begins.

Before the data was run through ArcGIS, we took several steps to pre-process it. For addresses in both datasets, we drop addresses that are not in Oregon, since the lottery requires eligible participants to have an Oregon address. We also remove addresses that could clearly not be geocoded: P.O. Boxes, addresses with all text and no number (e.g. "In Care Of John Smith"), addresses that are entirely numbers (e.g. "315"), and addresses with no street number or street identifier (e.g. no "St", "Rd", etc.; examples include "PMB 15", "SUITE 6A"). This pass to exclude non-geocodable addresses removed 12.11% of unique addresses in the reservation list and 8.57% of unique addresses in the Medicaid enrollment file.

Many reservation list members and Medicaid beneficiaries live at addresses with many units, and the reservation list and Medicaid enrollment file both allow individuals to specify a second address line to indicate the apartment, room, floor, or other detail about their unit (e.g. "Apt 3A"). However, ArcGIS does not extract this information. Given the importance of accurately linking reservation list households in buildings with multiple units, we extracted the second address line from both the reservation list and the Medicaid enrollment data and used it later in merging.

We parse the second address line using a series of regular expressions. Conceptually, we divide the second address line into two components: a designator (e.g. “Apt”) and level (e.g. “3A”); when we later merge between the reservation list and the enrollment file, we use only the level and ignore the designator. We standardize the level by removing the number prefix (e.g. “NO” from “NO 3”), any symbols (e.g. “#” from “#3A”), and any spaces within (e.g. “3 A” becomes “3A”). Among unique addresses in each dataset, we are able to identify and parse out a second address line for 25.7% of the reservation list addresses and 33.3% of the enrollment file addresses.

A.2. Geocoding addresses

After pre-processing the addresses, we next loaded them into ArcGIS running on the same secure, non-networked computer. For each address, ArcGIS attempts to identify its location and, if successful, produces a latitude-longitude pair. We use ArcGIS to take advantage of its powerful geocoding engine, which includes algorithms to resolve addresses written with abbreviations, different positions of address components (e.g. “3 Broadway NE” vs. “3 NE Broadway”), different names for address elements (e.g. “3 Main Ave” vs. “3 Main St”), and slight spelling errors. This flexibility is crucial for linking the reservation list to the Medicaid enrollment file because individuals might write the same address differently when joining the reservation list and enrolling in Medicaid.

For each address text imported to ArcGIS, ArcGIS looks for candidate addresses – addresses with the same or similar text as the input address – in its address locator database. For this work, we used the Street_Address_US address locator, a database of all US street addresses as well as their coordinates, to geocode (we note that this address locator will only geocode addresses with a house number).

For each candidate address, ArcGIS assigns a score based on the similarity between the input address and candidate address. The scores range from 0 to 100, with 100 being a perfect match. If no candidate address is found, or all candidate addresses have scores below the minimum threshold score, ArcGIS returns the status “unmatched”. Otherwise, ArcGIS will return the status “matched” along with the latitude-longitude coordinates and standardized address text of the candidate address with the highest match score.

The minimum match score, a user-adjustable parameter in ArcGIS, is the minimum score the best candidate address has to have in order for ArcGIS to return that address. We set the score to 85, the default score in ArcGIS (between 0 and 100). Lowering the minimum match score will result in more geocoded addresses, but the marginal geocoded address is expected to be mis-measured with greater probability. We found little documentation from ArcGIS on how the score measures match quality and thus opted to use the default threshold. We also note another user-set parameter for matching: the spelling sensitivity, which can be set from 0 and 100, with higher values requiring the spelling of the input address and the candidate address to match more closely. Again we found little documentation on the underlying spelling match algorithm, other than a note that reducing the sensitivity would yield more matches. Thus we again opted to use the default score, which was 80.

Besides “matched” and “unmatched”, ArcGIS returns the status “tied” if it finds multiple candidate addresses with the top match score (and this score is higher than the minimum match score threshold). Ties occur for fewer than 1 percent of addresses on the reservation list. We spot checked the ties and noted two reasons they occurred. First, the address locator can have more than one latitude-longitude pair for one address. In the spot check, this reason for a tie was quite rare, although we did observe it occurring. Second, if the input address is missing certain information (e.g. “2345 Orchard” without specifying “Street” or “Road”), it could match to “Orchard Street” and “Orchard Road”, with both having the same score and clearing the minimum threshold. For both of the two reasons, it was not possible to clearly identify the proper geocoded address even with manual inspection of addresses with ties. In turn, we treat tied addresses as unmatched in the study.

Ultimately, we remove all unmatched addresses, limiting the sample to addresses that could be successfully geocoded to one clear address with a sufficiently high match score.

A.3. Measuring enrollment

We now describe how we process Medicaid enrollment spell records to measure adult and child enrollment for reservation list households. We use enrollment spell records for Oregon Medicaid calendar years 2008, 2009, and 2010 (these records also include CHIP enrollment). The spell-level data include, for each spell, the begin and end date, the enrollee's name, Medicaid ID, date of birth, sex, and the Program Eligibility Resource Code (PERC).

The PERC field indicates the eligibility category of each enrollee. This field allows us to distinguish between OHP Standard, OHP Plus, and CHIP enrollment. For our analysis sample, we include enrollment spells for all Medicaid eligibility categories and CHIP categories. We exclude only the small fraction of spells indicating eligibility for secondary coverage for Medicare beneficiaries; this coverage is not well measured in our data and is also not the focus of this study.

A.4. Validity checks on address-based enrollment measures

After we used the geocoded addresses to link the reservation list and the Medicaid enrollment data, we sought to cross-validate our approach. As noted in the main text, the Medicaid enrollment data contains children and adults, and so in addition to observing children enrolled at each reservation list household, we also track enrollment of adults who were listed on the reservation list. To do so, we link the reservation list adults to their Medicaid enrollment spells using geocoded address (as described), birth date, and sex. Then, we bring in alternative data on enrollment to validate the geocoding approach.

In Finkelstein et al. (2012), the authors obtained Medicaid enrollment data for reservation list individuals from the state of Oregon produced by the state Division of Medical Assistance Programs (DMAP). These enrollment records provide a potential "gold standard" for assessing the validity of our match on address. We compare the Medicaid enrollment status of reservation list adults under our address-based match to their enrollment status under the DMAP match.

The two data sources largely agree. Among 52,873 reservation list household heads in the analysis sample (see main text), in December 2008, 92.0% had the same enrollment status in both datasets (11.5% were enrolled in both, and 80.5% were not enrolled in both). Treating the DMAP data as the gold standard, we also note a meaningful rate of apparent false negatives, consistent with failed address matches: 7.2% were enrolled in Medicaid in the DMAP data but not in our data. We also note some apparent "false positives" where the address-based match detected enrollment but the DMAP match did not – 0.8% among all household heads in the analysis sample. These findings are as expected given the inaccuracy that inevitably occurs when matching across administrative data from address text that must be geocoded. It is also possible that the DMAP match could mis-measure enrollment, i.e. what we call false positives may be properly measured enrollment. Regardless, the ability to observe a high quality measure of enrollment for reservation list adults informs our measurement error correction for children's enrollment (see Section 4.3 in the main text).

Appendix Figures

OHP Standard reservation list request

You can give us your reservation request in any of the following ways:

- **Electronically –** Use the link on www.oregon.gov/DHS/open to give us your information.
- **Mail –** Mail this form to OHP Standard, PO Box 14520, Salem, OR 97309-5044.
- **Fax –** Fax this form to: 503-373-7866 or 503-378-6295.
- **In person –** Drop this form off at any DHS field office (call 800-699-9075 for locations).
- **Phone –** Call 800-699-9075 or 503-378-7800 (TTY), Mon-Fri, 7a.m. - 7p.m. PST. The call will take 10-20 minutes.

1 Your name (Last, First, M.I.) Maiden or other names used

Phone Number ( ) Message Number ( )

Home Address City State ZIP

Mailing Address (if different) City State ZIP

2 List anyone 19 or older in your household you want to add to the reservation list.

Name (Last, First, M.I.)	Relation to you	Gender	Date of Birth	*(voluntary)* * Social Security Number
	Self	☐ M ☐ F		
		☐ M ☐ F		

*Providing a Social Security Number (SSN) is voluntary for the OHP Standard Reservation List request. DHS is allowed to ask for SSNs by OAR 461-135-1125(5) to help identify people to prevent duplicate reservations. DHS will not deny a request to be placed on the OHP Standard Reservation List if you do not provide an SSN.

3 If you need materials in a language other than English, check the appropriate box.

☐ Spanish ☐ Russian ☐ Vietnamese ☐ Other: ______________________

4 If you want written materials in a different format, check the box that applies:

☐ Braille – information is printed in Braille.
☐ Audio tape – information is recorded on an audiocassette tape.
☐ Large print – materials are printed in this size.
☐ Computer disk – information is saved as "plain text" on a 3.5-inch floppy disk.
☐ Spoken – information is read by a DHS employee in person or over the telephone.

I understand that this request is not an application for medical assistance.

Signature Date

OHP 3203 (10/25/07)

Appendix Figure A1 – Excerpt of Reservation List Request Form

Date of Request	Date Received by Branch	Program	Branch	Case Number	Worker ID
		Case Name			Route to:
		Prime Number		SSN	App Status
		Office use only			

Oregon Health Plan Application (OHP 7210)

If you need help filling this out, call 800-699-9075 or TTY 800-735-2900

DHS Oregon Department of Human Services

1 Name (Last, First, M.I.) Maiden or other names used

Telephone number ( ) Message number ( )

Home address – proof required, see **YELLOW** sheet City State ZIP

Mailing address (if different) City State ZIP

2 List yourself and everyone living with you. To list more than four people, use the OHP 7226 form, found in the **PINK** packet.

Social Security numbers (SSNs)* – If you don't have an SSN, write in "none."

Ethnicity/Racial Heritage – Write in all the codes that apply. Title VI of the Civil Rights Act of 1964 allows us to ask for this information. You can choose not to give this information. It will not affect your eligibility for benefits.

Ethnicity

H – Hispanic or Latino
N – Not Hispanic or Latino

Racial Heritage

A – Asian
B – Black or African American
I – American Indian/Alaska Native
P – Native Hawaiian or Other Pacific Islander
W – White

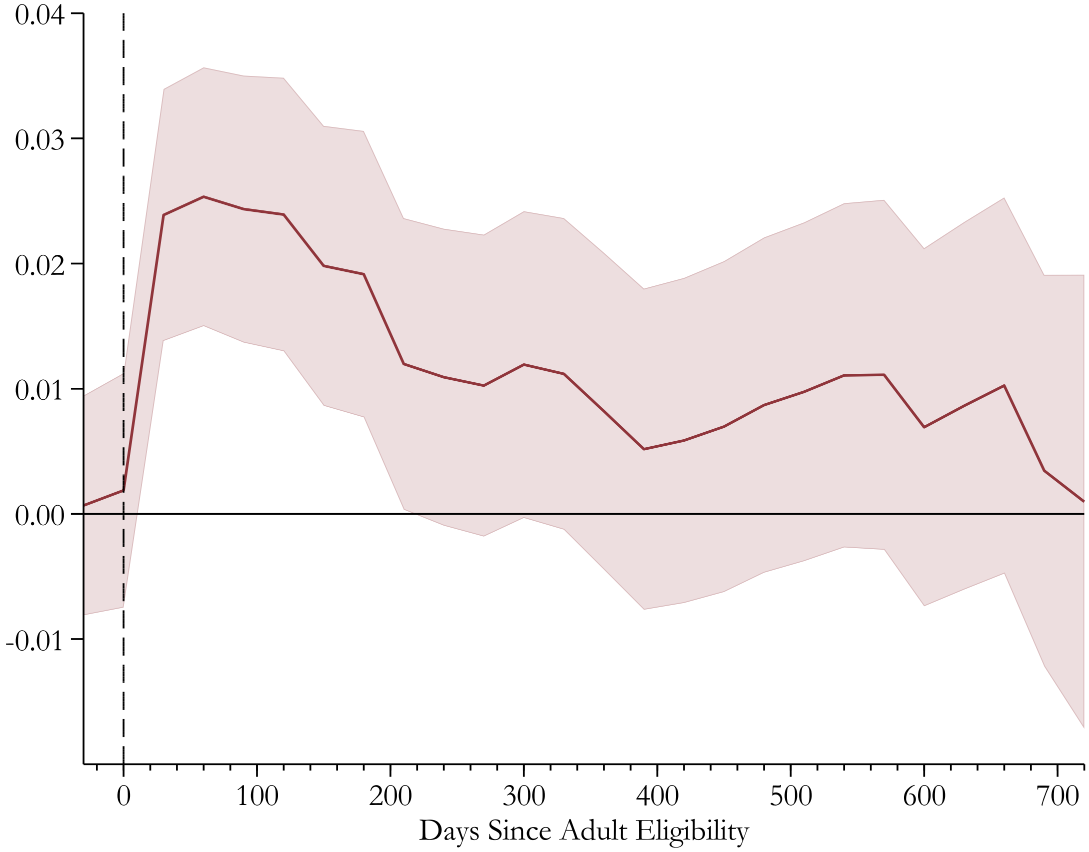
Name (Last, First, M.I.)	Relation to you	Sex	Date and city/state of birth	Applying for benefits	* Social Security Number	* U.S citizen? Proof required, see **YELLOW** sheet	Ethnicity / Racial Heritage
a.	**Self**	☐ M ☐ F		☐ Yes ☐ No		☐ Yes ☐ No, non-citizen# ____	
b.		☐ M ☐ F		☐ Yes ☐ No		☐ Yes ☐ No, non-citizen# ____	
c.		☐ M ☐ F		☐ Yes ☐ No		☐ Yes ☐ No, non-citizen# ____	
d.		☐ M ☐ F		☐ Yes ☐ No		☐ Yes ☐ No, non-citizen# ____	

* **Only required for people who are applying for benefits.**

OHP 7210 (Rev 04/08)

Appendix Figure A2 – Excerpt of Oregon Health Plan Application Form

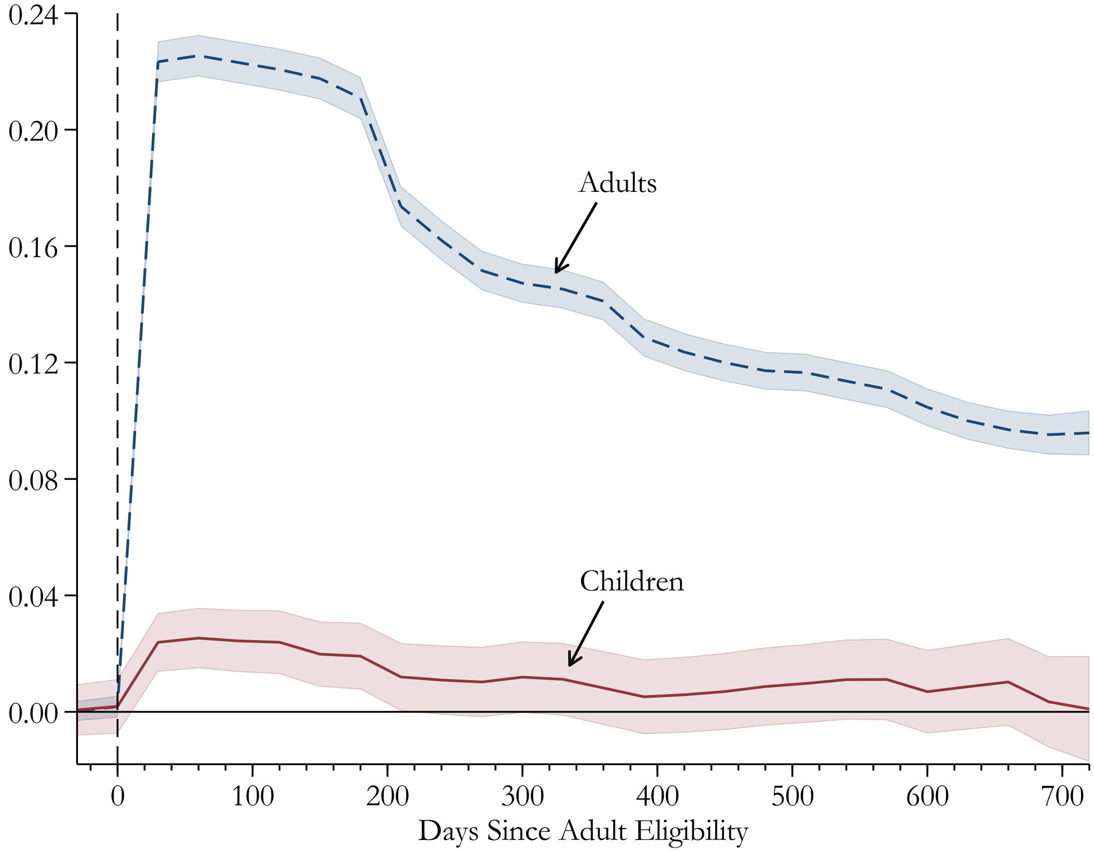
Effect of Winning the Lottery on Number of Children Enrolled, up to 720 days



Notes: This figure presents estimates of the effect of a household winning the lottery on the number of children in the household enrolled in Medicaid. Specifically, it plots estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); the outcome variables are the number of children enrolled at different 30-day durations (from -30 to 720) relative to the adult eligibility date. For estimates beyond one year, we use a reweighting approach (described in more detail in Finkelstein et al., 2016) to adjust for a new lottery for OHP Standard which the state conducted beginning in the fall of 2009. All regressions also control for household size indicators, lottery draw indicators, and the measures of baseline Medicaid enrollment. The shaded area indicates the 95% confidence interval for the effect estimates, based on robust standard errors.

Appendix Figure A3

Effect of Winning the Lottery on Number of Adults and Children Enrolled, up to 720 days



Notes: This figure presents estimates of the effect of a household winning the lottery on the number of reservation list adults (blue dashed line) or children (maroon solid line) enrolled in Medicaid. Specifically, it plots estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); the outcome variables are the number of children enrolled at different 30-day durations (from -30 to 720) relative to the date of adult eligibility. For estimates beyond one year, we use a reweighting approach (described in more detail in Finkelstein et al., 2016) to adjust for a new lottery for OHP Standard which the state conducted beginning in the fall of 2009. All regressions also control for household size indicators, lottery draw indicators, and the measures of baseline Medicaid enrollment. The shaded areas indicate the 95% confidence interval for the effect estimates, based on robust standard errors.

Appendix Figure A4

Appendix Tables

Table A1. Variable by Variable Balance

Sample and Level	(1) Analysis Sample Household Level		(2) Finkelstein et al. (2012) Household Level		(3) Finkelstein et al. (2012) Individual Level	
Variable	Control Mean (SD)	Treatment - Control Diff	Control Mean (SD)	Treatment - Control Diff	Control Mean (SD)	Treatment - Control Diff
A. Lottery list variables						
Year of birth	1968.4	0.132	1968.0	0.162	1968.0	0.162
	(12.329)	(0.112)	(12.342)	(0.100)	(12.255)	(0.100)
Female	0.577	-0.011	0.573	-0.008	0.557	-0.007
	(0.494)	(0.004)	(0.495)	(0.004)	(0.497)	(0.003)
English as preferred language	0.927	0.001	0.932	0.002	0.922	0.002
	(0.260)	(0.002)	(0.252)	(0.002)	(0.268)	(0.003)
Signed up self	1	0	1	0	0.918	0.000
	(0)	(0)	(0)	(0)	(0.274)	(0.000)
Signed up first day of lottery	0.093	0.001	0.092	0.001	0.093	0.001
	(0.290)	(0.003)	(0.289)	(0.002)	(0.290)	(0.002)
Gave phone number	0.863	-0.005	0.858	-0.003	0.862	-0.003
	(0.344)	(0.003)	(0.349)	(0.003)	(0.345)	(0.003)
Address a PO Box	0	0	0.116	0.001	0.117	0.000
	(0)	(0)	(0.321)	(0.003)	(0.321)	(0.003)
In MSA	0.821	-0.002	0.777	-0.003	0.773	-0.002
	(0.384)	(0.004)	(0.417)	(0.003)	(0.419)	(0.004)
Zip code median household income	39774.1	8.825	39256.0	48.373	39265.4	44.891
	(8436.936)	(77.785)	(8472.162)	(70.155)	(8463.542)	(72.887)
B. Pre-randomization hospital utilization						
Any hospital admission	0.037	0.000	0.038	-0.001	0.035	-0.001
	(0.189)	(0.002)	(0.192)	(0.002)	(0.184)	(0.001)
Any hospital admission (not thru ED)	0.014	0.000	0.015	-0.001	0.014	0.000
	(0.118)	(0.001)	(0.121)	(0.001)	(0.117)	(0.001)
Any hospital admission (thru ED)	0.027	0.000	0.027	-0.001	0.025	-0.001
	(0.161)	(0.002)	(0.162)	(0.001)	(0.156)	(0.001)
Hospital days	0.244	-0.008	0.245	-0.006	0.225	-0.005
	(2.227)	(0.021)	(2.185)	(0.019)	(2.095)	(0.017)
Hospital procedures	0.069	0.000	0.072	-0.002	0.066	-0.002
	(0.605)	(0.006)	(0.664)	(0.005)	(0.636)	(0.005)
Hospital charges	1150.820	-23.965	1169.554	-20.597	1075.539	-19.722
	(11508.577)	(113.548)	(11384.938)	(101.309)	(10915.704)	(88.912)
Hospital days (not thru ED)	0.088	0.014	0.090	0.007	0.083	0.006
	(1.315)	(0.015)	(1.292)	(0.013)	(1.238)	(0.011)
Hospital procedures (not thru ED)	0.030	0.003	0.031	0.002	0.029	0.002
	(0.370)	(0.004)	(0.388)	(0.003)	(0.371)	(0.003)
Hospital charges (not thru ED)	451.770	67.207	464.310	38.183	426.628	33.968
	(8737.394)	(93.584)	(8356.679)	(77.992)	(8006.786)	(68.440)
Hospital days (thru ED)	0.156	-0.022	0.155	-0.012	0.142	-0.011
	(1.602)	(0.013)	(1.581)	(0.013)	(1.516)	(0.011)
Hospital procedures (thru ED)	0.039	-0.003	0.041	-0.004	0.037	-0.004
	(0.452)	(0.004)	(0.502)	(0.004)	(0.481)	(0.003)
Hospital charges (thru ED)	699.049	-91.172	705.244	-58.780	648.910	-53.690
	(6973.385)	(59.395)	(7188.949)	(60.525)	(6894.160)	(53.114)
C. Baseline enrollment variables						
Number children enrolled	0.416	0.007				
	(0.927)	(0.009)				
Any children enrolled	0.218	0.003				
	(0.413)	(0.004)				
Number reservation list adults enrolled	0.027	0.001				
	(0.168)	(0.002)				
Any reservation list adults enrolled	0.026	0.001				
	(0.161)	(0.002)				

Notes: This table presents variable-by-variable balance tests for three samples (across the columns) and three sets of variables (across the rows). Specifically, we regress the given variable on an indicator for household lottery win as well as household size indicators and report estimates of the coefficient on the lottery win indicator. Regressions in Block B also control for lottery draw indicators. Robust standard errors in parentheses.
Column (1) is the analysis sample of this study of 52,873 households; it is the subset of column (2) that was successfully geocoded and did not have an outlier level of pre-randomization child enrollment (see text for details). Column (2) is a household-level version of the analysis sample used in Finkelstein et al. (2012) of 66,210 households (when households have multiple individuals, in Block A we take the lottery list variables of the household head; in Block B we produce the pre-randomization outcome variables by aggregating over the household members). Column (3) is the analysis sample of 74,922 individuals used in Finkelstein et al. (2012).
Block A, which reports the lottery list variables, contains demographics that were provided by participants when they signed up for the lottery or could be derived from this information. Block B, which reports the pre-randomization outcomes, contains measures of hospital utilization from January 1 through the notification date (i.e. pre-randomization) that are derived from a linkage to hospital discharge data. Block C, which reports the baseline enrollment variables, contains the four measures of child and adult enrollment on January 15, 2008 derived from our linkage to Medicaid enrollment data.

Table A2. Treatment - Control Balance, F-tests

Variable Set \ Sample and Level	(1) Analysis Sample Household Level	(2) Finkelstein et al. (2012) Household Level	(3) Finkelstein et al. (2012) Individual Level
A. Lottery list variables			
F-statistic	1.524	1.395	1.286
[p-value]	[0.154]	[0.193]	[0.239]
B. Pre-randomization hospital utilization			
F-statistic	0.766	0.505	0.543
[p-value]	[0.648]	[0.872]	[0.844]
C. Baseline enrollment variables			
F-statistic	0.264		
[p-value]	[0.901]		
D. All of the above			
F-statistic	0.950	0.922	0.915
[p-value]	[0.522]	[0.547]	[0.560]

Notes: This table presents omnibus balance tests for three samples (across the columns) and four sets of variables (across the rows). For a set of variables, we regress each component variable on an indicator for household lottery win as well as household size indicators. Regressions in Block B also control for lottery draw indicators. We use robust standard errors and cluster at the household level in all individual-level regressions. We report the F-statistic and p-value from the joint test that all lottery win effect estimates were zero.

Column (1) is the analysis sample of this study of 52,873 households; it is the subset of column (2) that was successfully geocoded and did not have an outlier level of pre-randomization child enrollment (see text for details). Column (2) is a household-level version of the analysis sample used in Finkelstein et al. (2012) of 66,210 households (when households have multiple individuals, in Block A we take the lottery list variables of the household head; in Block B we produce the pre-randomization outcome variables by aggregating over the household members). Column (3) is the analysis sample of 74,922 individuals used in Finkelstein et al. (2012).

Block A, which reports the lottery list variables, contains demographics that were provided by participants when they signed up for the lottery or could be derived from this information. Block B, which reports the pre-randomization outcomes, contains measures of hospital utilization from January 1 through the notification date (i.e. pre-randomization) that are derived from a linkage to hospital discharge data. Block C, which reports the baseline enrollment variables, contains the four measures of child and adult enrollment on January 15, 2008 derived from our linkage to Medicaid enrollment data. Block D tests all of the variables in the above blocks, with baseline enrollment variables only included for column (3). The component variables are presented in Appendix Table A1.

Table A3. Effects on Enrollment Corrected for Attenuation Bias

	(1)	(2)	(3)	(4)	(5)
	Treatment Effect for Adults		Correction	Treatment Effect for Children	
	Address Data	DMAP Data	Factor	Address Data	Corrected
Number Enrolled					
30 days after adult eligibility	0.224	0.313	0.715	0.023	0.032
	(0.004)	(0.004)	(0.008)	(0.005)	(0.007)
90 days after adult eligibility	0.223	0.312	0.714	0.024	0.034
	(0.004)	(0.004)	(0.008)	(0.005)	(0.008)
180 days after adult eligibility	0.211	0.295	0.714	0.020	0.028
	(0.004)	(0.004)	(0.009)	(0.006)	(0.008)
270 days after adult eligibility	0.152	0.211	0.718	0.010	0.014
	(0.003)	(0.004)	(0.012)	(0.006)	(0.009)
365 days after adult eligibility	0.141	0.192	0.733	0.008	0.011
	(0.003)	(0.004)	(0.013)	(0.007)	(0.009)
Member-Months					
90 days after adult eligibility	0.667	0.934	0.714	0.074	0.103
	(0.011)	(0.012)	(0.008)	(0.015)	(0.021)

N=52,873. Notes: This table presents estimates of the effect of the effect of a household winning the lottery on child Medicaid enrollment correcting for potential attenuation bias due to mis-measurement of addresses. Robust standard errors in parentheses.

Columns (1)-(3) show the calculation of the correction factor. In columns (1) and (4) we repeat estimates of the effect of winning the lottery on adult enrollment and child enrollment, respectively, using the address match (see Table 3). In column (2), we instead calculate the effect on adult enrollment using the "gold standard" measure of adult enrollment provided by the Oregon Division of Medical Assistance Programs (DMAP); this measure is what was used in prior work on the Oregon Health Study. Column (3) reports the ratio of the address-based and DMAP-based treatment effects. Column (5) reports the corrected estimates on child enromment by dividing the estimate in (4) by the correction factor in (3). The estimates in columns (3) and (5) involve nonlinear transformations of coefficients from multiple regressions; for these columns, we use seemingly unrelated regression (SUR) and the delta method to produce robust standard errors. Number enrolled is the count of members enrolled in Medicaid at the specified number of days after adult eligibility. Member-months is the total months of enrollment at the household during the specified period following adult eligibility.

Table A4. Sensitivity and Robustness of Effect Estimates

Alternative	(1) Baseline specification		(2) Omit baseline enrollment controls		(3) Contemporaneous address approach		(4) Remove outliers down to p95		(5) Don't remove outliers	
Outcome	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect	Control Mean	Treatment Effect
Number Enrolled	0.457	0.024	0.457	0.030	0.450	0.027	0.387	0.020	0.500	0.015
		(0.005)		(0.009)		(0.006)		(0.005)		(0.011)
Any Enrolled	0.234	0.013	0.234	0.015	0.231	0.014	0.220	0.012	0.237	0.013
		(0.003)		(0.004)		(0.003)		(0.003)		(0.003)
Member-Months	1.372	0.074	1.372	0.091	1.361	0.079	1.159	0.066	1.508	0.053
		(0.015)		(0.027)		(0.016)		(0.014)		(0.028)
N	52,873		52,873		52,873		51,762		53,147	

Notes: This table presents alternative estimates of the effect of a household winning the lottery on child and reservation list adult Medicaid enrollment outcomes 90 days after the adult eligibility date. Specifically, it reports estimates of β_1 (the coefficient on an indicator for the household winning the lottery) from equation (1); all regressions control for household size indicators and lottery draw indicators. Except for column (2), regressions also control for four measures of baseline enrollment on January 15, 2008. Robust standard errors in parentheses. Column (1) repeats estimates from the baseline specification (see Table 2). Column (2) runs the same analyses omitting the four measures of baseline enrollment from the regression. Column (3) does not fix Medicaid enrollees at their baseline (i.e. first) address on file and instead allows locations to evolve according to subsequent spells. Column (4) omits households above the 95th percentile of pre-randomization child Medicaid enrollment (3 children) rather than the baseline cutoff of the 99th percentile (5 children). Column (5) makes no outlier restriction.
Number enrolled is the count of members enrolled in Medicaid at 90 days after adult eligibility. Any enrolled is an indicator for number enrolled > 0. Member-months is the total months of enrollment at the household during the 90 day period following adult eligibility. See text for more details.