THE OREGON HEALTH INSURANCE EXPERIMENT: EVIDENCE FROM CRIMINAL CHARGES DATA

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Analysis Plan
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Introduction

In 2008, Oregon held a lottery to allocate a limited number of Medicaid slots to low-income uninsured adults on a waiting list. The goal of the analysis described here is to use this lottery (the Oregon Health Insurance Experiment) and data received from the Oregon Judicial Information Network (OJIN) to estimate the effects of expanding Medicaid availability to a population of low-income adults on criminal charges and convictions.

This document pre-specifies the planned analysis before comparing outcomes for treatment and control groups. Creating this record of our ex ante planned analysis helps to minimize issues of data mining and specification searching. Although this plan was completed prior to analysis of differences in outcomes, we do examine the distribution of the outcomes in the control group to make specification decisions and perform treatment-control comparisons of sample characteristics and insurance coverage to explore the validity of our empirical strategy. This plan was constructed after completion of analyses using the lottery to estimate the effects of insurance using different data sets: from a mail survey and administrative data collected approximately one year after the lottery (Amy Finkelstein et al., 2012), in-person interview data collected approximately two years after the lottery (Katherine Baicker et al., 2013b), social security administrative data (Katherine Baicker et al., 2013a), and administrative emergency department data collected approximately eighteen months later (S. L. Taubman et al., 2014). The methods proposed here follow those of our prior analyses very closely; however, the outcome measures are new.

Background

There are several potential pathways through which insurance coverage may affect criminal behavior, including providing financial resources and increasing access to care. Some of the potential pathways may lead to increased crime and others to decreased crime. Effects may also differ for different types of crimes. The empirical relationship has not been widely studied, so there is limited evidence on the net effects in practice. Furthermore, observational estimates are subject to bias from confounding factors that may affect both criminal behavior and insurance status.

Health insurance might affect crime by improving the financial circumstances of enrollees. Previous estimates from the Oregon HIE show that insurance coverage reduced financial strain, for example, virtually eliminating catastrophic out-of-pocket medical expenses, reducing bills sent to collection, and lessening enrollees' need to borrow money to pay bills (Amy Finkelstein et al., 2012).

The connection between financial well-being and crime is theoretically ambiguous. Higher income might reduce the incentive for income-generating illegal activity, and there is some evidence that crime is lower when employment rates are higher (Gary S. Becker, 1968); (Steven D. Levitt, 2004). However, higher income could increase crime, insofar as it increases ability to consume dangerous or illegal substances; there is some evidence that hospitalizations and emergency department visits for drug and alcohol-related causes rise around jumps in income from monthly cash transfer programs (Carlos Dobkin and Steven L. Puller, 2007) and economic stimulus payments (Tal Gross and Jeremy Tobacman, Forthcoming).

Insurance might also affect crime by increasing access to substance abuse and mental health treatment programs. Nationally, low income, uninsured adult populations suffer from substantial rates of substance abuse and poor mental health (Centers for Disease Control and Prevention, 2013, National Center for Health Statistics, 2012). This is true of the Oregon lottery population as well; for example, 30% of the control group suffered from depression, mood disorders accounted for more than 10% of the hospital admissions, and substance abuse issues accounted for approximately 4% of hospital admissions (Amy Finkelstein et al., 2012; Katherine Baicker et al., 2013). Treatment for these conditions might reduce criminal behavior,[1] and law enforcement officials have sought greater access to health insurance for prisoners because of perceived connections between health care, health, and recidivism.[2] Oregon Health Plan, the lotteried Medicaid program studied here, covers most substance abuse treatments and behavioral health services (Oregon Health Evidence Review Commission, 2008). Previous work has found that Medicaid reduced depression and improved self-reported health and happiness (Katherine Baicker et al 2013).

The net effect of insurance expansions on crime is thus not clear and may differ by type of crime. This study will evaluate those effects using a randomized controlled design that it not subject to the potential bias from confounding factors that limit observational study designs.

Methods

Randomization and Intervention

Oregon opened a waiting list for a previously closed Medicaid program in early 2008 and then conducted eight lottery drawings from the waiting list between March and September 2008. Selected individuals won the opportunity – for themselves and any household member – to apply for health insurance benefits through Oregon Health Plan Standard (OHP Standard). OHP Standard provides benefits to low-income adults who are not categorically eligible for Oregon's traditional Medicaid program. To be eligible, individuals must be: ages 19-64; not otherwise eligible for Medicaid or other public insurance; Oregon residents; U.S. citizens or legal immigrants; without health insurance for six months; with income below the federal poverty

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[1] The National Institute on Drug Abuse suggests that access to community-based drug abuse treatment reduces recidivism: "Studies show that for incarcerated individuals with drug problems, starting drug abuse treatment in prison and continuing the same treatment upon release – in other words, a seamless continuum of services—results in better outcomes: less drug use and less criminal behaviour" (**National Institute on Drug Abuse.** 2012. "Principles of Drug Addiction Treatment: A Research-Based Guide (Third Edition)," National Institute on Drug Abuse,). Those with access to programs participate at substantial rates: the Bureau of Justice Statistics estimates that 40% of state inmates who used drugs in the month before their offense participated in a drug abuse program while incarcerated (**Mumola, Christopher J and Jennifer C Karberg.** 2007. "Drug Use and Dependence, State and Federal Prisoners, 2004," Bureau of Justice Statistics,

[2] For example, San Francisco Sheriff Ross Mirkarimi requested in 2014 that his office be officially responsible for assisting inmates with their applications for insurance under the Affordable Care Act because, "there is nexus between repeat incarceration and poor chronic health, especially people suffering with mental illness or substance addiction." (**Lagos, Marisa.** 2014. "Mirkarimi Wants to Sign up Inmates for Health Coverage," *San Francisco Gate*. A model of correctional health care that connects prisoners to community health services has been successfully implemented in Hampden County, MA, Marion County, FL, and the District of Columbia (**Ashe, Michael J.** 2014. "To Improve Public Health and Safety, One Sheriff Looks Beyond the Jail Walls." *Health Affairs*, 33(3).

level and assets below $2,000. Among the randomly selected individuals, those who completed the application process and met these eligibility criteria were enrolled in OHP Standard. OHP Standard provides relatively comprehensive medical benefits (including prescription drug coverage) with no consumer cost sharing and low monthly premiums (between $0 and $20, based on income), provided mostly through managed care organizations. The lottery process and OHP Standard have been described in more detail elsewhere (Amy Finkelstein et al., 2012).

Data Sources

The state provided us with the initial lottery list and with detailed data on Medicaid enrollment for every individual on the list. We use this to construct our primary measure of insurance coverage during the study period. These are described in detail in Amy Finkelstein et al., 2012.

Data on criminal charges were obtained from the Oregon Judicial Information Network (OJIN). OJIN contains the judgment dockets and official Register of Actions from all Oregon State Courts, trial and appellate (Oregon Judicial Information Network). The circuit court in Oregon is the "trial court of general jurisdiction," and the OJIN dataset contains information from all of Oregon's 36 circuit courts (Oregon Judicial Department). The data do not include federal court cases. Data are given at the level of criminal charge with a case number variable (a criminal case can have multiple criminal charges). We perform the majority of our analysis at the level of criminal cases.

Our control sample has a much higher rate of criminal charges than the rest of the state population. There are 88,291 criminal cases in the data filed against individuals aged 19-64 in the year 2007. Based on an Oregon population of 3,745,455[3] in 2007, this is a rate of 2357 cases per 100,000 individuals. In our control sample in the same year, there are 6346 cases – a rate of 14075 cases per 100,000 individuals. This is consistent with evidence that lower income populations are more frequently charged with criminal offenses (Office of the Assistant Secretary for Planning and Evaluation, 2009).

Study Population and Time Frame

We probabilistically matched the Oregon Health Insurance Experiment population to the criminal charges data using LinkPlus software. This was done using name, date of birth and gender. Due to the protected nature of the lottery data, matching of the lottery data to the criminal charges data was done on a secure, non-networked computer, and all identifiers were removed before analysis.

For our primary analysis, we define the study period as March 10, 2008 (the first day that anyone was notified of being selected in the lottery) through July 15, 2010. A case is considered to fall "in the study period" if the first alleged incident date occurred within the study period.[4]

[3] **Proehl, Risa S.** 2008. "2007 Oregon Population Report," Population Research Center, Portland State University: 2.
[4] A case can have multiple incidents, and therefore multiple incident dates; however, for 95% of cases in the control sample, the first and last incident dates are the same. Where a given case had multiple incidence dates, we used the earlier date.

This 28-month observation period represents, on average, 25.1 months (standard deviation = 2.0 months) after individuals were notified of their selection in the lottery and 23.1 months (standard deviation = 2.5 months) after insurance coverage was approved for those selected by the lottery who successfully enrolled in OHP Standard. In Appendix Tables A2-A3, we also present results from March 10, 2008 to September 30, 2009, which is the end date used in some of our previous analyses (Amy Finkelstein et al. 2012; S.L. Taubman et al. 2014).

There are three relevant dates associated with each criminal case: the date the alleged incident occurred, the date the case is filed, and the date a decision is rendered ("disposition date"). We have data on all case filings through December 31, 2010, and data on all decisions rendered from January 1, 2007 until April 19, 2012.

As noted above, we define cases as within the study period if the date of the alleged incident falls within the study period. There are two potential ways that our results could be subject to censoring. First, if insufficient time elapses between the latest incident date we consider (July 15, 2010) and the last date for which we see case filings (December 31, 2010, 169 days later), we may not see cases that are filed long after the alleged incident. We are reassured that this is likely uncommon: when we consider incidents in the data occurring in 2007 (the earliest year for which we observe all cases which should thus be least affected by censoring), 88.7% of cases were filed within 169 days.[5] Second, if insufficient time elapses between the last incident date we consider (July 15, 2010) and the last date we observe dispositions (April 19, 2012, 626 days later), we may not see dispositions in cases that take the longest to resolve. Again, this seems likely to be uncommon: of incidents occurring in 2007, 88.8% had a disposition within 626 days.[6] We measure pre-randomization versions of our outcomes as those whose incident dates occur within the period January 1, 2007 to March 9, 2008.

Figure 1 shows the evolution of the study population from submitting names to inclusion in the criminal charges analysis. Table A4 shows treatment-control balance on inclusion in the criminal charges data and for the pre-randomization versions of the outcome variables used in this analysis (described in more detail below). There are no significant differences between treatment and control groups on the characteristics measured at the time of lottery sign-up (F-statistic 1.659; P= .103), on the pre-randomization versions of our outcomes (F-statistic 0.650; P= 0.948), or the combination of both (F-statistic .787; P= .843). For the supplementary analysis that uses a time period ending 30 September 2009, the study sample is also balanced on variables measured at the time of sign-up, (F-statistic=1.322, p-value=0.227), pre-randomization versions of the outcomes (F-statistic=0.623, p-value=0.962), or the combination of both (F-statistic=0.713, p-value=0.924).

[5]For incidents occurring in 2007, the mean time between incident date and case filing is 44 days, and the median is 13 days.
[6] For incidents occurring in 2007, the mean time between incident date and disposition date is 213 days, and the median is 108 days.

Analytic Specifications

Intent-to-Treat Effect of the Lottery (ITT)

Our treatment group is comprised of those selected in the lottery and our controls are those who were not. We estimate the intent-to-treat (ITT) effect of winning the lottery (i.e. the difference between treatment and controls) by fitting the following OLS equation:

$$y_{ih} = \beta_0 + \beta_1 LOTTERY_h + X_{ih}\beta_2 + V_{ih}\beta_3 + \varepsilon_{ih} \qquad (1)$$

where *i* denotes an individual and *h* denotes a household.

LOTTERY is an indicator variable for whether or not household *h* was selected by the lottery. The coefficient on *LOTTERY* (β_1) is the main coefficient of interest, and gives the average difference in (adjusted) means between the treatment group (the lottery winners) and the control group (those not selected by the lottery); it is interpreted as the impact of being able to apply for OHP Standard through the Oregon lottery.

We denote by X_{ih} the set of covariates that are correlated with treatment probability (and potentially with the outcome) and therefore must be controlled for so that estimates of β_1 give an unbiased estimate of the relationship between winning the lottery and the outcome. In all of our analyses, X_{ih} includes indicator variables for the number of individuals in the household 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 denote by V_{ih} a second set of covariates that can be included to potentially improve power by accounting for chance differences between treatment and control groups in variables that may be important determinants of outcomes. These covariates are not needed for β_1 to give an unbiased estimate of the relationship between winning the lottery and the outcome, however, as they are not related to treatment status. Our primary analysis adds the total number of cases in the pre-period. This is not required to avoid bias, but may improve the precision of the estimates by explaining some of the variance in the outcome.[7] As a secondary analysis, we will explore whether our results are sensitive to inclusion of additional V_{ih} covariates.

In all of our ITT estimates and in our subsequent instrumental variable estimates (see below), we estimate linear models even though a number of our outcomes are binary. Because we are interested in the difference in conditional means for the treatments and controls, linear probability models would pose no concerns in the absence of covariates or in fully-saturated models (Joshua D. Angrist, 2001, Joshua D. Angrist and Jörn-Steffen Pischke, 2009). Our models are not fully saturated, however, so it is possible that results could be affected by this functional form choice, especially for outcomes with very low or very high mean probability.

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[7] To determine whether to include these pre-randomization versions of the outcome, we estimated how much variance they explained in the control sample. The partial R^2s ranged from .0003 to 0.115 depending on the specific outcome.

We therefore explore the sensitivity of our results to an alternate specification using logistic regression and calculating average marginal effects for all binary outcomes.

In all of our analyses we cluster the standard errors on the household identifier since the treatment is at the household level. All analyses where outcomes are measured through July 15, 2010 are weighted to account for a new lottery conducted by the state starting in 2009 as described below.

Local Average Treatment Effect of Medicaid (LATE)

The intent-to-treat estimates from equation (1) provide an estimate of the causal effect of winning the lottery (i.e. winning the opportunity to apply for OHP Standard). This provides an estimate of the net impact of expanding *access* to public health insurance. We are also interested in the impact of insurance *coverage* itself. We model this as follows:

$$y_{ih} = \pi_0 + \pi_1 INSURANCE_{ih} + X_{ih}\pi_2 + V_{ih}\pi_3 + \nu_{ih} \tag{2}$$

where INSURANCE is a measure of insurance coverage and all other variables are as defined in equation (1). We estimate equation (2) by two stage least squares (2SLS), using the following first stage equation:

$$INSURANCE_{ih} = \delta_0 + \delta_1 LOTTERY_{ih} + X_{ih}\delta_2 + V_{ih}\delta_3 + \mu_{ih} \tag{3}$$

in which the excluded instrument is the variable *LOTTERY*.

We interpret the coefficient on insurance from instrumental variable estimation of equation (2) as the local average treatment effect of insurance, or LATE (Guido W. Imbens and Joshua D. Angrist, 1994). In other words, our estimate of π_1 identifies the causal impact of insurance among the subset of individuals who obtain insurance upon winning the lottery but who would not obtain insurance without winning the lottery (i.e. the compliers).

The LATE interpretation requires the additional identifying assumption that the only mechanism through which winning the lottery affects the outcomes studied is the lottery's impact on insurance coverage. We believe this is a reasonable approximation; in earlier work we discussed potential violations; where we could explore them we did not find cause for concern (Amy Finkelstein et al., 2012).

Analytic Weights

We use weights to adjust for a new lottery for OHP Standard which the state conducted beginning in the fall of 2009. Initially, the state mailed postcards to those on the original list that were not selected (our controls) asking if they would like to be included in this second lottery. An initial draw was done from among those returning this postcard. The state then opened the new waiting list to the general public (open continuously to anyone, including those on our original list) and conducted monthly drawings. After each drawing, we probabilistically matched (using LinkPlus software) the new waiting list to our study population to identify individuals who were eligible for selection by the state (called "opt-ins") and those who were actually selected in a given drawing (called "selected opt-ins"). Given the difficulty in interpreting the "treatment" received by those who were drawn in the new lottery, we drop the selected opt-ins from our analytic sample and use weights to correct for this, similar to those used in Baicker et. al (2013b).

The set of opt-ins is not a random sample of our study population (because signing up was optional), but selection from that list is: within any (even non-random) subset of the original study population, a randomly selected group can be weighted to stand in for the non-selected remainder based on the probability of that random selection (similar conceptually to (S. R. Cole and M. A. Hernán, 2008); (Graham Kalton, 1986)). We weight each observation at the time of each lottery drawing by the inverse probability of being in the sample, and we generate overall weights as the product of the weights across all time points. Weights are thus:

$$w_t(i) = \begin{cases} \frac{1}{1-p_t} \; if\ i\ in\ O_t\ and\ in\ S_t \\ 0\ if\ i\ in\ S_t \\ 1\ if\ i\ not\ in\ O_t \end{cases} \tag{4}$$

where O_t is the set of opt-ins in our study population eligible for new lottery drawing on date t, S_t is the set of opt-ins selected in drawing on date t, and p_t is the probability of an opt-in being selected. Selection probabilities varied by the number of household members on the new list, because once an individual was selected, all members of the household were eligible to enroll; we therefore estimated the selection probability separately by the number of household members on the new waiting list at time t. The final analytic weight W is the product all the weights w_t introduced up to July 15, 2010 (the last day before individuals were notified of selection in the first of a series of very large lottery draws that would have generated very large weights).

Table A4 gives the distributions of weights we use in the analysis. Over the entire sampling base, the weights have a mean very close to 1, and there are relatively few extreme weights. Among those with non-zero weights (who contribute to the analysis), the average weight is 1.15, with a 5th to 95th percentile range of 1.00 to 1.60. The control group is far more impacted by the weights than the treatment group as they were more likely to sign up for the new lottery.

Relationship between the Lottery and Insurance Coverage

Table A5 reports the control means and effects of lottery selection for various definitions of insurance coverage. Being selected in the lottery is associated with an increase of 23.4 percentage points (SE 0.39) in the probability of having Medicaid coverage during our study period; we use this increase in insurance coverage due to the lottery to estimate local average treatment effects. During the alternate study period (ending September 30, 2009), lottery selection is associated with an increase of 25.6 percentage points (SE=0.353) in the probability of ever having Medicaid.[8]

[8] There are two distinct Oregon Medicaid programs: the program for the traditional Medicaid population (OHP Plus) and the program for the expansion population (OHP Standard). We define someone as ever on "Medicaid" if they are on either Medicaid program, including both Plus and Standard. Since the lottery was for the OHP Standard program, that is where we would expect to find increases in coverage, and this is borne out in the data. In fact, the increase in OHP Standard is slightly greater than the increase in any Medicaid (25.9 percentage points compared to 23.4), suggesting that some of the increase in OHP Standard may have come from individuals who would have been on another Medicaid program at some point during the study period. The effect of the lottery on Medicaid coverage attenuates over time: using "current" enrollment (measured on July 15, 2010) reduces the lottery effect on insurance

Because the initial take-up of Medicaid was relatively low, lottery selection is associated with an average increase of 4.4 months on Medicaid (row 3) – both because only a subset of those selected in the lottery obtained coverage and because those who obtained coverage were not necessarily covered for the entire study period. For those who did obtain coverage through the lottery, there is an increase of 18.9 months on Medicaid. This is less than the 28 months in the study period for several reasons: lottery selection occurred in 8 draws between March and October 2008, initial enrollment in OHP took 1-2 months after lottery selection, and some of those enrolled in Medicaid through the lottery lost coverage by failing to recertify.

Planned Analyses of Criminal Outcomes

As described above, OJIN data contain information on charges for specific crimes, grouped into cases, as well as disposition of these cases. The most frequent criminal charges and criminal convictions in the control sample can be found in Tables A6-A7. The outcomes we analyze include whether or not individuals from the lottery have any charges, the number of charges, and the disposition of cases overall, as well as broken down into different types of infractions and for different subsets of the population. Note that in the descriptions of outcome tables below, only control means have currently been filled in.

Total Cases and Charges

Individuals are classified as having a **criminal case** and a **criminal charge** if there was an OJIN record of a criminal case. The extensive margin of "any criminal case" and "any criminal charge" are always equal (an individual must have a criminal case to have a criminal charge), but the total number of criminal cases and the total number of criminal charges may differ because each criminal case can have multiple criminal charges. For example, an individual could be prosecuted simultaneously for a robbery, an assault, and a weapons offense that took place during the same criminal incident.

Table A8 shows the frequency and percent of criminal cases and charges for the entire dataset and for our control sample – the units of observation here are criminal cases (row 1) and criminal charges. Each criminal case can have multiple criminal charges, and an individual may have more than one criminal case. The outcomes in this analysis are derived from this case-level information, and are defined at the level of the individual. Table A9 provides detail on the distribution of the outcome variables.

Table 1 reports individual-level results for criminal cases and criminal charges. Each individual can have multiple criminal cases, and each criminal case can have multiple charges. In our control sample, 11.6% of individuals were charged with at least one crime (had one criminal case

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coverage from 23.4 (row 1) to 9.6 (row 4). There are two reasons for this. First, those who successfully enroll in OHP (through the lottery or other means) are required to recertify eligibility every six months, leading to attrition in coverage. Additionally over time, those not selected in the lottery may obtain Medicaid coverage through the OHP Plus program.

filed) between 10 March 2008-15 July 2010. Conditional on having a criminal case, the average number of criminal cases in the control sample was 1.8, and the average number of charges was 3.83 (Table A9).

Characterization of Criminal Charges

We analyze criminal outcomes based on classification along two dimensions, shown in the next panels of Table 1.

Type of Criminal Charge

We classified criminal charges based on categories within the penal code of the state of Oregon. A **felony** is defined as a crime punishable by a maximum term of imprisonment of more than one year (OregonLaws). A **misdemeanor** crime is defined as a crime punishable by a maximum term of imprisonment of less than one year. A **violation** is an offense, but not a crime. Violations are typically not punishable by a term of imprisonment. In addition, **"**Conviction of a violation does not give rise to any disability or legal disadvantage based on conviction of a crime" (OregonLaws, statute 153.008). In the full data, 31.84% of charges are felony charges, 64.86% are misdemeanor charges, and 1.67% is violations. The remaining 1.63% of the charges are of unknown penal code (largely missing data). In our control sample, felony charges are less common than misdemeanors: 5.1% of the control sample has a felony charge compared to 9.7% who have a misdemeanor charge.

A criminal charge can only be classified as a felony, a misdemeanor, or a violation (the three are mutually exclusive). Since a criminal case can have multiple criminal charges, a single criminal case can involve felony, misdemeanor, and violation charges.

Type of Crime

We also grouped crimes into categories intended to correspond to pathways through which insurance is hypothesized to affect criminal behavior. This was an ad hoc classification chosen by the study group. We created three categories of crimes: **violent crimes, income-generating crimes,** and **crimes related to controlled substances.** A list of the crimes in each category can be found in tables A10-A12. These categories were based on the offense number (orsno) and description of the law. No additional information beyond the specific offense charged was available (for example, there is no administrative data on whether any income was actually generated by a charge of 'Theft of property greater than $1,000'). It should also be noted that these categories are not mutually exclusive; for example, the delivery of methamphetamine was considered both a substance abuse crime and an income-generating crime.

Violent criminal charges such as murder, manslaughter, rape, and assault represent 18% of charges in the full OJIN sample for this period. In our control sample, 3.2% of individuals have been charged with a violent crime. Crimes involving controlled substances represented 22% of charges. Of the control sample, 5.1% have been charged with a crime involving a controlled substance. Income-generating crimes represent 18% of the entire sample of criminal charges in Oregon. Of the control sample, 3.8% have been charged with an income-generating crime.

Disposition

In addition to analyzing the effect of the insurance lottery on the frequency and type of criminal charges, we also analyzed the effect on criminal **convictions** (a subset of charges). Convictions carry additional punitive consequences for individuals, public expense, and likely longer-term consequences.[9]

In the OJIN data, 41% of the charges result in a conviction (vs. dismissal or other dispositions). "Convictions" include the following dispositions from the raw data: Convicted, Convicted Lesser Chg, Convicted/Misd Treatment, Convicted/Viol Treatment, Finding of Guilty, Finding Glty Lesser Chg., and Finding Guilty Insane. We also separate convictions for each type of charge (felony, misdemeanor, and violations) and each type of crime defined above (violent crimes, substance abuse crimes, and income-generating crimes). Table A8 and A9 show the frequency and distribution of convictions.

In the control sample, 9.0% of individuals have a conviction, 3.8% have a felony conviction, 6.8% have a misdemeanor conviction, and .19% has been convicted of a violation.

Heterogeneity of Results

Table 3 explores the heterogeneity of results along the following dimensions: gender, age (19-49 vs. 50-64), language in which lottery materials were requested (English vs. Spanish), and prior criminal charges (any vs. none in the pre-lottery period).

Sensitivity of Results

In addition to our primary specifications outlined above and shown in the tables, we will test robustness to several alternative specifications. Our primary specification uses linear probability models for continuous and binary outcomes. For binary outcomes, we will also estimate logistic and negative binomial models and calculate marginal effects (Table A13). We will also investigate the sensitivity of results to adjustment for covariates: we will report our primary specification that includes adjustment for the total number of cases in the pre-period, as well as a specification without this adjustment and one adding controls for a more complete set of pre-randomization characteristics (Table A14).

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[9] Conviction of a felony crime has the most serious consequences including the longest term of imprisonment, disenfranchisement for the period of imprisonment, and the loss of firearms privileges. Oregon does not permanently disenfranchise those convicted of a felony – disenfranchisement ends at release or when the conviction is set aside. Oregon restores firearms privileges to non-violent offenders after a one-year waiting period, and automatically restores privileges to certain offenders after 15 years (**Love, Margaret Colgate.** 2013. "Chart #2 - State Law Relief from Federal Firearms Act Disabilities," National Association of Criminal Defense Lawyers,). Having any criminal record may also pose barriers to employment (**Solomon, Amy.** 2012. "In Search of a Job: Criminal Records as Barriers to Employment," National Institute of Justice,).

Figure 1: Study Population

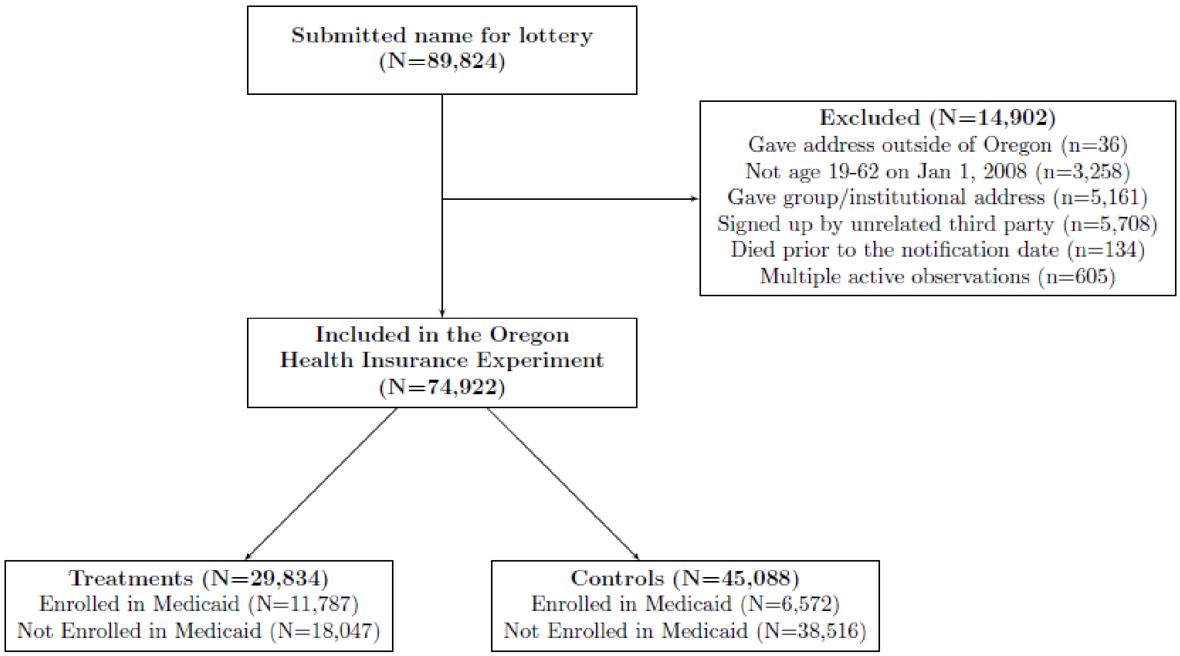

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Table 1: Criminal Charges

	Percent with any				Number			
	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Criminal Cases	11.627	XX	XX	XX	0.210	XX	XX	XX
		(XX)	(XX)		(0.889)	(XX)	(XX)	
Criminal Charges	11.627				0.443			
					(2.238)			
Charges by type of charge								
Felony charges	5.065				0.150			
					(1.225)			
Misdemeanor charges	9.732				0.166			
					(0.797)			
Violations	0.380				0.006			
					(0.158)			
Unknown penal code	0.5258				0.006			
					(0.085)			
Charges by type of crime								
Violent crimes	3.222				0.074			
					(0.573)			
Controlled substance	5.130				0.091			
					(0.572)			
Income-generating	3.841				0.085			
					(0.652)			
Other	7.723				0.218			
					(1.433)			

Notes: Variables are measured from 10 March 2008 - 15 July 2010 (inclusive). All regressions include controls for household size and the total number of criminal cases an individual had prior to the lottery (1 January 2007 - 9 March 2008). All regressions include weights that account for the probability of being sampled in the new lottery, and adjust standard errors for household clusters. Penal code classifications are given in administrative data. Crime classifications were defined (prior to analyzing treatment-control differences) by the study group (see Analysis Plan for additional details). Sample consists of entire sample universe (N= 74,922).

Table 2: Convictions

	Percent with any				Number			
	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Convictions	8.999	XX	XX	XX	0.195	XX	XX	XX
		(XX)	(XX)		(0.891)	(XX)	(XX)	
Convictions by type of charge								
Felony Convictions	3.715				0.063			
					(0.455)			
Misdemeanor Convictions	6.857				0.126			
					(0.662)			
Violation convictions	0.190				0.002			
					(0.062)			
Unknown penal code	0.236				0.003			
					(0.063)			
Convictions by type of crime								
Violent crime convictions	1.823				0.026			
					(0.226)			
Controlled substance	3.507				0.048			
					(0.329)			
Income-generating crimes	2.701				0.041			
					(0.300)			
Other	5.255				0.090			
					(0.536)			

Notes: Variables are measured from 10 March 2008 - 15 July 2010 (inclusive). All regressions include controls for household size and the total number of criminal cases an individual had prior to the lottery (1 January 2007 - 9 March 2008). All regressions include weights that account for the probability of being sampled in the new lottery, and adjust standard errors for household clusters. Penal code classifications are given in administrative data. Crime classifications were defined (prior to analyzing treatment-control differences) by the study group (see Analysis Plan for additional details). Sample consists of entire sample universe (N= 74,922).

Table 3: Heterogeneity

	N	First Stage	Percent with any case: Mean Value in Control Group	Percent with any case: Effect of Medicaid Coverage	Percent with any case: p-value	Number of cases: Mean Value in Control Group	Number of cases: Effect of Medicaid Coverage	Number of cases: p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full Sample	74922	22.8505	11.6	XX (XX)	XX	0.443 (2.238)	XX (XX)	XX
Gender								
Men	33673	24.514	17.637			0.734 (2.86)		
Women	41249	21.797	6.897			0.214 (1.55)		
Age								
Older (age 50-64)	20108	23.458	6.714			0.224 (2.03)		
Younger (age 19-49)	54814	22.607	13.445			0.524 (2.30)		
Requested English language lottery materials								
Yes	68482	23.555	12.369			0.473 (2.31)		
No	6440	16.137	2.974			0.094 (0.92)		
Had a criminal charge in the preperiod								
Prepriod charge	6166	27.822	40.753			2.006 (5.21)		
No preperiod charge	68756	22.428	8.961			0.300 (1.65)		

Notes: Table shows probabillity of any and number of criminal cases for different subpopulations. All regressions include controls for household size and the total number of criminal cases an individual had prior to the lottery (1 January 2007 - 9 March 2008), weights that account for the probability of being sampled in the new lottery, and adjust standard errors adjusted for household clusters.

Table A1: Criminal Charges

	Percent with any				Number			
	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Criminal Cases	8.976	XX	XX	XX	0.147	XX	XX	XX
		(XX)	(XX)		(0.692)	(XX)	(XX)	
Criminal Charges	8.976				0.312	-0.001	-0.005	0.911
					(1.783)	(0.012)	(0.046)	
By type of charge								
Felony charges	3.870				0.106			
					(0.978)			
Misdemeanor charges	7.377				0.116			
					(0.619)			
Violations	0.257				0.004			
					(0.128)			
Unknown penal code	0.3593				0.004			
					(0.068)			
By type of crime								
Violent crimes	2.386				0.052			
					(0.453)			
Controlled substance	3.713				0.063			
					(0.473)			
Income-generating	2.892				0.060			
					(0.547)			
Other	5.818				0.151			
					(1.128)			

Notes: Variables are measured from 10 March 2008 - 30 September 2009 (inclusive). All regressions include controls for household size and the total number of criminal cases an individual had prior to the lottery (1 January 2007 - 9 March 2008). All regressions adjust standard errors for household clusters. Penal code classifications are given in administrative data. Crime classifications were defined (prior to analyzing treatment-control differences) by the study group (see Analysis Plan for additional details). Sample consists of entire sample universe (N= 74,922).

Table A2: Convictions

	Percent with any				Number			
	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value	Mean Value in Control Group	Effect of Lottery Selection	Effect of Medicaid Coverage	p-value
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	8
Convictions	6.844	XX	XX	XX	0.136	XX	XX	XX
		(XX)	(XX)		(0.711)	(XX)	(XX)	
Conviction by type of charge								
Felony Convictions	2.846				0.046			
					(0.39)			
Misdemeanor Convictions	5.041				0.087			
					(0.516)			
Violation convictions	1.295				0.002			
					(0.05)			
Unknown penal code	0.173				0.002			
					(0.05)			
Conviction by type of crime								
Violent crime convictions	1.295				0.018			
					(0.187)			
Controlled substance	2.511				0.033			
					(0.268)			
Income-generating crimes	2.005				0.029			
					(0.248)			
Other	3.901				0.063			
					(0.434)			

Notes: Variables are measured from 10 March 2008 - 30 September 2009 (inclusive). All regressions include controls for household size and the total number of criminal cases an individual had prior to the lottery (1 January 2007 - 9 March 2008). All regressions adjust standard errors for household clusters. Penal code classifications are given in administrative data. Crime classifications were defined (prior to analyzing treatment-control differences) by the study group (see Analysis Plan for additional details). Sample consists of entire sample universe (N= 74,922).

Table A3: Treatment-Control Balance

	Control mean (1)	Treatment-control difference (2)	p-value (3)
Year of Birth	1968.010	0.139	0.203
		(0.109)	
Female	0.560	-0.010	0.008
		(0.004)	
English as preferred language	0.921	0.003	0.307
		(0.003)	
Signed up self	0.918	0.000	0.109
		(0.000)	
Signed up first day of lottery	0.093	0.000	0.924
		(0.003)	
Gave Phone Number	0.861	-0.002	0.596
		(0.003)	
Address is a PO Box	0.115	0.003	0.412
		(0.003)	
Zip code median household income	39300.96	-17.56	0.830
	(8465.18)	(81.72)	
F statistic for lottery list variables			1.659
			0.103

Notes: We report the control mean and the estimated difference (in the unit of the outcome or in percentage points) between treatments and controls for the outcome shown in the left-hand column (with standard errors in parentheses). Weights are used to account for the probability of being sampled in the new lottery. The final rows report the pooled F-statistics (and p-values) from testing treatment-control balance on sets of variables jointly. The sets of variables jointly tested are the variables recorded at the time of lottery sign-up, pre-lottery versions (measured 1 January 2007 - 10 March 2008) of the outcome variables in Tables 1 and 2, and the union of these two sets of variables. Sample consists of entire sample universe (N= 74,922).

Table A3: Treatment-Control Balance, continued

	Control mean	Treatment-control difference	p-value
	(1)	(2)	(3)
Any criminal case	0.084	0.004	0.052
		(0.002)	
Number of cases	0.132	0.003	0.521
		(0.004)	
Any criminal charge	0.084	0.004	0.052
		(0.002)	
Number of criminal charges	0.273	0.012	0.266
		(0.011)	
Has a felony charge	0.039	0.002	0.320
		(0.002)	
Number of felony charges	0.097	0.005	0.439
		(0.006)	
Any misdemeanor charge	0.066	0.004	0.045
		(0.002)	
Number of misdemeanors	0.168	0.006	0.364
		(0.007)	
Any violations	0.003	0.000	0.644
		(0.000)	
Number of violations	0.004	0.000	0.461
		(0.001)	
Any charge of unknown penal code	0.003	0.000	0.528
		(0.000)	
Number of charges of unknown penal code	0.003	0.000	0.326
		(0.001)	
Any controlled substance charge	0.039	0.000	0.802
		(0.002)	
Number of controlled substance charges	0.063	0.001	0.847
		(0.003)	
Any violent criminal charge	0.019	0.002	0.032
		(0.001)	
Number of violent criminal charges	0.040	0.005	0.130
		(0.003)	
Any income-generating crime charges	0.026	0.002	0.183
		(0.001)	
Number of income-generating crime charges	0.053	0.006	0.114
		(0.004)	
Any unclassified crimes	0.053	0.003	0.088
		(0.002)	

Number of unclassified crimes	0.129	0.002 (0.006)	0.712
Any convictions	0.065	0.004 (0.002)	0.047
Number of convictions	0.123	0.008 (0.005)	0.136
Any felony conviction	0.028	0.001 (0.001)	0.542
Number of felony convictions	0.045	0.002 (0.003)	0.460
Any misdemeanor conviction	0.046	0.003 (0.002)	0.087
Number of misdemeanor convictions	0.075	0.005 (0.003)	0.170
Any violation convictions	0.002	0.000 (0.000)	0.594
Number of violation convictions	0.002	0.001 (0.000)	0.000
Any unknown penal code conviction	0.001	0.000 (0.000)	0.824
Number of unknown penal code convictions	0.001	0.000 (0.000)	0.573
Any violent crime conviction	0.010	0.002 (0.001)	0.025
Number of violent crime convictions	0.013	0.002 (0.001)	0.123
Any controlled substance crime convictions	0.027	0.001 (0.001)	0.538
Number of controlled substance crime convictions	0.035	0.001 (0.002)	0.597
Any income-generating crime conviction	0.018	0.002 (0.001)	0.121
Number of income-generating crime convictions	0.026	0.003 (0.002)	0.103
Any unclassified crime conviction	0.035	0.002 (0.001)	0.208
Number of unclassified crime convictions	0.055	0.002 (0.003)	0.415
F statistic for prelottery outcomes			0.650
p-value			0.948
Joint F statistic (list variables and prelottery variables)			0.787
p-value			0.843

Table A4: Distribution of the Weights

	Mean	Standard Deviation	Minimum	Median	75th%ile	95%ile	Max	N
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Full Sample	0.9996	0.479	0	1	1	1.598	4.966	74922
Non-zero weights								
Full Sample	1.1491	0.3030	1.0000	1.0000	1.1308	1.5978	4.9661	65175
Controls	1.2170	0.3537	1.0000	1.0000	1.4428	1.7137	4.9661	37015
Treatments	1.0599	0.1846	1.0000	1.0000	1.0000	1.4428	2.9577	28160

Notes: Table shows the distribution of weights used to account for the new health insurance lottery that started in the fall of 2009.

Table A5: Insurance Coverage (First Stage Estimates)

	Control mean	Estimated FS
	(1)	(2)
Ever on Medicaid	18.84	23.42
		(0.39)
Ever on OHP Standard	4.46	25.92
		(0.32)
Number of Months on Medicaid	2.52	4.43
		(0.07)
On Medicaid at the end of the study period	13.37	9.59
		(0.33)

Notes: Column 1 reports the control mean for alternate definitions of "MEDICAID." Column 2 reports the coefficient (with standard error in parentheses) on LOTTERY from estimating the first-stage equation (2) using the specified definition of "MEDICAID." All regressions include indicators for the number of household members on the lottery list, adjust standard errors for household clusters, and include weights that account for the probability of being sampled in the new lottery. The study period starts on March 10, 2008 and ends on July 15, 2010. In all our analyses of the local-average-treatment effect of Medicaid in the paper, we use the definition in the first row: "On Medicaid at any point in the study period." Sample consists of entire sample universe (N= 74,922).

Table A6: Top Criminal Charges (Control Sample)

	Number of charges (1)	Percent of control charges (2)	Cumulative percent of control charges (3)
Panel A: All charges			
Assault - fourth degree	1329	5.21	5.21
Driving under the influence	1305	5.11	10.32
Theft - second degree ($100-1000)	1175	4.60	14.92
Harassment	1165	4.56	19.48
Unlawful posession of methamphetamine	1037	4.06	23.54
Theft - third degree (<$100)	954	3.74	27.28
Identity Theft	844	3.31	30.59
Criminal driving while suspended or revoked	698	2.74	33.33
Criminal trespass	694	2.72	36.05
Criminal mischief - second degree	634	2.48	38.53
Panel B: Misdemeanor Charges			
Driving under the influence	1265	7.72	7.72
Theft - second degree ($100-1000)	1175	7.17	14.89
Harassment	1165	7.11	22.00
Assault - fourth degree	1068	6.52	28.52
Theft - third degree (<$100)	954	5.82	34.34
Criminal trespass	694	4.23	38.57
Criminal driving while suspended or revoked	659	4.02	42.59
Criminal mischief - second degree	634	3.87	46.46
Disorderly conduct - second degree	529	3.23	49.69
Menacing	489	2.98	52.67
Panel C: Felony charges			
Unlawful posession of methamphetamine	1020	12.21	12.21
Identity Theft	843	10.09	22.30
Theft - first degree (>$1,000) or certain circums	561	6.71	29.01
Unlawful possession of cocaine	341	4.08	33.09
Unlawful posession of heroin	331	3.96	37.05
Burglary - first degree	294	3.52	40.57
Assault - fourth degree	261	3.12	43.69
Unauthorized use of a vehicle	250	2.99	46.68
Unlawful delivery of methamphetamine	224	2.68	49.36
Possession of weapons by certain felons	219	2.62	51.98

Notes: Table includes criminal charges from 10 March 2008 - 15 July 2010 (inclusive). For the criminal charge indicated in the left hand column, Column 1 shows the number of that type of charge in the control sample, and Column 2 indicates the percent of all control charges this represents for the given category.

Table A6: Top Criminal Charges (Control Sample) continued

	Number of charges (1)	Percent of control charges (2)	Cumulative percent of control charges (3)
Panel D: Violent Criminal Charges			
Assault - fourth degree	1329	33.18	33.18
Menacing	489	12.21	45.39
Recklessly endangering another person	464	11.58	56.97
Burglary - first degree	294	7.34	64.31
Strangulation	185	4.62	68.93
Assault - second degree	176	4.39	73.32
Assault - third degree	154	3.84	77.16
Robbery - second degree	115	2.87	80.03
Robbery - first degree	97	2.42	82.45
Robbery - third degree	89	2.22	84.67
Panel E: Controlled substance criminal charges			
Driving under the influence	1305	23.32	23.32
Unlawful posession of methamphetamine	1037	18.53	41.85
Manufacturing/Delivering a controlled substanc	418	7.47	49.32
Unlawful possession of cocaine	369	6.59	55.91
Unlawful posession of heroin	332	5.93	61.84
Unlawful delivery of methamphetamine	224	4.00	65.84
Unlawful posession of marijuana	196	3.50	69.34
Controlled substance in a park	188	3.36	72.70
Attempt to commit a crime	175	3.13	75.83
Unlawful delivery of marijuana	133	2.38	78.21
Panel F: Income-generating criminal charges			
Theft - second degree ($100-1000)	1175	24.07	24.07
Theft - third degree (<$100)	954	19.54	43.61
Theft - first degree (>$1,000) or certain circums	595	12.19	55.80
Burglary - first degree	294	6.02	61.82
Unlawful delivery of methamphetamine	224	4.59	66.41
Burglary - second degree	160	3.28	69.69
Forgery - second degree	141	2.89	72.58
Fraudulent use of a credit card	134	2.74	75.32
Unlawful delivery of marijuana	133	2.72	78.04
Forgery - first degree	117	2.40	80.44

Table A7: Top Criminal Convictions (Control Sample)

	Number of charges	Percent of control charges	Cumulative percent of control charges
	(1)	(2)	(3)
Panel A: All charges			
Driving under the influence	832	7.16	7.16
Theft - second degree ($100-1000)	693	5.97	13.13
Theft - third degree (<$100)	607	5.23	18.36
Unlawful posession of methamphetamine	569	4.90	23.26
Assault - fourth degree	513	4.42	27.68
Criminal driving while suspended or revoked	477	4.11	31.79
Identity Theft	339	2.92	34.71
Criminal trespass	322	2.77	37.48
Harassment	315	2.71	40.19
Theft - first degree (>$1,000) or certain circums	242	2.08	42.27
Panel B: Misdemeanor Charges			
Driving under the influence	798	10.37	10.37
Theft - second degree ($100-1000)	693	9.00	19.37
Theft - third degree (<$100)	607	7.89	27.26
Criminal driving while suspended or revoked	450	5.85	33.11
Assault - fourth degree	412	5.35	38.46
Criminal trespass	322	4.18	42.64
Harassment	315	4.09	46.73
Disorderly conduct - second degree	236	3.07	49.80
Criminal mischief - second degree	194	2.52	52.32
Recklessly endangering another person	157	2.04	54.36
Panel C: Felony charges			
Unlawful posession of methamphetamine	561	15.43	15.43
Identity Theft	338	9.30	24.73
Theft - first degree (>$1,000) or certain circums	239	6.57	31.30
Unlawful possession of cocaine	173	4.76	36.06
Unlawful posession of heroin	170	4.68	40.74
Unauthorized use of a vehicle	148	4.07	44.81
Burglary - first degree	140	3.85	48.66
Failure to appear - first degree	116	3.19	51.85
Unlawful delivery of methamphetamine	115	3.16	55.01
Possession of weapons by certain felons	105	2.89	57.90

Notes: Table includes criminal convictions from 10 March 2008 - 15 July 2010 (inclusive). For the criminal charge indicated in the left hand column, Column 1 shows the number of that type of charge in the control sample, and Column 2 indicates the percent of all control charges this represents for the given category.

Table A7: Top Criminal Convictions (Control Sample) continued

	Number of charges (1)	Percent of control charges (2)	Cumulative percent of control charges (3)
Panel D: Violent Criminal Charges			
Assault - fourth degree	513	35.65	35.65
Recklessly endangering another person	157	10.91	46.56
Burglary - first degree	140	9.73	56.29
Menacing	134	9.31	65.60
Assault - second degree	58	4.03	69.63
Assault - third degree	58	4.03	73.66
Robbery - third degree	50	3.47	77.13
Robbery - second degree	47	3.27	80.40
Strangulation	46	3.20	83.60
Robbery - third degree	89	2.22	85.82
Panel E: Controlled substance criminal charges			
Driving under the influence	832	27.25	27.25
Unlawful posession of methamphetamine	569	18.64	45.89
Unlawful possession of cocaine	176	5.76	51.65
Unlawful posession of heroin	170	5.57	57.22
Manufacturing/Delivering a controlled substanc	134	4.39	61.61
Controlled substance in a park	128	4.19	65.80
Unlawful delivery of methamphetamine	115	3.77	69.57
Unlawful delivery of marijuana	63	2.06	71.63
Attempt to commit a crime	51	1.67	73.30
Unlawful posession of marijuana	46	1.51	74.81
Panel F: Income-generating criminal charges			
Theft - second degree ($100-1000)	693	28.76	28.76
Theft - third degree (<$100)	607	25.19	53.95
Theft - first degree (>$1,000) or certain circums	242	10.04	63.99
Burglary - first degree	140	5.81	69.80
Unlawful delivery of methamphetamine	115	4.77	74.57
Burglary - second degree	83	3.44	78.01
Unlawful delivery of marijuana	63	2.61	80.62
Robbery - third degree	50	2.07	82.69
Forgery - second degree	47	1.95	84.64
Robbery - second degree	47	1.95	86.59

Table A8: Criminal charge statistics in different populations

	All		Adults (Aged 19-64)		Control Sample	
	N	Charges per case	N	Charges per case	N	Charges per case
	(1)	(2)	(3)	(4)	(5)	(6)
Number of Cases	339837	.	325517	.	20673	.
Number of Charges	723164	2.128	691101	2.123	41862	2.025
Number of Convictions	295668	0.870	284256	0.873	19048	0.921
Type of charge						
Felony charges	239818	0.7057	227710	0.6995	14035	0.6789
Felony convictions	92611	0.2725	88750	0.2726	6156	0.2978
Misdemeanor charges	460622	1.3554	441762	1.3571	26611	1.2872
Misdemeanor convictions	193633	0.5698	186576	0.5732	12415	0.6005
Violations	12133	0.0357	11417	0.0351	480	0.0232
Violation convictions	6346	0.0187	5945	0.0183	237	0.0115
Charges of unknown penal code	10591	0.0312	10212	0.0314	736	0.0356
Unknown penal code convictions	3078	0.0091	2985	0.0092	240	0.0116
Type of crime						
Violent crimes charges	128294	0.3775	119736	0.3678	6416	0.3104
Violent crime convictions	43213	0.1272	40705	0.125	2265	0.1096
Controlled substance crime charges	156090	0.4593	151645	0.4659	9423	0.4558
Controlled substance crime convictions	72957	0.2147	71230	0.2188	5219	0.2525
Income-generating crime charges	129919	0.3823	123226	0.3786	7975	0.3858
Income-generating crime convictions	57502	0.1692	54682	0.168	3916	0.1894
Unclassified criminal charges	346590	1.0199	331805	1.0193	20080	0.9713
Unclassified criminal charge convictions	137340	0.4041	132118	0.4059	8553	0.4137

Notes: Table shows statistics on criminal charges from 1 January 2007 - 15 July 2010 (inclusive). An individual can have multiple criminal cases, and each criminal case can have multiple criminal charges. Criminal charges are categorized by penal code classification which was given in the criminal charges data (felonies, misdemeanors, violations, and "unknown") and also divided into three groups based on offense code (criminal charges that are violent, involve a controlled substance, or are income-generating - see Analysis Plan for additional details). Category of criminal charge is given in the left-most column. The odd-numbered columns of this table show the number of criminal charges in each category for the entire sample, for adults aged 19-64, and for our control sample. The even-numbered columns of this table show the average number of the type of charge indicated per criminal case.

Table A9: Distribution of Variables in Control Sample

	Percent of Sample with Any	Conditional on Any				
		Mean	SD	Median	75th%ile	95%ile
All charges						
Criminal Cases	11.59	1.81	1.93	1	2	5
Criminal Charges	11.59	3.83	5.45	2	4	12
Convictions	9.00	2.17	2.13	1	2	6
By type of charge						
Felony charges	5.08	2.98	4.64	2	3	8
Felony convictions	3.76	1.71	1.65	1	2	4
Misdemeanor charges	9.69	1.70	1.92	1	2	4
Misdemeanor convictions	6.81	1.84	1.79	1	2	5
Violations	0.37	1.45	1.77	1	1	3
Violation convictions	0.19	1.22	0.59	1	1	2
Penal code unknown	0.56	1.10	0.39	1	1	2
Penal code unknown convictions	0.25	1.20	0.55	1	1	3
By type of Crime						
Violent crime charges	3.21	2.25	2.15	2	3	6
Violent crime convictions	1.78	1.44	0.90	1	2	3
Controlled substance charges	5.15	1.81	1.88	1	2	5
Controlle substance crime conviction	3.52	1.37	1.14	1	1	3
Income-generating charges	3.85	2.20	2.51	1	2	6
Income-generating crime convictions	2.72	1.50	1.06	1	2	4
Other charges	7.68	2.83	4.38	2	3	8
Other charges convictions	5.25	1.73	1.63	1	2	4

Notes: Table details the distribution the number of criminal charges of different types. The mean, standard deviation, median, 75th and 95th percentiles reflect non-zero observations only. Variables cover the time period 10 March 2008 - 15 July 2010 (inclusive). Sample consists of all members of the control group (N=45,088).

Table A10: Crimes classified as Violent

Law description	Statute Number
(1)	(2)
Aggravated Murder	163.095
Murder	163.115
Manslaughter – first degree	163.118
Manslaughter – second degree	163.125
Aggravated vehicular homicide	163.149
Rape – first degree	163.375
Sodomy – first degree	163.405
Unlawful sexual penetration – first degree	163.411
Robbery – first degree	164.415
Robbery – second degree	164.405
Robbery – third degree	164.395
Burglary – first degree	164.225
Assault – first degree	163.185
Assault – second degree	163.175
Assault – third degree	163.165
Assault – fourth degree	163.160
Kidnapping – first degree	163.235
Kidnapping – second degree	163.225
Arson – first degree	164.325
Sexual abuse – first degree	163.427
Sexual abuse – second degree	163.425
Sexual abuse – third degree	163.415
Subjecting another person to involuntary servitude – first degree	163.264
Subjecting another person to involuntary servitude – second degree	163.263
Trafficking in persons	163.266
Escape – first degree	162.165
Custodial sexual misconduct – first degree	163.452
Custodial sexual misconduct – second degree	163.454
Aggravated harassment	166.070
Intimidation – first degree	166.165
Criminal mistreatment – first degree	163.205
Criminal mistreatment – second degree	163.200
Assaulting a public safety officer	163.208
Unlawful use of an electrical stun gun, tear gas or mace – first degree	163.213
Criminally negligent homicide	163.145
Recklessly endangering another person	163.195
Riot	166.015
Strangulation	163.187
Vehicular assault of bicyclist or pedestrian	811.060
Menacing	163.190

Notes: Table shows list of offenses classified as "violent" for analysis purposes by the Oregon Health Study Group. Column 1 gives the description of the law, and Column 2 gives the statute number, or "orsno." Full descriptions of each offense are available at: http://www.leg.state.or.us/ors/ or http://www.oregonlaws.org/

Table A11: Crimes classified as Involving Controlled Substances

Law description	Statute Number
(1)	(2)
Unlawful manufacture of heroin within 1,000 feet of school	475.848
Unlawful manufacture of heroin	475.846
Unlawful delivery of heroin within 1,000 feet of school	475.852
Unlawful delivery of heroin	475.850
Unlawful possession of heroin	475.854
Unlawful manufacture of methamphetamine within 1,000 feet of school	475.888
Unlawful manufacture of methamphetamine	475.886
Unlawful delivery of methamphetamine within 1,000 feet of school	475.892
Unlawful delivery of methamphetamine	475.890
Unlawful possession of methamphetamine	475.894
Unlawful manufacture of 3,4-methylenedioxymethamphetamine within 1,000 feet of school	475.868
Unlawful manufacture of 3,4-methylenedioxymethamphetamine	475.866
Unlawful delivery of 3,4-methylenedioxymethamphetamine within 1,000 feet of school	475.872
Unlawful delivery of 3,4-methylenedioxymethamphetamine	475.870
Unlawful possession of 3,4-methylenedioxymethamphetamine	475.874
Unlawful manufacture of cocaine within 1,000 feet of school	475.878
Unlawful manufacture of cocaine	475.876
Unlawful delivery of cocaine within 1,000 feet of school	475.882
Unlawful delivery of cocaine	475.880
Unlawful possession of cocaine	475.884
Unlawful manufacture or delivery of controlled substance within 1,000 feet of school	475.904
Possessing or disposing of methamphetamine manufacturing waste	475.977
Unlawful manufacture of marijuana within 1,000 feet of school	475.858
Unlawful manufacture of marijuana	475.856
Unlawful delivery of marijuana within 1,000 feet of school	475.862
Unlawful delivery of marijuana	475.860
Unlawful possession of marijuana	475.864
Use of minor in controlled substance offense	167.262
Unlawful delivery to minors	475.906
Unlawful possession of inhalants	167.808
Unlawful possession of iodine in its elemental form	475.975
Unlawful possession of anhydrous ammonia	475.971
Unlawful possession of phosphorus	475.969
Unlawful possession of lithium metal or sodium metal	475.979
Driving under the influence of intoxicants	813.010
Operating boat while under influence of intoxicating liquor or controlled substance	830.325
Manufacture, fermentation or possession of mash, wort or wash	471.440
Prohibited sales, purchases, possession, transportation, importation or solicitation of alcoholic beverages	471.405
Purchase or possession of alcoholic beverages by person under 21	471.430
Violation of open container law	811.170
Alcohol on public property	*Missing*
Acquiring a controlled substance by fraud	*Missing*

Notes: Table shows list of offenses classified as "involving controlled substances" for analysis purposes by the Oregon Health Study Group. Column 1 gives the description of the law, and Column 2 gives the statute number, or "orsno." Full descriptions of each offense are available at: http://www.leg.state.or.us/ors/ or http://www.oregonlaws.org/

Table A12: Crimes classified as Income-Producing

Law description	Statute Number
(1)	(2)
Burglary – first degree	164.225
Burglary – second degree	164.215
Robbery – first degree	164.415
Robbery – second degree	164.405
Robbery – third degree	164.395
Buying or selling a person under 18 years of age	163.537
Trafficking in persons	163.266
Aggravated theft – first degree	164.057
Theft – first degree	164.055
Theft – second degree	164.045
Theft – third degree	164.043
Theft by extortion	164.075
Theft by deception	164.085
Theft by receiving	164.095
Theft of services	164.125
Theft of lost, mislaid property	164.065
Organized retail theft	164.098
Laundering a monetary instrument	164.170
Trademark counterfeiting – first degree	647.150
Trademark counterfeiting – second degree	647.145
Trademark counterfeiting – third degree	647.140
Promoting prostitution	165.013
Prostitution	167.007
Loitering to solicit prostitution	142.405
Forgery – first degree	165.013
Forgery – second degree	165.007
Trafficking in stolen vehicles	819.310
Possession of a stolen vehicle	819.300
Trafficking in vehicles with destroyed or altered identification numbers	819.430
Criminal possession of a rented or leased motor vehicle	164.138
Forging, altering or unlawfully producing or using title or registration	803.230
Fraudulent use of a credit card	165.055
Sale of Unregistered Securities	Missing
Securities Fraud	Missing
Prohibited sales, purchases, possession, transportation, importation or solicitation of alcoholic beverages	471.405
Unlawful manufacture of heroin within 1,000 feet of school	475.848
Unlawful manufacture of heroin	475.846
Unlawful delivery of heroin within 1,000 feet of school	475.852
Unlawful delivery of heroin	475.850

Notes: Table shows list of offenses classified as "violent" for analysis purposes by the Oregon Health Study Group. Column 1 gives the description of the law, and Column 2 gives the statute number, or "orsno." Full descriptions of each offense are available at: http://www.leg.state.or.us/ors/ or http://www.oregonlaws.org/

Table A12: Crimes classified as Income-Producing, continued

Law description	Statute Number
(1)	(2)
Unlawful manufacture of methamphetamine within 1,000 feet of school	475.888
Unlawful manufacture of methamphetamine	475.886
Unlawful delivery of methamphetamine within 1,000 feet of school	475.892
Unlawful delivery of methamphetamine	475.890
Unlawful manufacture of 3,4-methylenedioxymethamphetamine within 1,000 feet of school	475.868
Unlawful manufacture of 3,4-methylenedioxymethamphetamine	475.866
Unlawful delivery of 3,4-methylenedioxymethamphetamine within 1,000 feet of school	475.872
Unlawful delivery of 3,4-methylenedioxymethamphetamine	475.870
Unlawful manufacture of cocaine within 1,000 feet of school	475.878
Unlawful manufacture of cocaine	475.876
Unlawful delivery of cocaine within 1,000 feet of school	475.882
Unlawful delivery of cocaine	475.880
Unlawful manufacture or delivery of controlled substance within 1,000 feet of school	475.904
Possessing or disposing of methamphetamine manufacturing waste	475.977
Unlawful manufacture of marijuana within 1,000 feet of school	475.858
Unlawful manufacture of marijuana	475.856
Unlawful delivery of marijuana within 1,000 feet of school	475.862
Unlawful delivery of marijuana	475.860
Use of minor in controlled substance offense	167.262
Unlawful delivery to minors	475.906
Manufacture, fermentation or possession of mash, wort or wash	471.440

Table A13: Sensitivity of Results to Functional Form

	Percent with Any		Number	
	Linear Model	Logistic Model	Linear Model	Negative Binomial Model
	(1)	(2)	(3)	(4)
Criminal case	XX	XX	XX	XX
	(XX)	(XX)	(XX)	(XX)
	[XX]	[XX]	[XX]	[XX]
Criminal charge				
Type of charge				
Felony charge				
Misdemeanor charge				
Violation				
Unknown penal code				
Type of crime				
Violent				
Controlled Substance				

Notes: Table shows the estimated intent-to-treat effect of lottery selection: the coefficient on lottery selection, the standard error (in parentheses), and the p-value [in brackets]. Column 2 shows, for binary variables, the marginal effects from an alternate logit specification. Column 4 shows, for continuous variables, the marginal effects from a negative binomial regression. Marginal effects are evaluated at the mean of the independent variables. Outcome variables cover the time period March 10, 2008 - 15 July 2010. All regressions control for household size, pre-period versions of the outcomes, and total number of cases in the pre-period and adjust standard errors for household clusters. Sample consists of entire sample universe (N= 74,922).

Table A13: Sensitivity of Results to Functional Form, continued

	Percent with Any		Number	
	Linear Model	Logistic Model	Linear Model	Negative Binomial Model
	(1)	(2)	(3)	(4)
Income-generating	XX	XX	XX	XX
	(XX)	(XX)	(XX)	(XX)
	[XX]	[XX]	[XX]	[XX]
Other				
Convictions				
Felony conviction				
Misdemeanor conviction				
Violation conviction				
Conviction (unknown penal code)				
Violent conviction				
Controlled substance crime conviction				
Income-generating crime conviction				
Other crime conviction				

Table A14: Sensitivity of Results to Choice of Covariates

	Percent with Any			Number		
	Baseline results	Without total number of cases in the pre-period	With lottery list variables	Baseline results	Without total number of cases in the pre-period	With lottery list variables
	(1)	(2)	(3)	(4)	(5)	(6)
Criminal case	XX	XX	XX	XX	XX	XX
	(XX)	(XX)	(XX)	(XX)	(XX)	(XX)
	[XX]	[XX]	[XX]	[XX]	[XX]	[XX]
Criminal charge						
Type of crime						
Felony charge						
Misdemeanor charge						
Violation						
Unknown penal code						

Notes: Table shows the local average treatment effect estimates of lottery selection on the outcome indicated. Column 1 shows baseline results from Tables 1 and 2 which control for the total number of criminal cases an individual had prior to the lottery (1 January 2007 - 9 March 2008). Column 2 shows results without controlling for total number of cases in the pre-period. Column 3 shows results controlling for both the total number of pre-period cases and charactertistics recorded at lottery sign up: gender, requested english-language sign-up materials, signed self up for the lottery, lives in a zip code in a metropolitian statistical area, signed up for the lottery on the first day, gave a phone number, gave an address that was PO Box, and median household income in zip code. All regressions control for household size and adjust standard errors for household clusters. Sample consists of entire sample universe (N= 74,922).

Table A14: Sensitivity of Results to Choice of Covariates

	Percent with Any			Number		
	Baseline results	Without pre-randomization versions of outcome variables	With lottery list variables	Baseline results	Without pre-randomization versions of outcome variables	With lottery list variables
	(1)	(2)	(3)	(4)	(5)	(6)
Type of crime						
Violent crime	XX	XX	XX	XX	XX	XX
	(XX)	(XX)	(XX)	(XX)	(XX)	(XX)
	[XX]	[XX]	[XX]	[XX]	[XX]	[XX]
Controlled substance						
Income generating crime						
Other crime						
Convictions						
Conviction						
Felony conviction						
Misdemeanor conviction						
Violation conviction						
Conviction (unknown penal code)						

Table S14: Sensitivity of Results to Choice of Covariates

	Percent with Any			Number		
	Baseline results	Without pre-randomization versions of outcome variables	With lottery list variables	Baseline results	Without pre-randomization versions of outcome variables	With lottery list variables
	(1)	(2)	(3)	(4)	(5)	(6)
Violent crime conviction	XX (XX) [XX]	XX (XX) [XX]	XX (XX) [XX]	XX (XX) [XX]	XX (XX) [XX]	XX (XX) [XX]
Controlled substance crime conviction						
Income generating crime conviction						
Other crime conviction						