The Crime Ladder: Estimating the Impact of Different Punishments on Defendant Outcomes*

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November 22, 2019

Abstract

Most criminal justice systems use a "ladder" of punishments, starting with less severe punishments such as fines, and progressing to more severe punishments such as prison either as a defendant commits more crimes or more severe crimes. In this paper we present descriptive evidence that this ladder approach is salient, and then estimate the causal impacts of three of the most common punishments along the ladder - fines, probation, and prison - on defendants' future criminal and labor market outcomes. We find that fines have no impact on labor market outcomes, but increase future criminal activity, although this increase is concentrated among those committing less severe crimes. Probation does not impact labor market outcomes and may moderately decrease charges for those committing less severe crimes. Prison has a mixed impact, decreasing the number of future criminals charges but also decreasing future labor market earnings outcomes.

*We thank Jennifer Doleac, Naci Mocan, Magne Mogstad, Jack Mountjoy, Mike Mueller-Smith, Chelsea Temple, and Jeff Weaver for their insights and the participants at the All California Labor Conference, the Texas Economics of Crime Workshop, Conference on the Economics of Crime and Justice at the University of Chicago, ESPE, IRP Conference at University of Wisconsin-Madison, WEAI, Nordic Summer Institute in Labour Economics, Statistics Norway, and UC Irvine for their comments. This paper was supported by Academy of Finland Grant. All mistakes are our own.

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Introduction

Most criminal justice systems use a "ladder" of punishments in response to criminal activity, starting with less severe punishments such as fines, and gradually progressing to more severe punishments such as probation and incarceration either as a defendant commits more crimes or more severe crimes (Lappi-Seppälä (2016), Hinkkanen and Lappi-Seppälä (2011)). Understanding the impacts of different types of punishments on defendants is vital in order to determine how to implement such a ladder of punishments to reduce recidivism and promote rehabilitation. In this paper, we estimate the impacts of three of the most common types of punishments along the ladder - fines, probation, and incarceration - on defendants' future criminal and labor market outcomes.

Identifying the impact of fines, probation, and incarceration on defendants is challenging for three reason. First, rich data on criminal defendants and their outcomes is required. Second, observed and unobserved characteristics of defendants may be correlated with both the punishment type and the defendant's outcomes. Without a source of exogenous variation in assigned punishment, estimates will be biased. Third, all three punishments must be used frequently enough to be able to estimate causal impacts. In this paper we overcome these challenges. We collect data on every criminal court case and associated judge in Finland from 2000-2015. We link the criminal and judge data to administrative tax and school records. This allows us to look at a rich set of observable characteristics and outcomes. We identify the causal effects of each punishment by using the fact that cases are randomly assigned to judges and judges vary in their likelihood to give a fine, probation, or prison as a punishment. We measure each judge's fine, probation, and prison stringency and use these measures as instruments for fines, probation, and prison, respectively. We show that these stringency measures are highly predictive of receiving a given punishment, but not correlated with defendant characteristics.

We present three main sets of results. In the first set of results we present descriptive evidence that the ladder approach to crime is salient. Punishments do grow more severe as defendants commit either more severe crimes or a greater number of crimes. In the second set of results, we estimate the effect of fines, probation, and incarceration on future criminal activity. We find that punishing defendants with fines (as opposed to receiving another punishment or not guilty) leads to a small but significant increase in future criminal charges. These causal estimates are the opposite of the OLS results which suggest that fines reduce future criminal charges. While future charges is a standard outcome of interest when considering how to punish defendants, we might also wish to know the impact of a given punishment on the severity of future crimes. We propose a new measure to capture crime severity, which could easily be used in other contexts. Using this measure, we find that not only do fines cause a small increase in future charges, they also cause an increase in the severity of future crimes. These negative outcomes in terms of criminal activity are accompanied by no significant impacts on labor market activity, as neither employment nor earnings are significantly effected by fines. Turning to probation, we find no significant effects of probation on criminal outcomes, despite OLS estimates which suggest that probation causes an increase in crime committed by defendants. We additionally find that the negative and significant impacts on earnings and employment suggested by OLS estimates are no longer significant when turning to the IV estimates of the effect of probation.

In contrast to our estimated effects of fines on crime and labor market outcomes, we find that sending defendants to prison (as opposed to receiving another punishment or not guilty) substantially decreases the number of future criminal charges a defendant commits, although the effects are concentrated in the first few years after sentencing, consistent with an incapacitation effect of prison, not a long term crime reducing effect of prison. Consistent with the decrease in short-term future criminal charges we find a decrease in the severity of future crimes. These causal estimates are again in marked contrast to the OLS estimates which suggest that prison is associated with large increases in future criminal charges, even in the short run. In terms of labor market outcomes, we find that prison has little impact on employment, but leads to substantially lower earnings. These results are consistent with the OLS estimates, although the point estimates are smaller, suggesting that the impact of prison on labor market outcomes is less negative than naive OLS results would suggest.

Last, we provide even more detailed estimates on the effect of different punishments along the ladder of criminal activity by estimating the impact of fines, probation, and prison on less severe crimes versus more severe crimes, and on below median and above median criminals in terms of number of previous crimes committed. We find that the criminogenic effect of fines in terms of future charges is only true for less severe crimes and for defendants who have committed below median number of crimes. The crime-reducing effects of prison are concentrated amongst the most severe crimes and defendants with above median number of previous crimes. Thus, while fines do not appear to be criminogenic for more severe criminals, likewise prison is not crime-reducing for less severe crimes. Additionally, we find that the net neutral effects of probation in the main results masks some important heterogeneity. Probation causes substantial reductions in future charges for low severity crimes.

Together, these results suggest that there are distinct trade-offs when setting the thresholds for each punishment type. The thresholds policy makers ultimately choose will depend on how they value reducing number of charges, severity of crimes, and labor market outcomes of defendants. Additionally, considering how those punishment thresholds should differ in conjunction with the the severity or number of crimes a defendant has committed is an important exercise.

Our paper contributes to a large literature focused on the final rung in the ladder of possible punishments, estimating the impact of incarceration on defendant outcomes. The papers find mixed results. Most closely related to our paper, Mueller-Smith (2014) finds large negative effects of incarceration in Texas, showing that incarceration increases future criminal activity and reduces labor market incomes of the marginal prisoner. In contrast, Bhuller *et al.* (2016) find positive impacts of incarceration on the labor market and future criminal outcomes of marginal prisoners in Norway, with this result primarily driven by men who were unemployed at the time of the crime. The results from Bhuller *et al.* (2016) suggest that prison might in some circumstances by rehabilitative. Rose and Shev-Tov (2019) use a regression discontinuity design and find that prison reduces crime post sentencing both via incapacitation effects and with smaller impacts post prison. Additional papers in this literature include Kling (2006), Di Tella and Schargrodsky (2013), Green and Winik (2010), Aizer and Doyle (2015), and Dobbie *et al.* (2018a). Thus, the literature on the impacts of prison is not fully resolved, and our estimates contribute to this space.

Our results lie in the middle of current findings, as we show that prison reduces future charges (most likely through the incapacitation effect) but also negatively impacts future labor market outcomes. However, incarceration is not the only punishment of interest to policy makers. The need for more evidence on other punishments was noted in a 2016 report to the president of the United States on incarceration and the criminal justice system, stating "more research is needed to understand the impact of other criminal sanctions, including monetary sanctions and probation." (to the President of the United States (2016), pg. 38). In this paper, we attempt to address this gap.

As such, we are also related to a much smaller literature that looks at the impact of other punishments. For example, Mello (2018) finds that small fines associated with speeding tickets have large impacts on financially fragile individuals, lowering their employment probability by 8%. While that paper focuses only on speeding tickets, in Finland fines are used for a large range of crime types and we are able to look at the impacts of fines, probation, and prison on defendant outcomes. Di Tella and Schargrodsky (2013) estimate the impact of electronic monitoring versus prison in Argentina and find that electronic monitoring has a negative effect on recidivism compared to prison. By bringing an analysis of all three punishments together in one paper and in one setting with plausible identification, we are able to substantially add to this literature.

The remainder of the paper is arranged as follows. In Section 1 we provide an overview of the institutional context. In Section 2 we describe the data and report descriptive statistics on crime in Finland. In Section 3 we present and discuss descriptive results showing that the ladder approach to criminal punishments is salient. We review our empirical specification in Section 4 and report our main estimates in Section 5. Section 6 presents heterogeneous effects by severity of crime and number of previous crimes and Section 7 concludes.

1 Institutional Context

Figure 2 presents the structure of criminal investigations in Finland.[1] A criminal investigation may start in two ways: either the police receive a report that a crime has been committed or the authorities find out through surveillance that there is reason to suspect a crime has taken place. Based on the information acquired from the report or surveillance, police then decide whether to start a preliminary investigation.[2]

After the police complete a preliminary investigation, the case moves to a prosecutor who must file charges when probable grounds exist to support the guilt of the suspect. In this paper we focus only on cases that result in a court trial, since these are the cases for which we have data and causal identification. There are a few reasons why not all of the cases result in a court trial. In some cases, a prosecutor does not bring charges on a procedural basis, for example the prosecutor may decide that there is a lack of evidence. The prosecutor may also decide not to file charges when a crime is considered minor and the maximum possible expected punishment is fines. This will mean that we will largely be considering cases where fines is a possibility, but also more severe punishments could be chosen by the judge, such as probation or prison. Lastly, in offenses where a maximum sentence is six months of imprisonment, the prosecutor may use a penal proceeding and order a fine without a court trial. However, a penal order is possible only if a defendant has confessed to the offense and the police have issued a request for a fine.[3]

If the prosecutor decides to bring charges, the case is moved to a court trial and randomly assigned to a judge or a panel of judges. A court session is held and then the judges decide whether the defendant is guilty or not, and if the defendant is found guilty what the sentence should be. Random assignment to judges is a longstanding institutional feature, that has also been legally codified into the constitution of Finland. We use this fact in our analysis, but also

[1]Note that Figure 2 reports probability of each punishment type across all crimes in Finland, and does not include the restrictions we place on the sample we analyze (see Sections 2 and 4, but this includes standard restrictions such as requiring judges to see a certain number of cases and that courts have at least 2 judges to randomize across.), so the proportion of punishments will not align perfectly with the descriptive results we report later in the draft.

[2]See the Criminal Investigation Act of 1987 1:2 and 1:13, and the Criminal Investigation Act of 2011 2:1 and 3:1.

[3]Source: Criminal procedure act 1997 (https://www.finlex.fi/fi/laki/ajantasa/1997/19970689) and Rikosoikeus (Criminal law) - Lappi-Seppala et al. (2016).

provide supportive evidence confirming the institutional description of random assignment of judges to cases later in the paper.

The composition of the panel of judges depends on the severity of the crime. A typical criminal case is dealt with by either one judge or a panel of one professional judge and 3-4 lay judges.[4] The most severe cases are handled by a panel of three professional judges.[5] When assigning judge stringency to a defendant's case, we use either the professional judge or, in the few cases where there are multiple, the primary judge as provided to us in the data by the Court Registrar. Note that starting in October of 2006 it has been possible to settle minor confession cases through a written procedure with one judge and without a court trial. The written procedure can be applied if the maximum sentence for a given crime is 2 years, the defendant has confessed the crime and is willing to use the written procedure, and finally, a possible victim also agrees to a written procedure.[6]

After the court session, the judge or the panel decides on the verdict and sentence. When the panel has a lay judge member, the professional judge first explains to the lay judges the essential questions in the case and what are the relevant points of law to be considered. If the panel cannot reach a unanimous decision, the verdict and sentence are decided by a vote. The voting proceeds as follows. First, the panel votes on the verdict. Then if the defendant is found guilty, a second vote is held to determine whether the convicted is punished. Finally, if the panel decides to give a sentence, the content of the sentence is decided by a vote. The professional judges always vote first and then the lay judges vote in age order starting from the youngest. The side with the majority of votes wins. If the result is a tie, the least severe option from the point of view of the defendant is chosen regardless of which side the professional judge is on.[7]

In Finland, the criminal code defines a range of possible penalties for each crime. The principal punishments are fines, probation, and incarceration. For defendants under 18 years of age, there

[4]Lay judges are politically appointed "assistant judges" who are part of the judge panel in some criminal cases. A lay judge must meet several requirements; for example, they must be at least 25 but not over 65 years old (before 2014 the maximum age was 63) and cannot hold a position in a court or work as a prosecutor, police or lawyer.

[5]This rule is according to the Code of Judicial Procedure of 1734. Note that prior to 2014, the standard lay judge line up was one professional judge and three lay judges. However, the amendment which came into force on January 5, 2014 reduced the number of lay judges to two.

[6]See the Criminal Procedure Act of 1997

[7]See the Code of Judicial Procedure 1734 and the Criminal Procedure Act of 1997.

is also a specific juvenile punishment. Because younger defendants are treated differently, we do not include them in this paper. A prison sentence is only possible when it is indicated in the Finnish criminal code. Within theses ranges, only the stated maximum punishments are binding. Lower limits are not compulsory. In principle this means that although the criminal code stipulates in some cases that the minimum punishment is a prison sentence, a judge may use discretion and impose only fines. In contrast, if the maximum sentence is fines, a judge cannot send the defendant to prison. The reason why the lower limits are flexible is to allow the court to actively prevent overly harsh penalties, with this goal taking precedence over preventing overly lenient punishments.[8]

Figure 1: Layout of Helsinki District Court

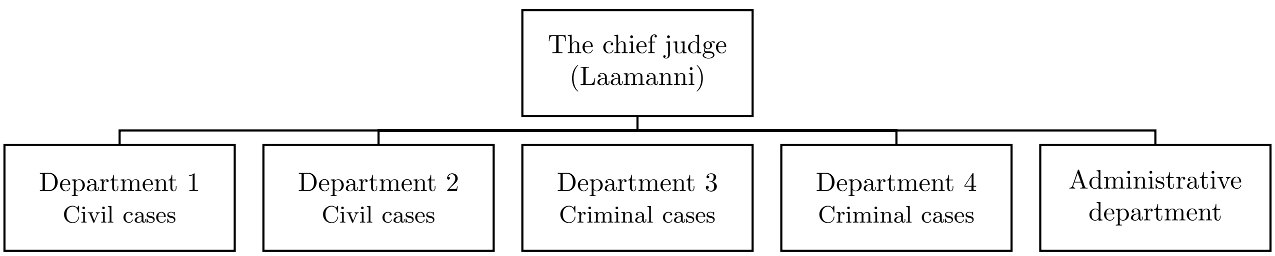
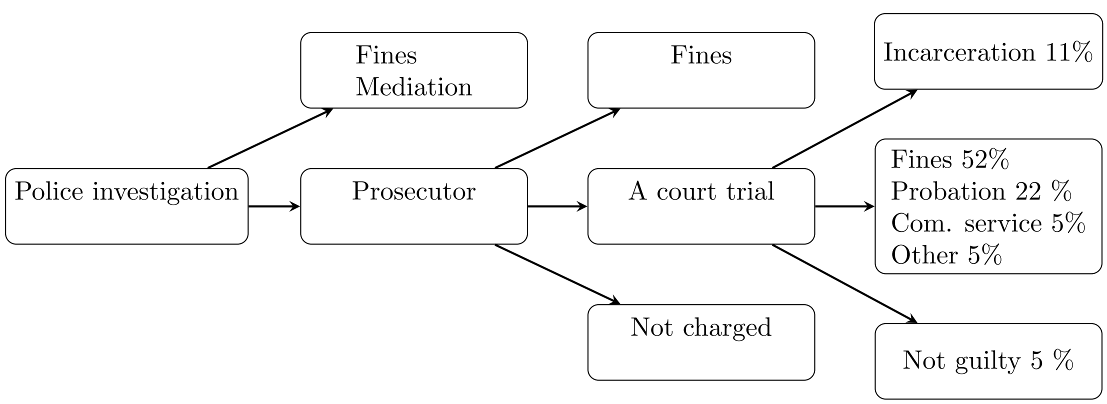


Figure 2: Sentencing Process in Finland



Finland provides a particularly useful institutional context for this study for three reasons. First, as described above, random assignment of judges is required. We additionally have verified

[8]See the Criminal Code of 1889 and Hinkkanen and Lappi seppala (2011).

that the random assignment is practiced through discussions at multiple levels of the judicial system, and all have confirmed this fact. Second, as described above, Finland actively tries to use more lenient punishments such as fines and probation, even in some cases for more severe crimes and for defendants who have already committed multiple crimes (we present descriptive evidence on this point in Section 3). This move towards leniency began in the 1960s, when Finland was an outlier compared to the rest of the world in terms of its per capita incarceration rate. The current system in Finland is in marked contrast to other judicial systems like the U.S., which tends to use more severe punishments more readily Perhaps as a result, the U.S. has one of the highest per capita incarceration rates in the world. This frequent usage of more lenient punishments is a major motivation for the focus on the causal impact of these other punishments, in addition to prison, in this paper. Third, we have been able to put together a unique data set using particularly rich data, which we describe in the next section.

2 Data

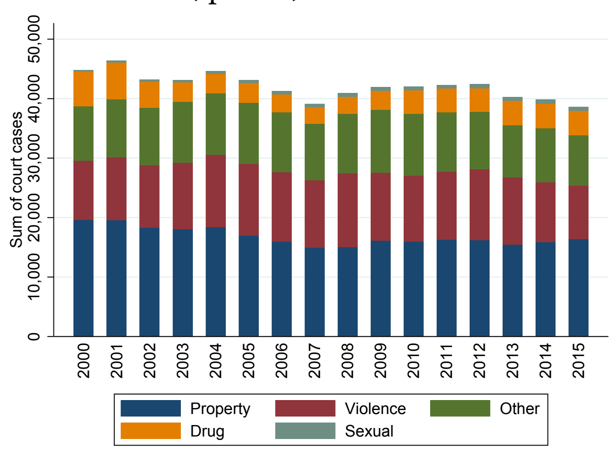
We use administrative data from Finland. We obtained data on every crime committed above age 15 for every individual in Finland from 1977-2015. Variables of particular interest include the category of crime (at the six digit level), the date the crime was committed, the dates when the case entered the court, the court decision date, and the sentence imposed by the judge. Note that it is possible for one case to include multiple crimes. When describing types of crimes, we use the designated primary crime from the records. The crime data initially lacked information on judges, so we coordinated with the court register to collect the data on every judge assigned to every criminal case in Finland. This data is only available electronically from 2000-2015, so we focus on these dates for our main analysis.[9] We link the crime data to the registry data which includes basic demographic variables such as income, labor market activity, and school completion for every defendant. We also have data on the GPA at age 16 for all individuals.

To better understand the Finnish context, in Figure 3 we present data on criminal activity in

[9]The data is available in hard copy prior to 2000. Due to cost constraints, we have focused on collecting and linking the 2000-2015 data on judges.

Finland during our period. The figure shows the total number of court cases involving defendants each year by principal crime category from 2000-2015.[10][11] In Appendix Figure 15 we repeat the exercise but separately for defendants who received a fine, probation or prison. These figures show that although Finland is a small country, we have a large number of cases each year. The majority of cases are property or violent crimes. The number of prison sentences has gone down over time, reflecting Finland's push toward more lenient sentences. This long term push has been largely successful, and during the period we study in this paper Finland has similar incarceration rates per capita as its European neighbors. Reflecting this trend, in our data fines are the most frequently used punishment, with 52% of cases resulting in a fine. In contrast, prison is used less frequently with 11% of cases result in incarceration. 22% of cases result in probation.

Figure 3: Court cases, prison, and fines over time in Finland



Note: The graph plots court cases for all defendants from 2000-2015.

Note that just over 90% of prison sentences in this period are below a year and the average sentence length is 188 days, or approximately 6 months. These sentence lengths are consistent with other European countries, but are shorter than sentences in the U.S., an outlier where the average sentence length is 2.9 years (see Aebi *et al.* (2015) and Bhuller *et al.* (2016)). Certain categories of fines are pegged to the defendant's income; since defendants are randomly assigned,

[10]We restrict to 2000-2015 because this is our sample of analysis for the paper, based on availability of digitized judge data. For completeness, we also include a figure documenting crime and prison sentences from 1977-2015 in the Appendix.

[11]In the case of multiple crimes for a given court case, the court designates a primary crime, and that crime in general is most closely linked with the court ruling.

this does not impact our main analysis.

In Table 1 we present descriptive statistics for all defendants in Finland from 2000-2015. In the first column we report statistics for all individuals who appear in court, and in the next three columns we present statistics for our relevant subsamples: those who appear in court and receive a fine, those who appear in court and receive probation, and those who appear in court and receive a prison sentence. All means are taken at the time of the court case unless otherwise specified.

From the table we can see that defendants who end up in prison are clearly worse off at the time of sentencing compared to the entire sample. Those who receive fines, on the other hand, appear to be positively selected from the population of defendants. This is consistent with the ladder approach to crime with earlier and less severe criminals receiving lighter sentences such as fines, while more severe cases receive harsher punishments like prison. These descriptive statistics also suggest substantial selection in terms of those who commit crimes and are sent to prison versus receive a fine, which is why it is important to go beyond simple OLS and identify the causal impact of different punishments; as we will show, identifying causal effects changes our estimates dramatically.

3 The Ladder of Punishments

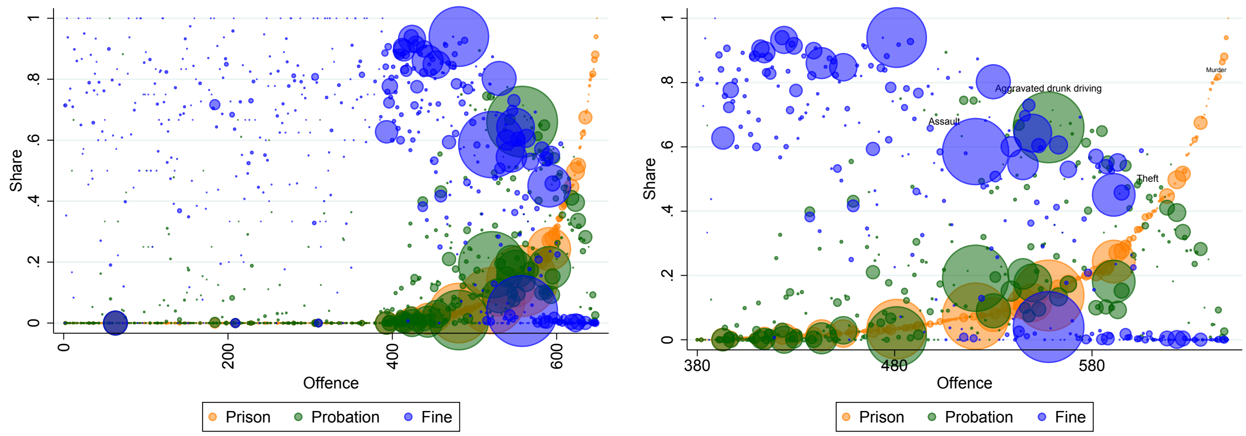
In this section we present descriptive evidence that the ladder approach to punishments is salient. We start with Figure 4. On the x-axis of this figure are the crime codes, ordered by the percent of cases in each crime code that are sent to prison. On the y-axis is the share of each crime code that receives a specific type of punishment. The points are weighted by the number of crimes committed during our period in each crime code - punishment type. The left hand figure shows all crime codes, while the figure on the right hand side focuses on the more frequently committed crimes. Note that a number of crime codes do not allow prison as a possible punishment. In Appendix 17 we graph the the maximum and minimum prison sentence lengths for each crime (recall the maximum is binding).

As can be seen in the figures, punishments with the lowest proportion of prison sentences instead experience a high proportion of fines. As the use of prison increases, the use of fines

Table 1: Descriptive statistics

	Full Court Sample	Sub-samples		
		Fined	Prison	Probation
Defendant characteristics	(1)	(2)	(3)	(4)
Age	36.54	36.73	33.74	37.25
	(10.44)	(10.58)	(8.673)	(10.51)
Kids	0.383	0.423	0.159	0.403
	(0.885)	(0.927)	(0.583)	(0.904)
Married	0.228	0.231	0.147	0.233
	(0.420)	(0.422)	(0.354)	(0.423)
Tertiary degree	0.0939	0.100	0.0210	0.0860
	(0.292)	(0.301)	(0.144)	(0.280)
Employed	0.442	0.496	0.157	0.497
	(0.497)	(0.500)	(0.363)	(0.500)
Income	13303.3	14518.8	5431.8	14037.5
	(16790.7)	(16690.2)	(9171.1)	(14120.2)
Native born	0.945	0.942	0.971	0.934
	(0.229)	(0.234)	(0.168)	(0.249)
Prison sentence at time t-1	0.124	0.0643	0.478	0.00500
	(0.329)	(0.245)	(0.500)	(0.0705)
Charged at time t-1	0.353	0.283	0.722	0.246
	(0.478)	(0.450)	(0.448)	(0.431)
Prison sentence at time t-2,t-3	0.158	0.0886	0.571	0.00967
	(0.365)	(0.284)	(0.495)	(0.0979)
Charged at time t-2,t-3	0.452	0.378	0.851	0.324
	(0.498)	(0.485)	(0.356)	(0.468)
Secondary degree	0.389	0.418	0.266	0.425
	(0.487)	(0.493)	(0.442)	(0.494)
Female	0.155	0.169	0.0696	0.172
	(0.361)	(0.374)	(0.254)	(0.377)
Number of cases	169602	82299	28321	31424

Figure 4: Ladder of punishments - Severity of crime

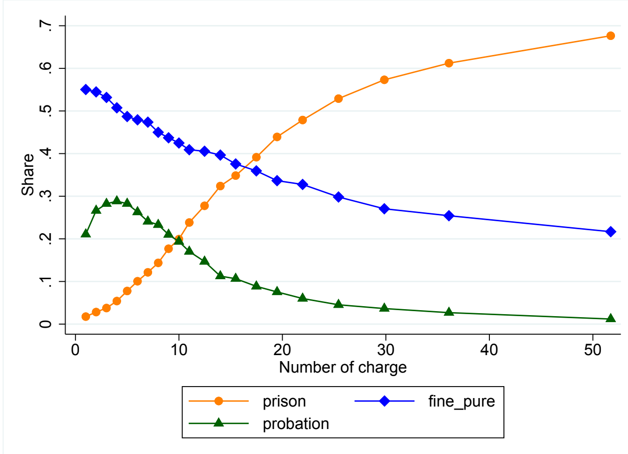


Note: The figures plot cases according to the crime code (x-axis) and share of crime code in each punishment type (y-axis). Each point is weighted by the number of cases. The crime code is in order of share of crime code sent to prison. In the left panel are all cases, the right panel zooms in on the right hand side of the left figure.

decreases. As fines decrease, the proportion of each crime type that are assigned to probation increases. Finally, the use of probation decreases as the use of prison continues to increase. The takeaway from these figures is that just as criminologists suggests, in the Finnish context lower level crimes are more likely to be punished with fines as punishment. Then, as the crime becomes more severe, punishments on average move next to probation and last to prison. However, the figure also shows that all three punishments are given for most crime codes. This is important as it means that the counterfactual for fines may not always be probation. If a defendant receives a particularly harsh judge compared to a particularly lenient judge, he may receive a prison sentence as opposed to a fine punishment. We will also use the fact that not all judges agree on the correct punishment for all defendants as a way to identify the causal impacts of the different punishments.

The previous figures suggest that as crimes become more severe, punishments become more severe, progressing from fines to probation to prison. Punishments also become more severe as defendants commit more crimes, as can be seen in the left panel of Figure 5. This figure shows that while prison is almost never used in the first instance when a defendant appears in court, as the defendant commits more crimes, the severity of the punishment increases. For early cases fines dominate, but as a defendant commits more crimes, the probability that the defendants recieves

Figure 5: Ladder of punishments - Number of Crimes



Note: The figure plots the number of crimes committed by the defendant (including the current crime) on the X-axis. The Y axis shows the percent of punishments allocated to fines, probation, or prison, depending on the number of previous charges.

probation increases, and then as the defendant continues to commit crimes, the probability that prison is given as a punishment increases. Note that most crimes are committed by a small subset of the population.

In the graphs described thus far we include all defendants. In Appendix Figures 16 we replicate these same graphs but restrict the sample to only include serial criminals (those who will commit 3 or more crimes). The results are identical, which suggest that the ladder approach to punishing crime is also relevant for serial criminals. Together, these results demonstrate that lower level punishments are not only relevant overall, but may also be important stepping stones for future serial criminals. Individuals who go on to commit multiple crimes do not generally start off at serious crimes that are likely sent to prison. Instead, they begin their criminal careers with minimal crimes and lower level punishments. As such, understanding the efficacy of early punishments could be informative regarding how to prevent potential serial criminals from continuing their criminal activity.

These results also suggest an additional outcome of interest. Specifically, to capture crime escalation we calculate the percent of each crime code that is sent to prison. We argue that the percent of each crime code sent to prison serves as a proxy for how severe each 6 digit crime code is. In Section 5 we estimate the impact of fines, probation, and prison on the severity of crime measured in this way to understand if there is crime escalation in response to each of these punishments.

4 Empirical Specification

To identify the causal effect of fines, probation, and prison on defendant outcomes we estimate the following two-equation system for punishment P where P stands for either fine, probation, or prison.

$$Y_{ict} = \beta_0 + \beta_1 P_{ict} + \beta_2 \boldsymbol{X}_{ict} + \varepsilon_{ict} \tag{1}$$

$$P_{ict} = \alpha_0 + \alpha_1 Z_{ij} + \alpha_2 \boldsymbol{X}_{ict} + \epsilon_{ict} \tag{2}$$

Y_{icft} is the outcome for defendant i who had a court case c in year t. P_{ict} is a dummy variable equal to one if the defendant i has a given punishment (either fine, probation, or prison sentence) associated with his court case c in year t. $\boldsymbol{X}_{ict}$ is a vector of case and defendant control variables (including court by year by crime type fixed effects) and ϵ_{ict} is the error term. OLS estimates of β_1 will be biased if unobserved characteristics of the defendant are correlated with receiving a given sentence. Recall that the descriptive statistics presented in Table 1 suggest selection that could lead to such bias in the OLS estimates.

To address this issue we use random assignment of cases to judges within courts to create exogenous variation in probability of a fine, probation, or prison sentences, which is captured via the instrument Z_{ij}, the leave out residualized incarceration or fine rate for each judge. We calculate Z_{ij} using a similar approach to previous papers:

$$P^*_{ict} = P_{ict} - \kappa \boldsymbol{X}_{ct}$$

$$Z_{ic} = \left(\frac{1}{n_j - n_{ij}}\right)\left(\sum_{k=0}^{n_j} P^*_{ik} - \sum_{c=0}^{n_{ij}} P^*_{ic}\right),$$

where $\kappa \boldsymbol{X}_{ct}$ represents court-by-year-by-crime fixed effects. In the first equation, we remove the court by year by crime type fixed effects to obtain P^*_{ict}. In the second equation we take the average of this residual fine, probation, or incarceration proclivity, but for each defendant we remove the defendant's own cases from the average fine, probation, or incarceration rate to create the leave out mean residual fine, probation, or incarceration rate for each defendant.

This strategy works if judges vary in their sentencing severity, and the assignment of defendants to judges is not correlated with unobserved characteristics of defendants associated with both likelihood of a given punishment and defendant outcomes. Under the principal of randomization of cases to judges within year, court, and crime type[12], which is a legal requirement in Finland, the latter condition should be met, although we also provide evidence supporting this exclusion restriction below.

Similarly to previous papers, to construct our judge stringency instrument we restrict our sample of judges to those for whom we observe at least 100 randomly assigned cases between the years 2000-2015.[13] We also restrict the judges to those for whom we observe at least two judges in the same court. In Appendix Table 12, we show how each of these restrictions decreases the number of judges, courts, and defendants in our sample.[14]

It is worth noting that the interpretation of the judge stringency measure for probation is not as straightforward as for fines and prison. Judges in Finland are supposed to start by giving fines, then move on to probation, and then move on to prison. Thus, a judge who has a high fine stringency measure will tend to be a more lenient judge, with judge leniency decreasing as the judge's fine stringency measure decreases and we move to judges who tend to give more severe punishments such as probation or prison.[15] Similarly, a judge with a high prison stringency measure will be a stricter judge, and judges will grow more lenient as the associated prison stringency measure decreases, representing the fact that more lenient judges give fewer prison sentences

[12]Note that we can use either 2 digit or 6 digit crime type codes and the results are similar. We also checked that there is a large number of cases within each cell and found this to be the case.

[13]Some papers require only 50 cases per judge. We were more cautious here, but requiring only 50 cases does not materially change the estimates.

[14]In a very small minority of cases where the defendant's first language is Swedish, the defendant is required by law to have access to a Swedish speaking judge. This will also violate random assignment (in some cases there is only 1 Swedish judge in a court) so we drop these cases. Last, we require the defendant's age to be above 22 as younger defendants are treated differently.

[15]One might consider not guilty a more lenient outcome. However, not guilty would theoretically occur across the distribution of crime severity (i.e. someone who was at risk for prison may be found not guilty just as well as someone at risk for a fine), so it is not necessarily ordered before fines from the judge's perspective.

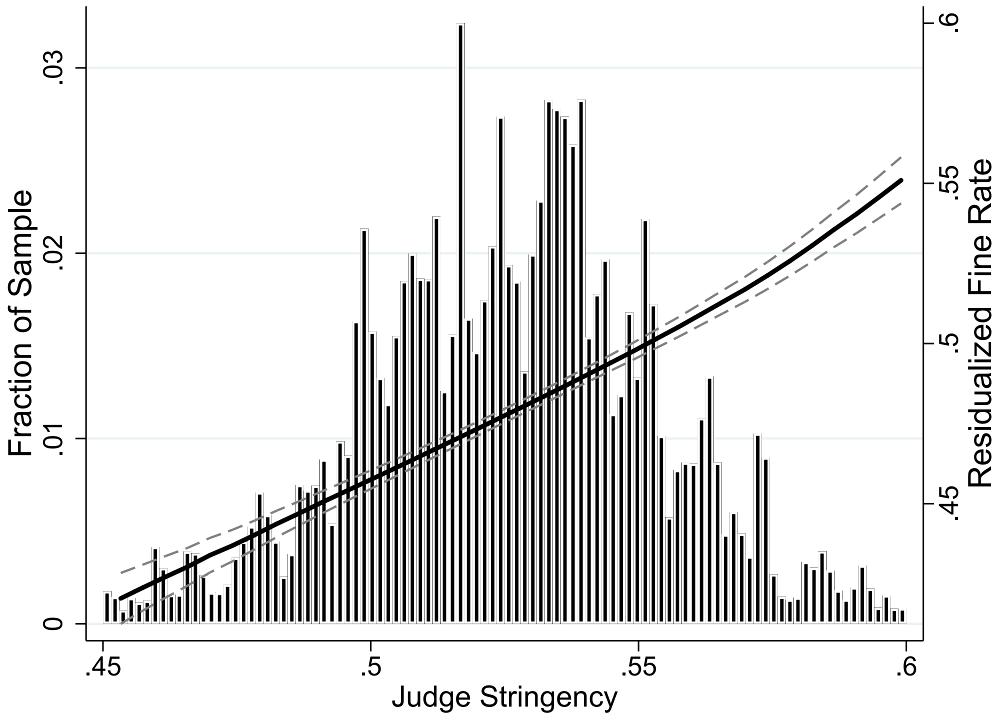
conditional on court by year by crime type fixed effects. We show that this leads to a strong negative correlation between calculated judge fine stringency and judge prison stringency in Figure 18. In contrast, judges with a low probation stringency will include both more lenient judges who are more likely to punish defendants with fines and stricter judges who are more likely to punish defendants with prison. Thus, the leniency of the judge is no longer monotonically related to the probation stringency measure. While the instrument is still valid, in the sense that having a judge with a higher probation stringency will cause the defendant to be more likely to receive probation, as we show in Table 4, the interpretation is arguably less straightforward compared to the fines and prison judge stringency.

Our prison stringency instrument can be interpreted in much the same way as the rest of the literature, i.e. the effect of receiving a prison sentence (due to random assignment to a stricter judge) relative to the counterfactual punishments (primarily a fine or probation). Our fine stringency instrument can be interpreted similarly, as the effect of being randomly assigned (through the judge assignment) to a fine as opposed to the counterfactual harsher (at least by law) punishments of probation or prison; and our probation stringency measure will allow us to identify the effect of receiving probation as a punishment as opposed to other possible punishments. As we showed in Subsection 3, there are crime categories where all three punishments are used, so we cannot assume that the counterfactual to fines is always probation, the next step on the ladder. For the same defendant, a very lenient judge might give a fine, a middle of the road judge might give the defendant probation, and a harsh judge might give the defendant a prison sentence. In the last section of the paper, we report effect heterogeneity that allows us to say more on this point.

4.1 Judge Instrument

We report the standard judge stringency graph for fines in Figure 6, probation in Figure 7, and incarceration in Figure 8. The figures show that there is substantial variation in judge stringency in all three punishments. The fitted lines suggest that there is a strong first stage - as the judge stringency increases, the residualized fine, probation, and incarceration rates also increase. We

Figure 6: Judge Stringency Variation - Fines



also report the first stage estimates from equation 2 separately for fines, probation, and prison in Table 2. The coefficients are all large and significant. In Panel A we report the estimates without controls, and then add demographic controls in Panel B. If our instrument is valid, we would not expect to see the addition of demographic controls to significantly change our estimates, so the estimates in Panels A and B should be similar. This is indeed what we find.

In terms of the first stage estimates, we find that being assigned to a judge who is 10 percentage points more likely to fine leads to an increase in the probability of receiving a fine of approximately 7.0 percentage points. For probation we find that being assigned to a judge who is 10 percentage points more likely to assign probation as a punishment leads to an increase in the probability of probation of 5 percentage points. In terms of incarceration, we find that being assigned to a judge who is 10 percentage points more likely to incarcerate leads to an increase in the probability of incarceration of approximately 4.9 percentage points. All three of these estimates suggest that the instruments are relatively strong in predicting the type of punishment of interest.

Figure 7: Judge stringency variation - Probation

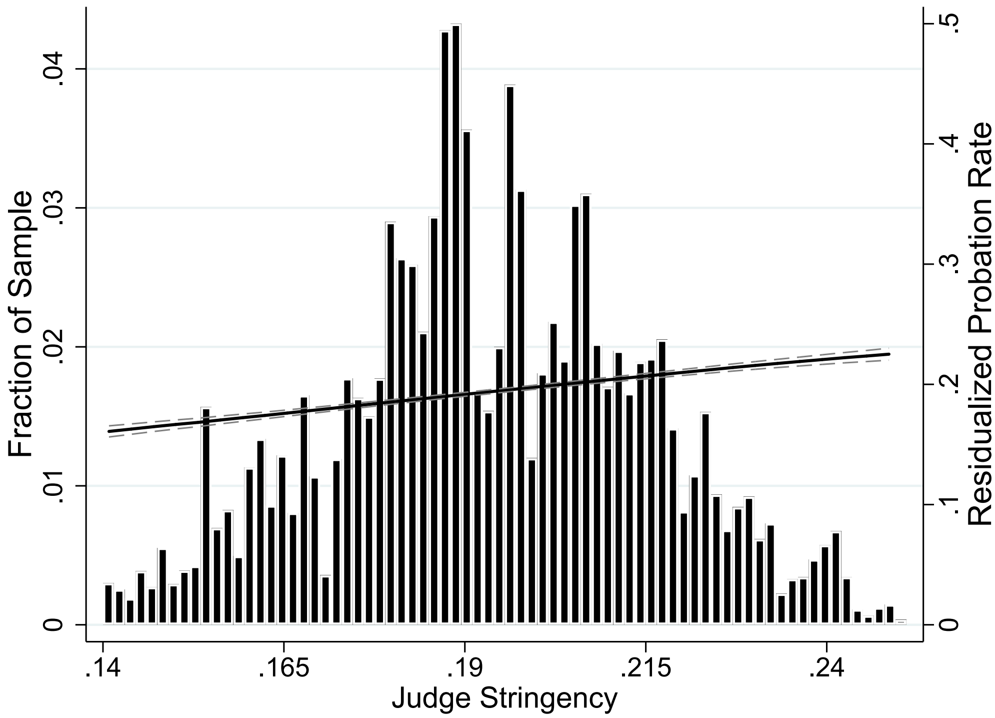


Figure 8: Judge stringency variation - Prison

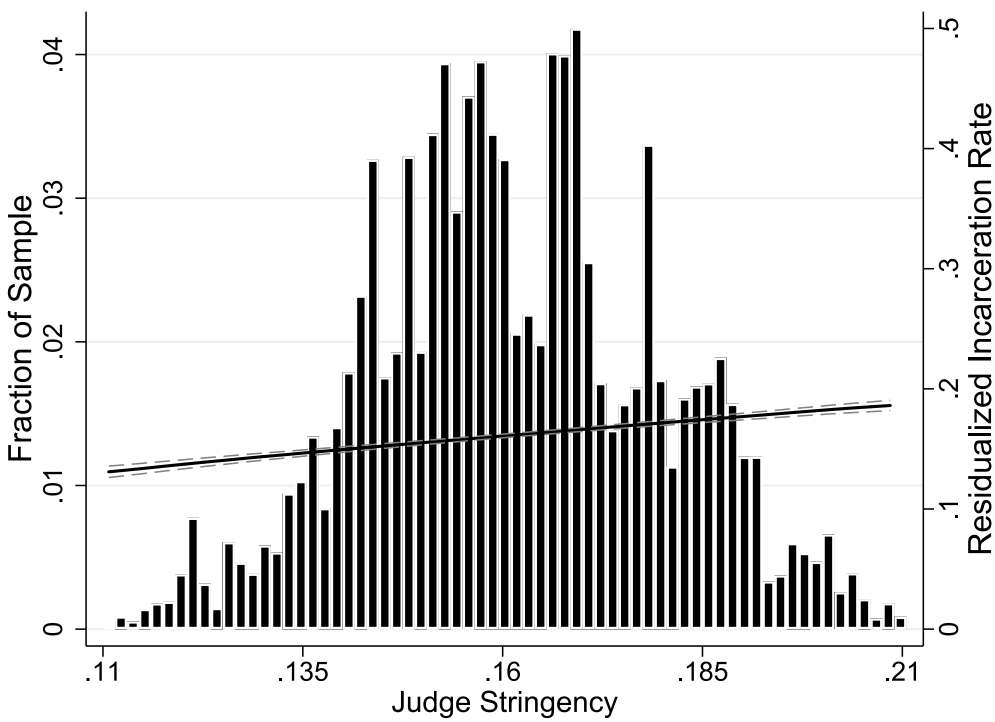


Table 2: First stage

Dependant variable	P(Fine) (1)	P(Probation) (2)	P(Prison) (3)
A. Court by Year by Crime fixed effects			
Judge Stringency	0.714***	0.500***	0.498***
se	(0.0554)	(0.0527)	(0.065)
B. Add controls			
Judge Stringency	0.720***	0.512***	0.539***
se	(0.0553)	(0.0513)	(0.057)
Dependent mean	0.485	0.185	0.167
F	165.7	90.07	58.299
N	169602	169602	169602

Having established that the instrument has sufficient variation and a strong first stage, we now turn to tests of the validity of the instrument. Beyond the institutional characteristics of the Finnish court system that support the exclusion restriction, we also report balance test results in Table 3. In column (2) we report the estimates from a regression of defendant characteristics on judge stringency for fines. We find that none of the coefficients are significant, and the joint test for significance has an F test statistic of 0.562 and a p-value of 0.884. Thus, defendants do appear to be randomly assigned to judges. The balance test passes despite the fact that these characteristics are highly correlated with fines, as shown in column (1). Almost every variable is significantly associated with fines and the p-value is zero. The same is true when we turn to probation and prison. Again, none of the characteristics are significant in predicting the judge stringency for probation (column (7)) and prison (column (5)), with the joint test for significance having an F test statistic of 0.705 with a p-value of 0.758, and an F test statistic of 0.663 with a p-value of 0.799, respectively. Again, this is despite the fact that these characteristics are highly correlated with whether the defendant receives a probation sentence or prison sentence, as shown in columns (3) and (5).

In Table 4, we show the trade-offs made by judges when deciding on punishments. The table reports the estimates from equation (2) where the outcome of interest is each of the three dif-

Table 3: Balance tests - Fines and Prison

	P(Fine)	Fine IV	P(Prison)	Prison IV	P(Prob)	Prob. IV
Demographics						
Age	-0.0010***	0.0000	-0.0004***	-0.0000	0.0002	-0.0000
	(0.0002)	(0.0000)	(0.0001)	(0.0000)	(0.0001)	(0.0000)
Kids	0.0076***	-0.0000	-0.0070***	0.0000	-0.0046***	0.0001
	(0.0016)	(0.0001)	(0.0008)	(0.0001)	(0.0012)	(0.0001)
Married	-0.0325***	-0.0000	0.0071***	0.0000	-0.0081**	-0.0002
	(0.0035)	(0.0002)	(0.0020)	(0.0001)	(0.0027)	(0.0001)
Tertiary degree	-0.0158**	-0.0001	-0.0149***	-0.0002	-0.0513***	-0.0002
	(0.0053)	(0.0003)	(0.0025)	(0.0002)	(0.0042)	(0.0002)
Employed	0.0311***	-0.0001	-0.0398***	-0.0001	-0.0015	-0.0001
	(0.0032)	(0.0002)	(0.0022)	(0.0001)	(0.0027)	(0.0002)
Income	0.0000	-0.0000	-0.0000***	0.0000	-0.0000***	0.0000
	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)	(0.0000)
Native born	0.0012	0.0002	0.0194***	0.0000	-0.0052	-0.0005
	(0.0069)	(0.0003)	(0.0034)	(0.0002)	(0.0052)	(0.0003)
Past criminal history						
Prison at time t-1	-0.1140***	-0.0000	0.2764***	-0.0002	-0.1063***	0.0001
	(0.0048)	(0.0003)	(0.0051)	(0.0002)	(0.0025)	(0.0002)
Charged at t-1	-0.0500***	-0.0002	0.0446***	-0.0000	-0.0097***	0.0001
	(0.0035)	(0.0002)	(0.0025)	(0.0001)	(0.0028)	(0.0002)
Prison at time t-2,t-3	-0.1335***	-0.0001	0.2946***	0.0000	-0.1467***	0.0002
	(0.0043)	(0.0002)	(0.0049)	(0.0002)	(0.0024)	(0.0002)
Charged at t-2,t-3	-0.0454***	0.0002	0.0520***	-0.0001	-0.0309***	-0.0001
	(0.0033)	(0.0002)	(0.0021)	(0.0001)	(0.0029)	(0.0001)
Secondary degree	0.0168***	-0.0002	-0.0170***	0.0001	-0.0043*	0.0001
	(0.0027)	(0.0002)	(0.0019)	(0.0001)	(0.0019)	(0.0001)
P-value	0.0000	0.8841	0.0000	0.7994	0.0000	0.7589
F-static	464.6603	0.5625	1420.2643	0.6635	667.3610	0.7054
Number of cases	169602	169602	169602	169602	169602	169602

Note. All estimations include controls for court by court entry year by crime type fixed effects. Standard errors clustered two-way at judge and defendant level. Standard errors are below the coefficients. *p<0.1, **p<0.05, ***p<0.01

ferent punishments: fines, probation, and prison. We find that being randomly assigned a judge with higher fine stringency (i.e. a more lenient judge) is associated with a decrease in the probability that a defendant receives probation or prison (we also repeat the first stage estimates for completeness). Being randomly assigned a judge with a higher prison stringency measure (i.e. a harsher judge) is associated with a decrease in the probability that the defendant receives fines, but an increase in the probability the defendant receives probation. The impact of fine stringency on prison and the impact of prison stringency on fines are both straightforward and consistent with predictions of the model, i.e. more lenient judges should be more likely to give fines and stricter judges more likely to give prison. The effect on probation is less straightforward and at first glance the negative impact of prison stringency on probation may appear counter-intuitive. If, as we show in the first stage estimates reported in Table 2, higher prison stringency results in a higher probability of prison, shouldn't this also coincide with fewer probation cases? The problem with this naive prediction is as follows. We can think of the prison stringency measure as a proxy for stricter judges. If all cases involved a decision between probation and prison, then we would expect that stricter judges would tend to choose prison, resulting in a negative coefficient on probation. However, as shown in Figure 2, the majority of cases end in fines. The problem is that we observe all cases but cannot distinguish between cases where judges are deliberating between fines and probation versus cases where the judge is deliberating between probation and prison. Given the preponderance of fines, it is likely true that in most cases the judge is deciding between fines and probation, not between probation and prison. When deciding between fines and probation, we would expect stricter judges to tend to choose probation. Thus, if the majority of marginal cases are cases between fines and probation (as opposed to probation and prison) we would expect to see a positive association between prison stringency and probation and a negative association between fine stringency and probation, which is precisely what we find in column (2). In sum, the results in Table 4 show that a) judges are trading off between different punishment types, b) make it clear that the counterfactual for fines is both probation and prison and the counterfactual for prison is both fines and probation.

These estimates make clear the fact that in the IV analyses that follows estimating the impact of the different punishments, we are estimating the impact of each punishment relative to the counterfactual of multiple alternative punishments. In many cases this is precisely the policy parameter of interest. However, in order to fully understand the impact of different punishments as crimes change in severity or defendants change in terms of the number of previous crimes committed, i.e. two motivating dimensions for the ladder of punishments, in the last part of the paper we will explore the heterogeneity of the impact of the different punishments on these two dimensions.

Table 4: Effect of Judge Stringency on All Three Punishments

Dep. variable	P(Fine) (1)	P(Probation) (2)	P(Prison) (3)
Fine Stringency	0.946***	-0.382***	-0.252***
(No controls)	(0.063)	(0.027)	(0.025)
Probation Stringency			
(No controls)			
Prison Stringency	-0.525***	0.261***	0.551***
(No controls)	(0.054)	(0.043)	(0.054)
N	169602	169602	169602

4.2 Complier Analysis

As we will show, the IV estimates in this paper differ dramatically when compared to OLS estimates. It is thus important to understand why these estimates might be so different from each other. There are two reasons OLS and IV results might differ. The first is selection, which we have already discussed in detail, and is the motivation for carefully estimating causal impacts. The second possibility is that both OLS and IV are causal estimates, but there are heterogeneous effects and OLS and IV are estimating effects on different samples. To try and disentangle these explanations for the main results, we re-estimate the OLS using complier weights calculated separately for fines, probation, and prison. In this section we briefly discuss how we construct the weights.

As Bhuller *et al.* (2016), Dobbie *et al.* (2018a), Dobbie *et al.* (2018b), and Abadie (2003) discuss, while we cannot identify specific compliers in the data set, it is possible to extend the judge fixed effects analysis in order to analyze the set of compliers in the data. In addition to the OLS results we report the reweighted OLS results throughout the main results, and in this section we briefly describe how we do this analysis and who the compliers are. The intuition for these estimates is that a subset with a stronger first stage relative to other subsets contains more compliers. We report the results in Appendix Figures 19-21. The results show that for fines, compliers are not very strongly selected, but do appear to be less likely to commit violent crimes, more likely to commit property crimes, and more likely to be married. For prison, those without a degree and with previous charges are more likely to be compliers while those who are employed and accused of violent crimes are less likely to be compliers.

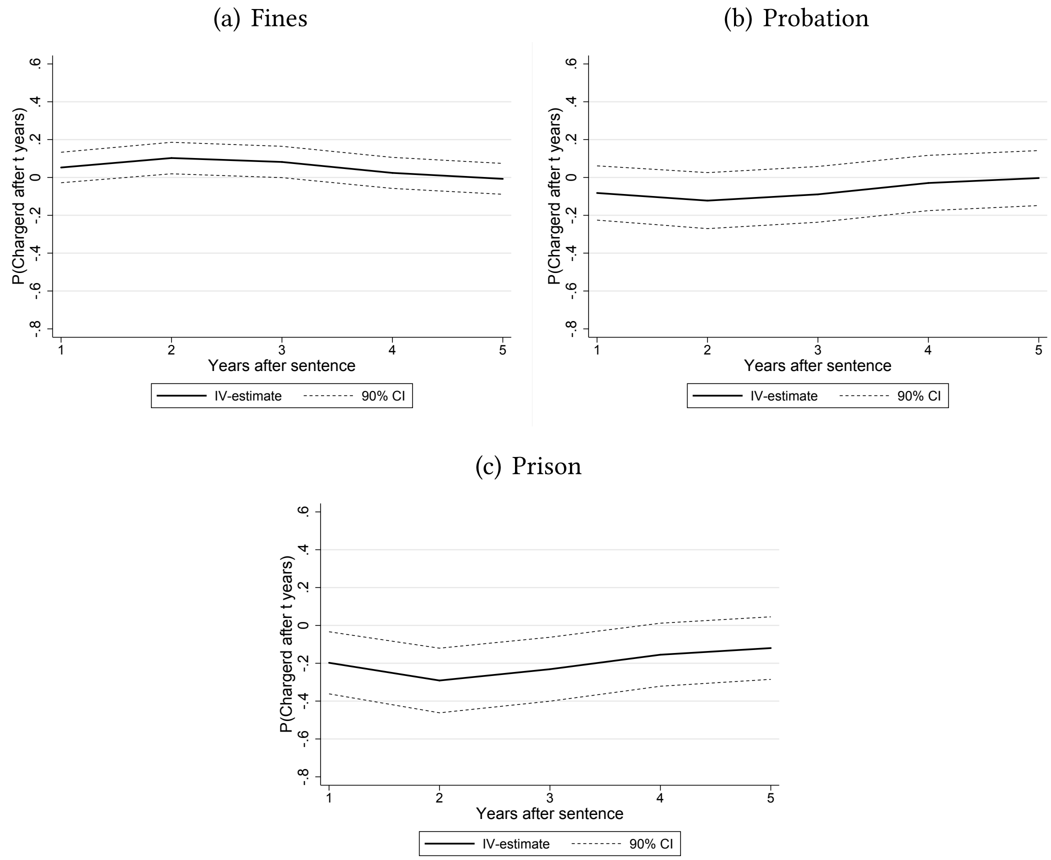
5 Main Results

Criminal Activity. We first present the impact of different punishments on future criminal charges. In Table 5 we present the impact of fines (top panel), probation (middle panel), and prison (bottom panel) on whether the defendant is charged with another crime in the year after sentencing, the first 2 years after sentencing, or the first 5 years after sentencing. OLS results with controls suggest that fines decrease the probability of future charges while porbation and prison sentences are associated with an increase in the probability of subsequent charges. However, when we turn to the IV estimates we find the opposite: fines cause a small increase in the probability of future criminal charges after sentencing, and the effect is significant at the 10% level 2 years after the sentence. The reverse is true for probation and prison. In the IV estimates the sign flips and we find that probation and prison causes a decrease in the probability of charges after sentencing. This result is significant in the first year and the first two years after charging for prison, although it is never significant for probation. The reweighted OLS results look very similar to the OLS results. Together, these estimates suggest that the OLS evidence is misleading and likely due to selection - prison causes a significant decrease in charges while fines cause an increase in charges. In Figure 9 we present graphs showing the cumulative impacts of each punishment on the probability of being charged over time. The results, along with the estimates in column (5) of Table 5 suggest that the impacts of prison on charges may be driven by the incapacitation effect, since the decrease in crime caused by prison is concentrated in the first two years after sentencing, and there is a smaller impact in later years, and no significant impact when we focus only on the 3-5 years after sentencing.

Thus far we have seen that prison causes a large decrease in future charges that may be driven primarily by incapacitation, fines causes a smaller but still meaningful increase in future charges, and probation leads to a small (but always insignificant) decrease in charges. However, it is also interesting to know if the increase in charges is also accompanied by an increase in the severity of crimes committed. We propose two measures of crime severity. First, does the defendant return to prison in the next five years? In Appendix Table 13 we repeat the same exercise as with charges but now with the outcome of whether the defendant is sent to prison in the following five years. While OLS results again suggest that punishing defendants with fines decreases the probability of future prison sentences and punishing defendants with a prison sentence increases the probability of later prison sentences (probation, interestingly, is associated with a decrease in prison in OLS), these results go away in the IV, where we find no significant impact of either punishment on future prison sentences in the three years following the sentence. However, it is important to realize that prison is an imperfect proxy for crime severity, since probation and prison sentences can mechanically lead to future prison sentences based on the law in Finland, which is also the case in other countries where prison has been used as an outcome of interest. Given this issue, we suggest an alternative measure of crime severity that does not suffer from this mechanical link, namely the share of each crime code that is sent to prison as discussed in Section 3.[16] We find that while OLS results suggest that prison increases future crime severity and fines decrease future crime severity, the opposite is true in IV - Fines increase the severity of future crimes in the first two years after treatment, and significantly so in the second year. Prison decreases the severity of future crimes in the three years after charging, and significantly so for the second year. Probation has no significant effects on the severity of future crimes, but the point estimates suggest a reduction in severity of future crimes.

[16]Note that when an individual does not commit a crime in the following year, the value we assign for his crime escalation variable is zero.

Figure 9: Cumulative Impacts of Different Punishments on Future Charges



Note: The figures show the cumulative impact of each punishment type on the probability that the defendant has been charged for a new crime in the preceding years.

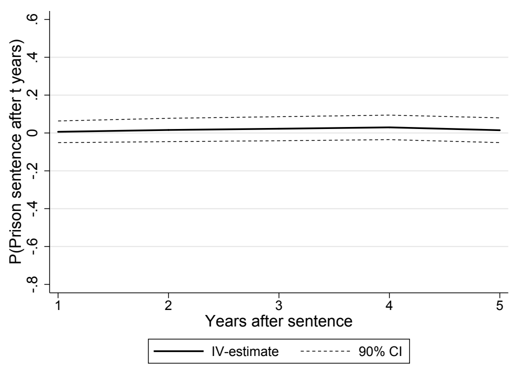
Overall, our IV results suggest that prison, and not fines or probation, decreases the probability of future charges, likely due to an incapacitation effect. Similarly, prison decreases severity of future crimes while fines increase severity of future crimes. However, future criminal activity may not be the only outcome of interest. We turn next to the impacts of these different punishments on labor market outcomes of defendants.

Table 5: Impact on Future Charges

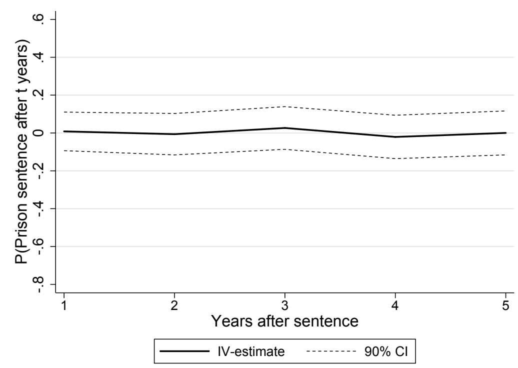
Dep. variable	Pr(Charged)			
name	1 year after	1-2 years after	1-5 years after	3-5 years afer
Fine				
OLS	-0.093***	-0.105***	-0.105***	-0.103***
No controls	(0.003)	(0.003)	(0.003)	(0.003)
OLS	-0.010***	-0.010***	-0.013***	-0.015***
Controls	(0.002)	(0.002)	(0.002)	(0.002)
OLS	-0.009***	-0.010***	-0.013***	-0.015***
Controls and Weights	(0.002)	(0.002)	(0.002)	(0.002)
IV	0.053	0.103*	-0.007	-0.121*
Controls	(0.044)	(0.046)	(0.053)	(0.055)
Probation				
OLS	-0.085***	-0.084***	-0.071***	-0.088***
No controls	(0.003)	(0.004)	(0.004)	(0.004)
OLS	0.001	0.011***	0.018***	0.002
Controls	(0.003)	(0.003)	(0.003)	(0.003)
OLS	0.007*	0.016***	0.023***	0.007*
Controls and Weights	(0.003)	(0.003)	(0.003)	(0.003)
IV	-0.082	-0.122	-0.003	-0.031
Controls	(0.090)	(0.093)	(0.098)	(0.084)
Incarceration				
OLS	0.329***	0.364***	0.361***	0.361***
No controls	(0.005)	(0.004)	(0.003)	(0.004)
OLS	0.054***	0.050***	0.058***	0.074***
Controls	(0.004)	(0.004)	(0.003)	(0.004)
OLS	0.047***	0.039***	0.045***	0.061***
Controls and Weights	(0.005)	(0.004)	(0.003)	(0.004)
IV	-0.198*	-0.291**	-0.120	0.033
Controls	(0.099)	(0.104)	(0.106)	(0.096)
Dep. mean	0.324	0.435	0.565	0.424
Number of cases	169602	169602	169602	169602

Figure 10: Cumulative Impacts of Different Punishments on Prison

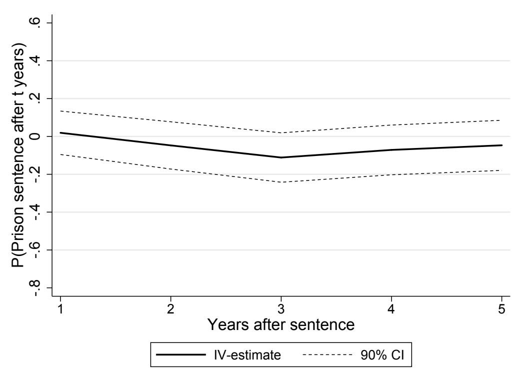
(a) Fines



(b) Probation



(c) Prison



Note: The figures show the cumulative impact of each punishment type on the probability that the defendant has been sent to prison for a new crime in the preceding years.

Table 6: Impact on Crime Severity

Dep. variable	Severity of Crime		
	1 year after	2 years after	3 years after
Panel A: Fine			
OLS:	-0.029***	-0.023***	-0.024***
	(0.001)	(0.001)	(0.001)
OLS: Controls	-0.007***	-0.005***	-0.006***
	(0.001)	(0.001)	(0.001)
OLS: Reweighted	-0.007***	-0.004***	-0.006***
	(0.001)	(0.001)	(0.001)
IV: Controls	0.015	0.028*	-0.003
	(0.015)	(0.013)	(0.011)
Panel B: Probation			
OLS:	-0.025***	-0.021***	-0.021***
	(0.001)	(0.001)	(0.001)
OLS: Controls	-0.001	0.000	-0.001
	(0.001)	(0.001)	(0.001)
OLS: Reweighted	0.001	0.001	0.000
	(0.001)	(0.001)	(0.001)
IV: Controls	-0.065	-0.145	-0.093
	(0.088)	(0.088)	(0.079)
Panel C: Prison			
OLS:	0.096***	0.079***	0.078***
	(0.002)	(0.002)	(0.002)
OLS: Controls	0.027***	0.018***	0.022***
	(0.001)	(0.001)	(0.001)
OLS: Reweighted	-0.043	-0.071	-0.050
	(0.041)	(0.039)	(0.038)
IV: Controls	-0.023	-0.052*	-0.033
	(0.030)	(0.026)	(0.026)
Dep. Mean	0.061	0.052	0.047
Cases	169602	169602	169602

Labor Market Outcomes. In Table 7 we report the impact of fines (top panel), probation (middle panel), and prison (bottom panel) on whether the defendant was employed in the first year, the first 2 years, and the first five years following the sentence. The OLS estimates suggest that fines increases the probability of employment while probation and prison decreases the probability of employment, even when including a rich set of controls, and even in the reweighted OLS estimates. However, the IV results suggest no significant impacts of fines, probation, or prison on employment.

Next, in Table 8 we report the impacts on the defendant's earnings. The Table reports the impact of fines (top panel), probation (middle panel), and prison (bottom panel) on the cumulative earnings in the first year, the first two years, and the first five years after sentencing. We find that the OLS estimates suggest positive impacts of fines on earnings, and negative impacts of probation and incarceration on earnings. However, in this case the IV estimates suggest similar results, and suggest that the negative impacts of prison on earnings are as large as or even larger than what OLS estimates would suggest. In contrast, probation no longer has a significant impact on earnings, and the point estimates, while negative, are all small. Fines have a small but not significant positive impact on earnings in every column. These results suggest that prison causes negative labor market outcomes for defendants, while fines and probation do not cause a reduction in labor market outcomes for defendants, when compared to other punishments. In Figure 11 we graphically represent the IV impacts on employment and in Figure 12 we graphically represent the IV impacts on earnings.

Table 7: Impact on Employment

Dep. variable	Pr(Employed)			
	1 year after	2 years after	5 years after	3-5 years afer
	(1)	(2)	(3)	(4)
Fine				
OLS	0.108***	0.107***	0.099***	0.095***
No controls	(0.003)	(0.003)	(0.003)	(0.003)
OLS	0.025***	0.021***	0.014***	0.013***
Controls	(0.002)	(0.002)	(0.002)	(0.002)
OLS	0.025***	0.021***	0.014***	0.013***
Controls and Weights	(0.002)	(0.002)	(0.002)	(0.002)
IV	0.008	-0.072	-0.010	0.062
Controls	(0.043)	(0.046)	(0.045)	(0.047)
Probation				
OLS	0.034***	0.044***	0.049***	0.040***
No controls	(0.004)	(0.004)	(0.004)	(0.004)
OLS	-0.020***	-0.014***	-0.009**	-0.014***
Controls	(0.003)	(0.003)	(0.003)	(0.003)
OLS	-0.020***	-0.015***	-0.010***	-0.015***
Controls and Weights	(0.003)	(0.003)	(0.003)	(0.003)
IV	-0.049	0.091	0.025	-0.113
Controls	(0.071)	(0.074)	(0.076)	(0.079)
Incarceration				
OLS	-0.323***	-0.325***	-0.306***	-0.288***
No controls	(0.003)	(0.004)	(0.005)	(0.004)
OLS	-0.075***	-0.070***	-0.057***	-0.049***
Controls	(0.003)	(0.003)	(0.004)	(0.004)
OLS	-0.046***	-0.043***	-0.038***	-0.031***
Controls and Weights	(0.003)	(0.003)	(0.004)	(0.004)
IV	-0.094	-0.013	-0.064	-0.117
Controls	(0.086)	(0.090)	(0.095)	(0.091)
Dep. mean	0.361	0.419	0.518	0.448
Number of cases	166931	169602	169602	169602

Table 8: Impact on Earnings

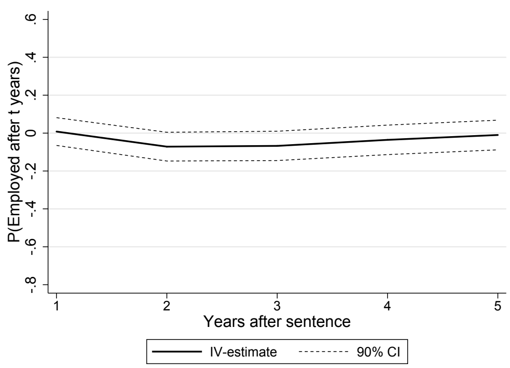
Dep. variable	Earnings			
	1 year after	2 years after	5 years after	3-5 years afer
Fine				
OLS	3083.673***	5969.114***	14560.677***	8591.563***
No controls	(125.392)	(243.578)	(598.173)	(368.334)
OLS	546.471***	939.972***	2052.101***	1112.129***
Controls	(75.637)	(150.730)	(363.826)	(236.048)
OLS	552.698***	943.329***	2055.949***	1112.620***
Controls and Weights	(76.127)	(151.286)	(365.529)	(237.439)
IV	1235.575	1441.236	5380.823	3939.587
Controls	(1684.482)	(3203.852)	(7870.718)	(5089.904)
Probation				
OLS	-461.787**	-882.462**	-2187.919**	-1305.457**
No controls	(145.020)	(276.603)	(668.422)	(408.573)
OLS	-1327.381***	-2624.054***	-6577.408***	-3953.354***
Controls	(94.721)	(173.713)	(411.724)	(276.729)
OLS	-875.412***	-1777.341***	-4605.558***	-2828.217***
Controls and Weights	(83.432)	(150.342)	(354.473)	(236.296)
IV	-594.346	1197.172	-4324.465	-5521.636
Controls	(3218.169)	(6026.044)	(15117.122)	(9811.856)
Incarceration				
OLS	-9835.156***	-19161.001***	-46588.815***	-27427.814***
No controls	(111.875)	(219.726)	(534.460)	(330.169)
OLS	-1390.882***	-2459.351***	-5430.960***	-2971.609***
Controls	(97.371)	(181.913)	(426.112)	(284.261)
OLS	-734.437***	-1252.136***	-2918.330***	-1666.194***
Controls and Weights	(69.867)	(133.495)	(303.862)	(199.766)
IV	-8902.718*	-15649.736*	-28879.477	-13229.741
Controls	(3743.534)	(6970.660)	(16319.371)	(10132.314)
Dep. mean	10133	20101	50729	30627
Number of cases	166931	169602	169602	169602

5.1 Robustness Checks

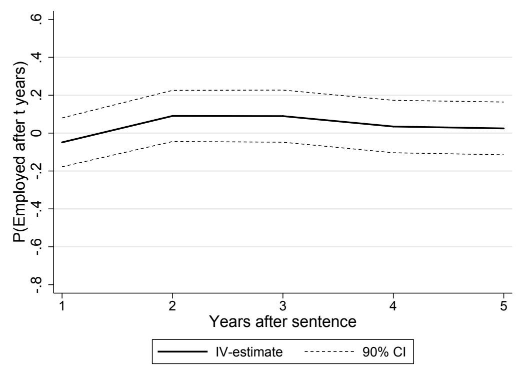
As discussed in Mueller-Smith (2014), two important assumptions that should always be checked in these settings are: no multidimensional sentencing (to avoid violating the exclusion restriction)

Figure 11: Cumulative Impacts of Different Punishments on Employment

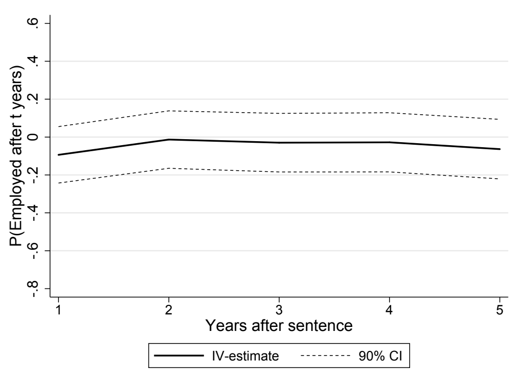
(a) Fines



(b) Probation



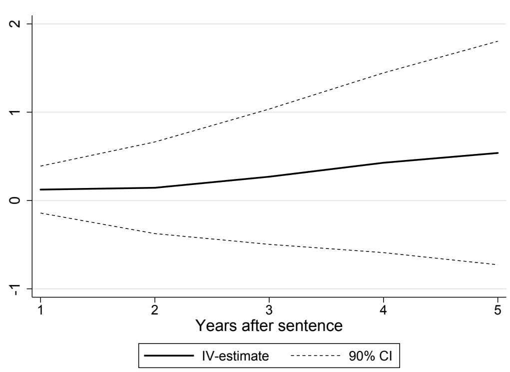
(c) Prison



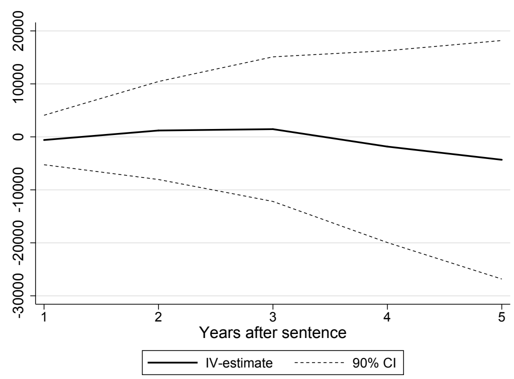
Note: The figures show the effects of each punishment on future employment.

Figure 12: Cumulative Impacts of Different Punishments on Earnings

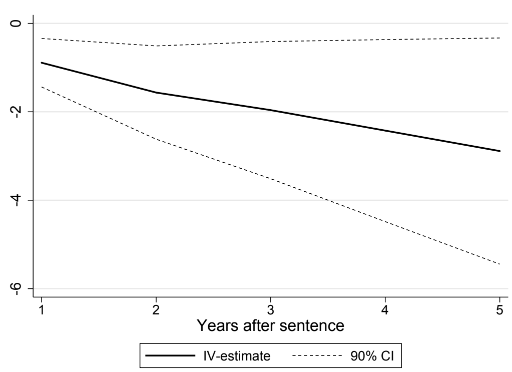
(a) Fines



(b) Probation



(c) Prison



Note: The figures show the effects of each punishment on cumulative earnings.

and monotonicity. Multi dimensional sentencing is to some extent illegal in Finland, as only one punishment can be assigned to a single crime. However, if multiple crimes are committed at the same time, it is possible for a judge to assign multiple punishments. In order to check if this is a major issue, we examined the data to see if multi-dimensional sentencing is a frequent occurence. We found almost no incidents of multi-dimensional sentencing in the data, so we do not believe this is a major concern in our setting. Of course, the judge might impact the defendant in ways other than punishment, for example a more lenient judge might also be kinder when speaking to defendants. We do not observe anything about the judge behavior aside from the punishment, but our hypothesis is that such violations, if they occur, do not strongly impact defendants.

To check if our instrument is consistent with the monotonicity assumption, we take a similar approach as in Bhuller *et al.* (2016), and do two things. First, we show that the first stage is similarly strong and positive across a number of sub samples. Next, we perform a "reverse sample instrument test". Specifically, for a series of different variables we take a subset of the sample to construct the judge instrument, and then estimate the first stage using the other part of the sample (which was not used to construct the judge instrument). We present these results in the Appendix.

6 Heterogeneity by Crime Severity and Number of Crimes

In the main analysis, we simply estimate the LATEs for each punishment type given existing thresholds, which vary by judge. In many cases, these are the policy parameters of interest. These LATEs identify the impact of prison (for example) relative to the mixture of alternative possible punishments for compliers. Only under very strong assumptions can we use the estimated LATEs to pin down the impact of prison versus fines separately from the impact of prison versus probation (similarly for fines and probation), and these assumptions do not hold in our context.

However, as we showed in Section 3, punishments tend to grow more severe as a defendant commits more serious crimes and as a defendant commits a greater number of crimes. One of the main reasons we might want to pin down more direct comparisons between different types of punishments is because compliers in the fine analysis (for example) likely committed less severe crimes compared to the compliers in the prison and probation analysis, given the ladder of punishments approach. Thus, it is difficult to directly compare the impact of prison versus the impact of fines based on our LATE estimates alone. We end the paper by presenting suggestive evidence on this point. We estimate the impact of each punishment type separately for more severe versus less severe crimes and also separately for defendants who have committed above median versus below median number of crimes [the heterogeneity results by number of crimes are completed but have not yet been released for presentation by Statistics Finland, so are still in progress for this draft]. We define more severe crimes as crimes that are above the median using our severity of crime measure from this paper (see Section 3 for a description of this measure). This arguably helps us narrow down the possible set of conterfactuals. For example, when examining the impact of more severe crimes the counterfactual for probation is likely to be prison, while for less severe crimes the counterfactual for probation is more likely to be prison.

First, we present estimates of the cumulative effect of different punishments on charges on Table 9 and Figure 14 by crime severity. These estimates show that there are clear differences in the results by crime severity. For less severe crimes, fines increase charges and probation decreases charges. The mirror image of fines and probation for less severe crimes reported in Figure 12 may reflect the fact that probation is the likely counterfactual for fines for low severity crimes. We see no effect of fines or probation for the group of defendants who have committed above median severity crimes, perhaps reflecting the fact that fines are less often used in this category. While prison does still cause decreases in future charges for low severity crimes, this is only in the first years after sentencing which suggests an incapacitation effect drives these results. On the other hand, prison does appear to cause longer term reductions in future charges for more severe crimes. These results also suggest that the reductions in future charges that come from prison are primarily driven by above median severity crimes. In contrast, probation appears to be quite effective at reducing future charges for low severity crime, and the criminogenic effect of fines is concentrated in low severity crimes. The results thus indicate that for severe punishments prison appears to decrease future charges more effectively than other punishments.

Table 9: Heterogeneity by severity - Charges

Dep. Var	P(Charged)			
	Low severity		High Severity	
Dep. Var	1 year after	1-2 years after	1 year after	1-2 years after
Panel A. Impact of fines	0.101	0.165*	0.019	0.058
	(0.064)	(0.071)	(0.076)	(0.066)
Panel B. Impact of Probation	-0.200	-0.340*	0.005	0.045
	(0.131)	(0.146)	(0.132)	(0.125)
Panel C. Impact of Prison	-0.461	-0.326	-0.123	-0.313**
	(0.249)	(0.270)	(0.103)	(0.109)
ymean	0.245	0.348	0.403	0.522
N	84946	84946	84656	84656

For less severe crimes probation seems to cause the largest reduction in future charges.

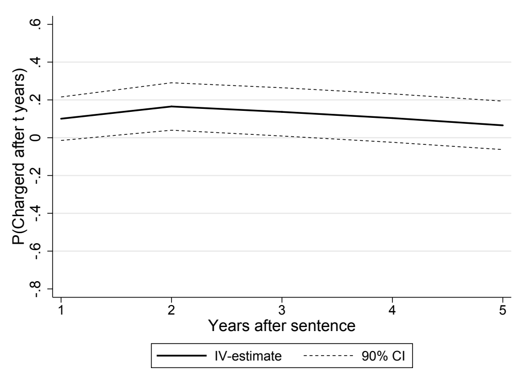
Table 11: Heterogeneity by severity - Earnings

Dep. Var	Earnings			
	Low severity		High Severity	
	1 year after	1-2 years after	1 year after	1-2 years after
Panel A. Impact of fines	267.420	-70.770	1267.306	1210.076
	(2895.708)	(5490.525)	(1657.466)	(3395.453)
Panel B. Impact of Probation	4772.146	13612.227	-4227.829	-7363.371
	(6010.051)	(10943.324)	(3355.329)	(6718.330)
Panel C. Impact of Prison	-16166.227	-26412.040	-4725.944	-9113.224
	(10966.869)	(20853.271)	(3047.314)	(5700.699)
ymean	14059	27781	6188	12394
N	83662	84946	83269	84656

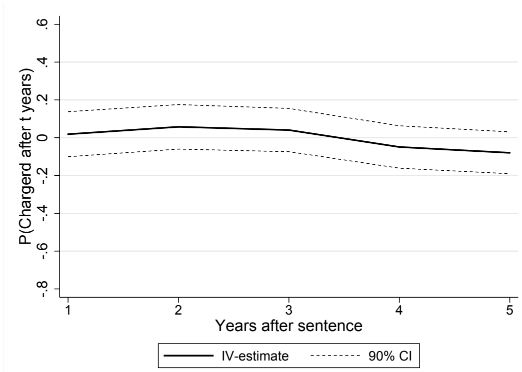
Figure 13: Cumulative Impacts of Punishments on Charges by Severity

Fines

(a) Low Severity

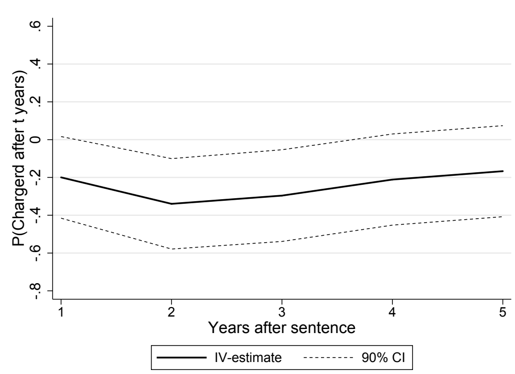


(b) High Severity

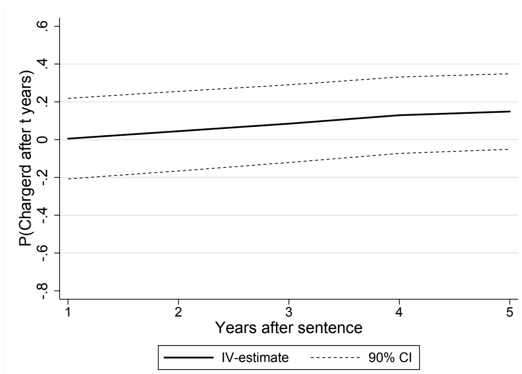


Probation

(c) Low Severity

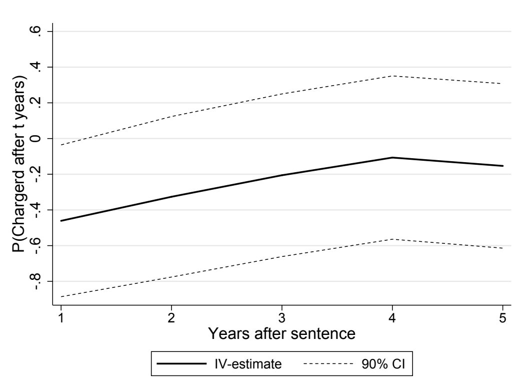


(d) High Severity

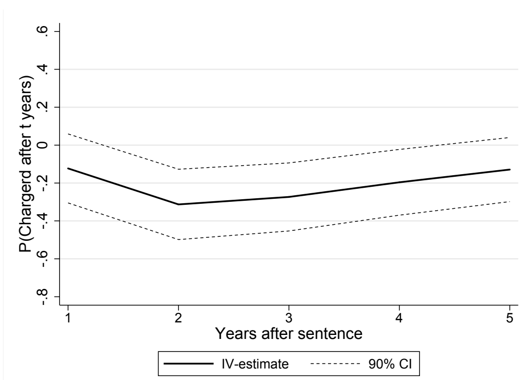


Prison

(e) Low Severity

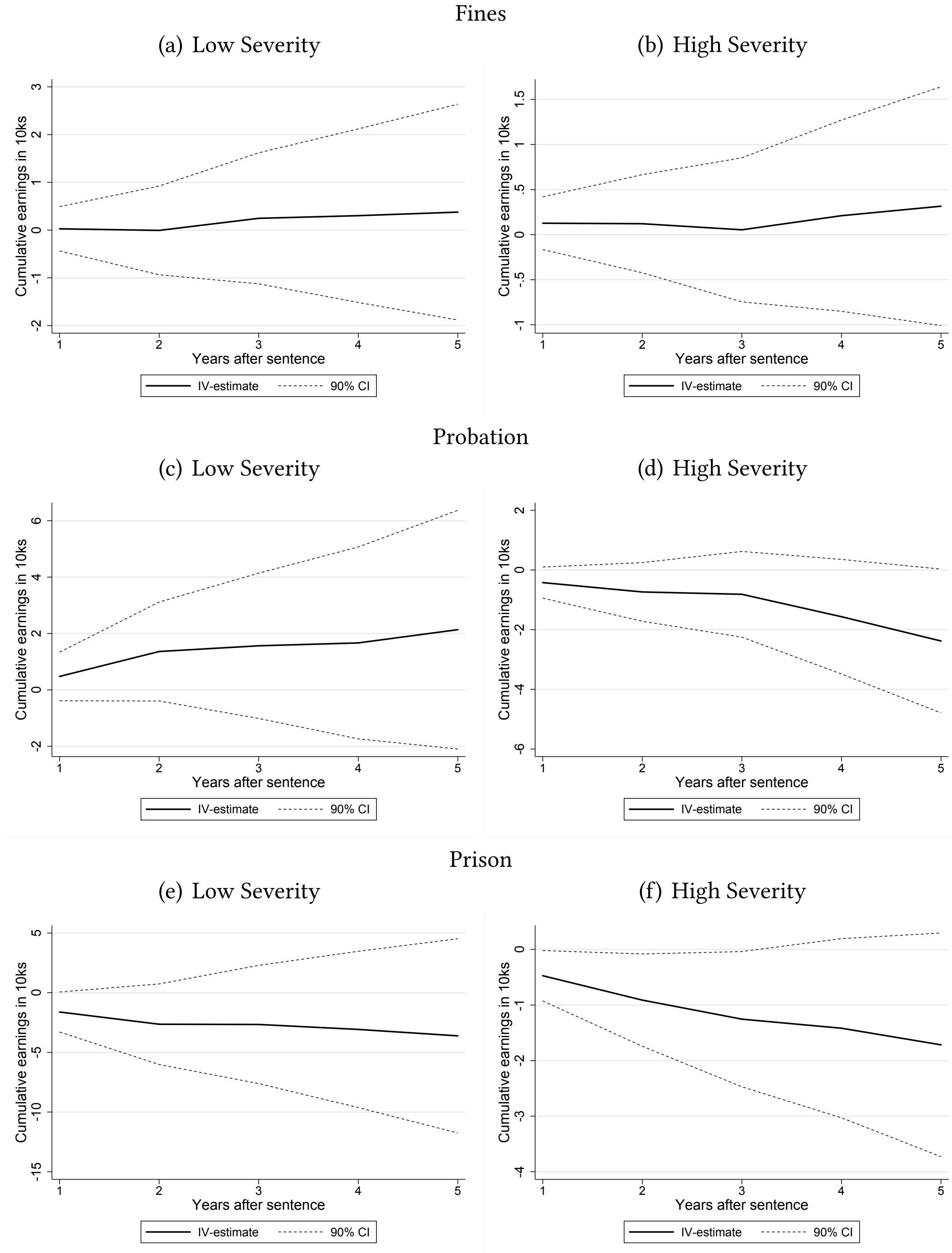


(f) High Severity



Note: The graph shows the cumulative effects of each punishment type on charges separately for less severe (left panel) and more severe (right panel) crimes.

Figure 14: Cumulative Impacts of Punishments on Earnings by Severity



Note: The graph shows the cumulative effects of each punishment type on earnings separately for less severe (left panel) and more severe (right panel) crimes.

Table 10: Heterogeneity by severity - Employment

Dep. Var	**P(Employed)**			
	Low severity		High Severity	
	1 year after	1-2 years after	1 year after	1-2 years after
Panel A. Impact of fines	-0.052	-0.109	0.052	-0.061
	(0.069)	(0.072)	(0.059)	(0.063)
Panel B. Impact of Probation	-0.012	0.055	-0.053	0.174
	(0.117)	(0.114)	(0.110)	(0.109)
Panel C. Impact of Prison	0.079	0.048	-0.147	-0.033
	(0.248)	(0.257)	(0.095)	(0.102)
ymean	0.464	0.518	0.257	0.319
N	83662	84946	83269	84656

7 Conclusion

In this paper, we have shown that while sentencing defendants to prison lowers the number of future charges, it also lowers future labor market outcomes of defendants. Moreover, the decrease in future charges is accompanied by a decrease in the severity of future crime, although both crime reducing effects appear to be concentrated in the first few years after sentencing, which may be consistent with an incapacitation effect. In contrast, sentencing defendants to fines increases future criminal activity and escalates criminal activity. Fines do not have the negative impacts on later labor market outcomes of defendants that prison does. When we turn to the heterogeneous effects of fines, probation, and prison on two dimensions of the criminal ladder - severity of crime and number of crimes - we find that the increase in charges caused by fines is concentrated in the low severity crimes, while the decrease in charges from prison is concentrated in the high severity crimes. We also see that the zero average impacts of probation overall masks heterogeneity in the effect by crime severity. Probation causes a reduction in future charges for low severity crimes. These results suggest that probation is most effective at deterring future criminal activity for low severity criminals, while prison is effective for more severe criminals.

As Becker stated in his seminal paper on crime, if fines are effective at deterring crime then "social welfare is increased if fines are used *whenever possible*" (Becker (1968), pg. 28). Yet despite the frequent use of punishments other than prison and these early statements by Becker at the start of the economics of crime literature, before this paper we knew relatively little about the impact of other punishments, such as fines and probation, and their relative trade-offs compared to prison and each other. Our results suggest that the original Becker suggestion, to use fines whenever possible, is the right approach if one wants to minimize labor market impacts to defendants, but it is not the right approach in order to minimize criminal activity, particularly for low severity crimes where probation appears to be most effective. Moreover, probation not only decreases future charges for below median severity crimes, it also does not exhibit the negative earnings effects that accompany prison sentences.

Note, however, that these mixed results are drawn from the Finnish context. Finland is a country that uses fines much more frequently than most other countries, which allowed us to carry out the analysis done in this paper. However, whether probation will be equally effective at preventing future crimes for lower level crimes in other countries remains to be seen. We also point out that the impacts of fines on future criminal activity are small, so even in Finland the criminal justice system could use fines even more frequently without large negative consequences in terms of increases in criminal activity.

The direct impact on defendants is not the only important aspect of punishments that requires analysis. In Huttunen *et al.* (2019), we extend the analysis in this paper to also look at the spillovers on children and partners of fines and prison. These are important externalities to consider when optimally assigning punishments. Additionally, punishments might differentially deter criminal activity of peers, which is also an area for future research. Understanding the full impact of different punishments in even more detail and in additional contexts is clearly important in order to optimally implement a ladder of criminal punishments.

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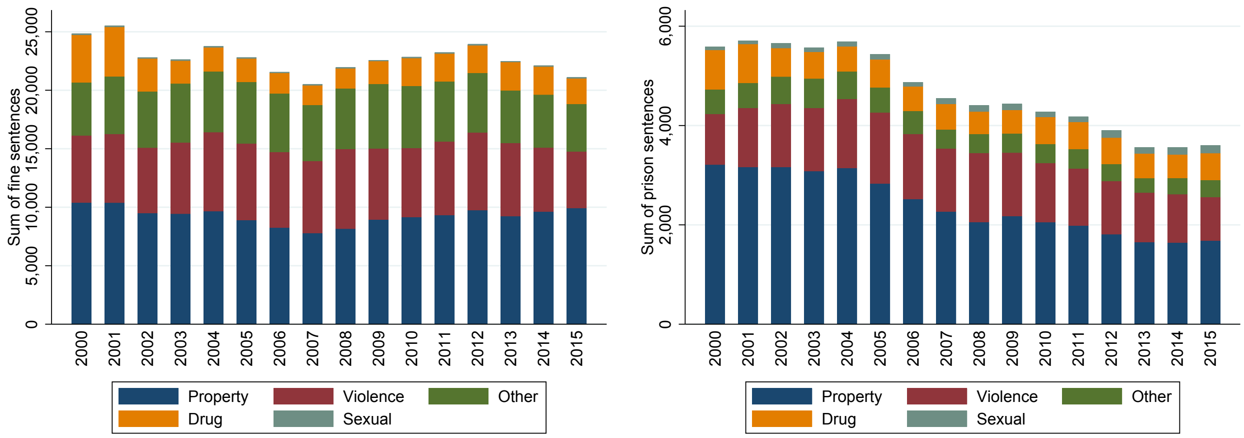
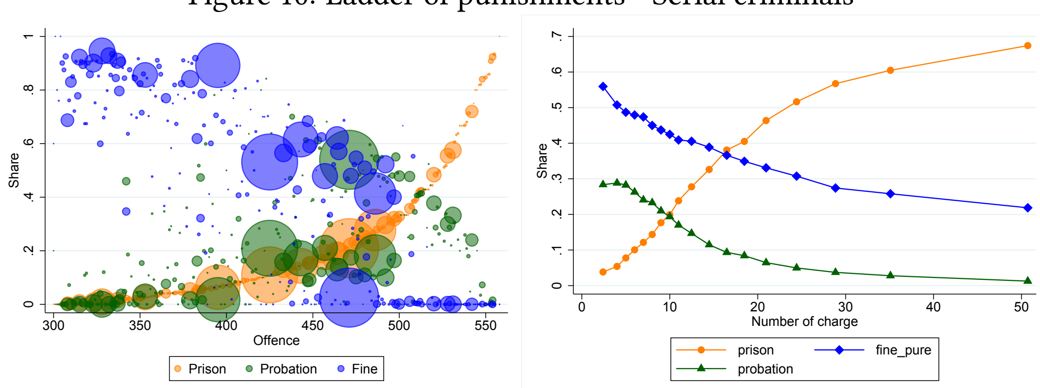
A Appendix

Figure 15: Court cases, prison, and fines over time in Finland



Note: The graphs plot all court cases for all defendants from 2000-2015. The left panel plots court cases that result in a fine while the right panel plots court cases that result in prison.

Figure 16: Ladder of punishments - Serial criminals



Note: These figures restrict the sample to individuals who commit more than 3 crimes in their lifetime.

Figure 17: Maximum and minimum prison sentence

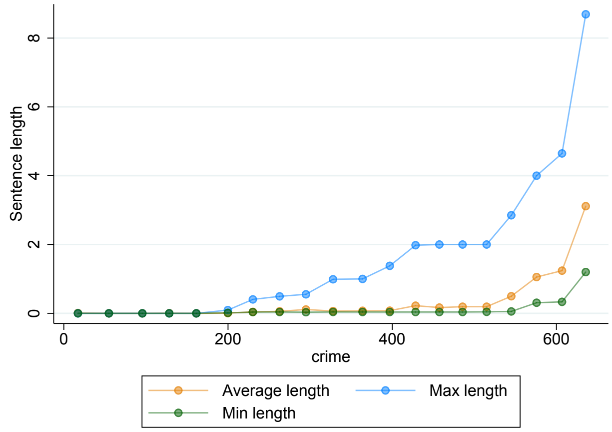


Figure 18: Correlation between prison and fine stringency

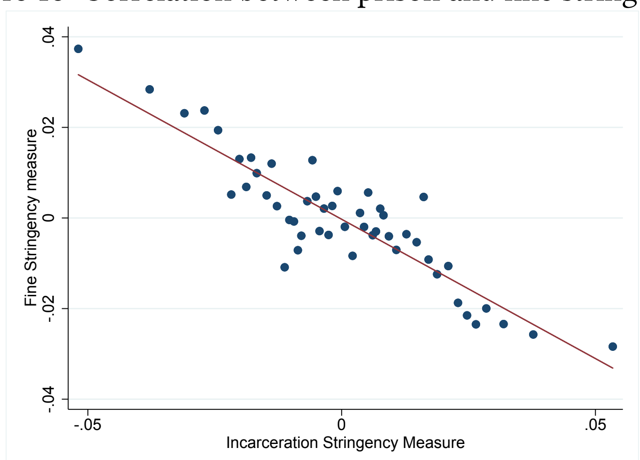


Table 12: Sample restrictions for judges from 2000-2015

	Sample size after each restriction (in each row)			
	A. Judge Stringency Panel			
Number of	Cases	Defendants	Judges	Courts
No restrictions	388829	202408	3361	65
Drop training judges	304326	168882	1035	65
Swedish speaking	296245	163688	1034	65
Drop judges < 100 over career	282135	157644	680	65
Drop courts <2 judges	282119	157637	680	65
	B. Panel of Analysis for cases decided between 2000-2013			
Number of	Cases	Defendants	Judges	Courts
Analysis data	220677	126760	668	65

Figure 19: Complier Weights - Fines

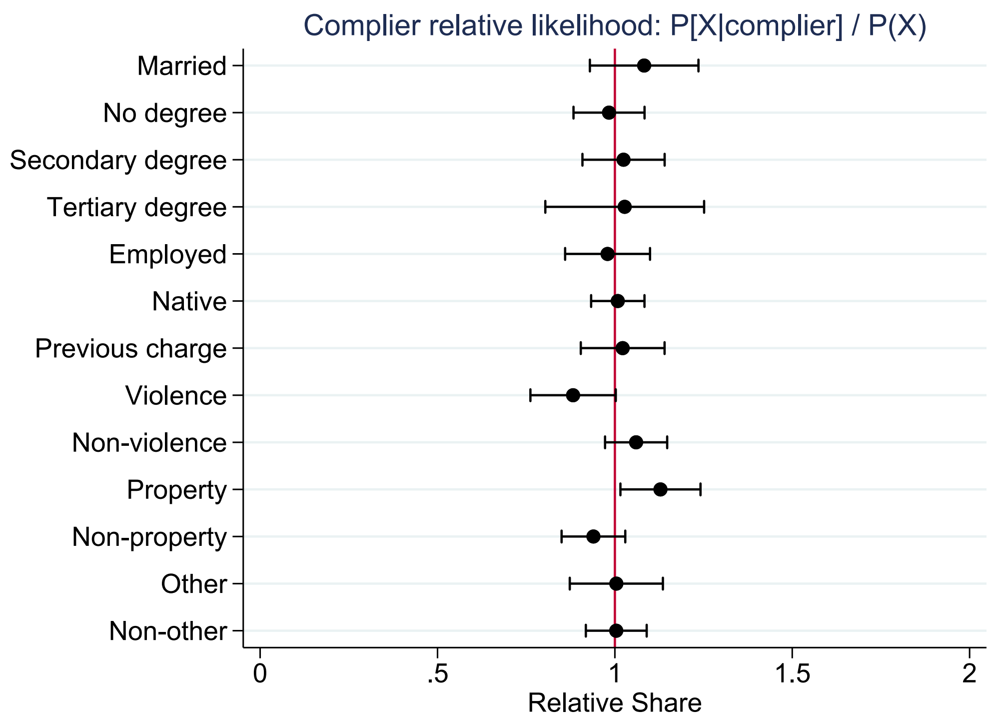


Figure 20: Complier Weights - Probation

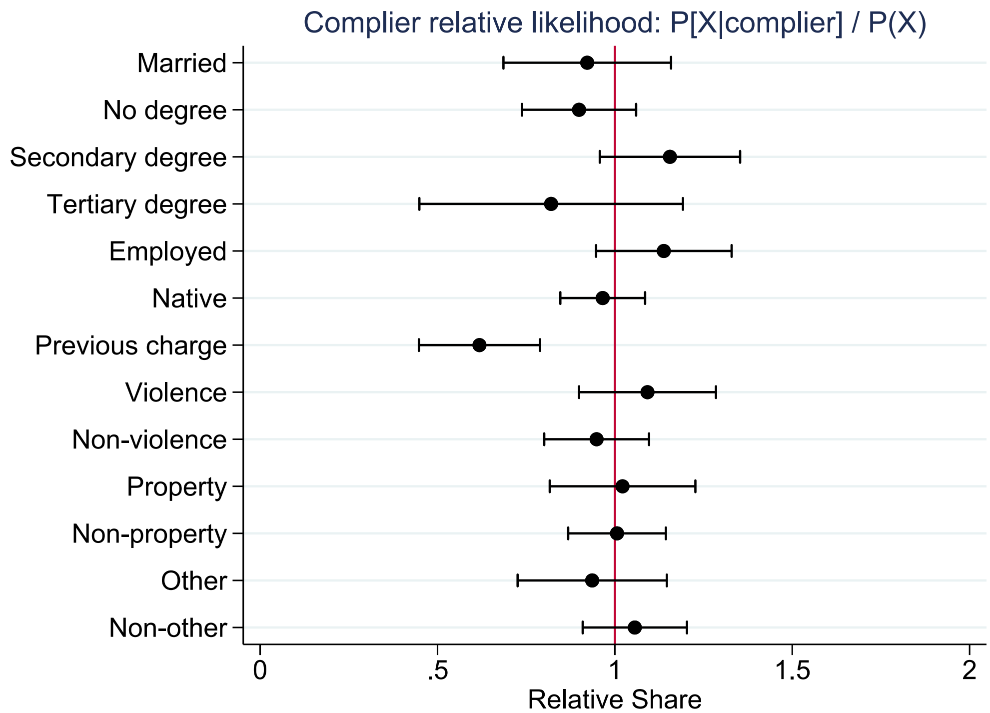
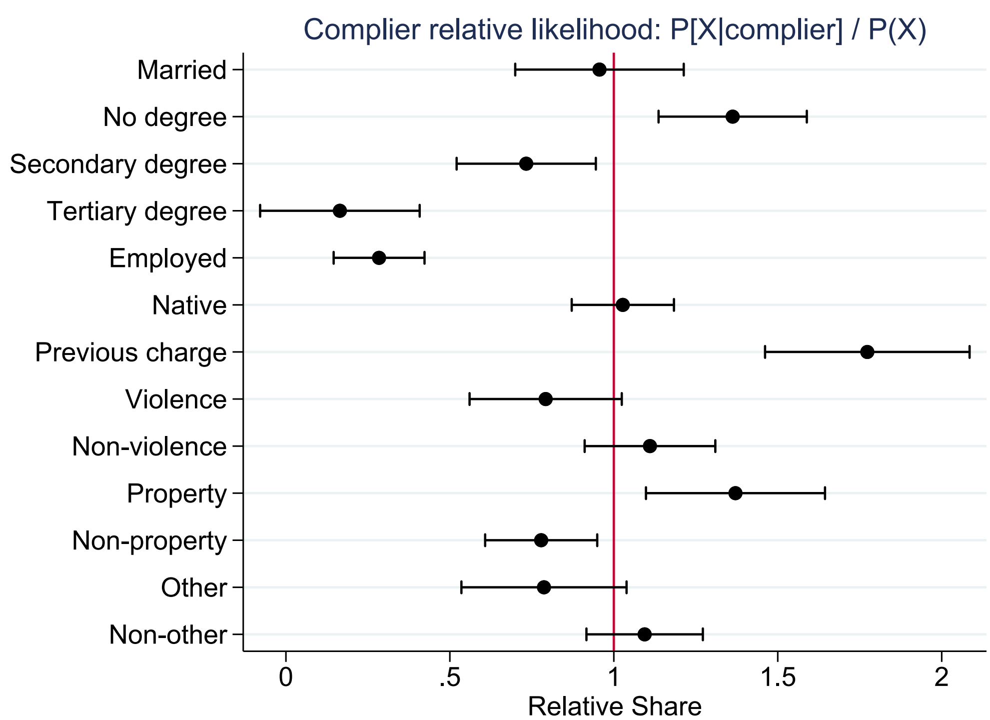


Figure 21: Complier Weights - Prison



Sub-sample:	Baseline instrument First stage P(Incarcerated)	Reverse-sample Instrument First stage P(Incarcerated)
Any post compulsory education		
Estimate	0.389	0.331
(se)	(0.064)	(0.051)
Observations	53993	56488
No post compulsory education		
Estimate	0.581	0.598
(se)	(0.079)	(0.078)
Observations	69731	72886
Previously Employed		
Estimate	0.150	0.116
(se)	(0.052)	(0.041)
Observations	48096	50297
Previously non-Employed		
Estimate	0.729	0.456
(se)	(0.080)	(0.107)
Observations	75703	79134
Married		
Estimate	0.379	0.431
(se)	(0.089)	(0.083)
Observations	41074	42825
Not married		
Estimate	0.610	0.391
(se)	(0.064)	(0.046)
Observations	82913	86820
Over 30 years old		
Estimate	0.497	0.411
(se)	(0.006)	(0.057)
Observations	80863	84386
Less than 30 years old		
Estimate	0.667	0.555
(se)	(0.095)	(0.077)
Observations	42953	45094
Violence crimes		
Estimate	0.363	0.285
(se)	(0.075)	(0.062)
Observations	45637	47779
Property crimes		
Estimate	0.563	0.489
(se)	(0.0986)	(0.099)
Observations	43298	45138
Other crimes		
Estimate	0.398	0.422
(se)	(0.099)	(0.100)
Observations	24074	25351

Table 13: Impact on Prison

Dep. variable	Pr(Prison sentence)			
	1 year after (1)	2 years after (2)	3-5 years after (3)	5 years after (4)
Fine				
OLS	-0.119***	-0.155***	-0.137***	-0.187***
No controls	(0.002)	(0.002)	(0.002)	(0.002)
OLS	-0.044***	-0.059***	-0.052***	-0.075***
Controls	(0.001)	(0.002)	(0.002)	(0.002)
OLS	-0.043***	-0.058***	-0.051***	-0.075***
Controls and Weights	(0.001)	(0.002)	(0.002)	(0.002)
IV	0.006	0.016	-0.040	0.015
Controls	(0.035)	(0.037)	(0.038)	(0.040)
Probation				
OLS	-0.110***	-0.134***	-0.111***	-0.147***
No controls	(0.002)	(0.002)	(0.002)	(0.003)
OLS	-0.020***	-0.020***	-0.011***	-0.017***
Controls	(0.002)	(0.002)	(0.002)	(0.002)
OLS	-0.012***	-0.011***	-0.004*	-0.005**
Controls and Weights	(0.001)	(0.002)	(0.002)	(0.002)
IV	0.008	-0.006	0.014	0.000
Controls	(0.062)	(0.067)	(0.068)	(0.071)
Incarceration				
OLS	0.384***	0.482***	0.413***	0.557***
No controls	(0.002)	(0.002)	(0.002)	(0.002)
OLS	0.163***	0.197***	0.155***	0.226***
Controls	(0.002)	(0.002)	(0.003)	(0.003)
OLS	0.160***	0.185***	0.146***	0.201***
Controls and Weights	(0.002)	(0.002)	(0.003)	(0.002)
IV	0.019	-0.047	0.063	-0.047
Controls	(0.070)	(0.076)	(0.076)	(0.080)
Dep. mean	0.137	0.188	0.175	0.246
Number of cases	169602	169602	169602	169602