

# Does Visitation in Prison Reduce Recidivism?

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September 25, 2020

## Abstract

Visitation in prison is associated with a low recidivism rate after release. However, it is not clear whether visitation has a causal effect. This paper tries to estimate the effect of visitation experience on the recidivism outcome of state prisoners in Missouri, using an instrumental variable approach. In particular, the instrumental variable used for identification is the distance from a prison to an address before incarceration, since prisoners are less likely to be visited when they are assigned to prisons far from home. The results support that visitation has a causal effect on recidivism. The visitation effect within one year is robust to different sample, control variables, and specifications, but becomes ambiguous after one year. Hence, the key difference from other studies is the timing of the measured recidivism outcome. Moreover, visitation improves employment outcomes; therefore, employment is an important channel of the visitation effect. However, no discernible effect on housing stability is found.

**JEL classification:** C26, J68, K42, R23

**Keywords:** recidivism, reentry, visitation, causal inference, instrumental variable

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<sup>†</sup>I appreciate the staff of the Missouri Department of Correction for providing the dataset for the research project. I sincerely thank my supervisor Ian Fillmore for his support, comments, and suggestions. I would also like to thank Marcus Berliant, George Gayle, and Robert Pollak for beneficial discussions, comments, and advice. I also thank internal seminar participants at Washington University in St. Louis. The views expressed in this paper are those of the author and do not necessarily reflect the view of the Missouri Department of Corrections.

# 1 Introduction

Since 1976, the prison population in the United States has grown rapidly such that by 2008 there were 2.3 million prisoners. Although the number of prisoners has gradually declined since then, it has remained near peak levels over the last forty years (Bronson and Carson, 2019), and the U.S. has one of the highest incarceration rates in the world (Walmsley, 2015). Since most prisoners are eventually released, a high prison population implies a high rate of people with a criminal record in society. Indeed, Kaebler and Glaze (2016) estimated that in 2015, about 7 million individuals were either in prison, in jail, or under parole or probation, and 4.9 million people had experienced incarceration in their past. However, it is not easy for offenders to overcome recidivism. According to Alper et al. (2018), 68% of prisoners released in 2005 from correctional facilities in 30 states were arrested within three years of release and 83% were arrested within nine years.

This high recidivism rate could be attributed to demographic differences. Prisoners are demographically different from those who have no criminal record: more male, more black (Bronson and Carson, 2019), less formally educated (Motivans, 2017), and less healthy (Maruschak et al., 2015). However, the high rate of recidivism is partially due to the collateral consequences of incarceration. Incarceration experience and criminal records cause many problems such as discrimination in the labor market (Pager, 2003) and low employment probability (Bhuller et al., 2018; Mueller-Smith, 2015) and is associated with unstable housing (Harding et al., 2013). Hence, removing these obstacles could be a way to reduce the recidivism rate, and it is important to know what policies can help the reentry of prisoners into normal life.

Strong social bonds are considered as mitigating these obstacles for ex-offenders. A social bond here means a good relationship with family, friends, and neighbors. Family and friends can provide employment opportunities through their networks, stable housing, and emotional support.<sup>1</sup> Strong social bonds increase the chance of getting this support, which is useful to overcome the obstacles. Hence, the support by family and friends is helpful for the successful reentry of prisoners into society, that is, reduction of recidivism.

However, since imprisonment physically separates prisoners from family and friends,

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<sup>1</sup>Visher and Travis (2003) surveyed literature focusing on prisoner transition back to the community. They pointed out the importance of family ties for successful reentry, in particular, through housing security and emotional support.

they have a hard time maintaining social ties. Correctional facilities offer several ways for prisoners to keep in communication with those who are out of prison: letters, phones, and visitation. In particular, as seen in the literature on social bonds and recidivism, prison visitation is considered to be an important way for prisoners to keep in communication with family and friends (Laub et al., 1998; Rocque et al., 2013).<sup>2</sup> The relationship between visitation and recidivism are analyzed in the literature (Visher and Travis, 2003; Brunton-Smith and McCarthy, 2017; Bales and Mears, 2008; Mears et al., 2012; Cochran and Mears, 2013; Derkzen et al., 2009; Mitchell et al., 2016; Cochran, 2019; Lee, 2019; Cochran et al., 2020).<sup>3</sup> The literature, for example Visher and Travis (2003), finds that visitation experiences in prison are associated with a low recidivism rate and claims that this effect is through social ties maintained or improved by prison visitation. Hence, it is claimed prisons should adopt policies that encourage visitation, relying on the idea that there is a causal effect of visitation on the reduction of recidivism. However, most of these papers claim causality under the assumption that there is no omitted variable bias, which is unlikely true.

Although visitation seems to be an important tool to maintain and improve social ties and hence reduce reoffending, it is not easy to identify a causal effect of visitation on recidivism due to endogeneity issues. Many papers have mentioned that the relationship may be causal, but most of the papers do not have a strong identification strategy to estimate the causal effect of visitation on recidivism. We cannot conclude that visitation has a causal effect on lower recidivism rates only from the fact that visited prisoners have a lower recidivism rate than non-visited prisoners. It may be strong social ties that increase prison visitation experience and reduce the recidivism rate of ex-offenders through housing, employment, and other channels. If there is no causal relationship, visitation experiences work as a good predictor of recidivism, but a marginal increase in visitation may not affect the recidivism rate.

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<sup>2</sup>In criminology, several theories are provided to explain the link between visitation and recidivism: (1) the social bond theory, (2) the social capital theory, (3) the general strain theory, and so on. For example, social bond theory, provided by Hirschi (1969), argues that strong social bonds with family, friends, and community help to form norms and values that deter recidivism. The social capital theory puts more emphasis on the support provided through strong family ties, such as money, housing, and employment opportunities.

Although there are many theories, the focus of this paper is not to test each theory but to provide solid evidence for those theories; these theories rely on a causal relationship existing between visitation and recidivism, but the causality has not yet been formally investigated.

<sup>3</sup>Since visitation can be defined in various ways, many aspects have been investigated with a recidivism outcome: relationship with visitors (Bales and Mears, 2008), frequency (Mears et al., 2012), timing (Cochran and Mears, 2013; Bales and Mears, 2008), and length of visit (Derkzen et al., 2009). Recently, using UK data, Brunton-Smith and McCarthy (2017) concluded visitation by parents improves family ties and lowers reoffending of inmates.

Policymakers need to know if the relationship is actually causal, since providing visitation opportunities requires more staff for each facility, which is costly. Despite this, if there is any causal impact of actual visitation, it may be better to provide actual visitation opportunities even so. Specifically, this paper identifies how much of recidivism could be reduced by one visitation and estimate the monetary costs that could be saved by possible policies.

This paper investigates the causal effect of visitation on recidivism. To check the causal effect and to investigate the channels of the effect, this paper uses data from state prisoners in Missouri released between 2012 and 2015. For the identification of the causal effect, the regression analysis is based on an instrumental variable approach. In particular, the instrumental variable (IV) is the distance of the incarcerated prison from the home address of the prisoner. Individuals are likely to have a social network in their community. Hence, when prisoners are assigned to a prison that is far from their home, they are less likely to be visited by family members or friends, simply because the prison is far from the community; in other words, the opportunity cost of visitation for visitors is high.

The regression results show that a negative and statistically significant effect of visitation on recidivism: one visit per month reduces the reincarceration rate by 5-7% points. In particular, the short-run effects are robust under different samples, control variables, and specifications.

Using the same IV approach, I also investigate the two potential channels of the effect of visitation: employment and housing stability. According to the social capital theory, a strong social bond is considered to provide better employment opportunities and a labor-market opportunity is a key deterrence factor. The results indicate that visitation increases employment probability and reduces the time to get the first job. Similarly, housing stability is considered as another important factor since homelessness and frequent movement are associated with a higher recidivism rate. However, the estimation results do not show any effect on the housing stability. As a result, the findings suggest that policymakers should encourage visitation in prison, and the state government can save about 34 million dollars if every prisoner were assigned to the closest prison.

This paper advances the literature in two ways. First, this paper provides empirical support for the literature about visitation and recidivism. An official report by the Minnesota Department of Corrections (Minnesota Department of Corrections, 2011)

concludes one visitation reduces the risk of recidivism by 13% for felony convictions and 25% for technical violation revocation. However, the report is based on a simple Cox hazard model and hence, as mentioned in the report, the estimator shows a correlation rather than causality. Most of other papers show a correlation between visitation and recidivism. Cochran et al. (2020) and Lee (2019) are two recent papers that use a similar IV approach to check the causal effect of visitation on recidivism using state prisoners in Florida and Iowa, respectively.<sup>4</sup> They cast doubt on visitation, since they did not find a causal effect on recidivism. However, they measured a recidivism outcome only at three years from release. Using administrative data in Missouri, this paper supports that visitation has a causal effect and is helpful for successful reentry. The results suggest that the key differences are the time when the recidivism outcome is measured.

Second, this paper contributes to the literature about the channels of the visitation effect: specifically employment and housing. We know that better employment opportunity decreases recidivism rate (Yang, 2017; Schnepel, 2018). Higher wages (Yang, 2017) and more vacancies (Schnepel, 2018) in local labor markets reduce the recidivism rate. Unstable housing is associated with higher recidivism outcomes (Geller and Curtis, 2011). However, the visitation literature mainly focuses its effect on recidivism, but the channels of the effect are not well-investigated (Cochran, 2019). This paper fills this gap by investigating the effect on employment and housing outcomes. The results provide evidence that visitation improves employment outcomes but no evidence of improvement on housing stability.

## 2 Theory

Figure 1 summarizes the conceptual framework of why visitation improves the recidivism outcome. Prisoners are sent to a prison with an initial level of social ties. Social ties in this context mean connections with families, friends, and communities. While the imprisonment, the level changes through visitation experiences. The visitation experiences are affected by the initial level of social ties as well as the distance to their home from the prison. The initial level of social ties and visitation experiences deter-

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<sup>4</sup>Cochran et al. (2020) used the distance to the first prison assigned to as an IV to predict visitation experiences, and Lee (2019) checked several measures of distance from prison. In both papers, the result of the instrumental variable regression shows an insignificant effect of visitation on recidivism within three years, and hence they are skeptical of any causality.

mine the social ties at release, and the social ties affect post-release behavior. Social ties affect the recidivism outcome both directly and indirectly through employment and housing situation.

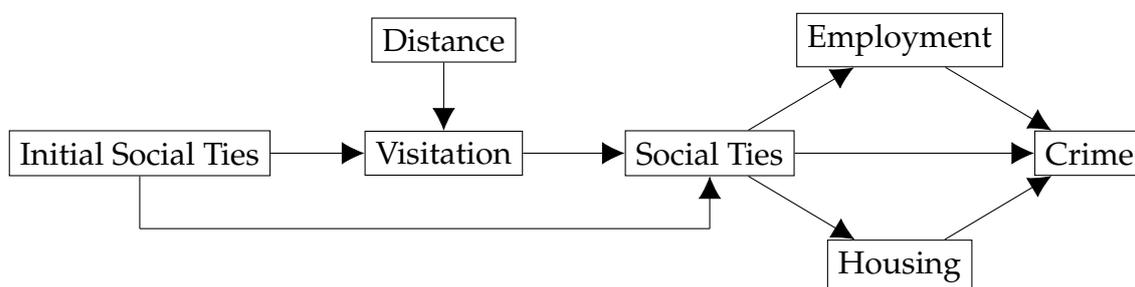


Figure 1: Conceptual framework

Strong social ties increase opportunities to get job offers after release. Having more and reliable connections with others increases job opportunities through their networks. Employment has been considered as a desistance tool. Chalfin and McCrary (2017) surveyed the literature on crime and employment and concluded that employment is a tool to reduce crime. One reason is that legal income becomes the opportunity cost of crime (Becker, 1968). Another reason is time allocation: engaging in a legal job as an occupation reduces the time spent on illegal activities. This relationship holds for ex-prisoners. Schnepel (2018) found that released prisoners are less likely to recidivate when local labor markets are strong: that is, more vacancies. Yang (2017) also reached a similar conclusion using different data.

Social ties are also considered an essential factor for the stability of the housing situation (Visher and Travis, 2003). Geller and Curtis (2011) summarized why housing security is important for ex-prisoners.<sup>5</sup> Stable housing helps to become employed, to access to social services such as healthcare, and to keep contact with parole officers. Moreover, loitering or homelessness increases contact with police officers, which increases the probability of reincarceration.<sup>6</sup>

The relationship between the housing situation and crime relates to housing policies. Housing support could be helpful to get a job, and employment eventually reduces crime through the opportunity cost. For example, low-income housing developments reduce violent crimes in poor neighborhoods (Freedman and Owens, 2011),

<sup>5</sup>Frequent movement or homelessness is considered as a bad signal for recidivism. Harding et al. (2013) found a low rate of homelessness but high residential mobility among former prisoners, partially due to discrimination in the housing market.

<sup>6</sup>However, movement to a new location may reduce recidivism. Moving to a place far from home makes people less likely to recidivate, since the move makes it difficult to keep the former criminal network around the community (Kirk, 2009).

and an emergency financial assistance for those who cannot pay the rent for the current month reduces crime (Palmer et al., 2019).<sup>7</sup>

There are other channels through which social bonds affect recidivism. A line of literature in criminology emphasizes the importance of support from others. In particular, family support is considered an important factor in reducing recidivism. Using survey data, Naser and La Vigne (2006) found that prisoners rely on family for both material and emotional support. For example, material support, such as social welfare, health care, and transportation, could affect recidivism. Another important channel is the emotional channel, which could directly affect criminal behavior. For example, peer effects of criminal behavior have been analyzed in network literature in economics. Depending on the peers, the peer effect could improve or worsen post-release behavior (Corno, 2017). Moreover, social ties construct social norms that emotionally deter criminal behavior as described by the general strain theory.

Although I explained these channels separately, they are interrelated. Stable housing helps to have a job, and a job helps to have stable housing, since it guarantees the rent payment. Family support helps stable housing, since ex-prisoners can live together with their family or receive help to rent an apartment. Also, family and friends' support can introduce job opportunities through their existing networks. Hence, it is important to note that this paper aims to estimate the overall effect of visitation on a recidivism outcome.

In summary, visitation improves social ties and improved social ties change post-release criminal behavior through employment, housing stability, and other channels.

## 3 Data

### 3.1 Summary Statistics

The data used for this paper are an administrative data obtained from the Missouri Department of Corrections. The sample for the analysis consists of parolees and probationers in Missouri released between 2012 and 2015. Although the analysis in this paper is limited to parolees and probationers, they account for more than 90 % of released prisoners. Each observation is based on a cycle defined by the admission date and the release date. For each observation, the data contain residential and em-

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<sup>7</sup>Since the financial assistance could be used for another purpose, the result may represent an income effect.

ployment information during supervision and recidivism outcomes until 2019 August, hence the data contain complete information on recidivism for at least three years.<sup>8</sup>

A recidivism measure in the paper is defined as a return to incarceration. By definition, it contains a supervision condition violation.

Visitation could be measured in several ways. In particular, this paper uses the following two measures: *visit dummy* and *visit frequency* over the entire sentence period. *Visit dummy* is a binary measure of visitation experience that takes one if someone (family, friends, etc.) visits the offender while incarcerated, and zero otherwise. *Visit frequency* is the number of total visitations over incarcerated months.

Among all released prisoners on parole or probation, the sample used for the analysis satisfies the following conditions: (1) male, (2) at working age, (3) living only in Missouri during supervision, and (4) serving an original sentence. Given that most prisoners are male, it is reasonable to focus on the male sample for the analysis. Moreover, gender might have correlated with the distance between home and prisons, since most of the prisons are for males. To focus on the employment channel, the sample is limited to those who were at working age (20–65) at release. An out-of-state sample is excluded to avoid a selection problem.<sup>9</sup> Lastly, this paper focuses on an initial cycle for a sentence: in other words, not a cycle for parole revocation. Some observations are dropped during the data cleaning process such as missing values. Finally, 33,971 observations are used for the analysis. Note that since each observation consists of one cycle from incarceration to release, one person could have multiple observations when the person is released, incarcerated, and released again between January 2012 and December 2015.

Basic demographics are summarized in Table 1. The mean age at release is 35.1, and 70% of observations are below the age of 40. Non-Hispanic whites and blacks account for almost all observations and other ethnic groups such as Hispanics, Asians, and Native Americans are rare.

Table 2 compares demographics by visitation experience. The visited group is prisoners who experienced visitations at least once while in prison. The visited group has similar characteristics with the non-visited group, but the sentence length is longer. This is likely because the more time they spend in prison, the more chances they will

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<sup>8</sup>Recidivism is recorded in Missouri only. Hence, the recidivism outcome may not be in the data if a person were incarcerated in another state.

<sup>9</sup>Out-of-state sample has a lower recidivism rate because of the following two reasons. One is that return to prisons in other states is not recorded in the Missouri database. Another reason is that prisoners have to behave well to get the approval for the interstate supervision.

be visited.

### 3.2 Post Release Outcomes

Figure 2 summarizes the recidivism rate for up to three years since release. At six months from release, 8.6% of the visited group returns, while 11.5% of the non-visited group returns. The difference remains stable over time. At three years since release, 48.2% of visited prisoners return, while 51.3% of non-visited prisoners return. Overall, as seen on the graph, visitation experience is associated with a relatively lower recidivism rate by about 3% points.

As seen in Table 2, the visited group has a higher supervision completion rate and are more likely to have employment since release. More than half of the released prisoners experienced at least one movement (change of the address) after release.

### 3.3 Visitation

Figure 3 shows the visitation timing over the sentence period. The fraction of people who have ever been visited increases over time. However, the total counts of visits peak in the middle and then decrease as the release date approaches.

Figure 4 summarizes the visitation experience by the relationship between prisoners and visitors. The fractions indicate those who have been visited by the visitor type at least once during incarceration. The category *Others* contains persons such as attorneys and clergy. The number does not sum up to one, since visitation by multiple types of people is possible. The figure indicates that 48% of the sample has an experience of visitation by someone at least once. 38.7% of the sample is visited by relatives and 25.4% is visited by friends. Visitation by relatives is more common than friends or others. Among relatives, mothers are the most common as a single category, and 1 in 5 observations were visitation by a mother. Only 6.2% of prisoners experience visitation by a spouse, but since 20% of the sample reported being married at the initial classification, 1 in 4 married observations experienced spousal visitation.

## 3.4 Prison environment in Missouri

### 3.4.1 Prison assignment process

Before the regression analysis, this section summarizes the prison assignment process in Missouri. Once the sentence is determined, prisoners are sent to one of the Diagnostic Intake Centers for initial classification. Based on gender, special needs, and the risk level determined by the classification, an offender is assigned to an initial prison.<sup>10</sup> During incarceration, the risk level is updated periodically. Typically, the first reclassification of the risk level happens about six months from the initial assessment, and after that, reclassification is completed every 12 months.

Each prisoner is assigned one of three levels of risk: minimum, medium, and maximum. The risk level is determined by the maximum of two scores: institutional score (I score) and public risk score (P score). The I score is calculated by certain variables: age, most serious offense, mental health, education, vocational skill, and conduct violations (for both the initial and re-assessment), employment status, marital status, revocations, incarceration history (only for an initial assignment), and program failure (only for reassessment). The P score is based on the seriousness of the pending charge, remaining sentence, program completion, conduct violation, and prior escape. As of June 30, 2015, 36.4% of male prisoners are assigned the lowest risk and 35.9% and 27.7% are assigned medium and maximum level, respectively (Nixon and Lombardi, 2015).

### 3.4.2 Prison locations

In Missouri, there were 22 correctional facilities as of the end of 2015. Since two prisons among them were for females<sup>11</sup> and another one had switched from a community release center to a prison in late 2015, the analysis focuses on 19 correctional facilities. Figure 5 shows the locations of the facilities. Prisons are roughly concentrated along a line from northwest to southeast, and the southwest region has a few prisons only. Missouri has two major cities: St. Louis and Kansas City. There are multiple maximum-security facilities near St. Louis but not many near Kansas City. Each

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<sup>10</sup>See Missouri Department of Corrections (2013) for a complete description of the classification process.

<sup>11</sup>There are only two facilities for female prisoners, which are located in the north of Missouri (Audrain County and Livingston County). Both can accommodate prisoners of any risk level. Since the possible variation of distance is limited, the main section of this paper focuses on male prisoners. The analysis of female prisoners is in Section 5.2.1.

facility has its security level: Minimum, Medium, and Maximum. Some facilities accommodate offenders of multiple security levels. Six prisons have all security levels and two facilities that have medium and maximum levels locate next to other levels of prisons.<sup>12</sup>

Figure 5 also shows the number of reported crimes by county from 2012 to 2015. The number is high in large cities such as St. Louis City and County, Kansas City, and Columbia. Prison locations are not concentrated in high crime rate counties, however.

### 3.4.3 Visitation process

In order to receive visitation, Missouri prisoners have to submit a list of potential visitors, and the list can have at most 20 persons. Prisoners can update the list at most twice a year.<sup>13</sup> Generally, prisons accept visitors from 9:30 to 13:30 and 14:30 to 18:30 on Friday, Saturday, and Sunday, although there are slight differences across facilities.

## 4 Approach

### 4.1 Regression model

The regression is based on the following specification:

$$y_{itpc} = \alpha + \beta_{visit}visit_{it} + \beta_X X_{it} + \eta_t + \eta_p + \eta_c + \epsilon_{itpc}. \quad (1)$$

An outcome variable  $y_{itpc}$  is a binary indicator of outcome after the release of a person  $i$  who is from a county  $c$ , incarcerated in a prison  $p$ ,<sup>14</sup> and released at time  $t$ .  $Visit_{it}$  is a measure of visitation experience while imprisoned.  $X_{it}$  is a vector of control variables at the time of release.<sup>15</sup>  $\eta_t$  and  $\eta_c$  are time and county fixed effects, respectively. The prison fixed effects  $\eta_p$  capture the prison-specific factor such as job

<sup>12</sup>Most prisons were open during the entire sample period (2003–2015), except ERDCC and JCCC, which opened in 2003 and 2004, respectively. Some inmates were assigned to facilities other than the 19 discussed above. For example, two prisons existed for a short time in the sample period: the Missouri State Penitentiary (MSP), which closed in 2004, and the Kansas City Reentry Center (KCRC), which switched from the Kansas City Community Release Center in 2015. Moreover, inmates could also be assigned to community release centers during incarceration. However, this paper does not use these cycles for the analysis because they are rare.

<sup>13</sup>For more information about the regulations, see Precy and Greitens (2018).

<sup>14</sup>Offenders can be assigned to multiple prisons over one sentence.  $p$  is defined as the initial prison where a prisoner is assigned after the initial risk assessment.

<sup>15</sup>The list and details of the control variables are in the appendix A.

training and an education program. The regression coefficient of interest is  $\beta_{visit}$  and the coefficient measures the effect of visitation experience on recidivism.

The regression is based on a linear probability model (LPM). Since visitations are count data, Poisson and negative binomial models are standard, especially, in the literature in criminology. However, this paper uses LPM rather than nonlinear models because LPM is superior when interpreting the marginal effect. Since the objective is to check the effect of an additional visit on recidivism, and this paper uses different measures of visitation including continuous measures, LPM is better than other nonlinear models such as Logit and Probit. The coefficient under the LPM captures the local average treatment effect (LATE).

As claimed in the literature, the expected sign of  $\beta_{visit}$  is negative. However, the OLS regression may suffer an omitted variable bias. Possibly the bias stems from the strength of social bonds. When strong social bonds increase visitation as well as decrease reoffending behavior, the OLS estimator could overestimate the negative impact of visitation in magnitude. Hence, this paper uses an instrumental variable approach to check a causal effect.

## 4.2 Explanatory variables

Control variables are demographics (age at release, race/ethnicity, and number of dependents) and crime information (felony class, the primary type of crime, sentence length).<sup>16</sup> The complete list and detailed information of control variables are in the Appendix. Three fixed effects are included in the model: prison, time, and county fixed effects. Prison fixed effects capture the difference across prisons such as a rehabilitation program offered in a specific prison. Time fixed effects are to capture the effect by economic conditions, since, as Schnepel (2018) and Yang (2017) pointed out, better economic conditions at the time of release provide better employment opportunities and better opportunities in legal sectors of the economy eventually decrease criminal behavior. County fixed effects capture time-invariant county characteristics. Hence, the county fixed effects control a consistently higher crime rate in big cities such as St. Louis and Kansas City. Most importantly, the fundamental distance to

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<sup>16</sup>Lee (2019) used LSI-R score to control existing family factors. However, MDOC uses the Salient Factor Score instead of LSI-R to calculate the risk of recidivism. Moreover, incarceration history is not available. The Salient Factor (SF) score is an index based on some demographic variables, criminal history, and behavior while incarcerated. Since visitation could affect the SF score through misconduct, the score is not included as a control variable in the main regression. The regression results with the SF score are in Section 5.2.1.

correctional facilities is captured by the county fixed effects. As Bedard and Helland (2004) found, criminals may commit a crime taking less visitation into account when their home is far from any prison. By including the county fixed effects, the distance term in the first stage regression captures the unexpected variation of distance.

### 4.3 Instrumental variable

The identification of the causal effect relies on an instrumental variable approach. An instrumental variable for visitation is a distance from prisoners' home to the prison they were in.<sup>17</sup> The reason why distance could be correlated with the visitation experience is that people have social ties locally based on the residential location, and families and friends likely live in the neighborhood. Hence, when prisoners are assigned to a prison that is far from their home, they are less likely to be visited by their family members or friends. The literature found a correlation between more distant prisons and less visitation (Mears et al., 2012; Cochran et al., 2020).

Since the data do not have the exact address of each prisoner before incarceration, the county of conviction is used as a proxy of an initial address before incarceration following Schnepel (2018) and Cochran et al. (2020).<sup>18</sup> The measure of distance used in the analysis is the linear distance from the geometric center of counties to prisons.<sup>19</sup> Since there are 115 county-equivalent areas<sup>20</sup> and 19 state correctional facilities for male prisoners in Missouri, there are 2185 pairs of a county and a prison.

The prison used to compute the distance is set to the first prison assigned after the initial risk assessment. Sometimes prisoners experience a transfer from the first facility to another correctional facility. In the data, 38% of the observations experience more than one transfer. However, this paper does not use the distance to the second or later prisons since the transfer decisions take into consideration some factors potentially problematic to the validity of the instrumental variable (Precy and Greitens, 2018). For example, to keep good institutional conduct is one of the factors but this may generate a correlation between the distance and family ties, since the distance may

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<sup>17</sup>Physical distance has been used as an instrumental variable in other papers (McClellan et al., 1994; Baiocchi et al., 2010; Cochran et al., 2020; Lee, 2019).

<sup>18</sup>County of conviction is determined by the place of the offense. This may not be a good proxy of residential address when people commit crimes at the place far from their homes. However, crime is a local phenomenon; Bernasco (2010) showed that 75% of burglaries are committed within five kilometers and about 90% is committed within ten kilometers from home in the Hague, Netherlands.

<sup>19</sup>Road distance could be the best proxy. However, since location data is county level and travel time within a county could be large, this paper does not use the travel time.

<sup>20</sup>Missouri state has 114 counties and one independent city (St. Louis City).

affect institutional misconduct through visitation as showed in Mears et al. (2012). Another problematic factor is the request from prisoners to be assigned to a facility close to their families. The request could also generate a correlation between distance and family ties. Hence, this paper uses the distance to the first facility after the initial risk assessment. The distribution of the distance is in Figure 6.

#### 4.3.1 Identification assumptions

This paper uses a distance from prisoners' homes to their prison as an instrument. With the instrumental variable approach and some conditions, the estimated coefficient  $\beta_{visit}$  in the equation (1) is the local average treatment effect (LATE) of visitation (Imbens and Angrist, 1994). For the estimation of the LATE, this paper assumes the following conditions: (1) the distance correlates with the visitation variable (relevance), (2) the distance is correlated with an outcome variable only through the visitation variable (exclusion restriction), and (3) visitation decreases with distance (monotonicity).

Relevance and monotonicity are confirmed in Figure 8. Figure 8 plots visitation experience and distance. Both figures show that the longer the distance, the lower the fraction of prisoners that experiences visitation. The extensive margins of visitation seem to have a linear relationship. However, the means of the intensive margins drop more at a lower distance. The non-linear relationship for intensive margins was also found in Lee (2019). Hence, the figures support the relevance and monotonicity conditions of the instrumental variable.

The exclusion restriction holds because of the quasi-randomized assignment. Since the sample period is during the mass incarceration period, the correctional facilities in Missouri have chronically faced a shortage of available beds for prisoners. Hence, the assignment contains randomness. Figure 7 shows the origin of prisoners at each correctional facility. The assignment is not deterministic: people from the same county are assigned to different facilities.<sup>21</sup>

However, the exclusion restriction may be violated because of potential confounders. For example, in Figure 7, each prison tends to have more prisoners from nearby counties. If prisons are built close to counties with some characteristics such as high crime rates, the distance correlates with the county-specific factors. To control for these county-specific factors, the explanatory variables include the county fixed effects. The

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<sup>21</sup>Each facility has different security levels. The security levels are controlled in the regression analysis.

fixed effects capture the average distance, since the prison location is fixed during the analysis period.<sup>22</sup>

Table 3 confirms the correlation of distance with observable variables. The result shows that distance correlates with some variables. The positive correlations with sentence length and the violent crime indicator are because of the severity of the crime. Longer sentence length and violent crime tend to assign higher risk. Since high-security level prisons are relatively rare, a higher risk level correlates with longer distance. The negative correlation with drug crime was also confirmed by Lee (2019), although it was insignificant in Lee (2019). Lastly, non-Hispanic blacks tend to have longer distance than non-Hispanic white, since blacks concentrate in particular counties<sup>23</sup>. In the sample, 59% of non-Hispanic blacks come from the top three counties (St. Louis city, St. Louis county, Jackson county), while only 15% of non-Hispanic whites are from the top three counties (St. Louis county, St. Charles county, Greene county).

In summary, the key factors to decide the assignment are the risk level and the origin of prisoners. Conditional on the same risk level and the same sentencing county, the assignment could be considered as random.

## 5 Main results

### 5.1 First stage

The first stage regression results confirm the distance has a strong correlation with visitation in Table 4. For the estimation shown in Table 4, all control variables and fixed effects are used as explanatory variables. The estimated coefficients show that an increase in the distance by 100 miles reduces the chance of visitation by 7.8 percentage points and the monthly frequency by 18.5 percentage points. The large first-stage F statistics indicate that the distance is a strong instrumental variable for the two measures of visitation (Stock and Yogo, 2005). Hence, the first-stage results support that the distance is a valid instrumental variable in terms of the strength of the correlation.

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<sup>22</sup>Mcclellan et al. (1994) used a distance to the hospital as the instrumental variable. They also conditioned on the distance to the closest hospital to avoid potential confounders such as urban-rural differences.

<sup>23</sup>Section 5.2.3 runs the main regression separately by race to check the sensitivity.

## 5.2 The effect on recidivism

The regression results are summarized in Table 5 and 6. The first column shows the OLS results and the second column shows the IV regression results. Each row shows a result of recidivism outcomes at four points (6, 12, 24, and 36 months from release). Visitation is measured by a dummy variable in Table 5, and by frequency per month in Table 6.

In the OLS, the estimated coefficients show a negative correlation between visitation and recidivism. Visitation experience is associated with 3–6% point lower recidivism rates, and one visitation per month is associated with a 1–3% point lower recidivism rates.

The IV results have larger negative effects than the OLS results, which is also confirmed by Cochran et al. (2020). Based on the estimators in Table 5, those who are visited while in prison are about 13 to 16% points less likely to return to prisons. At six months from release, the visited group has a 16% point lower recidivism rate, but the magnitude is decreasing over time. At three years from release, the visitation effect is 12.8% points. The result in Table 6 indicates that a marginal increase in visits per month decreases re-incarceration within six months by 6.7% points, and hence additional one visit per year decreases re-incarceration by 0.56% points ( $-0.067/12 = -0.0056$ ). Similarly, the marginal increase in visitation reduces recidivism by 0.52, 0.45, 0.45% points and 1, 2, and 3 years from release, respectively. The coefficients up to one year from the release show a statistically significant effect of visitation experience. Similar to a binary case, the magnitude of the negative effect declines gradually over time, and the standard errors increase.

Under the IV regression, the visitation effect is confirmed at each point for up to 3 years. However, decreasing the magnitude and increasing standard errors over time suggest the long-run outcomes may be affected by other factors and may not be appropriate to measure the visitation effect.

### 5.2.1 Sensitivity checks

The main results confirm the negative effect of visitation on recidivism. To check the robustness of the effect, I check the sensitivity of the results with three different specifications and samples.

Tables 7 and 8 check the results with different control variables. The first column

uses actual imprisonment length as a substitute for the sentence length. The magnitude of the visitation effects becomes smaller in the short run, and hence the short-run negative effect is partially mediated by a shorter incarceration length. However, shorter incarceration may be harmful in the long run, since the magnitude of the visitation effect is larger compared to Table 5 and Table 6. The second column includes a recidivist dummy variable as an additional control. It is worth noting that the recidivist dummy variable is an imperfect measure. The recidivist dummy variable takes a value of one from the second or more time a prisoner appears in the data. Since the data period is limited, some prisoners might not be counted as a recidivist when the previous incarceration cycle ends before the sample period. The result shows a significant effect only at six months from release. The point estimates indicate that the magnitude declines and the standard errors increase over time. Lastly, the third column uses dummy variables for each SF score. The SF score is used as another imperfect measure of crime records, since the score reflects crime history as well as other factors (conviction, drug history, treatment completion, behavior in prison, and so on). The results are similar to those with a recidivist dummy variable. The negative effect of visitation is confirmed in the short run, but it loses statistical significance at three years from release.

The main sample is restricted to residents in Missouri only. However, the estimation results may underestimate the effect of visitation due to sample selection, and so Tables 9 and 10 show additional analysis with different samples. The first and second columns include observations with an out-of-state address. In Missouri, St. Louis and Kansas City are the two biggest cities and are on the border with other states. In the first column, the sample contains residents in the Kansas City and St. Louis metropolitan areas as well as residents just in Missouri. They have a much less re-incarceration rate for two reasons. One is that the re-incarceration rate for them may be underestimated, since recidivism outcomes are measured in Missouri only. Another reason is selecting a better sample, since prisoners must have a reason to be out of state: having families or relatives who support the released prisoners or good behavior in the short run in Missouri. The regression results for long-run outcomes show a significantly negative effect now but this may be due to the measurement problem. The second column expands samples for all out-of-Missouri observations and the estimated results are similar.

When the regression use samples for technical violation serves, the magnitude of

the negative effect becomes smaller both for short- and long-run outcomes. Hence, since parole or probation violators are more likely to return in prison, a visitation effect is less effective for them.

Finally, the last column shows the results using female prisoners. There are only two prisons for females, and the sample size is smaller than the male case. Due to the small sample size, the estimated coefficients have high standard errors, so most of them are not statistically significant. However, the results show that visitation reduces reoffending at six months from release.

### 5.2.2 Discussion

This paper found a negative effect of visitation on recidivism, while Cochran et al. (2020) and Lee (2019) found no effect taking a similar approach like mine. Here this paper presents a list of potential reasons why these results are different.

The first reason is the state difference. The recidivism rate in Missouri is higher than that of Florida (Cochran et al., 2020) and Iowa (Lee, 2019). The recidivism rate is not directly comparable between states since each state is different in various dimensions: demographics, the legal system, etc. Hence, these differences may generate different results.

The second difference is the outcome measures. Their papers use a recidivism measure at three years from release. However, three years may be too long and noisy to measure the effect of visitation. The main estimation results suggest that visitation seems to have an effect at least within one year, but the standard errors increase over time. Hence the outcome measure may be a key difference from the two papers.

The third difference is that they include both females and males for regression. This paper focuses only on male prisoners, but they include females and males and control the difference by a binary variable in the regression. However, since not many facilities are for female prisoners, they would have a longer distance to their homes than male prisoners. In this case, the distance correlates with a gender indicator variable and violates the assumption as an instrumental variable.

The fourth difference is the reason for incarceration. The sample used for the analyses is either on parole or probation. Moreover, for those who are on supervision, a technical violation could be a reason for re-incarceration. Tables 9 and 10 shows the results including the cycles for technical violations. It shows the large negative effect of visitation in the short-run, but the long-run effect becomes unclear.

Lastly, although Cochran et al. (2020) and Lee (2019) use crime history in their regression, this paper does not use criminal history information in the main results due to data limitations. I check the sensitivity to crime history in Tables 7 and 8 using two measures of crime history (a recidivist dummy, and the SF score).<sup>24</sup> The results with a recidivist dummy show negative effects in the short run. However, although the coefficients are negative, the long-run effects become insignificant. The similar results are obtained when the SF score is included. Hence, the short-run effect is robust to the inclusion of crime history measures.

To clarify the points discussed above, I replicate the results in the two papers using the Missouri data. Table 11 shows the replication results. Although I could not replicate the exactly same regression,<sup>25</sup> both specifications show a negative but statistically insignificant effect only. However, in the second column where the outcome variable is reincarceration within 6 months and the sample is male only, I confirm the significant visitation effect, at least, for Lee (2019).

In summary, the visitation effect within a year is quite robust, but the effect becomes unclear as the time from release becomes longer. Hence, compared to Cochran et al. (2020) and Lee (2019), this paper reaches a similar conclusion about the causal effect at three years from release. Although the causal effect may be from state-specific factors, it is fair to say that visitation has a causal impact in the short run but it does not have a persistent effect in the long run.

### 5.2.3 Heterogeneous effects

So far, the visitation effect is treated as uniform across individual characteristics, but there may be heterogeneity of the effect. This section investigates the heterogeneity of the visitation effect by racial groups, crime types, and age groups. To check the heterogeneous effects, I run the IV regression using the interaction terms. The distance is interacted with the group dummies in the first stage, and then the predicted visitation measure is interacted with the group dummies in the second stage.

Table 12 and 13 show the results for different racial groups (Non-Hispanic White, Non-Hispanic Black, and Other). Non-Hispanic White is the base group in the regres-

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<sup>24</sup>Note that both are imperfect measure of crime history. The recidivist dummy only captures the recidivists during the sample period, and the SF score is based on crime history as well as other factors such as employment history.

<sup>25</sup>Some variables are not available in Missouri. The details of the difference are described in the notes in Table 11.

sion and the coefficients are negative. Since the majority of the sample consists of non-Hispanic White, the baseline results are similar to the white group. The white group has statistically significant coefficients in the short run. Coefficients for the interaction terms show negative signs and some of them are statistically significant. This implies that visitation effect is stronger and lasts longer for blacks and other racial groups.

Next, Table 14 and 15 confirm the heterogeneity by the primary offense type, using property crime as the base. Although the visitation effect is significant up to 3 years, the interaction terms with violent crime and drug crime are insignificant. The negative effect is confirmed except property crime offenders. For "other" type, the negative effect is confirmed up to 3 years from release. For drug offenders, the effect becomes positively significant at 3 years. The opposite sign indicates that visitation could be harmful for some type of offenders.

Lastly, Table 16 and 17 check the heterogeneity by three age groups. For the age groups below 40, the negative effect is confirmed in the short run. The most elderly group has negative effects in more than 2 years from release.

The heterogeneity analyses show additional implications of the main results. Especially, the heterogeneity by crime type seems an important aspect. Although the crime heterogeneity is captured by indicator variables in the literature, the positive effect on drug offenders suggests the necessity of separate regressions by crime type. This heterogeneity is worth investigating further.

### **5.3 The effect on supervision outcome and employment**

I also investigate the effects on other outcomes in Table 18. In the first column, the outcome variable is supervision completion. Possible supervision outcomes are discharge, revocation, interstate, and death. Supervision completion is defined as discharge over the entire sample excluding death or interstate supervision.<sup>26</sup> Under the IV regression, a visited person has a 14% point higher chance of successful completion and one visit per month increases the completion rate by 6% points.

Similarly, visitation has a positive effect on employment. It increases the chance of being employed after release by 32.1% points. I also use a measure of employment status at three months and six months from release. Excluding those who are caught

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<sup>26</sup>Although the sample consists of the prisoners released on supervision, it may not be the case when the cycle is for parole revocation. Hence, only the cycles for the original sentence are used for the regression.

by the time, visitation increases the chance of being employed at both points in time. Conditional on not being incarcerated, visited prisoners are 15.9% points and 13.0% points more likely to be working at three and six months from release. Hence, the results support a positive effect of visitation on employment status.

#### **5.4 The effect on the housing situation**

Finally, this section checks whether visitation has any effect on the housing situation. The visitation does not significantly increase movement when movement is measured by a dummy variable. However, this could be because the non-visited return to prison faster than the visited. When the frequency is used as another measure of movement, the coefficients are negative but are still insignificant.

Another hypothesis is that visitation helps a move to a better neighborhood. A measure of neighborhood difference across movements is based on a comparison of a median wage in the location before and after the first movement. The definition of the upward movement is the movement to a neighborhood where the median wage is higher than the previous location and vice versa. However, it is also possible that visited prisoners live in a good place as the first location. Hence, as the last measure of movement, I compare the log of the median income of the first address.

Table 19 shows the results. Against the initial expectations, visitation changes the probability of neither the upward movement nor the downward movement. Hence, since it does not change the probability or frequency of movements, visitation does not improve housing stability. However, it is worth noting that the visited prisoners live in a relatively better neighborhood as their initial address after release.

In summary, visitation has a negative impact on recidivism and a positive impact on labor market outcomes, but no effect is found on housing stability.

#### **5.5 Duration analysis**

The linear probability model focuses on the outcome at an arbitrary point in time from the release date. However, we are also interested in the duration until the reincarceration happens. I also perform a duration analysis based on the Cox proportional hazard model. As is the case in the linear probability model, it is necessary to control the endogeneity of visitation. Hence, the Cox model also uses the distance as an IV for visitation. Since the Cox model is non-linear, the estimation is based on

a control function approach. The method is based on two-stage residual inclusion (2SRI), introduced by Terza et al. (2008), and details of the method are in Appendix C.1. Similar to the previous sections, I perform the basic analysis to confirm the effects on recidivism, employment, and housing situation, and the results are in Appendix C.2. Specifically, the outcome variables are the time to be incarcerated again, time to get the first job, and time to change the address. The estimation results in Appendix C.2 are consistent with the linear probability model: visitation reduces the hazard rate of recidivism, increases the hazard rate of getting a job, and has no effect on movement.

## 6 Counterfactual analysis

The main results confirm that visitation reduces re-incarceration. This section considers two counterfactual policies. One is a policy that every prisoner is assigned to the closest prison from home. Another is the location of a new prison that minimizes the recidivism rate.

In the main sample, prisoners are assigned 114.31 miles away from their home, on average. If everyone were assigned to the closest prison conditional on the initial risk level, it would be 42.50 miles.<sup>27</sup> The reduction by 71.8 miles increases the mean time to reincarceration by 46 days.<sup>28,29</sup>

In the fiscal year of 2016, 12,874 male offenders were released on supervision. According to the 2016 annual report by the Missouri Board of Probation and Parole, the daily cost of incarceration is 57.25 dollars. A total of 16.67 out of the 57.25 dollars are the direct cost of incarceration, which includes health care, wage, discharge costs, food costs, and operational expenses and equipment. The rest of the total cost is the cost to keep the institution such as labor and maintenance costs. Hence, 46 days longer time to be incarcerated would decrease the direct cost per inmate by 767 dollars, and the annual direct cost of incarceration by about 10 million dollars. Similarly, the total daily cost of incarceration would decrease by about 34 million dollars.

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<sup>27</sup>The calculation does not consider the capacity constraint of each facility.

<sup>28</sup>To estimate the mean time, we need to fix the baseline hazard. Here, the Weibull model is assumed, and the number is from the estimated model.

<sup>29</sup>The linear model is used in the main results. The LATE derived from the IV regression tells that the recidivism rate at six months from the release decreases by 0.9% points under the policy. Alternatively, we can estimate the policy-relevant treatment effect (PRTE) based on the marginal treatment effect (MTE) (Heckman and Vytlacil, 2005; Andresen, 2018). The PRTE estimator is  $-14\%$  points, so a reduction by 73.16 miles reduces the recidivism rate at 6 months from release by 0.81% points.

Given the assignment policy, we can identify where is the best location for a new prison to minimize recidivism. Given the distribution of prisoners in the sample, St. Louis County is the county for a prison location that minimizes the weighted distance to a prison with the minimum security level. Although St. Louis County is not far from a prison with the minimum security, a high population of prisoners from the neighborhood makes St. Louis County the best location. However, for the medium- and maximum-security levels, the best location is Greene County, where Springfield is located, since the southwest area in Missouri is far from a prison with higher security levels and a new prison in the area reduces the weighted distance.

## 7 Conclusion

This paper investigates the effect of the visitation on post-release outcomes and the channels of the effect. The results show that visitation has a large negative effect on recidivism. The results also confirm that visitation improves employment outcomes. However, visitation does not change the probability nor frequency of movement, and hence it has no impact on housing stability.

This paper has two limitations. Although this paper focuses on the in-person visitation, most prisons provide other opportunities to communicate with the outside. Recently, some states have started to permit video visitation instead of in-person visitation, and video visitation is replacing actual visitation because of lower costs (Rabuy and Wagner, 2015). Besides, phone calls and letters could also be substitutes for prison visitation. This paper could not compare other communication tools, but they could be a more cost-effective approach to reduce recidivism.

Another limitation is that since this paper focuses on the prisoner's side, the visitors' decisions are ignored. For example, new public transportation for better access to the prisons might change the effect of distance on visitation decisions. However, the reaction for the new transportation will be different by wealth status. For example, some people may have a car and others not. Moreover, high-income earners may face a higher opportunity cost of visitation. Since visitation is the endogenous choice of visitors, it would be helpful for better policy design to know the decisions of visitors. Hence, further analysis of the visitation decision from a visitor's side is necessary for the better visitation policy design.

Lastly, although visitation is mostly associated with a lower recidivism rate, Bedard

and Helland (2004) pointed out another possibility that encouraging visitation could be harmful to the overall crime rate. They investigate the effect of distance to the nearest prison on the female crime rate of counties and find that an increase in the distance caused by prison closure decreases the local crime rate. They claim that this is likely because the expectation of lower visitation works as an emotional cost of crime and decreases the crime rate. Although Bedard and Helland (2004) focused on the effect of visitation on recidivism, we have to consider the side effects of visitation policy for evaluation.

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# Appendices

## A Control variables

The list of control variables is summarized in Table 20.

[Insert Table 20]

## B Identification assumptions

This section formally describes the identification assumptions. Let  $Y_i$ ,  $V_i$ , and  $D_i$  be an outcome variable, a measure of visitation, and a distance measure of an individual  $i$ .  $Y_i \in \{0, 1\}$  and  $D_i \in \mathbb{R}_+$ ,  $V = \{0, 1\}$  when visitation is measured in a binary manner, and  $V \subset \mathbb{R}_+$  when measured by frequency. Let me define the following two conditions:

1. (Independence) for any  $d' \in D$ , the triple  $(Y_{i1}, Y_{i0}, V_i(d'))$  is jointly independent of an instrument  $d_i \in D$ .
2. (Monotonicity)  $\forall \alpha, \beta \in D \subset \mathbb{R}_+$  such that  $\alpha > \beta$ ,  $E(V|D = \alpha) - E(V|D = \beta) < 0$ , where  $V$  is a measure of visitation and  $D$  is the distance.

Under the two conditions, Theorem 2 in Imbens and Angrist (1994) implies that the IV estimator of visitation is in the following form:

$$\alpha_g^{IV} = \frac{Cov(Y, P(Z))}{Cov(D, P(Z))} = \sum_{k=1}^K \lambda_k \alpha_{z_k, z_{k-1}}, \quad (2)$$

where

$$\lambda_k = \frac{(P(z_k) - P(z_{k-1})) \sum_{l=k}^K \pi_l (g(z_l) - E[g(Z)])}{\sum_{m=1}^K (P(z_m) - P(z_{m-1})) \sum_{l=m}^K \pi_l (g(z_l) - E[g(Z)])}, \quad (3)$$

$\pi_k = P(Z = z_k)$ , and  $\alpha_{z_k, z_{k-1}}$  is the LATE  $E[Y_{i1} - Y_{i0} | D_i(z_k) = 1, D_i(z_{k-1}) = 1]$ .

## C Duration analysis

### C.1 Method

I run a regression on the time by re-incarceration, getting first job, and the first movement. The estimation is based on the Cox proportional hazard model using the same

IV. The Cox proportional hazard model is defined by the following hazard function:

$$h(t|V_i, X_i, U_i) = \lambda_0(t) \exp(\beta_V V_i + \beta_X X_i + \beta_U U_i) \quad (4)$$

where  $t$ ,  $V$ ,  $X$ , and  $U$  are time, treatment (visitation), observable characteristics, and unobservable characteristics. Our coefficient of interest is  $\beta_V$ . However, since we do not observe  $U$ , we cannot run the regression directly. To estimate  $\beta_V$  consistently under non-linear setting, this paper uses a control function approach: the two stage residual inclusion (2SRI) proposed by Terza et al. (2008).<sup>30</sup> The first step is to estimate  $V_i$  using the distance as an instrument  $Z_i$ .

$$V_i = \alpha_X X_i + \alpha_Z Z_i + \epsilon_i \quad (5)$$

From the results, we obtain the residual as  $\hat{U}_i = V_i - \hat{V}_i$ . The second stage is to estimate the hazard function using the residual.

$$h(t|V_i, X_i, U_i) = \lambda_0(t) \exp(\beta_V V_i + \beta_X X_i + \beta_U \hat{U}_i) \quad (6)$$

The equation gives a consistent estimator of  $\beta_V$ .

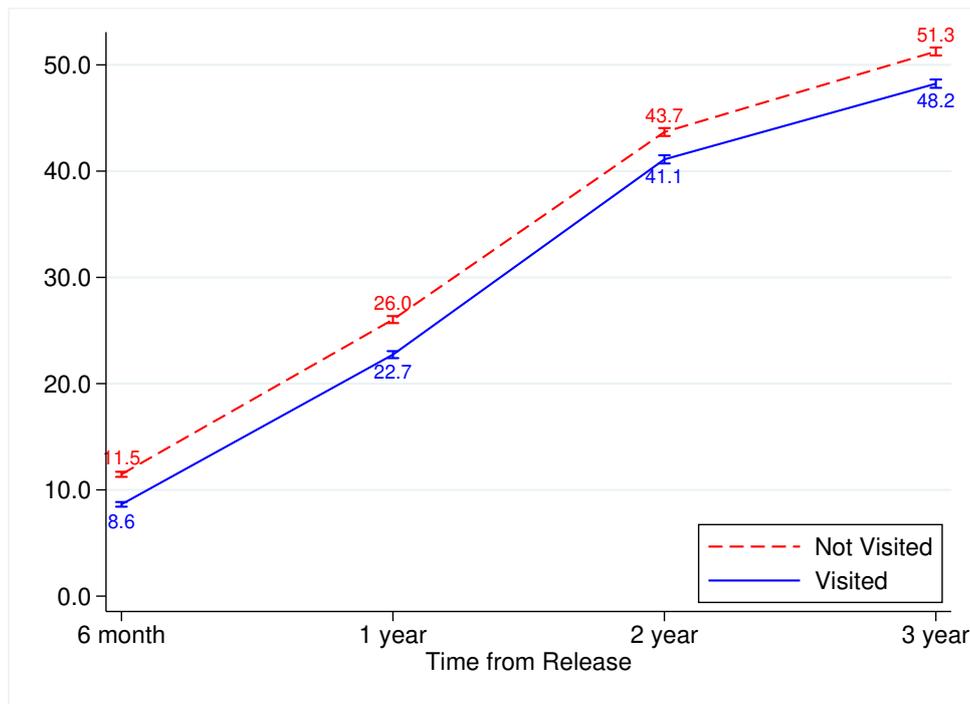
## C.2 Results

The results are in Table 21. The numbers in the table show the ratio of the hazard rates of recidivism. Visitation decreases the hazard rate of re-incarceration. When the instrumental variable is used, the estimator shows a larger effect on the hazard rate. The estimator implies that the hazard rate of recidivism is 30% points less for those who are visited. As for employment outcomes in Table 22, visitation increases the hazard rate of having the first job. Without an instrument, the effect is positive but the magnitude is amplified when the IV is used. Both a visitation dummy and visitation frequency show significantly positive effects. The visited have 141% higher the hazard rate of getting the first job. Hence, visitation makes released prisoners get a job faster in expectation.

The Cox regression in Table 23 shows a negative effect of the days until the first movement for both a visitation dummy and visitation frequency. However, once the

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<sup>30</sup>2SLS estimator is not consistent under non-linear models.



Notes: The lines show the recidivism rate of male prisoners over time with the confidence interval (CI). The CI is at 95% level.

Figure 2: Re-incarceration rate over time

omitted variable bias is controlled by an instrumental variable approach, visitation does not have a significant effect on the time to first move.

In summary, both linear probability models and duration analysis show similar effects of visitation post-release outcomes. Visitation improves recidivism and employment outcomes but does not improve the housing situation. The robustness of the main results and the duration analysis are in the appendix section.

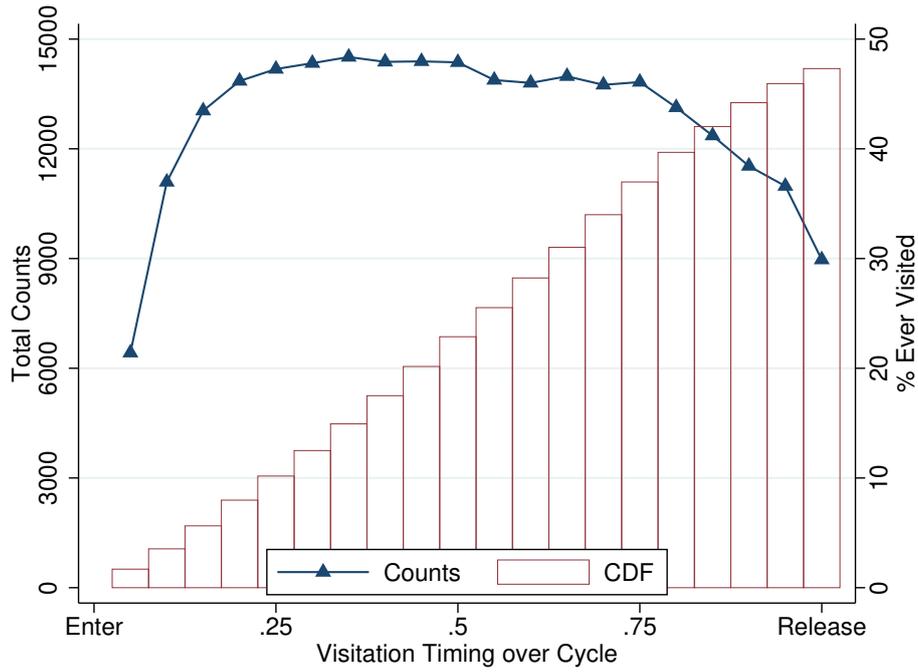
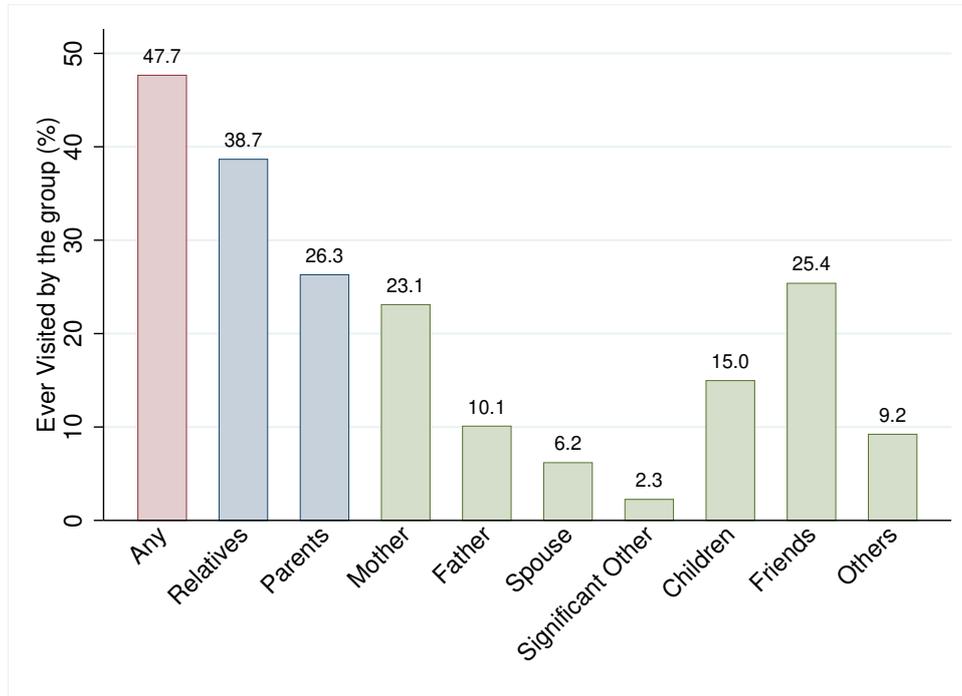
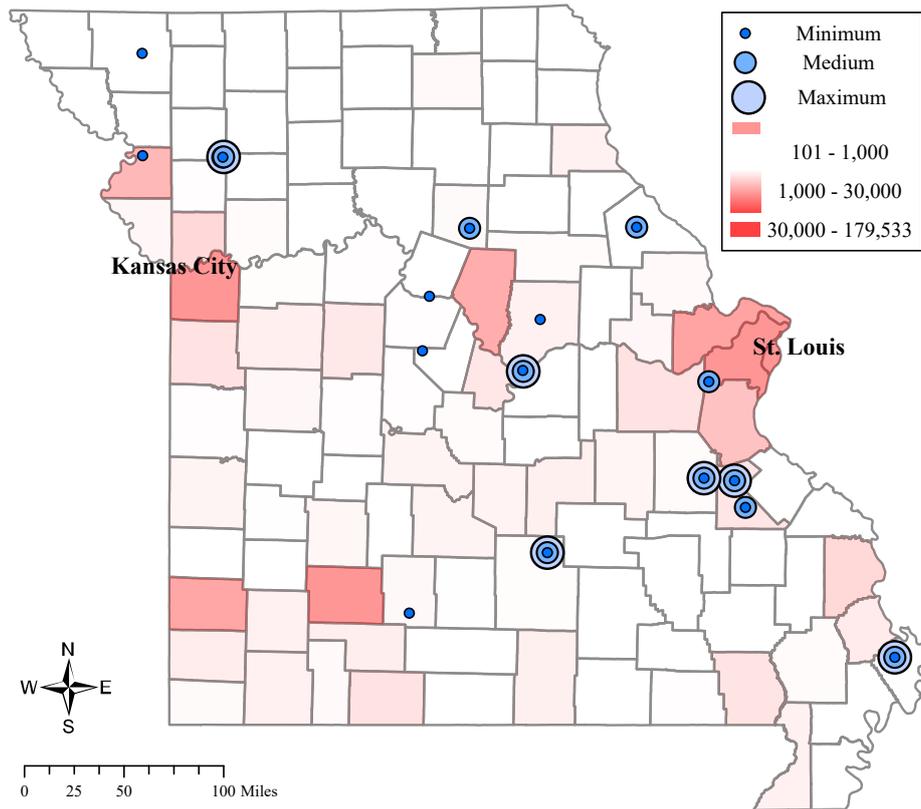


Figure 3: Visitation timing



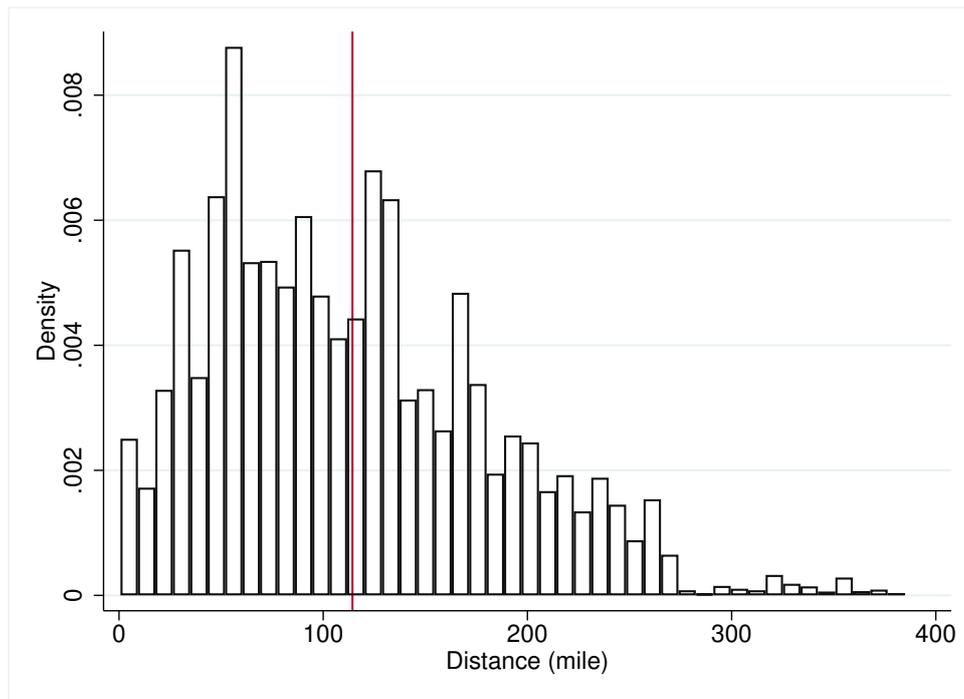
Notes: This graph shows the fraction of prisoners visited by the category during incarceration. Relatives and parents are aggregated categories. Relatives include parents, spouses, children, and other relatives, and parents contain mother and father. The sum of the fractions of mother and father is not equal to the fraction of parents, since some prisoners experience visitation by both.

Figure 4: Visitation by relationship



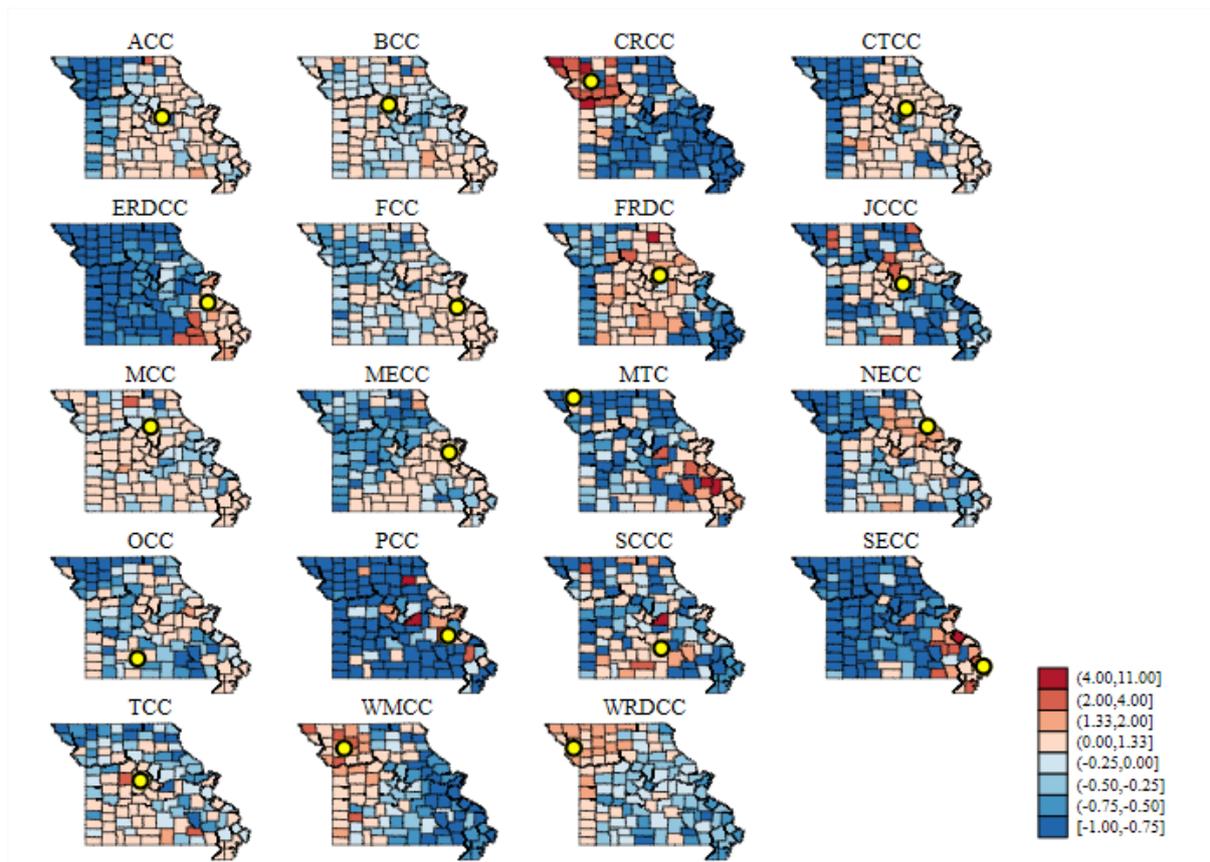
Notes: There are 19 correctional facilities for male prisoners in Missouri and each facility has its security levels. Prisons with small, medium, and large circles indicate minimum, medium, maximum security levels, respectively. There are only 16 points in the map, since 3 facilities are adjacent to other facilities. The gradation of red color is based on total crime counts over 4 years (2012–2015).

Figure 5: Missouri state prisons for male



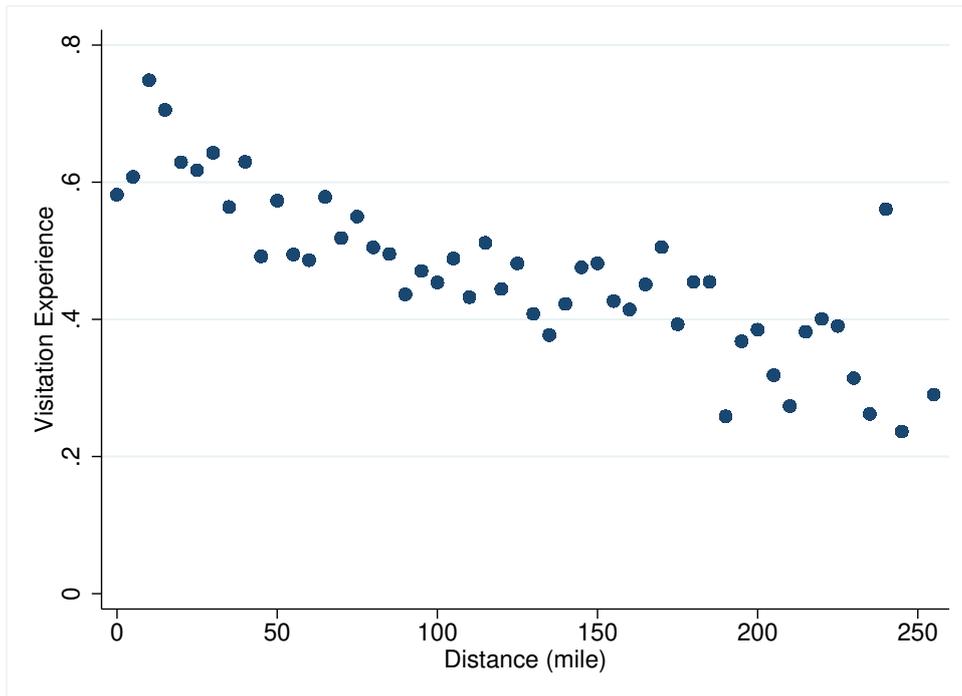
Notes: The vertical line is at the mean. Home address is based on counties of conviction.

Figure 6: Distance from home

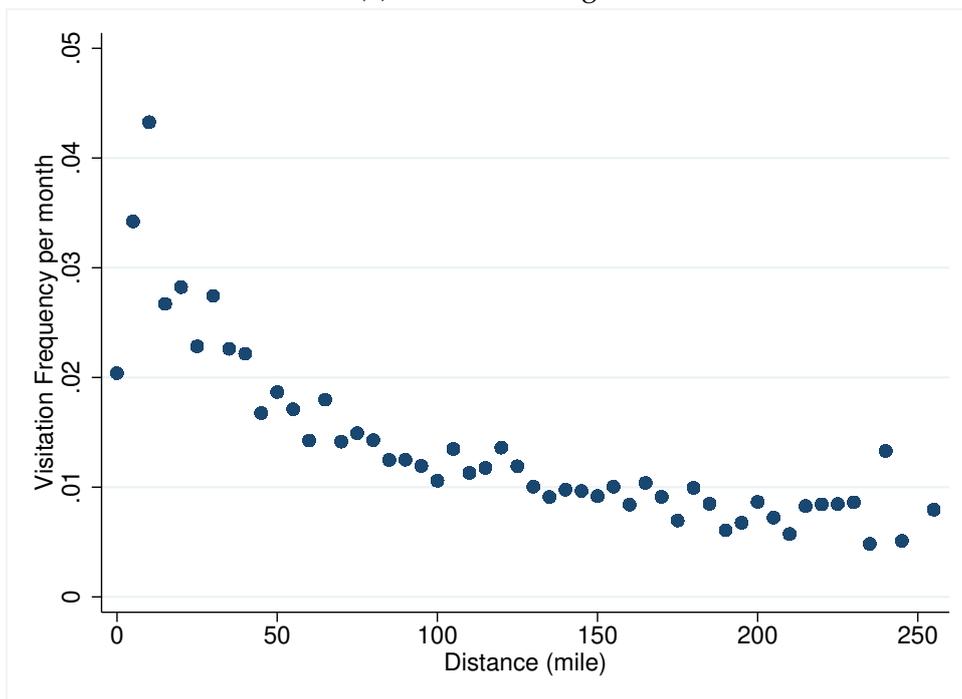


Notes: A circle in each graph represents the location of the facility. The color of each county is based on the share of prisoners from the county relative to the state average. A red (blue) color in a graph means the share of prisoners from the county is higher (lower) than the share of prisoners in the entire sample.

Figure 7: Origin of prisoners by prison compared to the statewide mean



(a) Extensive margin



(b) Intensive margin

Notes: The point at the longest distance in the figure is the mean of all observations that exceed 250 miles.

Figure 8: Visitation experience by distance

Table 1: Summary statistics

N=33,971	Mean	S.D.	Min	Max
Distance (mile)	114.31	68.79	.706	385
Age at Release	35.09	10.18	20	64.9
<b>Race/Ethnicity</b>				
White (Non-Hispanic)	0.66	0.47	0	1
Black (Non-Hispanic)	0.24	0.43	0	1
Other Race	0.10	0.29	0	1
Sentence Length	5.58	3.06	0	50
Parole	0.70	0.46	0	1
<b>Primary Crime Type</b>				
Property	0.29	0.46	0	1
Violent	0.13	0.34	0	1
Drug	0.28	0.45	0	1
Other Crime	0.30	0.46	0	1
<b>Felony Class</b>				
A (10-30 year)	0.02	0.15	0	1
B (5-15 year)	0.17	0.38	0	1
C (3-10 year)	0.65	0.48	0	1
D (-7 year)	0.15	0.36	0	1
<b>Re-incarceration</b>				
within 6 month	0.10	0.30	0	1
within 1 year	0.24	0.43	0	1
within 2 year	0.42	0.49	0	1
within 3 year	0.50	0.50	0	1
Supervision Completion	0.35	0.48	0	1
<b>Employment</b>				
ever since release	0.47	0.50	0	1
at 3 month from release	0.23	0.42	0	1
at 6 month from release	0.29	0.45	0	1
Fulltime (ever since release)	0.39	0.49	0	1
Movement (Dummy)	0.55	0.50	0	1
Movement (Freq. per month)	0.07	0.16	0	15

Notes: Supervision completion is defined as a share of “Discharge” over sum of “Abscond”, “Revoke”, and “Discharge”. The other outcome “Death”, which account for 6.7% of overall sample, is not included.

Table 2: Mean by visitation experience

	Not Visited N=17,784		Visited N=16,187	
	Mean	S.D.	Mean	S.D.
Distance (mile)	125.7	70.9	101.8	64.1
Age at Release	35.7	10.6	34.5	9.71
<b>Race/Ethnicity</b>				
White (Non-Hispanic)	0.64	0.48	0.68	0.47
Black (Non-Hispanic)	0.26	0.44	0.23	0.42
Other Race	0.098	0.30	0.093	0.29
Sentence Length	5.16	2.81	6.04	3.26
Parole	0.63	0.48	0.77	0.42
<b>Primary Crime Type</b>				
Property	0.29	0.45	0.30	0.46
Violent	0.10	0.30	0.16	0.37
Drug	0.30	0.46	0.25	0.44
Other Crime	0.31	0.46	0.29	0.45
<b>Felony Class</b>				
A (10-30 year)	0.012	0.11	0.038	0.19
B (5-15 year)	0.14	0.35	0.21	0.41
C (3-10 year)	0.68	0.47	0.62	0.49
D (-7 year)	0.17	0.37	0.13	0.34
<b>Re-incarceration</b>				
within 6 month	0.11	0.32	0.086	0.28
within 1 year	0.26	0.44	0.23	0.42
within 2 year	0.44	0.50	0.41	0.49
within 3 year	0.51	0.50	0.48	0.50
Supervision Completion	0.32	0.47	0.39	0.49
<b>Employment</b>				
ever since release	0.40	0.49	0.54	0.50
at 3 month from release	0.19	0.39	0.28	0.45
at 6 month from release	0.24	0.43	0.33	0.47
Fulltime (ever since release)	0.32	0.47	0.47	0.50
Movement (Dummy)	0.54	0.50	0.56	0.50
Movement (Freq. per month)	0.079	0.19	0.070	0.12

Table 3: Correlation with distance

Distance	(1) All	(2) Not Visited	(3) Visited
Age at Release	-0.0442 (0.0300)	-0.0463 (0.0380)	-0.186*** (0.0472)
Sentence Length	0.683*** (0.122)	0.795*** (0.168)	0.752*** (0.174)
Black (Non Hispanic)	1.927** (0.829)	-1.559 (1.081)	3.364*** (1.243)
Other Race	-0.793 (1.032)	-0.735 (1.352)	-1.797 (1.531)
Dependents	-0.293* (0.164)	-0.171 (0.221)	0.00118 (0.237)
Violent Crime	3.442*** (0.972)	5.487*** (1.400)	2.861** (1.331)
Drug Crime	-2.302*** (0.781)	-2.716*** (1.009)	-2.226* (1.180)
Other Crime	0.145 (0.836)	0.407 (1.098)	0.385 (1.239)
Felony Class B	-1.650 (2.050)	-2.178 (3.653)	-1.852 (2.499)
Felony Class C	-2.140 (2.078)	-3.733 (3.658)	-2.014 (2.569)
Felony Class D	-4.044* (2.298)	-6.455* (3.876)	-2.600 (2.970)
Controls	Y	Y	Y
Prison FE	Y	Y	Y
County FE	Y	Y	Y
Time FE	Y	Y	Y
Observations	33,971	17,784	16,187

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Table 4: First stage

Visitation	(1) Dummy	(2) Frequency
Distance (100 miles)	-0.0778*** (0.00481)	-0.185*** (0.00874)
Controls	Y	Y
Prison FE	Y	Y
County FE	Y	Y
Time FE	Y	Y
Observations	33,971	33,971
First-Stage F Statistic	261.5	450

Table 5: Main results: visitation measured by a binary variable

	(1)	(2)
Visitation (Dummy)	OLS	IV
6 month		
$\beta$	-0.0335***	-0.160***
S.E.	(0.00350)	(0.0406)
1 year		
$\beta$	-0.0431***	-0.148***
S.E.	(0.00494)	(0.0565)
2 year		
$\beta$	-0.0458***	-0.130**
S.E.	(0.00558)	(0.0639)
3 year		
$\beta$	-0.0554***	-0.128**
S.E.	(0.00562)	(0.0642)
Controls	Y	Y
Prison FE	Y	Y
County FE	Y	Y
Time FE	Y	Y
Observations	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Each row uses different outcome variables. Each pair of coefficient and the standard error is from different regression.

Table 6: Main results: visitation measured by frequency per month

	(1)	(2)
Visitation (Frequency)	OLS	IV
6 month		
$\beta$	-0.0146***	-0.0670***
S.E.	(0.00180)	(0.0169)
1 year		
$\beta$	-0.0191***	-0.0622***
S.E.	(0.00258)	(0.0237)
2 year		
$\beta$	-0.0268***	-0.0544**
S.E.	(0.00296)	(0.0267)
3 year		
$\beta$	-0.0296***	-0.0538**
S.E.	(0.00304)	(0.0269)
Controls	Y	Y
Prison FE	Y	Y
County FE	Y	Y
Time FE	Y	Y
Observations	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ . Each row uses different outcome variables. Each pair of coefficients and the standard errors are from different regressions. Frequency is defined as the total number of visits over incarcerated month.

Table 7: Different control variables: dummy

Visitation (Dummy)		(1) Days	(2) Recidivist	(3) SF
6 month				
	$\beta$	-0.153***	-0.133***	-0.134***
	S.E.	(0.0386)	(0.0396)	(0.0391)
1 year				
	$\beta$	-0.150***	-0.0931*	-0.110**
	S.E.	(0.0539)	(0.0529)	(0.0546)
2 year				
	$\beta$	-0.144**	-0.0594	-0.0861
	S.E.	(0.0612)	(0.0587)	(0.0618)
3 year				
	$\beta$	-0.150**	-0.0611	-0.0888
	S.E.	(0.0616)	(0.0597)	(0.0623)
Incarcerated days		Y	N	N
Recidivist		N	Y	N
SF score		N	N	Y
Controls		Y	Y	Y
Fixed effects		Y	Y	Y
Observations		33,971	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: The same control variables are used except sentence length in the first column. Instead of sentence length, actual incarcerated length is used.

Table 8: Different control variables: frequency

		(1)	(2)	(3)
Visitation (Frequency)		Days	Recidivist	SF
6 month	$\beta$	-0.0661***	-0.0555***	-0.0573***
	S.E.	(0.0166)	(0.0164)	(0.0167)
1 year	$\beta$	-0.0650***	-0.0388*	-0.0473**
	S.E.	(0.0233)	(0.0220)	(0.0234)
2 year	$\beta$	-0.0624**	-0.0248	-0.0369
	S.E.	(0.0264)	(0.0245)	(0.0265)
3 year	$\beta$	-0.0650**	-0.0255	-0.0380
	S.E.	(0.0266)	(0.0249)	(0.0267)
Incarcerated days		Y	N	N
Recidivist		N	Y	N
SF score		N	N	Y
Controls		Y	Y	Y
Fixed effects		Y	Y	Y
Observations		33,971	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: The same control variables are used except sentence length in the first column. Instead of sentence length, actual incarcerated length is used.

Table 9: Different sample: visitation measured by a binary variable

Visitation (Dummy)		(1) MSA	(2) Out of Missouri	(3) Tech. violation	(4) Female
6 month	$\beta$	-0.162***	-0.143***	-0.148***	-0.171**
	S.E.	(0.0400)	(0.0374)	(0.0397)	(0.0850)
1 year	$\beta$	-0.153***	-0.141***	-0.102*	-0.169
	S.E.	(0.0558)	(0.0527)	(0.0534)	(0.125)
2 year	$\beta$	-0.136**	-0.131**	-0.0935	0.0653
	S.E.	(0.0631)	(0.0602)	(0.0591)	(0.150)
3 year	$\beta$	-0.132**	-0.126**	-0.101*	0.257
	S.E.	(0.0635)	(0.0609)	(0.0591)	(0.161)
Controls		Y	Y	Y	Y
Fixed effects		Y	Y	Y	Y
Observations		34,476	37,480	41,641	7,830

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: Each row uses different outcome variables. Each pair of coefficients and the standard error are from the unique regression. The MSA column uses the baseline sample and the sample released to the St. Louis MSA and Kansas City MSA. The St. Louis MSA includes Bond, Calhoun, Clinton, Jersey, Macoupin, Madison, Monroe, and St. Clair counties in Illinois state. The Kansas City MSA includes Johnson, Leavenworth, Linn, Miami, and Wyandotte counties in Kansas state. The "Out of Missouri" column uses all samples regardless of the location after release. The technical violation column uses actual incarceration days in place of sentence length, since sentence length is not applicable to the technical violation served.

Table 10: Different sample: visitation measured by frequency per month

Visitation (Frequency)	(1) MSA	(2) Out of Missouri	(3) Tech. violation	(4) Female
6 month				
$\beta$	-0.0679***	-0.0623***	-0.0642***	-0.122**
S.E.	(0.0167)	(0.0163)	(0.0171)	(0.0620)
1 year				
$\beta$	-0.0642***	-0.0618***	-0.0441*	-0.121
S.E.	(0.0234)	(0.0230)	(0.0231)	(0.0905)
2 year				
$\beta$	-0.0571**	-0.0572**	-0.0405	0.0467
S.E.	(0.0264)	(0.0263)	(0.0256)	(0.108)
3 year				
$\beta$	-0.0555**	-0.0553**	-0.0436*	0.184
S.E.	(0.0266)	(0.0266)	(0.0256)	(0.116)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	34,476	37,480	41,641	7,830

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: Each row uses different outcome variables. Each pair of coefficients and the standard error are from the unique regression. Frequency is defined as the total number of visits over incarcerated month. The MSA column uses the baseline sample and the sample released to the St. Louis MSA and Kansas City MSA. The St. Louis MSA includes Bond, Calhoun, Clinton, Jersey, Macoupin, Madison, Monroe, and St. Clair counties in Illinois state. The Kansas City MSA includes Johnson, Leavenworth, Linn, Miami, and Wyandotte counties in Kansas state. The "Out of Missouri" column uses all samples regardless of the location after release. The technical violation column uses actual incarceration days in place of sentence length, since sentence length is not applicable to the technical violation served.

Table 11: Replication results

	(1)	(2)
	Original	Modified
<b>Lee (2019)</b>		
Visitation (Frequency)	-0.00505 (0.0162)	-0.0290** (0.0138)
Observations	55,580	45,956
<b>Cochran et al. (2020)</b>		
Visitation (Dummy)	-0.0530 (0.0402)	-0.0156 (0.0350)
Observations	55,580	45,956

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: Each coefficient is from separate regression. The first column is based on the original specification in each paper: the sample contains both males and females and the dependent variable is reincarceration within 3 years by a new conviction. Instead, the second column uses male prisoners and the dependent variable is reincarceration within 6 months for any reason.

For Lee (2019), both linear and quadratic distance measures are used as instruments. The control variables are a gender dummy, the number of dependents, a recidivist dummy, category dummies (by age groups, racial groups, and crime types), crime rate at the county of conviction, and fixed effects (year, prison, and county). Since LSI-R and total crimes committed are not in the data, they are not controlled. Age is grouped by the deciles and racial groups are divided into four (non-Hispanic white, non-Hispanic black, Hispanic, other). Quarter fixed effects are substituted by year fixed effects.

For Cochran et al. (2020), the distance is discretized every 50 miles and there are 7 distance groups in total: from 0–50 miles to 300 or above. The control variables are a gender dummy, a recidivist dummy, age at the admission date for the sentence, category dummies (by racial groups, and crime types), sentence length, actual time served, and county fixed effects. Age is as of the admission date. Prior prison conviction, misconduct, and prison commitment are not available in my dataset: instead, the recidivist dummy is used. As crime type, sex offense is categorized into "other" category. Sentence length is the original sentence for those who served for technical violations. Time served and months remained are substituted by actual time served.

Table 12: Heterogeneity by race: visitation measured by dummy

Recidivism	(1) 6 month	(2) 1 year	(3) 2 year	(4) 3 year
$\widehat{visitation}$	-0.146*** (0.0390)	-0.136** (0.0549)	-0.109* (0.0623)	-0.116* (0.0627)
Non-Hispanic Black	-0.00779 (0.0113)	-0.0261 (0.0159)	-0.0277 (0.0180)	-0.0331* (0.0181)
Other	-0.00934 (0.0154)	-0.0556** (0.0217)	-0.0819*** (0.0246)	-0.0772*** (0.0248)
$\widehat{visitation} \times$ Non-Hispanic Black	-0.0365* (0.0212)	-0.0467 (0.0299)	-0.0785** (0.0339)	-0.0867** (0.0342)
$\widehat{visitation} \times$ Other	-0.0557* (0.0305)	-0.0384 (0.0429)	-0.0855* (0.0487)	-0.0920* (0.0490)
Observations	33,971	33,971	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: Each column uses a different dependent variable. The regressions use the same control variables and fixed effects (prison, county, time). The base category is non-Hispanic white.

Table 13: Heterogeneity by race: visitation measured by frequency per month

Recidivism	(1) 6 month	(2) 1 year	(3) 2 year	(4) 3 year
$\widehat{visitation}$	-0.0576*** (0.0156)	-0.0511** (0.0220)	-0.0407 (0.0250)	-0.0445* (0.0252)
Non-Hispanic Black	-0.00991 (0.00828)	-0.0291** (0.0117)	-0.0375*** (0.0132)	-0.0460*** (0.0133)
Other	-0.0129 (0.0117)	-0.0520*** (0.0164)	-0.0726*** (0.0186)	-0.0580*** (0.0188)
$\widehat{visitation} \times$ Non-Hispanic Black	-0.0182 (0.0172)	-0.0287 (0.0243)	-0.0507* (0.0276)	-0.0518* (0.0278)
$\widehat{visitation} \times$ Other	-0.0455* (0.0241)	-0.0436 (0.0340)	-0.111*** (0.0385)	-0.142*** (0.0388)
Observations	33,971	33,971	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: Each column uses a different dependent variable. The regressions use the same control variables and fixed effects (prison, county, time). The base category is non-Hispanic white.

Table 14: Heterogeneity by crime type: visitation measured by dummy

	(1)	(2)	(3)	(4)
Recidivism	6 month	1 year	2 year	3 year
$\widehat{visitation}$	-0.198*** (0.0421)	-0.183*** (0.0593)	-0.165** (0.0673)	-0.155** (0.0677)
Violent Crime	-0.0338* (0.0177)	-0.0550** (0.0249)	-0.0867*** (0.0282)	-0.0758*** (0.0284)
Drug Crime	-0.0473*** (0.0113)	-0.0646*** (0.0159)	-0.0746*** (0.0180)	-0.0697*** (0.0182)
Other Crime	-0.0532*** (0.0123)	-0.0797*** (0.0173)	-0.0860*** (0.0197)	-0.0964*** (0.0198)
$\widehat{visitation} \times$ Violent Crime	0.0514* (0.0292)	0.0161 (0.0411)	0.0238 (0.0466)	-0.0136 (0.0470)
$\widehat{visitation} \times$ Drug Crime	0.0352 (0.0226)	0.0471 (0.0318)	0.0684* (0.0361)	0.0575 (0.0364)
$\widehat{visitation} \times$ Other Crime	0.0850*** (0.0236)	0.0720** (0.0333)	0.0366 (0.0377)	0.0353 (0.0380)
Observations	33,971	33,971	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: Each column uses a different dependent variable. The regressions use the same control variables and fixed effects (prison, county, time). The base category is property crime.

Table 15: Heterogeneity by crime type: visitation measured by frequency per month

	(1)	(2)	(3)	(4)
Recidivism	6 month	1 year	2 year	3 year
$\widehat{visitation}$	-0.0874*** (0.0194)	-0.0799*** (0.0273)	-0.0772** (0.0310)	-0.0811*** (0.0312)
Violent Crime	-0.0272** (0.0113)	-0.0569*** (0.0160)	-0.0854*** (0.0181)	-0.0918*** (0.0183)
Drug Crime	-0.0341*** (0.00782)	-0.0512*** (0.0110)	-0.0611*** (0.0125)	-0.0621*** (0.0126)
Other Crime	-0.0303*** (0.00824)	-0.0555*** (0.0116)	-0.0735*** (0.0132)	-0.0897*** (0.0133)
$\widehat{visitation} \times$ Violent Crime	0.0253 (0.0201)	0.00339 (0.0283)	0.00895 (0.0321)	0.00279 (0.0323)
$\widehat{visitation} \times$ Drug Crime	0.0221 (0.0163)	0.0333 (0.0229)	0.0550** (0.0260)	0.0566** (0.0262)
$\widehat{visitation} \times$ Other Crime	0.0388** (0.0161)	0.0215 (0.0227)	0.0101 (0.0257)	0.0223 (0.0259)
Observations	33,971	33,971	33,971	33,971

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Notes: Each column uses a different dependent variable. The regressions use the same control variables and fixed effects (prison, county, time). The base category is property crime.

Table 16: Heterogeneity by age: visitation measured by dummy

	(1)	(2)	(3)	(4)
Recidivism	6 month	1 year	2 year	3 year
$\widehat{visitation}$	-0.136*** (0.0423)	-0.134** (0.0597)	-0.0704 (0.0677)	-0.0815 (0.0681)
age (30–40)	0.00634 (0.0119)	0.00993 (0.0168)	0.0588*** (0.0190)	0.0649*** (0.0192)
age (40–65)	-0.0138 (0.0148)	-0.00426 (0.0209)	0.0590** (0.0237)	0.0739*** (0.0239)
$\widehat{visitation} \times$ age (30–40)	-0.0324 (0.0210)	-0.0232 (0.0297)	-0.0712** (0.0336)	-0.0560* (0.0339)
$\widehat{visitation} \times$ age (40–65)	-0.0246 (0.0213)	-0.0375 (0.0300)	-0.104*** (0.0340)	-0.0927*** (0.0342)
Observations	33,971	33,971	33,971	33,971

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Notes: Each column uses a different dependent variable. The regressions use the same control variables and fixed effects (prison, county, time). The base category is age (20–30).

Table 17: Heterogeneity by age: visitation measured by frequency per month

	(1)	(2)	(3)	(4)
Recidivism	6 month	1 year	2 year	3 year
$\widehat{visitation}$	-0.0473** (0.0186)	-0.0400 (0.0262)	-0.0172 (0.0297)	-0.0284 (0.0299)
age(30–40)	0.00234 (0.00859)	0.0155 (0.0121)	0.0432*** (0.0137)	0.0513*** (0.0138)
age(40–65)	-0.000621 (0.0125)	0.00696 (0.0176)	0.0427** (0.0199)	0.0581*** (0.0201)
$\widehat{visitation} \times \text{age}(30-40)$	-0.0253* (0.0143)	-0.0363* (0.0201)	-0.0433* (0.0228)	-0.0313 (0.0230)
$\widehat{visitation} \times \text{age}(40-65)$	-0.0523*** (0.0153)	-0.0613*** (0.0216)	-0.0743*** (0.0245)	-0.0627** (0.0247)
Observations	33,971	33,971	33,971	33,971

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Notes: Each column uses a different dependent variable. The regressions use the same control variables and fixed effects (prison, county, time). The base category is age (20–30).

Table 18: Supervision and employment outcomes

VARIABLES	(1) Supervision completion	(2) Emp (ever)	(3) Emp (3 month)	(4) Emp (6 month)
Visitation (Dummy)	0.142** (0.0600)	0.321*** (0.0663)	0.159*** (0.0567)	0.130** (0.0649)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	33,369	33,971	32,183	28,944

VARIABLES	(1) Supervision completion	(2) Emp (ever)	(3) Emp (3 month)	(4) Emp (6 month)
Visitation (Frequency)	0.0599** (0.0253)	0.135*** (0.0278)	0.0675*** (0.0240)	0.0512** (0.0255)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	33,369	33,971	32,183	28,944

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Notes: Frequency is defined as the total number of visits over incarcerated month. “Supervision completion” excludes those who died during supervision and who were assigned interstate supervision. “Emp (ever)” is whether prisoners are employed since the release. “Emp (3 month)” and “Emp (6 month)” are based on the employment status at 3 months and 6 months from release, conditional on not incarcerated at the time.

Table 19: Movement outcomes

VARIABLES	(1) Move (Dummy)	(2) Move (Dummy)	(3) Move (Freq.)	(4) Move (Freq.)
Visitation (Dummy)	0.0801 (0.0661)		-0.0212 (0.0216)	
Visitation (Frequency)		0.0336 (0.0277)		-0.00894 (0.00911)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	33,971	33,971	33,867	33,867

VARIABLES	(1) Move up	(2) Move up	(3) Move down	(4) Move down	(5) <i>ln(income)</i>	(6) <i>ln(income)</i>
Visitation (Dummy)	-0.00367 (0.0535)		0.0961* (0.0547)		0.114*** (0.0380)	
Visitation (Frequency)		-0.00150 (0.0219)		0.0393* (0.0223)		0.0464*** (0.0155)
Controls	Y	Y	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y	Y	Y
Observations	32,629	32,629	32,629	32,629	32,000	32,000

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: Movement frequency is defined as the total number of movements over the months under supervision. A total of 103 observations are dropped for the frequency regression since the supervision end date is missing. "Move up" and "Move down" are based on the comparison of the median income between the initial address and the second address at the zip code level. Non-movers are treated as zero.  $\ln(\text{income})$  is the log of the median income at the initial address at the zip code level. The sample size difference is due to an invalid address or addresses without median income information.

Table 20: Control variables

Variable name	Type	Category
Age at release	Numeric	
Sentence length (year)	Numeric integer	
Dependents	Numeric	
Race and Ethnicity	Categorical	White (NH), Black (NH), Other
County	Categorical	114 counties and St. Louis City
Prison	Categorical	19 correctional facilities
Time	Categorical	Quarter
Crime type	Categorical	Property, Violent, Drug, Other
Felony class	Categorical	A, B, C, D

Notes: Each category in the categorical variables is put in the regression as a binary variable and the first category is used as the base. White and Black are non-Hispanic (NH), and Hispanic is in the "Other" category.

Table 21: Duration analysis (recidivism)

	(1) Cox	(2) 2SRI	(3) Cox	(4) 2SRI
Recidivism				
Visitation (Dummy)	0.855*** (0.0135)	0.694** (0.127)		
Visitation (Frequency)			0.911*** (0.00891)	0.868* (0.0669)
Residuals		1.233 (0.227)		1.050 (0.0817)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	33,971	33,971	33,971	33,971

Standard errors in parentheses. \*\*\*  $p < 0.01$ , \*\*  $p < 0.05$ , \*  $p < 0.1$ .

Notes: The estimated hazard ratios are in the table.

Table 22: Duration analysis (first job)

First Job	(1) Cox	(2) 2SRI	(3) Cox	(4) 2SRI
Visitation (Dummy)	1.343*** (0.0230)	2.407*** (0.468)		
Visitation (Frequency)			1.103*** (0.00913)	1.424*** (0.117)
Residuals		0.555*** (0.108)		0.772*** (0.0637)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	32,905	32,905	32,905	32,905

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Notes: The estimated hazard ratios are in the table.

Table 23: Duration analysis (first move)

First Move	(1) Cox	(2) 2SRI	(3) Cox	(4) 2SRI
Visitation (Dummy)	0.844*** (0.0138)	0.922 (0.174)		
Visitation (Frequency)			0.903*** (0.00872)	0.980 (0.0778)
Residuals		0.915 (0.173)		0.921 (0.0738)
Controls	Y	Y	Y	Y
Fixed effects	Y	Y	Y	Y
Observations	31,987	31,987	31,987	31,987

Standard errors in parentheses. \*\*\* p<0.01, \*\* p<0.05, \* p<0.1.

Notes: The estimated hazard ratios are in the table.