Does Distance from Home Matter in Prison? Effects on Visitation and Recidivism

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Abstract

This paper studies how the distance between prison and an individual's home affects their likelihood of recidivism. Leveraging a unique dataset covering more than 20,000 incarcerated individuals and over 200,000 prison visits, I exploit quasi-random variation in home-to-prison distance generated by facility assignment rules. I find that a 100-mile increase in placement distance raises prison readmission within 3 years by 3.5 percent. This effect is driven by a reduction in visitation, with individuals placed farther from home being significantly less likely to receive visits. While social support is theorized to reduce recidivism, there is limited causal evidence on how maintaining these connections during incarceration affects recidivism. To address this, I use distance as an instrument for visitation, and find that visitation lowers the likelihood of re-incarceration by about 8 percentage points within one year and 10 percentage points within three years. Additionally, I show that visitation also shortens the fraction of sentence served by nearly 4 percentage points and reduces housing instability by 16 percentage points, the former consistent with a reduction in misconduct and the latter an important mechanism for successful post-release outcomes. Counterfactual estimates suggest assigning individuals closer to home could reduce recidivism by 2 to 4 percent.

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1 Introduction

The United States incarcerates more people than any other country in North America or Europe with an imprisonment rate of about 530 per 100,000 residents. For comparison, Canada's rate is roughly 85 per 100,000, Germany's is 70 per 100,000, and the United Kingdom's is 130 per 100,000 (Fair & Walmsley, 2024). A large portion of the United States prison population consists of people who have previously been incarcerated: approximately 87 percent of individuals released from prison reoffend within ten years (Carson & Kluckow, 2023). Despite extensive academic and policy efforts to reduce recidivism, empirical evidence on what improves post-release outcomes is mixed.[1] Although existing research spans programming, sentencing policy, and social-policy levers such as welfare and labor-market support, one consequential feature of incarceration—where individuals are housed—has received little empirical attention.

Within a state, departments of correction operate multiple prison facilities, and each incarcerated individual is assigned to serve their sentence in one specific facility. This placement determines the distance between a person's home and the prison, which varies substantially across and within states and may influence post-release outcomes. However, identifying the causal effect of distance on post-release outcomes is challenging. Placement decisions may not be random, and individuals housed closer to home may differ in ways related to recidivism. In addition, comprehensive data linking criminal histories, incarceration spells, home locations, and detailed visitation records are not readily available. In this paper, I assemble a unique dataset that links these features for more than 20,000 incarcerated individuals and over 200,000 visits in Washington State prisons. I leverage plausibly exogenous variation from security and capacity constraints on facility assignment to estimate the causal effect of placement distance on recidivism.

Departments of correction generally have wide discretion in assigning incarcerated individuals to prison facilities. While each state runs its own corrections system and develops its own policies, common practices include an initial period at a reception facility that includes interviews and assessments to determine recidivism risk level, security classification, and ultimately their facility placement. Policies are often explicit about how security levels are assigned, but placement in a particular facility is less transparent. The clearest and most explicit rules tend to govern proximity to home or family. Even then, only a handful of states provide clear guidance: the Federal Bureau of Prisons requires incarcerated individuals to be placed within 500 miles driving distance of the residence (First Step Act, 2019), Arkansas attempts to place parents 250 miles or less from minor children (Code of Arkansas, 2024), Hawaii considers family contact for placement decision (Hawaii Revised Statutes, 2024), and New York requires parents to be placed as close to minor children as

[1] Doleac (2023) provides a comprehensive overview of empirical studies on programs aimed at reducing recidivism.

practically possible (NYDOCCS, 2023). However, even where placement policies exist, implementation is often constrained by security and capacity.

I estimate the causal effect of home-to-prison distance on recidivism using quasi-random variation in placement distance generated by Washington's facility assignment process. Upon admission to prison all individuals undergo an intake process which includes security classification. Individuals are then assigned to a security-appropriate facility subject to capacity constraints. This process does not consider family or proximity to home, and therefore generates plausibly exogenous variation in distance from home. I find that placing someone 100 miles farther from home, approximately 1.3 standard deviations, increases the probability of prison re-admittance by 0.8 percentage points, a 9 percent increase, within one year of release and by 1.1 percentage points, a 4 percent increase, within three years. To contextualize this distance, driving 100 miles in Washington state typically takes 1.5 to 3 hours, depending on location and traffic conditions.

A primary mechanism linking distance to recidivism is in-person visits. Maintaining contact with family and friends during incarceration provides emotional and practical support, and prior research shows that greater distance substantially reduces the likelihood of visits (Casey-Acevedo & Bakken, 2002; Cochran et al., 2016; Duwe & Clark, 2013). I document this pattern in Washington: an additional 100 miles in placement distance reduces the likelihood of receiving any visits by 11 percentage points (a 25 percent reduction from a 44 percent baseline) and decreases the average number of monthly visits by 0.6 (a 60 percent reduction from a baseline of one visit per month).

Research in sociology and criminology consistently highlights the role of social support networks in shaping reentry outcomes. Theories of social and informal control emphasize that strong ties to family, peers, and institutions can deter criminal behavior and promote desistance. More recent evidence shows that incarcerated individuals rely heavily on family and close friends for housing, financial support, and emotional stability during reentry (see Hirschi (1969), Laub and Sampson (1993), La Vigne and Naser (2006), La Vigne et al. (2009)). One of the main ways individuals maintain contact with their non-incarcerated social network while incarcerated is through prison visitation.[2] A large body of correlational research finds that visitation is associated with lower recidivism. For example, a meta-analysis by Mitchell et al. (2016) estimates that visitation reduces recidivism by about 26 percent, and Bales and Mears (2008) report that each additional visit lowers the odds of reoffending by 3.8 percent.[3] However, this literature cannot disentangle whether these effects reflect the causal effect of visitation or the fact that individuals with stronger social ties are

[2]Depending on the jurisdiction incarcerated individuals may also write letters, talk on the phone, and participate in video calls.

[3]Other studies include Cochran (2014), Duwe and Clark (2013), Mears et al. (2012), and Ryan and Yang (2005).

both more likely to receive visits and less likely to reoffend.

Other potential channels through which distance might affect recidivism in Washington are less convincing. Prisons of the same security level offer comparable programming, and I find no evidence that distance is systematically correlated with access to programming, education, or prison jobs. Distance is also not correlated with observable characteristics such as offense type or sentence length once security classification is accounted for. This leaves family and social connections as the most plausible mechanism: greater distance raises the direct costs to family and friends of maintaining contact with an incarcerated loved one. Although individuals can communicate through letters, phone calls, or video visits, these alternatives are also costly.

I estimate the impact of visitation on recidivism by using placement distance as an instrument for visitation. I find that receiving in-person visits from family and friends reduces the probability of being readmitted to prison by almost 8 percentage points within one year, and by 10 percentage points within three years (roughly a 36 percent reduction over three years). The intensity of visitation also matters: each additional visit per month reduces one-year recidivism by 1.4 percentage points and three-year recidivism by 1.9 percentage points. These effects are large relative to other reentry interventions such as housing assistance (18 percent decrease in re-arrest over one year; Palmer et al. (2019)), welfare expansion (10 percent decrease in re-incarceration over one year; Yang (2017)), and diversion programs (50 percent decrease in re-offense over 10 years; Mueller-Smith and Schnepel (2021)).

Beyond recidivism, I also examine the effect of visitation on the fraction of a sentence served as a proxy for disciplinary outcomes. During intake, individuals receive an Earned Release Date reflecting a potential reduction of 10 to 50 percent of their sentence. Earned release time can be revoked for disciplinary infractions or failure to participate in required programming, so fraction of sentence actually served provides a measure of disciplinary behavior in prison. I find that visitation reduces the fraction of a sentence served by nearly four percentage points, which is equivalent to about 43 fewer days at the median sentence length of 578 days. Combining this reduction with the decrease in future re-incarceration, visitation lowers total time served in the five years following sentencing by 141 days. At an estimated cost of \$174.32 per incarcerated individual per day, this translates into approximately \$24,600 in savings per person visited.

To understand how visits improves reentry outcomes, I examine a key mechanism: access to stable housing after release. Stable housing is central to successful reentry, and many individuals leaving prison face housing insecurity. In Washington State, individuals without an approved release address cannot be released at their earned release date. To avoid continued incarceration solely due to lack of housing, the Department of Corrections issues housing vouchers to all eligible individuals. Voucher receipt therefore provides a direct measure of housing instability. I find that incarcerated individuals who receive visits are 16 percentage points less likely to require a voucher. Additionally, address verification for release begins six months prior to release, and I find that receiving visits near the end of a prison spell has the strongest effect on reducing voucher use.

Next, I simulate placement under alternative regimes that prioritize proximity to home and calculate the resulting effects on recidivism. I begin with the population incarcerated as of January 1, 2010 and then assign each individual admitted after this date to their closest facility. First, I do this without constraints and then I impose security level and facility capacity constraints. When placement policies emphasize assigning individuals to facilities closer to home, subject to capacity and security level, the predicted effect is a 0.4 percentage-point reduction in recidivism within one year of release a 0.5 percentage-point reduction in recidivism within three years of release. Relative to the non-treated baseline recidivism rates, these correspond to a 4 and 2 percent reduction.

This project contributes to a large literature on recidivism and interventions aimed at reducing recidivism. Prior work has examined interventions ranging from incarceration itself, such as Bhuller et al. (2020a), who leverage a random judge design in Norway to show that incarceration can reduce future offending, to diversion programs, with Mueller-Smith and Schnepel (2021) documenting large reductions in recidivism. Other studies emphasize interventions within prisons. Alsan et al. (2025) demonstrate that an education program in county jails reduces both misconduct and reoffending, while Lee (2019b) finds that none of the prison programming in Iowa decreased recidivism. Beyond incarceration, studies have shown that improving labor market opportunities can lower reoffending by increasing the outside option to crime (Agan & Makowsky, 2018b), and that DNA databases can significantly reduce recidivism by raising the perceived probability of detection (Doleac, 2017). Evaluations of reentry programs providing wraparound services often report null effects (Cook et al., 2015; D'Amico & Hui, 2018; Doleac, 2019; Grommon et al., 2013; Wiegand & Sussell, 2016), although some evidence suggests that expanding access to welfare programs such as the EITC and food stamps can reduce recidivism (Agan & Makowsky, 2018b; Tuttle, 2019; Yang, 2017). This paper examines prison placement as a policy margin that indirectly shapes reentry outcomes.

This project also contributes to a growing body of economics literature examining the role of familial bonds in shaping criminal justice outcomes, such as the effect of parental criminal justice involvement on children's long-term criminal behavior and well-being (e.g., Arteaga (2023), Dobbie et al. (2018), Finlay et al. (2023), and Norris et al. (2021)) and the relationship between family formation and parents' future criminal activity (Massenkoff & Rose, 2024). Prison visitation is one of the key ways in which families interact with their incarcerated loved ones.

One closely related paper to this project is Lee (2019a), which also uses distance as an instrument for visitation and finds that visitation does not significantly impact the probability an incarcerated individual is re-admitted in Iowa. However, with large standard errors, he is also not able to rule out substantial positive effects. In fact, my point estimates are qualitatively similar to Lee, but with a sample size that is twice as large I am able to provide more precise estimates. Additionally, I am able to demonstrate the importance of visitation for housing stability post-release.

The paper proceeds as follows: Section 2 provides institutional background information on how incarcerated individuals are placed in prisons and how visitation works, Section 3 describes the data, Section 4 details the empirical strategy, Section 5 presents results, and Section 6 discusses the housing mechanism, Section 7 implements alternative placement policies, and Section 8 concludes.

2 Background

Washington State has a population of nearly 8 million, with a demographic profile that is whiter than the nation overall but with a larger share of Asian and multiracial residents, and a mix of urban and rural communities. Its prison population of about 14,000 translates to an imprisonment rate of roughly 180 per 100,000 residents, which is well below the national average and lower than rates in neighboring Oregon, California, and Idaho.

2.1 Facility Placement

The Washington Department of Corrections (WADOC) is responsible for the oversight of all men and women sentenced to state prison and community supervision in the state of Washington. After sentencing, all convicted individuals are transferred to the reception prison facility.[4] The reception center for men is the Washington Corrections Center and the reception center for women is Washington Corrections Center for Women.[5] Incarcerated individuals spend an average of 30 days in the reception center where they undergo an intake process formally called classification. The goal of classification is to determine the incarcerated individual's risk for re-offense, what programming is best suited for them and what if any medical care they

[4]Depending on the violation, some individuals returned to prison for violating conditions of community supervision may not go through the formal reception process.

[5]Reception centers are regular prison facilities that have been designated as a reception center. These prisons can also house incarcerated people for their entire sentence.

require.

As part of the intake process, each individual is assigned a recidivism risk score based on a range of factors, including demographics, current offense and sentence, criminal history, substance use history, and family structure.[6] This type of risk-based classification is not unique to Washington; similar systems are widely used across the country to categorize incarcerated individuals. In Washington, individuals are assigned to one of several risk categories: low risk, moderate risk, high drug risk, high property risk, high violent risk, or high diverse risk (indicating high risk across violent, drug, and property offenses). The classification system is hierarchical: high diverse supersedes high violent, which supersedes high property, which in turn supersedes high drug, moderate, and low. For example, an individual assessed as both high violent and high property will be classified as high violent; someone assessed as both high property and high drug will be classified as high drug.

The risk classification helps determine an incarcerated individual's initial security level, referred to as the Initial Custody Designation in Washington state. Individuals can be designated as "close custody", "medium custody, or "minimum custody."[7] Specific facility placement is then based on this custody classification in combination with the individual's programming needs (including work, education, and treatment, when applicable), as well as health requirements, safety concerns, and institutional capacity. According to Washington Department of Corrections policy, individuals are to be placed in the least restrictive facility that can accommodate both their programming and security needs. Importantly, incarcerated individuals have no input in their placement, and placement decisions are not subject to appeal.

As program availability is an explicit input to placement, it is useful to consider how programming varies across facilities. All facilities offer core services—basic education/GED, sobriety support (e.g., AA), and prison employment. Each facility also runs an animal-training program. Beyond these basics, offerings differ: some prisons provide vocational programs (e.g., construction trades, vehicle maintenance) or sustainability initiatives, and work opportunities vary (e.g., metal shop versus upholstery). These differences are largely stable over my study window; accordingly, facility fixed effects in the regressions absorb time-invariant programming differences across prisons.

The initial placement facility is the facility in which an incarcerated individual will serve either their

[6] This score is generated using the Washington Offender Needs Evaluation tool, which applies a weighted point system to produce an objective assessment of felony re-offense risk.

[7] One subset of minimum custody is MI3 custody, which requires individuals to be placed in the same type of facility as medium custody individuals, and so I classify these individuals as medium custody as well. Individuals placed directly into community supervision are those serving less than 1 year and are designated as MI1 custody. WADOC also operates maximum security housing, which is a higher security designation than close custody. However, this is not one of the Initial Custody Designations but is assigned based on behavior while incarcerated.

entire sentence or the majority of their sentence. In my data fifty-six percent of incarcerated individuals are released from the same facility they are initially placed in. Incarcerated individuals generally re-do the risk assessment questionnaire every six months to determine if there are changes to their security classification or programming needs. If an incarcerated individuals security level has been downgraded based on program participation, lack of infractions and time served they may be transferred to a lower security facility if capacity allows. Alternatively, an incarcerated individual can be moved to a higher security facility due to disciplinary infractions. Incarcerated individuals may also request transfers, which are considered conditional on security classification and capacity constraints.[8] All transfers can be impacted by prisoner behavior or preferences, and so I solely focus on initial placement facility in this paper.

Between 2010 and 2019 Washington state had ten facilities for men and two for women.[9] Seven of the ten male facilities in Washington state house incarcerated individuals of various custody levels, while three house only minimum security incarcerated individuals. There are five facilities that can house maximum security incarcerated individuals, seven for medium security and eight for minimum. Both women's facilities house minimum custody incarcerated individuals and one additionally houses incarcerated individuals with higher level custody classifications. A map of the current prison facilities is provided in Figure 1.

[8] Of those who do not stay in their placement facility 44 percent are released from a work release facility or reentry center (both are minimum level facilities meant to help incarcerated individuals at the end of their sentences), 32 percent are released from a facility further from home (can include work release facilities), and 65 percent are released from a facility closer to home (can include work release facilities).

[9] There was one facility that closed over this time period. I exclude this facility and anyone placed in it from all analysis.

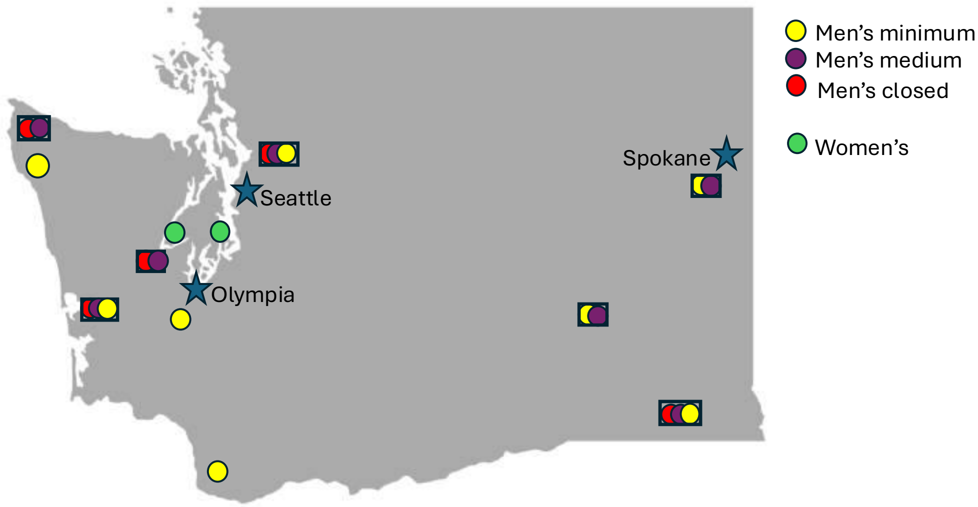

Figure 1: Washington State Prisons

Note: This figure plots the location of all state prison facilities. Locations are based on Washington Department of Corrections facility addresses. Yellow dots denote men's minimum security facilities. Purple dots denote men's medium security facilities. Red dots denote men's close security facilities. Green dots denote women's facilities. Some facilities house multiple security levels. Boxes with multiple colored dots indicate a prison facility that houses multiple security levels. Blue stars denote the three largest cities: Seattle, Olympia and Spokane. These are the three largest population centers in Washington.

As indicated by Figure 1, facilities are spread across the state resulting in substantial variation in home-to-facility distances across incarcerated individuals. Figure 2 illustrates the distribution of incarcerated individual placement distances. The left panel presents a density plot of placement distances, showing that incarcerated individuals are housed between zero and three-hundred miles from home, with a median distance of ninety-nine miles. The right panel ranks prison facilities from closest to farthest for each incarcerated individual with in security level. There are 4 close security level facilities, 7 medium security level facilities, and 6 minimum security level facilities. Each incarcerated individual receives a ranking from one (closest) to four, six or seven (farthest) based on their security level and assigned facility. For example, if a minimum security individual is placed in the 3rd furthest facility from their home county they would be in the 3rd bucket for minimum security. The plot shows that approximately 36 percent of minimum security incarcerated individuals are placed in their closest facility, and 25 percent of medium and close. Almost 8 percent of minimum and medium security level individuals are assigned to the farthest one, and almost 35 percent of maximum security.

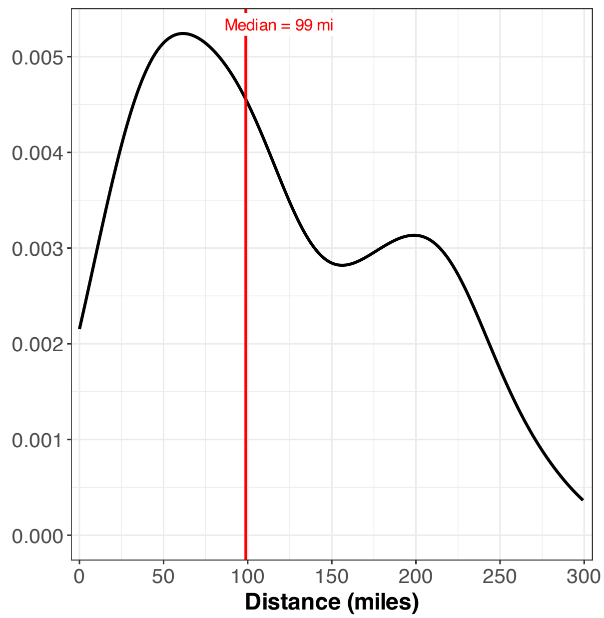

Figure 2: Distance Distribution

Note: This figure presents the distribution of placement distances for individuals incarcerated in Washington state from 2010 through 2016. The left panel plots the density of placement distance measured in miles from home county to prison facility. The red line shows the median placement distance of 99 miles. The right panel plots histograms of placements by the distance rank of the placement facility, within security level. A minimum security individual has 6 possible facilities, each given a rank of 1 to 6 based on its distance from the individual's home county. A medium security individual has 7 possible facilities, each given a rank of 1 to 7 based on its distance from the individual's home county. A close security individual has 4 possible facilities, each given a rank of 1 to 4 based on its distance from the individual's home county. Data comes from Washington Department of Corrections admissions data which includes each individual's home county and placement facility.

2.2 Visitation

Across the United States, including in Washington, visitation by family and friends is considered a privilege rather than a guaranteed right.[10] However, all prison facilities in the state permit some form of visitation, including in-person contact visits, non-contact visits, video visits, and overnight family visits. This aligns with the practice of most other states—Washington falls within the majority of states that Boudin et al. (2013) characterize as promoting visitation in official policy. Across jurisdictions, in-person contact visits are the primary mode of visitation, and Washington follows this pattern, with approximately ninety-nine percent of visits being in-person contact visits.[11] This paper focuses specifically on in-person contact visits.[12]

There are two main categories of visitors: professionals (such as legal teams and clergy) and family and

[10] Attorney visits are legally protected.

[11] Contact visits allow for brief physical contact at the beginning and end of visits and are generally held in a communal visitation room. Non-contact visits forbid any form of contact and may be held in rooms where visitors are separated from incarcerated individuals by glass or another physical barrier.

[12] Overnight visits are extremely rare with only 4 states allowing them. Video visitation is becoming more common but still puts Washington in the minority.

friends. This paper specifically examines visits by family and friends and abstracts from the effect of professional visitation. By law, all incarcerated individuals nationwide are guaranteed the right to legal visits and so this is not the policy relevant channel. In Washington, each facility sets its own visiting hours and guidelines, which are posted on their respective websites. Closures are also posted on the website. Generally, in-person visits are permitted on Friday, Saturday, Sunday and Monday in the afternoons and evenings. For example, visiting hours for the Minimum Security Unit at the Monroe Correctional Complex, the largest prison in Washington, are Fridays and Mondays from 1pm to 5:30pm and 6pm-8:30pm and Saturdays and Sundays from 1pm-8:30pm. Visits operate on a first-come, first-served basis, and entry may be denied if the visitation room reaches capacity.[13]

To participate in visitation, individuals must submit a visitor application, undergo a review process by the Department of Corrections, and receive approval from both the department and the incarcerated person. The review process includes identity verification and a criminal history background check. While a criminal record does not automatically disqualify someone from visiting, certain individuals, such as victims of the incarcerated person's crimes, co-conspirators, and those currently on community supervision with restrictions on interacting with known criminals, are generally denied visitation. Visitors may only be on one incarcerated individual's approved visitor list at a time unless they have multiple immediate family members who are incarcerated. Minors are permitted to visit but must be accompanied by a non-incarcerated legal guardian or designated escort. At the time of their visit, all visitors must have a current photograph on file, present valid photo identification, and be on the incarcerated individual's approved visitor list.

The Washington DOC provides limited travel assistance for visitors who live more than 150 miles away, reimbursing up to $50 for gas or lodging no more than twice a month. To qualify, visitors must apply at least 10 days in advance, submit receipts after the visit, and then wait for reimbursement, which is only issued once a month on the 10th. At 2010 gas prices ($2.90 per gallon), driving 300 miles round trip would require about 12 gallons of fuel, or roughly $70, which already exceeds the maximum reimbursement, and that does not include potential overnight lodging. Because the support comes in the form of reimbursement rather than upfront assistance, many families may lack the resources to cover these costs in advance. Moreover, with the median incarcerated individual placed 99 miles from home, most visitors are not even be eligible for this program.

[13] Visits are only recorded if they are completed. There is no record if someone showed up for visitation but was denied access or capacity was reached.

3 Data

The data for this project come from Washington Department of Corrections records and include every prisoner admitted on or after January 1, 2010 and released as of December 31, 2016.[14] Each observation is at the prisoner-spell level as some prisoners can exit and re-enter prison more than once in this time period. Most people appear only once, but 12 percent of individuals do appear more than once in my data. Data includes date of entry, date of release, sentence length, crimes committed, race, gender, date of birth, county of sentence, number of previous prison admits and those associated crimes, initial prison facility assignment, the prison facility released from, whether the individual is released into community supervision, the address a person moves to when released, the name of the person responsible for the incarcerated individual's post-release housing and whether the individual is re-admitted to prison within three years of release.

The outcome of interest is readmission to prison for a new criminal offense. The data on prison admissions for community supervision violations do not allow for a clear distinction between technical violations and new criminal conduct, as new crimes may be recorded as violations, and the type of readmission is inconsistently classified[15]. To address this ambiguity, I define recidivism as readmission to prison accompanied by a new sentence, which provides a cleaner and more consistent measure. The one year recidivism rate is 10 percent and the three year recidivism rate is 28 percent putting Washington state below the national average of around 37 percent (Gelb & Velazquez, 2018). The data additionally includes all visits the prisoner received during their prison spell. This includes information on the date of the visit as well as the relationship of the visitor, the visitor's age, and the visitor's home county.

The primary sample consists of only men with a non-missing home ZIP code in Washington state who's placement facility was a standard facility (not a medical center or work release facility) as their initial placement.[16] Visits are limited to only those from family or friends whose home county is within Washington state. Table 1 presents summary statistics on the study sample. The data covers more than 24,000 unique spells in prison with an average incarcerated individual spending 11 months incarcerated. Just under half of the sample ever receives a visit. The restriction to men is due to their only being two women's facilities and only one of those facilities houses anyone above minimum custody. The restriction to incarcerated individuals and visitors from within Washington state because I can only observe individuals who are re-admitted to

[14]Given that the data spans from 2010 to 2016, the maximum sentence an individual in this sample can serve is 6 years, thereby excluding anyone with a longer sentence or a life sentence. However, at most 1 percent of individuals admitted per year are sentenced to life and only between 1-7 percent of individuals are sentenced to longer than 6 years, meaning that this restriction is not particularly consequential.

[15]Violators can be sent to specific violator facilities, or to prison for up to 3 week sanctions, or can be re-confined to prison depending on context and so are not always captured accurately in the prison admission data.

[16]I drop Garfield and Wahkiakum counties due to extremely small sample size.

prison within Washington state. Importantly, if someone is incarcerated in another state after their release in Washington they will be classified as a non-recidivist in my data. One factor that eases this concern is that approximately 70 percent of the individuals in my sample are released under community supervision, which mandates release to an approved address within the sentencing county. This requirement reduces the likelihood that the majority of individuals will move out of state, at least during the first year after release. Additionally, Harding et al. (2013) found that only 1.2 percent of prisoners from Michigan had an out-of-state address 2 years post-release, which suggests that formerly incarcerated individuals may not move out-of-state very often.

Table 1: Main Sample Descriptive Statistics

	Overall	Never Visited	Visited
N Incarceration Spells	24,338	13,563	10,775
N Incarcerated Individuals	21,389	12,090	10,113
% First admit	0.52	0.49	0.55
Median time served (days)	329	270	423
Median sentence length (days)	578	517	669
% Property crime	0.34	0.34	0.33
% Drug offense	0.25	0.26	0.25
% Violent offense	0.17	0.13	0.22
% Sex offense	0.05	0.04	0.06
% White	0.62	0.59	0.67
% Black	0.15	0.17	0.13
% Hispanic	0.13	0.14	0.12
% Native American	0.05	0.06	0.04
% Asian	0.03	0.04	0.03
Mean Age at admit	33.5	35.06	31.52
% Visited	0.44	0.00	1.00
Mean No. visits per month	0.91	0.00	2.05
Median placement distance (miles)	98.65	111.94	86.37
% Readmitted within 1 year	0.09	0.10	0.07
% Readmitted within 3 years	0.26	0.28	0.22

Notes: This table presents summary statistics for all men incarcerated in Washington state prisons admitted on or after January 1, 2010 and released by December 31, 2016. Data is at the prison spell level. Incarcerated individuals are categorized as "visited" if they received one or more visits during the given spell. Offense types are not mutually exclusive and are binary indicators for if any of the crimes associated with the current spell fall in the given category. Crime category definitions are taken from the Revised Code of Washington. Distance is calculated as the Euclidean distance from the geographic centroid of a prisoner's home ZIP code to the geographic centroid of their placement facility's ZIP code. Data comes from Washington Department of Corrections records and statistics are calculated by the author.

The visitation sample covers over 200,000 visits and about 23,000 unique visitors. Table 2 presents descriptive statistics on visitation in Washington. The plurality of visits are from parents, and this is predominantly by mothers. Friends are the next most frequent visitor. It is important to note that "friend" could encompass a life partner and/or co-parent – so long as they are not married they are coded as "friend". For this reason, I define "partner" as a visitor who is of the opposite sex as the incarcerated individual and is within a 5 year age-range of the incarcerated individual. The vast majority of friend visitors fall into this category. I next investigate which incarcerated individual characteristics are associated with receiving visitation. Table 3 presents the results of regressing a binary indicator for visitation on each indicated characteristic separately. White incarcerated individuals, violent offenders, sex offenders, older admits and those sentenced to longer sentences are more likely to receive visits.

Table 2: Visit Descriptive Statistics

N visits	207,501
N visitors	23,058
% of visited incarcerated individuals who get one visit	0.09
% of visitors who visit once	0.28
Mean days between visits for incarcerated individual	17.65
Mean days between visits for visitor	49.84
<u>% of visits by visitor relationship</u>	
% Parent	0.35
% Mom	0.25
% Friend	0.31
% Partner	0.25
% Child	0.08
% Spouse	0.07

Notes: This table presents summary statistics for all prison visits by family and friends for men incarcerated in Washington state prisons admitted on or after January 1, 2010 and released by December 31, 2016. Visitors can only visit Friday-Monday, so days between visits includes the fact visitors cannot visit for 5 days. "Mom" is a sub-category of "parent" - 70% of parent visits are by a mom. "Partner" is a sub-category of"friend" - 80% of friend visits are by a partner. Partner is defined as a visitor of the opposite sex within a 5-year age range of the incarcerated individual. Data comes from Washington Department of Corrections visitation records and statistics are calculated by the author.

In addition to my primary sample, I utilize supplementary risk assessment data available for all individuals incarcerated in 2018 or later.[17] This dataset includes each person's overall risk score, subcomponent scores for violent, drug, and property-related offenses, as well as responses to all underlying assessment items. These

[17]WADOC switched to a new risk assessment tool, the Washington Offender Needs Evaluation Tool, in 2018 and this is the data that was readily available.

items cover domains such as family structure, peer associations, physical and mental health, substance use history, prior labor market attachment, program participation, and attitudinal measures. Although this dataset does not overlap with my main analytic sample, I use it to validate my empirical strategy and provide descriptive evidence on the relationship between individual characteristics and prison placement. Summary statistics for this supplementary sample can be found in Appendix Table A16.

Who Receives Visits?

I begin by examining which individuals are more likely to be visited under current placement practices. To identify which characteristics are associated with visitation, I estimate a series of OLS regressions. In each specification, the dependent variable is an indicator for receiving any visit, and the right-hand side includes a single observable characteristic with fixed effects for admit year, home county and placement facility. Individuals convicted of violent or sex offenses typically receive longer sentences, so their higher visitation rates may partly reflect the mechanical relationship between sentence length and the likelihood of receiving visits. To disentangle this effect I then re-estimate these regressions adding sentence length as a control.

Results are presented in Table 3. Columns (1) and (2) are the results for a binary indicator for visitation and Columns (3) and (4) are the results for visit count within the visited sample. Columns (2) and (4) add sentence length as a control.

Visitation is most common among individuals convicted of violent and sex offenses, those serving longer sentences, and younger individuals. Within the visited population, people convicted of violent or sex offenses and younger individuals also receive more visits per month, while property offenders, drug offenders, and recidivists tend to receive fewer. Interestingly, despite being more likely to receive visits, those with longer sentence lengths are actually receive fewer visits per month.

Once sentence length is included as a control, the selection patterns remain largely unchanged, indicating that the associations between these characteristics and visitation are not solely driven by the mechanical effect of sentence length elongated the potential treatment period.

Table 3: Selection into Visitation

	Visit Received		Visit Count (per Month)	
	(1)	(2)	(3)	(4)
Non-white	-0.072***	-0.0718***	0.2109**	0.2127***
	(0.007)	(0.0069)	(0.072)	(0.0721)
Violent crime	0.1691***	0.1519***	0.9626***	0.978***
	(0.0095)	(0.0094)	(0.1053)	(0.1053)
Property crime	0.0313***	0.0233***	-0.2968***	-0.2921***
	(0.0064)	(0.0064)	(0.06)	(0.0599)
Drug crime	-0.0125*	-0.0031	-0.1118*	-0.1168*
	(0.0073)	(0.0072)	(0.0649)	(0.0648)
Sex crime	0.0658***	0.033**	0.503**	0.5277***
	(0.0145)	(0.0146)	(0.1853)	(0.187)
Recidivist	-0.1205***	-0.1189***	-0.8683***	-0.8666***
	(0.0069)	(0.0068)	(0.0635)	(0.0634)
Age at admit	-0.0079***	-0.0082***	-0.0156***	-0.0152***
	(0.0000)	(0.0000)	(0.003)	(0.003)
Sentence length	0.0053***		-0.0039**	
	(0.0000)		(0.0018)	
Sentence Length Control		X		X
Sample	Full	Full	Visited	Visited
Observations	24,338	24,338	10,775	10,775

Notes: *p<0.1, **p<0.05, ***p<0.01. This table shows patterns of selection into visitation across observable characteristics. Each cell shows the coefficient from a separate regression with standard errors clustered at the individual level in parentheses. Columns 1 and 3 omit sentence length as a control, while Columns 2 and 4 include it (except when sentence length is the predictor). Fixed effects for admit year, placement facility, and home county are included in all models. The dependent variable in Columns 1–2 is an indicator for any visit. Columns 3–4 are restricted to those who received at least one visit. The dependent variable is the number of visits per month served. Non-white, violent crime, property crime, drug crime, sex crime and recidivist are all binary indicators for said characteristic. Age is measured in years. Sentence length is measured in months. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code. Underlying data comes from merged Washington Department of Corrections admissions and visitation records.

4 Empirical Strategy

This section outlines my empirical strategy for identifying the causal effects of both prison distance and visitation on recidivism. I begin by outlining my research design to estimate the causal effect of prison distance on recidivism. I then examine visitation as the core mechanism linking distance to recidivism, and use distance as an instrument for visitation to estimate the causal effect of visitation on recidivism.

4.1 The Effect of Distance on Recidivism

To estimate the effect of distance on recidivism, I estimate the following equation:

$$R_{is} = \beta_1 Dist_{is} + W_{is}'\beta_2 + \lambda_{t(is)} + \delta_{f(is)} + \theta_{h(is)} + \epsilon_{is} \quad (1)$$

where R_{is} is the recidivism outcome for individual i serving spell s. Recidivism is measured as both a binary indicator for re-admit within 1 year of release and within 3 years of release. $Dist_{is}$ is the placement distance from home. Distance is calculated as the Euclidean distance from the geographic centroid of an incarcerated individual i's home ZIP code to the geographic centroid of the ZIP code of their placement facility in spell s.[18] Distance is in 100-mile units. W consists of controls for race, an indicator for whether this is individual i's first spell in prison, the class of worst crime committed for spell s,[19] sentence length for spell s individual i's age at admit for spell s, and an indicator for whether the sentence comes with mandatory time under community supervision after release[20]. $\lambda_{t(is)}$ are admit year fixed effects, $\delta_{f(is)}$ are placement facility fixed effects, and $\theta_{h(is)}$ are home county fixed effects. Standard errors are clustered at the individual level since some individuals serve more than one spell in my data and I want to allow for within-individual correlation.[21]

Let $R_{is}(z)$ be the potential outcome for individual i serving spell s when placed at distance z. Let C_{is} collect the variables necessary for exogeneity: sentence length, prior admit history, and facility and county fixed effects. The remaining elements of W_{is} are included to improve precision. The identifying assumption is:

$$\left\{ R_{is}(z) : z \in [0, z_{max}] \right\} \perp Dist_{is} \mid C_{is}.$$

In words this means that conditional on security level, home county, and placement facility, distance is independent of potential recidivism outcomes. Identifying variation comes from the fact that, even within a given security level and county, not all individuals are sent to the same facility, and within a given facility there are individuals from multiple counties.

In Washington, facility assignment is determined primarily by security classification, not by individual

[18] Another option would be to use drive-time rather than Euclidean distance. However, drive-time and distance are highly correlated as shown in Appendix Figure A1.

[19] Crimes are classified as violent, sexual, property, drug or other.

[20] Sentence length is used rather than time served because time served can be impacted by incarcerated individual behavior while incarcerated which could be impacted by treatment (visitation). If an individual is released prior to their sentence end due to Earned Release Time, they will also be placed into community supervision. This indicator is for whether or not the initial sentence included mandatory time under community supervision if the full sentence is served.

[21] Versions with clustering at the ZIP code level and county level to allow for within-geography and within-jurisdiction correlation are shown in Appendix Table A5, Table A6 and Table A7.

preference or other individual characteristics. Therefore, conditional on security level, this process induces plausibly exogenous variation in distance from home. Although initial placement is exogenous, transfers may be influenced by incarcerated individual behavior. To avoid this source of endogeneity, I measure distance using the initial placement facility.

While I do not directly observe security level in the data, I demonstrate that combinations of observable prior incarceration history and sentence length create a reliable proxy. Based on these, I classify individuals as "minimum," "medium," or "close" security. Although many facilities house incarcerated individuals across multiple security levels, some facilities are designated for only minimum-security individuals, while others do not accommodate those above medium security, as illustrated in Figure 1. If the constructed security classification is valid, individuals labeled as "close" should be effectively excluded from minimum-security-only facilities, and those labeled "minimum" should be excluded from higher-security prisons. To assess this, I estimate a multinomial logit model with placement facility as the outcome and assigned security level as the predictor. I then examine the average predicted probability of assignment to each facility by security level. The results show that individuals assigned to "close" security have less than a 1 percent predicted probability of assignment to any of the three minimum-security-only facilities (Olympic Corrections Center, Larch Corrections Center, Cedar Creek Corrections Center). Likewise, those classified as "minimum" have predicted probabilities of 5 percent or less of being assigned to the two facilities that do not house minimum-security incarcerated individuals (Washington Corrections Center, Clallam Bay Corrections Center)[22]. While exceptions exist due to individual-specific considerations (e.g., gang affiliation, safety concerns, medical needs), the classification scheme performs well overall. Figure A3 in the Appendix presents these results.

One concern may be the placement of prison facilities in relation to large population centers. Nearly half of Washington state's population lives in the Seattle-Tacoma Metropolitan area and so placement distance could be reflecting how far someone is placed from a population center. This would be problematic if we think that it is not distance from an incarcerated individual's home that matters, but distance from a population center for matters. For instance, it is possible that the farther a prison facility is from a population center, the harder it is to staff and therefore, it may be that prisons farther from population centers have worse staff and produce worse outcomes. To address this concern I include facility and home county fixed effects in all specifications. This means that the exogenous variation in distance exploited is the two-way variation from both home county and facility. This is feasible because not all incarcerated individuals from a given home county are placed in the same facility, and not all incarcerated individuals in a given facility

[22]While Coyote Ridge Corrections Center does not house close security individuals, it does house long-term minimum security level individuals. This can be individuals with long sentences for violent offense but who are not classified as needing restrictive housing.

are from the same county.

After residualizing distance with respect to security level, home county, and placement facility, an incarcerated individual's pre-determined characteristics should not systematically predict how far they are placed from home. To assess this, I regress distance (measured in one-mile units) on the individual's race and on each of three crime-type indicators in four separate regressions, including controls for security level, admit history, home county, and placement facility. I additionally test whether the type of programming an individual participates in while in prison can be predicted by distance. Specifically, I test whether distance is correlated with participation in parenting classes, any educational class (GED-prep, college courses, college readiness, HS level classes, ESL), being in a work crew (fire fighting for the Department of Natural Resources), having a prison job, participating in special reentry planning classes, or being in an undisclosed course. Undisclosed courses include prescribed mental health and substance abuse programming. Results are shown in Table 4. Crime type, race, age and programming cannot predict how far an incarcerated individual will be placed from home.[23]

As previously mentioned, when explicit placement policies exist, they are related to the placement of families. Although WADOC policy does not formally account for family ties or proximity in placement decisions, such considerations could still influence actual placements. If individuals with children or close families are placed closer to home, the impact of distance may be conflated with the influence of an underlying social support network. I use supplementary risk score data available for individuals incarcerated between 2018 and 2020 to test whether indicators of family connections, including having children, being married or in a long-term relationship, and reporting good relationships with family, are correlated with placement distance. While the main sample covers 2010 through 2016, placement policies did not change from this period through 2020, so this supplementary data reflects the same assignment process as in my main sample. I find no evidence of such correlations between positive family relationships and placement distance. Results are presented in the "Family and Risk" section of Table 4.[24].

[23]Reentry planning is correlated with distance but in the opposite direction of concern.
[24]Full balance results for the supplementary sample can be found in Appendix Table A17.

Table 4: Balance on Distance to Initial Placement

	Coefficient
Demographics (main sample)	
Non-white	-0.7578
	(0.8708)
Violent crime	-2.4832
	(1.4055)
Property crime	-0.8260
	(0.9354)
Age at admit	0.0415
	(0.0393)
Programming Participation (main sample)	
Parenting program	0.0011
	(0.0010)
Education	0.0002
	(0.0009)
Work crew	0.0003
	(0.0014)
Prison job	0.0057
	(0.0039)
Reentry planning	0.0025*
	(0.0010)
Undisclosed	-0.0080
	(0.0041)
Family and Risk (supplementary sample)	
Long-term partner	-2.003
	(6.3508)
Children	4.550
	(6.295)
Good family relationship	4.478
	(6.866)
Low-risk	-8.620
	(7.038)
Moderate-risk	-7.910
	(9.932)
High-risk	10.037
	(6.300)
Observations (main sample)	24,338
Observations (supplementary sample)	590

Note: ***: 0.01, **: 0.05, *: 0.1. This table presents correlations between distance and observable characteristics, prison program participation, family relationships, and DOC-calculated recidivism risk. Each row is a separate regression of distance (in 1-mile units) on the given pre-determined characteristic or programming indicator, controlling for sentence length and first admit status, with fixed effects for admit year, placement facility, and home county. Standard errors clustered at the individual level are in parentheses. Demographics and programming regressions are estimated using the main sample. Family and Risk regressions are estimated using the supplementary sample of individuals incarcerated between 2018–2020 with intake records. Risk is WADOC's recidivism classification, calculated at intake. High-risk combines individuals classified by WADOC as high risk of drug crime re-offense, high risk of property crime re-offense, and high risk of violent crime re-offense. No controls or fixed effects are included for Family and Risk. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

4.2 The Effect of Visitation on Recidivism

Next, I analyze visitation as the primary mechanism through which placement distance impacts recidivism. Visitation requires time, travel, and resources, individuals placed farther from home may be less likely to receive visits or may receive them less frequently, (see, e.g., Casey-Acevedo and Bakken (2002); Duwe and Clark (2017); Cochran et al. (2016); Lee (2019a)). Ex ante, it is not obvious whether visitation improves or worsens reentry outcomes. Some visitors may offer emotional support, stability, or tangible resources that facilitate reintegration. Others, however, may reinforce harmful behaviors, relationships, or stressors. As such, the effect of visitation on recidivism is ultimately an empirical question.

To estimate the effect of visitation on recidivism, I employ an instrumental variables framework with distance as an instrument for visitation and estimate the following set of equations:

$$R_{is} = \gamma_1 V_{is} + W'_{is}\gamma_2 + \lambda_{t(is)} + \delta_{f(is)} + \theta_{h(is)} + e_{is} \tag{2}$$

$$V_{is} = \alpha_1 Dist_{is} + W'_{is}\alpha_2 + \lambda_{t(is)} + \delta_{f(is)} + \theta_{h(is)} + u_{is} \tag{3}$$

where R_{is} is the recidivism outcome for individual i serving prison spell s. Recidivism is measured as either a binary indicator for re-admit within 1 year of release and within 3 years of release. V_{is} is visits for individual i serving prison spell s and is measured as either a binary indicator for whether incarcerated individual i received any visits in spell s or as the count of visits incarcerated individual i received in spell s normalized by the number of months served in spell s. $Dist_{is}$ is the distance from home to prison. W consists of race, an indicator for whether this is individual i's first spell in prison, the class of worst crime committed for spell s,[25] sentence length for spell s individual i's age at admit for spell s, and an indicator for whether the sentence comes with mandatory time under community supervision after release. $\lambda_{t(is)}$ are admit year fixed effects, $\delta_{f(is)}$ are placement facility fixed effects, and $\theta_{h(is)}$ are home county fixed effects. Standard errors are clustered at the individual level.

Let $R_{is}(v)$ be the potential outcome for individual i serving spell s who receives v visitation (either binary or count of visits). Let C_{is} collect the variables necessary for exogeneity: sentence length, prior admit history, and facility and county fixed effects. Interpretation of the estimated effect $\hat{\gamma_1}$ as the causal effect of visitation on recidivism, requires the following assumptions:

1. Relevance (First stage):
   $\mathbb{E}\big[\, V_{is} \mid Dist_{is} = z_1,\, C_{is} \big] \;<\; \mathbb{E}\big[\, V_{is} \mid Dist_{is} = z_0,\, C_{is})\big] \quad \text{for } z_1 > z_0.$

[25] Crimes are classified as violent, sexual, property drug or other.

2. Exogeneity and Exclusion:
$\left\{ R_{is}(v) : v \in [0, v_{max}] \right\} \perp Dist_{is} \mid C_{is}$. (count V)

$\left\{ R_{is}(0), R_{is}(1) \right\} \perp Z = Dist_{is} \mid C_{is}$. (binary V)

Relevance requires that distance shifts visitation, and in this setting, distance weakly reduces the likelihood and intensity of visits. Exogeneity requires that, conditional on security level, placement facility, and home county, distance is independent of potential recidivism. Exclusion means that distance influences recidivism only through its effect on visitation. Modeling visitation as a binary indicator implies that the effect of visits is the same when receiving only one visit as when receiving multiple visits. However, modeling visitation as the count of visits allows distance to affect recidivism through the intensity of visits. I estimate both specifications to assess whether distance matters by impacting access to any visit (extensive margin) or by impacting visit frequency (intensive margin).

For distance from prison to an incarcerated individual's home to be a relevant instrument for visitation, the distance from an incarcerated individual's home must influence the distance that the incarcerated individual's potential visitors need to travel. This implies that an incarcerated individual's potential visitor pool must reside near their home. As reported by the New York Times (Bui & Miller, 2015), the average American only lives about 18 miles from their mother, and those who do live further are often highly educated and wealthy, characteristics that do not often define the population of people who end up incarcerated. Individuals who are incarcerated often have limited work history and make well below the average income even prior to incarceration (Looney & Turner, 2018). Therefore, home county is likely a valid proxy for the location of an individual's pool of potential visitors. Furthermore, Table 6 and Figure 3 show that the distance from an incarcerated individual's home to their first facility is highly correlated with whether they receive any visits and with how many visits they receive.

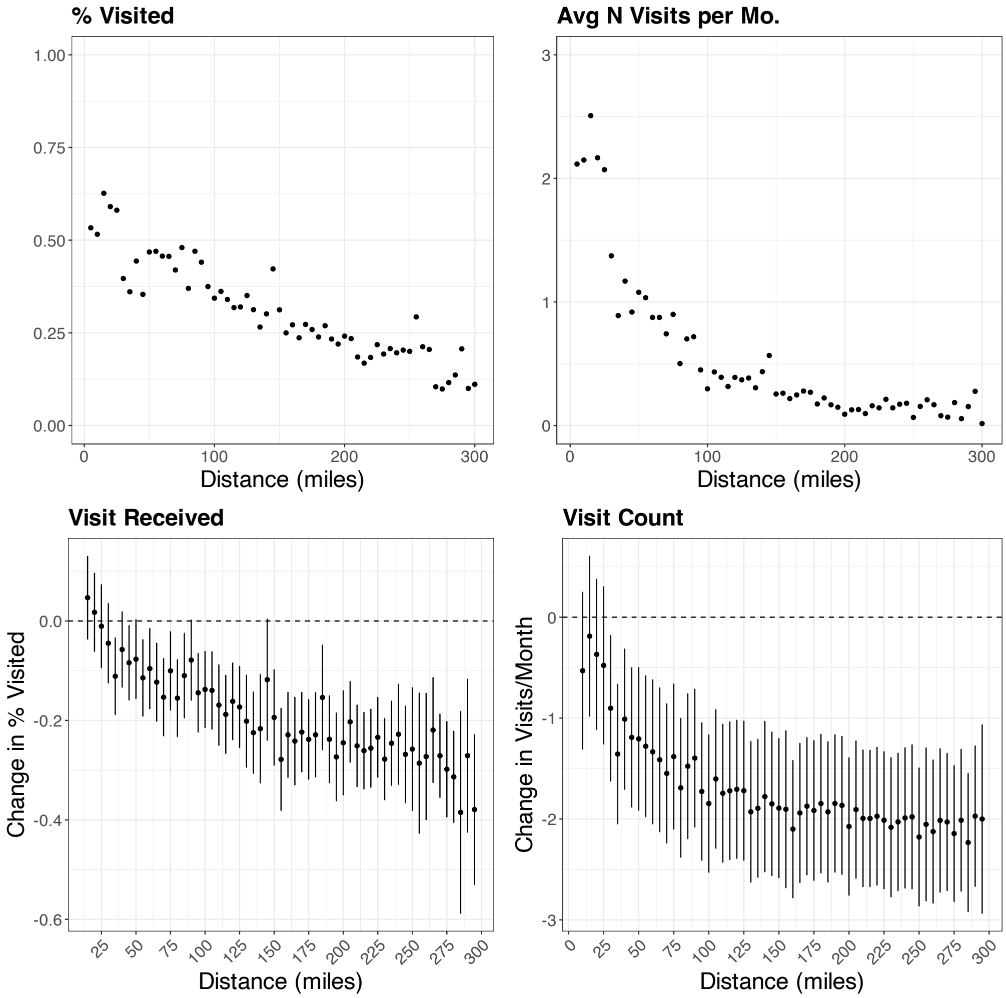

Figure 3: First Stage

Note: This figure illustrates the relationship between distance and visitation rates. In the left panel, visits are normalized by number of months spent in prison. Distance is calculated from each incarcerated individual's home county to their original placement facility. The right panel plots the rate of visitation. Averages are taken over 5-mile buckets. The top two figures plot the raw data, the bottom two figures present the residualized first stage - coefficients from the regression of visitation on dummies for 5-mile distance buckets and covariates. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

The other key requirement for using distance as an instrument is that (conditional on security level, home county, and placement facility) placement distance must be as-good-as-randomly assigned. A specific concern is that social support could confound the effect of visitation, since individuals with stronger family ties may be more likely to receive visits and also less likely to reoffend. Exogeneity would also fail if distance is correlated with predetermined individual characteristics or with prison programming because both can impact recidivism. The same issues were discussed in Section 4.1 when estimating the effect of distance of recidivism. The balance test reported there (Table 4) shows that demographics, crime type, participation in prison programs, and indicators of social support are not systematically related to placement distance, supporting the exogeneity of the instrument in this framework as well.

Exclusion then requires distance only influences recidivism through its impact on visitation. Distance could be correlated with the facility's environment, in the sense that individuals placed farther from home may be more likely to be housed in rural prisons since the modal individual lives in the Seattle metropolitan area. This could theoretically influence incarcerated individuals through the prison's surrounding community. However, incarcerated individuals do not leave their facility during their sentence, and so the surrounding community should not directly influence them. Moreover, incarcerated individuals are released back to their sentencing county, so neither prison location nor distance affects where individuals reenter society.

While the external environment is unlikely to matter directly, the facility's geographic location could still influence the quality of incarceration, particularly through staffing or programming. If prisons draw staff from the surrounding area, geographic variation in local labor markets could shape the quality of staff or available services. To address this, I include fixed effects for both the placement facility and the incarcerated individual's home county in all specifications.[26]

5 Results

5.1 The Effect of Distance on Recidivism

I begin by estimating the effect of distance from home on recidivism. Table 5 presents the results. Columns (1) and (4) present specifications without any controls or fixed effects, Columns (2) and (5) add fixed effects, and Columns (3) and (6) include the full set of controls and fixed effects. Given the previously demonstrated lack of systematic relationship between distance and pre-determined characteristics, it is both expected and reassuring that the estimates remain largely unchanged with the inclusion of controls. A 100-mile increase in the distance between an individual's home county and their assigned facility is associated with a 0.8 percentage point increase in the likelihood of being readmitted to prison within one year of release, and a 1.1 percentage point increase within three years. These results suggest that being incarcerated farther from home has a statistically significant and negative impact on reentry outcomes. Compared with recidivism rates of 9 percent within one year and 26 percent within three years for individuals placed more than 99 miles from home (the median placement distance), these estimates correspond to increases of roughly 9 percent

[26] I also estimate a version where I exclude King, Pierce and Snohomish counties, the counties that encompass the Seattle-Tacoma Metropolitan area. Effects are consistent with the main results. See Appendix Table A11.

and 4 percent, respectively.

For context, Palmer et al. (2019) finds that emergency housing assistance reduces re-arrest within one year by 18 percent, while Yang (2017) shows that expanded eligibility for welfare and food stamps lowers one-year reincarceration rates by 10 percent. Mueller-Smith and Schnepel (2021) reports that diverting first-time offenders from prison reduces reoffending by 50 percent over ten years. The effect of being incarcerated farther from home is smaller in magnitude to these post-release interventions, but instead, reflects a consequence of existing placement practices rather than implementation of a new policy.

Table 5: The Effect of Distance on Recidivism

	Readmit in 1 year			Readmit in 3 years		
	(1)	(2)	(3)	(4)	(5)	(6)
Distance (100 miles)	0.0048*	0.0094***	0.0084**	0.0087**	0.0126**	0.0111**
	(0.0025)	(0.0035)	(0.0034)	(0.0038)	(0.0050)	(0.0048)
Controls	No	No	Yes	No	No	Yes
Fixed-effects	No	Yes	Yes	No	Yes	Yes
Outcome Mean (> 99 miles)	0.09	0.09	0.09	0.26	0.26	0.26
Observations	24,338	24,338	24,338	24,338	24,338	24,338

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. Estimates are from OLS regressions. The outcome variable for Columns (1)-(3) is a binary indicator for whether an incarcerated individual was readmitted to prison within 1 year of release. The outcome variable for Columns (4)-(6) is a binary indicator for whether an incarcerated individual was readmitted to prison within 3 years of release. Columns (1) and (4) present specifications without any controls or fixed effects. Columns (2) and (5) add fixed effects for year of admission, home county and security level-by-facility. Columns (3) and (6) include controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility. The outcome mean is the average rate of recidivism for individuals placed greater than 99 miles from home, which is the median placement distance. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

5.2 The Effect of Distance on Visitation

I next turn to visitation as the mechanism through which distance may affect recidivism. As demonstrated in Section 4, distance is unrelated to pre-existing characteristics or other in-prison programming linked to reentry outcomes, making visitation the most plausible pathway through which distance impacts recidivism. The first stage estimates of distance and visitation are shown in Table 6. Columns (1) and (2) display the relationship between distance and the probability of ever receiving a visit, while Columns (3) and (4) display the relationship between distance and the total number of visits received (normalized by months served). The relationship between the distance of a prisoner's placement facility and visitation is negative and statistically significant: the farther someone is from home, the less likely they are to receive visits, and the fewer visits they receive. On average, being placed 100 miles farther from home reduces the probability of receiving any visit by 11 percentage points and is associated with approximately 0.6 fewer visits per month. The median person in the sample is placed 99 miles from home, so a 100-mile increase represents a relevant margin. For reference, the visitation rate in the sample is 44 percent, so an 11 percentage point decline is substantial.[27]

Table 6: The Effect of Distance on Visitation

	Visit Received		Visit Count (per Mo.)	
	(1)	(2)	(3)	(4)
Distance (100 miles)	-0.1067***	-0.1069***	-0.6653***	-0.5935***
	(0.0042)	(0.0048)	(0.0211)	(0.0255)
Controls	No	Yes	No	Yes
Fixed-effects	No	Yes	No	Yes
Observations	24,338	24,338	24,338	24,338
F-test	557.60	492.80	981.22	540.41

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. This table presents estimates from OLS regressions. The outcome variable for Columns (1) and (2) is a binary indicator for whether a prisoner received any visits. The outcome variable for Columns (3) and (4) is the count of visits received in a given spell normalized by the number of in-prison months for a given prisoner-spell. Columns (2) and (4) include controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

5.3 The Effect of Visitation on Recidivism

I now turn to results for the effect of visitation on recidivism by using distance as an instrument for visitation. The two-stage least squares estimates are presented in Table 7. In Table 7, the top panel presents results when treatment is a binary indicator for visitation receipt. The bottom panel presents results when treatment is the number of visits received normalized by months served. Columns (1) and (2) give the causal effect of visitation on the probability of being readmitted within 1 year and Columns (3) and (4) show the same for 3 year readmittance probability. All estimates include all controls and fixed effects discussed in Section (4). Receiving visitation (versus never receiving a visit) reduces the probability of being readmitted to prison by 8 percentage points within 1 year and 11 percentage points within 3 years. One additional visit

[27] Facilities are not uniformly distributed across the state, and so another margin of interest may be the effect of being placed in an individual's second- or third-closest facility relative to their closest, regardless of exact distance. To test this, I restrict to individuals predicted to be medium-security and replace $Dist$ in Equation (3) with a set of binary indicators for whether an individual is placed in their first- through seventh-closest facility. These results are presented in Table A4.

per month reduces the probability of being readmitted to prison by 1.5 percentage points within 1 year and 1 percentage points within 3 years. Given a re-incarceration rate of 12 percent for non-visited incarcerated individuals within 1 year of release and 30 percent within 3 years of release for never-visited incarcerated individuals, this represents a 66 percent reduction in the probability of being readmitted within 1 year and a 36 percent reduction within 3 years. The difference between the IV and OLS estimates will be discussed further below.

These results are quantitatively similar to Lee (2019a), although his results are not statistically significant, where mine are. The point estimates in Lee (2019a) for the effect of receiving any visits on 3-year reincareration is an 8 percentage point reduction and for receiving one additional visit per month is a 1 percentage point reduction. Relative to other studies of visitation, my estimates fall within the mid-to-upper range of previous findings summarized in the meta-analysis by Mitchell et al. (2016), who reports effects ranging from a 3 percent to 62 percent reduction in recidivism.

Results showing heterogeneity by age, current crime type, and race can be found in Appendix Table A23, heterogeneity by subsequent crime type can be found in Appendix Table A24 and analysis of heterogeneity by visitor relationship can be found the Appendix Section C.4.

Table 7: The Effect of Visitation on Recidivism

	Readmit in 1 year		**Readmit in 3 years**	
	OLS	2SLS	OLS	2SLS
Visit Received	-0.0296***	-0.0781**	-0.0529***	-0.1036**
	(0.0039)	(0.0318)	(0.0059)	(0.0451)
Visit Count (per Mo.)	-0.0052***	-0.0141**	-0.0112***	-0.0187**
	(0.0005)	(0.0057)	(0.0009)	(0.0081)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,338	24,338	24,338	24,338
Untreated Mean	0.10	0.10	0.28	0.28

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. This table presents both OLS and 2SLS estimates of the effect of visitation on prison readmission. Visit count (per mo.) is the count of visits received in a given spell normalized by the number of in-prison months for a given prisoner-spell. The outcome variable for Columns (1) and (2) is a binary indicator for whether a prisoner is re-admitted within 1 year and the outcome variable for Columns (3) and (4) is a binary indicator for whether a prisoner is re-admitted within 3 years. Controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility are included. The untreated mean is the rate of recidivism for non-visited incarcerated individuals. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

5.3.1 Other Effects of Visitation: Time Served

Visitation may shape not only post-release outcomes but also experiences during incarceration. While I cannot directly observe disciplinary records, I am able to measure time served against original sentence length. Almost all incarcerated individuals are eligible to receive early release, with time off earned through good behavior and program participation. Indeed, 94 percent of the individuals in the sample leave prison prior to the completion of their sentence. Disciplinary action as well as refusal to participate in recommended work or education programming can result in the revocation of days of earned time (Washington Administrative Code 137-28-350). Visitation is also a privilege that can be revoked in response to infractions (Washington Administrative Code 137-28-350). It is important to note that disciplinary action is often at the discretion of the corrections officer, and may not be an accurate reflection of true misconduct. Washington currently has a "some evidence" standard, which means an officer's statement is sufficient to support disciplinary action (Office of the Corrections Ombuds, 2023).

Prior correlational work in criminology shows that visitation is associated with less misconduct in prisons

(Cochran, 2012). Lee (2019a) also finds that visitation reduces misconduct as well as days served. Several theories from psychology and criminology exist as to why visitation may reduce misconduct. The first is that contact with family and friends can serve as a coping mechanism, which reduces stress and reduces misbehavior (Wooldredge, 1999). Alternatively, maintaining contact with family may encourage individuals to avoid misconduct (which can lead a reduction in early release time) in order to complete their sentence as quickly as possible and be reunited with loved ones. Finally, because visitation is a privilege that be revoked for misconduct, it can serve as an incentive for good behavior.

To estimate the effect of visitation on time served, I use Equations (2) and (3) and replace the outcome variable with fraction of sentence served. Table 8 reports the estimates. Receiving at least one visit reduces the fraction of sentenced served by nearly four percentage points less of the original sentence, and each additional visit reduces the fraction served by about 0.07 percentage points. Non-visited individuals serve, on average, 61 percent of their sentence, so a four-point reduction represents roughly a 6.5 percent decrease. Given that the average non-visited individual is sentenced to 654 days, this effect translates into about 43 fewer days in prison. Taking fraction of sentence served as a proxy for disciplinary action, these results indicate visitation reduces disciplinary action while incarcerated

Table 8: The Effect of Visitation on Time Served

	Fraction of Sentence Served	
Visit Received	-0.0372**	
	(0.0167)	
Visit Count (per Month)		-0.0070**
		(0.0031)
Controls	Yes	Yes
Fixed-effects	Yes	Yes
Observations	22,440	22,440
Non-visited fraction served	0.61	0.61

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. Fraction of sentence served is equal to the days served by individual i in spell s divided by the number of days of individual i's original sentence for spell s. All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted on or after January 1, 2010 to Washington state prisons who were placed in a standard facility. One percent of the sample has an indeterminate sentence length and are dropped from estimation.

Time served matters not only because it can serve as a proxy for behavior during incarceration, but also because the amount of time spent in prison can shape post-release outcomes. Mueller-Smith (2015) reports criminogenic effects, with longer incarceration actually causing higher rates of post-release criminal charges. In other work, Rose and Shem-Tov (2021) find that incarceration reduces recidivism, but that the effects are diminishing – incarceration versus no incarceration decreases crime but longer sentences do not decrease crime more than shorter sentences. Taken together, these findings imply that, for people already in custody, prolonging imprisonment through earned-time revocations may do little to decrease post-release criminal activity and decreased time may actually reduce future crime. Visitation may therefore decrease recidivism by decreasing time spent in prison.

I next consider the cost savings associated with reduced incarceration. As shown, closer placements increase visitation, which in turn lowers both fraction of sentence served as well as re-incarceration. To estimate the reduction in incarceration due to visitation, I estimate a 2SLS model analogous to Equation 3, replacing the outcome with the total number of days incarcerated in the five years following date of sentence. For each individual, starting on the date of sentence, I count days spent incarcerated over the subsequent five-year window, including the current incarceration spell. This approach incorporates both the reduced time served in the given spell as well as the effect of reduced re-incarceration. Estimates imply that receiving visits reduces time served in the five years following sentencing by 141 days on average. The average non-visited individual spends 509 days of the five years post-sentence in prison, making this a 28 percent reduction in incarceration time.

According to budget documentation from the Washington DOC, in 2022 the cost per incarcerated individual per day was \$174.32.[28] The 141 day reduction of days incarcerated then results in savings of \$24,584 per person diverted from prison due to visitation.[29] These savings represent the expected reduction in incarceration costs due to visitation effects under the current placement system.

5.3.2 Interpretation of Results

I interpret the results using the Imbens and Angrist (1994) LATE framework. With the added assumption that the instrument moves treatment in the same direction for everyone (monotonicity), Imbens and Angrist (1994) show that the population can be partitioned into four groups according to their response to the instrument. In this context, monotonicity means that increasing placement distance must weakly decrease the probability of receiving a visit for every individual. Always-takers receive visits regardless of how close or far

[28]This is calculated by dividing the total 2022 Fiscal Year expenditures by the average daily population, and then by 365 to get the daily average (see Washington Department of Corrections (2022a)).

[29]Assuming costs stay fixed, converting the per day cost of \$174.32 in 2022 to 2010 dollars using the CPI gives a per-day cost of approximately \$129.89. This implies savings of \$18,307. Using 2016 dollars, the cost is \$142.96 per day and gives savings of \$20,167.

they are placed from home. Never-takers never receive visits, regardless of placement distance. Compliers are visited when placed close to home, and are not visited when placed far from home. Defiers, who would be visited only when placed far from home, are assumed not to exist. In this setting, it is reasonable to assume that a shorter distance would weakly motivate people to visit more.

Under this framework, compliers are the only group whose visitation is affected by placement distance. As a result, two-stage least squares identifies the Local Average Treatment Effect (LATE), which is the causal effect of visitation on recidivism for the complier group.[30] These individuals are the policy-relevant margin, since they are precisely those whose outcomes can be influenced by changes in placement distance.[31].

Under the usual positive-selection story in which incarcerated individuals with families with strong ties both visit more and would reoffend less even absent visits, OLS overstates the benefit of visitation, so an IV correction should yield a smaller effect than OLS. Here however, although 2SLS is imprecise, the point estimates are more negative than OLS.

First, I test for evidence of selection using the Black et al. (2022) test, which tests for selection by checking whether the instrument predicts outcomes within the visited population and within the non-visited population. Under valid exclusion, significant coefficients on the instrument indicate selection in levels that would bias OLS relative to IV.[32] I fail to reject the null hypothesis that selection is present. Given the large IV standard errors, I see this as inconclusive. Full test details and estimates appear in Appendix Section D.2.

Measurement error is another possible explanation for the 2SLS estimate being larger in magnitude than the OLS estimate. If unobserved family support both raises visitation and lowers recidivism, OLS estimates would be too negative because they confound the effect of visitation with the effect of support. Measurement error in the visit indicator would instead attenuate OLS estimates. These forces can offset, yielding OLS and 2SLS estimates that look similar even when selection exists. In this setting, however, substantial misclassification seems unlikely. To misclassify someone as “not visited” under a binary treatment definition, either every visit would have to be missing from the data or every visit would have to be recorded as happening for someone else. This seems most plausible for individuals who received only a single visit, and so I recode anyone with only one recorded visit as “not visited” and re-estimate the model. The resulting estimates change very little, as shown in Appendix Table A9, suggesting that measurement error is unlikely to be driving the results.

[30]Derivation can be found in Appendix Section D.

[31]Results using a binary instrument indicating placement at greater than the median distance of 99 miles from home, are quite similar to the main results using a continuous measure of distance and can be found in Appendix Table A12)

[32]With heterogeneous effects, OLS and 2SLS target different parameters and so the traditional Wu-Hausman test for endogeneity is not informative.

Finally, OLS and 2SLS differ in which populations they weight. 2SLS identifies the effect for compliers and gives more weight to the observations where the instrument moves treatment more, while OLS estimates the difference in treated and untreated mean outcomes and with controls gives more weight to observations in cells with greater treatment variance.[33] It can be useful to look at the characteristics of the populations each estimate weights. In a similar spirit to the method in Abadie (2003) used to characterize always-takers, compliers and never-takers in the case of binary treatment and a binary instrument, Hull (2025) defines the effective population for a given estimand (see Appendix Section D for the derivation). For the pre-determined characteristics in the main sample, I compare the OLS and 2SLS effective populations and they appear quite similar across most characteristics, with the main difference being the 2SLS effective population is somewhat whiter (see Appendix Table A29).

However, important dimensions on which selection may operate, such as pre-existing family relationships income, are only observed in the supplementary data and so I cannot apply either complier characterization method. Instead, I look at a subset of the sample who participate in Extended Family Visits (EFV), Washington's multi-day private visitation program. There are both stringent program requirements as well as significant travel and time costs associated with these multi-day visits, suggesting that EFV participants are highly motivated and extremely committed to their incarcerated loved one. Consistent with very high motivation and support, distance weakly predicts EFV participation (see Appendix Table A30), so EFV recipients are conceptually similar to always-takers (those individuals who would receive visits regardless of distance). I therefore use EFV recipients as a proxy for always-takers to contrast with compliers within the visited population.

Appendix Table A32 shows that as expected, both regular visitation recipients and EFV recipients are positively selected. Both groups are more likely to report having a long-term partner, having a good family relationship and to report having children than the non-visited individuals. However, while regular visitation recipients are more positively selected than never visited people, they are much less so than the EFV recipients. Compared to regular visitation recipients, EFV recipients are much more likely to be rated low risk of recidivism and are also disproportionately in the highest income bracket. This provides suggestive evidence on why the 2SLS estimate may be larger in magnitude than the OLS estimate, because 2SLS is placing weight on this regular visitation population (the compliers), who are less advantaged and plausibly have larger returns to visits.

[33] A derivation of what OLS estimates in terms of the LATE-groups is in the Appendix.

5.3.3 Interpretation of 2SLS with Covariates

The preceding estimates rely on parametric functional–form assumption, namely that the linear projection of the instrument on covariates approximates the instrument's conditional expectation. As Blandhol et al. (2022) show, causal interpretation of 2SLS estimates with covariates requires that the linear projection of the instrument on the covariates equals its conditional expectation: $L(Z|X) = E[Z|X]$.[34] A sufficient condition for $L(Z|X) = E[Z|X]$ is when the covariate specification is fully saturated in X, meaning it includes indicators for all possible combinations of covariate values. I estimate alternative specifications that include saturated fixed effects.

In my context, Z (distance) is as good as randomly assigned conditional on security level, making this the key variable for exogeneity to hold. An individual's home county also impacts the possible distances an individual could be placed, as well as recidivism risk through differing economic opportunities etc. An individual's placement facility could additionally impact recidivism risk in ways separate from its distance to the incarcerated individual's home if we think that incarceration in a certain facility is a unique experience. Fully saturating the model with respect to both home county and placement facility would require conditioning on all 1,170 possible combinations, which is unwise given the sample size, and would soak up the vast majority of variation in distance. To address this, I construct a proxy for security level using sentence length, crime type, and prior prison admissions[35] and then estimate models with increasingly rich fixed-effects. Specifically, I present results from specifications that include: (i) fixed effects for the proxy security level alone, (ii) interactions between security level and home county, and (iii) interactions between security level, home region, and placement facility. Home regions aggregate counties into three broad groups: the Seattle–Olympia metro area, Southwestern Washington, and Eastern–Central Washington.

Table 9 presents the results for alternative covariate specifications. Columns (1) presents the main specification for 1-year and 3-year readmission, respectively, which include a full set of additive controls and fixed effects. Column (2) includes fixed effects for security level only, Columns (3) includes fixed effects for each security level-home county pair and Column (4) report estimates from a specification that includes indicators for every security level–facility–region combination. These saturated estimates are generally smaller in magnitude than the additive control models but are broadly consistent with the main results. Overall, I find

[34] Alternatively, one can assume the potential–outcome means are linear in covariates: $E[Y(t)|X] = \alpha_t + X'\beta_t, \quad t \in \{0, 1\}$. This implies for any treatment level t, the average potential outcome varies linearly with covariates. This rules out nonlinear relationships between covariates and outcomes—such as threshold effects, interactions, or diminishing returns. However, as Abadie (2003) cautions, this assumption has a problematic implication: even if the instrument Z is a deterministic or nonlinear function of X (clearly not exogenous), 2SLS may still yield an unbiased estimate of the ATE.

[35] Individuals who committed violent crimes and have a history of prior prison admissions are designated as "close" security. Individuals who did not commit any violent or sex offense and have sentence lengths equal to 13 months or less are designated "minimum" security. Individuals over 50 are designated as minimum. All others are designated as "medium".

consistent evidence that visitation causally reduces the likelihood of readmission.

Table 9: Visitation Effects, Alternate Models

	Main (1)	Security (2)	Security-County (3)	Region-Security-Facility (4)
Readmit in 1 year				
Visit Received	-0.0771**	-0.0482**	-0.0527**	-0.1158**
	(0.0234)	(0.0225)	(0.0227)	(0.0450)
Readmit in 3 years				
Visit Received	-0.1046**	-0.0854**	-0.1072***	-0.1381**
	(0.0355)	(0.0340)	(0.0341)	(0.0689)
Controls	Yes	No	No	No
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,338	24,338	23,847	24,102
F-test (1st stage)	492.8	715.9	720.5	171.9

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. This table presents 2SLS results using alternate covariate specifications. The outcome variable for the top panel is a binary indicator for whether an incarcerated individual is readmitted within 1 year of release. The outcome variable for the bottom panel is a binary indicator for whether an incarcerated individual is readmitted within 3 years of release. Column (1) presents the main results that include controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators for the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility. Column (2) contains fixed effects for security level only. Column (3) is saturated by security level-home county level. Column (4) is fully saturated in that they contain indicators for every security level-facility-home region combination. The specifications in Columns (3) and (4) include only cells with 30 or more individuals. Individuals are grouped into security levels using sentence length and history of prison admissions. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

6 Mechanism: Housing Stability

Prior research highlights both the difficulty formerly incarcerated individuals face in securing stable housing and the critical role that stable housing plays in successful reentry. For instance, Gottlieb and Jacobs (2020) provides suggestive evidence that housing instability is prevalent among individuals released on probation, 25 percent lacked stable housing, and that this instability is associated with a 35 percent increase in the risk of recidivism. Similarly, Palmer et al. (2019) shows that emergency financial assistance for housing significantly reduced the likelihood of rearrest by 18 percent. Furthermore, qualitative research underscores the importance of social networks in securing housing after release. La Vigne et al. (2004) documents that 42 percent of individuals released from prison moved into a family member's home immediately upon release. Likewise, Deess et al. (1999) finds that approximately 80 percent of parolees resided with family members.

If visitation allows individuals to maintain relationships with family, and individuals who receive visits are more likely to secure stable housing upon release, housing is a plausible channel through which visitation operates. I therefore examine housing as a candidate mechanism linking visitation to reentry outcomes.

Most individuals released from a Washington State prison are required to submit a post-release address and sponsor for approval by the Department of Corrections.[36] A sponsor is any person willing to allow an incarcerated individual to live with them post-release, subject to several restrictions such as not having a criminal history and not being a victim of the individual's crimes.[37] While in theory an incarcerated individual could live alone when released, in practice this is exceedingly rare due to high housing costs and the financial circumstances of most released individuals. Release plans are initially developed during intake, but a staff member from the Reentry Division begins working with incarcerated individuals one-year from release to finalize a plan, and release address verification begins at 6 months from release. If an individual cannot provide an acceptable living plan, WADOC will delay release until an address is secured or until the sentence is fully served, as opposed to releasing someone a their Earned Release Time.[38] After recognizing that many individuals were remaining in prison solely due to the lack of a housing plan, WADOC launched the Reentry Housing Assistance Program in 2009.[39] Support is offered through both referrals to transitional housing programs and direct rental subsidies. The latter takes the form of a voucher that covers up to $700 in monthly rent for a maximum of six months following release.

While the goal is to understand how visitation effects post-release housing stability, the data do not directly measure this. Instead, I can proxy for instability with whether an individual uses a housing voucher at release. Requiring assistance due to the absence of a sponsor or the inability to secure housing independently strongly signals a lack of stable housing. Those who end up using a house voucher are much less likely to have been visited than those who did not – 11 percent of those who were ever visited use a housing voucher compared to 25 percent of those who were not visited.[40] Additionally, those who receive a housing voucher have higher rates of re-admittance to prison than those who do not – 29 percent of individuals who received a voucher are re-admitted within 3 years of release versus 24 percent of individuals who did not require a voucher.

[36] Individuals whose sentence does not require community supervision after release or are serving a misdemeanor sentence are exempt from this requirement.

[37] Residences are also reviewed for weapons and drugs. Some incarcerated individuals may not live with children or animals, and this is also reviewed. All members of the household are reviewed for criminal history, not just the sponsor.

[38] incarcerated individuals earn time off of their sentence for "good behavior", which includes participation in required programming and not receiving disciplinary action. Most non-violent individuals are eligible to earn up to 50 percent of their sentence off.

[39] The DOC noted that it was spending thousands of dollars per month to hold individuals past their early release date due to unmet housing requirements.

[40] Appendix Table A18 presents descriptive statistics for the entire sample by housing voucher status. Appendix Table A19 presents descriptive statistics on individuals who used housing vouchers by visitation status.

To better understand how housing vouchers may impact re-admittance to prison, it is also important to examine where individuals who receive this assistance tend to live after release. Eighty-six percent of individuals who used housing assistance were released to transitional housing, compared to only 15 percent of those who did not require housing assistance.[41] These settings are commonly known as "halfway houses" and they provide short-term, non-DOC-operated housing for people leaving prison. Placements may be motivated by needs, such as sober-living support, or by religious values. However, in practice, release to transitional housing is closely tied to use of a housing voucher. Transitional housing environments vary significantly in quality and services offered, complicating causal inference of their impact on post-release outcomes. However, a common feature is communal living with structured supervision. Lee (2023) shows that mandated residential housing for high-risk individuals increases the risk of re-incarceration, largely due to heightened exposure to technical violations under intensive monitoring. This suggests that transitional housing may also be a potential mechanism of prison readmission.

First, I document the relationship between housing assistance and recidivism. I estimate OLS models with a binary indicator for prison readmittance as the dependent variable and housing assistance as the independent variable. I include the full set of controls and fixed effects from the main specifications. Table 10 presents the results. Columns (1), (3) and (5) include a binary indicator for whether an individual required a housing voucher upon release from prison. Columns (2), (4) and (6) add a binary indicator for use of transitional housing post-release. Across all specifications, the need for housing assistance is positive correlated with prison admission. Estimates at six months are small, suggesting that housing vouchers may provide short-term stability – they are valid for only six months, but even individuals who need assistance are able to maintain housing during this period. However, the effects grow at one and three years, a pattern consistent with persistent underlying housing instability among voucher recipients. If the association were driven mainly by voucher recipients living in transitional housing, where intensive supervision could potentially increase detection of illegal activity, then adding the indicator for transitional housing should substantially attenuate the voucher coefficient. Instead, the voucher effect is persistent, which is more consistent with underlying housing instability and limited support, rather than halfway houses, being the key determinant.

[41] I define transitional housing as either a housing address where more than 5 incarcerated individuals have been released or with a sponsor name or address name such as "Sober Living Community" or "Group home".

Table 10: Housing and Recidivism

	Readmit in 6 mo.		Readmit in 1 year		Readmit in 3 years	
	(1)	(2)	(3)	(4)	(5)	(6)
Voucher	0.0065*	0.0039	0.0210***	0.0155**	0.0481***	0.0334***
	(0.0034)	(0.0040)	(0.0060)	(0.0071)	(0.0085)	(0.0100)
Transitional Housing		0.0040		0.0087		0.0232***
		(0.0034)		(0.0059)		(0.0086)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	20,038	20,038	20,038	20,038	20,038	20,038
Non-voucher Readmit Rate	0.02	0.02	0.08	0.08	0.24	0.24

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. Transitional housing is a binary indicator for whether an individual was released to an address indicating transitional housing. Assistance is a binary indicator for whether an individual required housing assistance to obtain an approved living situation post-release. The outcome variable for Columns (1)-(2) is a binary indicator for whether an incarcerated individual was readmitted within 6 months of release. The outcome variable for Columns (3)-(4) is a binary indicator for whether an incarcerated individual was readmitted within 1 year of release. The outcome variable for Columns (5)-(6) is a binary indicator for whether an incarcerated individual was readmitted within 3 years of release. All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code. Six percent of spells are missing information on post-release housing and are excluded. Non-voucher readmit rate is the rate of readmittance for the given time frame for individuals who did not use a housing voucher.

I now estimate the causal effect of visitation on housing stability by using distance as an instrument for visitation. As shown, distance is uncorrelated with family relationships, pre-determined characteristics, and other programming. Therefore, it is plausible distance only impacts housing stability through visitation. Table 11 presents the results. Visitation reduces housing voucher use by 16 percentage points and each additional visit per month reduces use by 3 percentage points.

Table 11: The Effect of Visitation on Housing Stability

	Housing Voucher Used	
Visit Received	-0.1618***	
	(0.0424)	
Visit Count (per Month)		-0.0305***
		(0.0080)
Controls	Yes	Yes
Fixed-effects	Yes	Yes
Observations	20,038	20,038
Non-visited Voucher Use Rate	0.25	0.25

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. This table presents 2SLS estimates of the effect of visitation on housing voucher use. The outcome variable is a binary indicator for whether an incarcerated individual's required a housing voucher in the given spell. Both models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code. Six percent of spells are missing information on post-release housing and are excluded.

To further investigate whether visits reduce prison readmissions through improved housing stability, I estimate IV models using the binary visitation measure and joint outcomes of recidivism and housing status as dependent variables. I define four mutually exclusive and exhaustive categories: readmitted and used a housing voucher, readmitted and did not use a housing voucher, not readmitted and used a housing voucher, and not readmitted and did not use a housing voucher. Each category represents a distinct combination of post-release housing stability and recidivism outcomes and so the estimated effects can be interpreted as reallocations across the categories. Results are presented in Figure 4 and point estimates are reported in Appendix Table A33.

Results show movement from the least favorable state, *Readmit, Voucher*, into the most favorable state, *No Readmit, No Voucher*, which is consistent with housing stability being a mediating factor for recidivism. The magnitudes suggest partial mediation rather than full mediation indicating that housing stability is an important pathway but that visits also influence recidivism through other channels such as emotional or psychological support.[42][43]

[42] Importantly, the measured housing channel likely encompasses both material and relational support, as individuals living with friends or family also likely receive other non-measured support.
[43] A numerical example under full mediation and full independence can be found in Appendix Table A34.

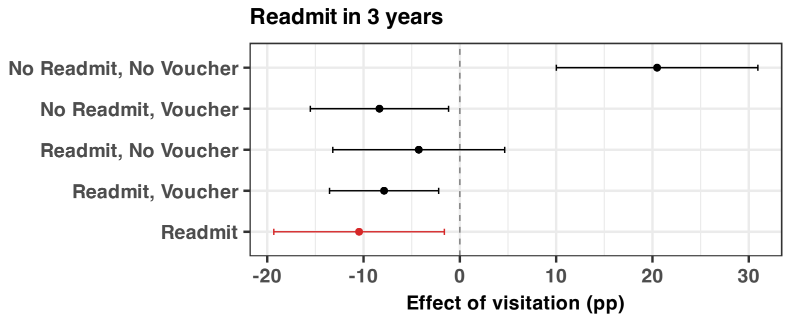

Figure 4: Joint Housing and Recidivism Outcomes

Note: This figure plots the IV estimates of the effect of visitation on joint outcomes for housing instability and recidivism. Point estimates are indicated by dots and the lines indicate 95% confidence intervals. Each row (point estimate and line) represents a separate regression. Outcomes consists of four mutually exclusive and exhaustive categories of binary indicators for prison readmission within three years and receipt of a housing voucher. The red point and line is the marginal effect of visits on the probability of being readmitted in three years.

As address verification for release plans begins 6 months prior to release, I investigate if visitation at the end of a spell is especially meaningful for re-offense in general and for housing stability specifically. For individuals who spent at least 14 months incarcerated, I look at the relationship between voucher receipt and visitation in the last year, last 6 months, and last 3 months.[44] To do this I regress a binary indicator for voucher use on mutually exclusive categories of visitation timing: an individual's last visit was more than 1 year prior to their release date, their last visit was between 6 and 12 months prior to release, their last visit was between 3 and 6 months prior to release, or their last visit was less than 3 months prior to release. The excluded group is individuals who received no visits. Individuals visited in the final three months of their spell are half as likely to require a housing voucher as those whose visits occurred only early in the spell. The increasing magnitude in Column (3) is consistent with housing plans being finalized close to release, and with making visitation salient for securing stable housing.

[44] I restrict the sample to 14 months to allow for everyone to receive a visit at least 1 year prior to release.

Table 12: Visit Timing and Housing Stability

	Housing Voucher Used		
	Any Visit	Any Visit	Visit Timing
	(1)	(2)	(3)
Visit Received	-0.1296***	-0.1545***	
	(0.0055)	(0.0090)	
Last Visit > 1 year before release			-0.0912***
			(0.0149)
Last Visit $6-12$ mo. before release			-0.1533***
			(0.0114)
Last Visit $3-6$ mo. before release			-0.1665***
			(0.0114)
Last Visit < 3 mo. before release			-0.1837***
			(0.0107)
Controls	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes
Observations	20,038	8,506	8,506
Non-visited Voucher Use Rate	0.25	0.29	0.29

Note: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. This table presents OLS estimates of the relationship between visitation and housing voucher use. The outcome variable is a binary indicator for whether an incarcerated individual's required a housing voucher in the given spell. All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. Six percent of spells are missing information on post-release housing and are excluded from Model (1). The sample for Models (2) and (3) are individuals who spent at least 14 months in prison. The excluded category is no visits. Eight percent of spells lasting 14 months ore more are missing information on post-release housing and are excluded. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

One alternative could be that visitation does not affect housing at all, and that having a place to live simply proxies for pre-existing social support. If that were true, outcomes should be similar for visited and non-visited individuals within each housing-assistance group. However, they are not. Among those with assistance, 8 percent of visited are readmitted versus 13 percent of non-visited. I also verify this pattern in my supplementary data where I have self-reported family relationship status at intake.[45] Visitation has a stronger correlation with not needing housing assistance than self-reported "good family relationship" at intake. Among those who report not having a good relationship 35.5 percent of non-visited used a housing voucher compared to only 13.4 percent of visited individuals (a 22.1 percentage point difference). For comparison, among those who do report a good family relationship, 19.9 percent of non-visited individuals used a housing voucher relative to only 12.1 percent of visited individuals (a 7.8 percentage point difference). These patterns are consistent with visits reinforcing support relevant for post-release housing, beyond just

[45] See Appendix Table A20 and Appendix Table A21 for descriptive statistics on voucher use within the supplementary sample.

reflecting pre-existing support.

7 Counterfactual Placement Policies

Facility placement is an administrative decision, and as such is a potential policy mechanism. To gauge what a proximity-based rule would imply for Washington, I evaluate counterfactual placement policies that minimize home-to-facility distance. Using my estimated effects of distance on visitation and of visitation on recidivism, I simulate outcomes under three policies: (i) assign each individual to the nearest facility with no constraints; (ii) assign to the nearest eligible facility subject to security-level eligibility and facility capacity, with random tie-breaking; (iii) a targeted program that first assigns those with the largest expected benefits to the nearest eligible beds before filling remaining capacity.

For the first simulation, I set all prisons to 0 occupancy and I assign every individual admitted on or after January 1, 2010 to their nearest facility, ignoring any capacity constraints or security levels. I then compute the change in distance relative to the status quo by taking the difference between the average placement distance in the data and the average placement distance under this simulated regime. I translate this distance change into a change in the probability of being visited using the first-stage estimate of the effect of change in distance on visitation probability from Equation 2.[46] I then map the resulting change in average visitation probability into a change in recidivism using the 2SLS estimates of visitation's effect on one and three-year prison readmission, from Equation 3.[47] This two-step procedure yields the counterfactual change in recidivism for each person, which I then aggregate to report the average change in recidivism from this counterfactual policy. Aggregating across individuals, the policy moves people 82 miles closer to home on average and increases the probability of being visited by 8.7 percentage points. This results in a 0.7 percentage point reduction of predicted readmission at one year and 1.0 percentage point reduction at three years. Although unrealistic, given real capacity constraints and security level considerations, this can be thought of as the greatest possible change in recidivism from altering placements.

For the second simulation, I impose security-level eligibility and facility capacity on the counterfactual placements. I set each facility's capacity to the stated WADOC capacity and initialize occupancy to the observed headcount on January 1, 2010, and am therefore leaving anyone admitted prior to January 1, 2010 in their regularly assigned facility. The simulation then proceeds month by month from January 2010

[46] This approach uses a local linear approximation for the effect of distance on visitation.

[47] This approach assumes constant effects across individuals. This does not allow counterfactual placements to change visitation and recidivism probabilities differently.

through the end of the sample. In each month, I take the set of new admissions for the month and, for each person, rank security-level appropriate facilities by home-to-facility distance. For example, let Individual A, Individual B, and Individual C all be admitted in January 2010. Individual A is minimum security, Individual B is medium security, and Individual C is close security. I rank all minimum security facilities by distance from Individual A's home county, all medium security facilities by distance from Individual B's home county and all close security facilities by distance from Individual C's home county. If Individual A's closest security-appropriate facility has open occupancy, they are assigned there. If not, I move to the second closest and so on until there is occupancy. When there are multiple individuals of the same security level admitted in the same month with the same facility ranking, I break ties randomly. After assigning everyone admitted that month, I release all individuals with release dates that month. Occupancy at each facility is updated each month as admissions arrive and as observed releases create vacancies. I then proceed to the next month, all the way through December 2016. This produces capacity-feasible counterfactual placements. After everyone is placed I compute the counterfactual change in distances and map this into visitation using the first stage effect of distance change on visitation and then to recidivism changes using the second stage estimated effects of visitation on recidivism. Under this assignment regime, people are moved 40 miles closer to home on average and the probability of being visited increased by 4 percentage points. This results in a 0.3 percentage point reduction of predicted readmission at one year and 0.4 percentage point reduction at three years.

Finally, I use the same dynamic monthly assignment procedure as in the second simulation, but now I prioritize older individuals. I do this by ranking every individual to be admitted in the given month by age and admitting the oldest individuals first so that they are more likely to be placed closer to home. For example, let Individual D and Individual E both be medium security custody and be admitted in the same month and have the same facility distance ranking. Individual D is 50 years old and Individual E is 27. I would assign Individual D to their closest facility before I assign Individual E. The choice to prioritize older individuals is informed by the heterogeneity analysis done in Appendix Section F that suggests older individuals have larger treatment effects than younger individuals. I use the coefficients from this heterogeneity analysis to scale both the first stage and second stage effects. This results in a 4 percentage point increase in visitation, a 0.4 percentage point reduction of predicted readmission at one year and 0.5 percentage point reduction at three years.

Next, I consider the added reduction in incarceration days and associated cost-savings from these counterfactual placement policies that prioritize distance from home. The additional reduction from the placement policy that prioritizes older individuals translates to 5 fewer days incarcerated in the 5 years post-sentence for the average person. This translates to and an additional savings of $871.60 (using the 2022 cost of incarceration) in savings per person.

While effects for the capacity constrained simulations are modest, these changes are meaningful relative to overall recidivism rates. Relative to the one-year readmittance rate of 10 percent, a 0.3 or 0.4 percentage point reduction in recidivism translates to a 3-4 percent decrease. This is comparable to the reductions found in Agan and Makowsky (2018b), which showed a 50 cent increase in the average minimum wage reduced one-year recidivism by 2.8 percent.

8 Conclusion

This paper shows that prison placement distance from home is an important policy margin. Leveraging quasi-random variation in initial facility assignment, I show that an increase of 100 miles in distance from home increases the probability of re-admission by 9 percent within one year and 4 percent within three years.

I show that distance impacts recidivism through its impact on contact with family and friends. Each additional 100 miles decreasing the probability of visitation by 11 percentage points. I then build on this by estimating the causal effect of in-person prison visitation on recidivism using an instrumental variables strategy. Receiving at least one in-person visit reduces re-incarceration by about 8 percentage points within one year and by about 11 percentage points within three years. The intensive margin of visitation also matters: each additional visit per month reduces re-incarceration by 1.5 percentage points at one year and 2 percentage points at three years. These effects are comparable to some of the most effective reentry interventions.

In addition to recidivism, visitation reduces the amount of time individuals spend in prison for a given spell, which is consistent with visitation decreasing in-prison misconduct. Visited individuals spend almost 6.5 percent less time in prison, which translates to about 43 days fewer at the median. Combining this reduction with the reduction in re-incarceration results in significant cost-savings of around $25,000.

I also provide evidence consistent with a housing stability mechanism for visitation. Visited individuals are 16 percentage points less likely to require a post-release housing voucher and visits toward the end of a prison spell are most predictive of not needing a voucher. This aligns with reentry practice, where address verification occurs in the months before release.

These results imply that reducing distance and therefore increasing visitation can improve reentry outcomes. At a time when some county jails are eliminating in-person visitation programs in favor of video visitation, it is important to note that visitation does improve reentry outcomes. Importantly, it is also something that occurs during incarceration, rather than as an additional program requirement post-incarceration.

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Appendix

A Robustness

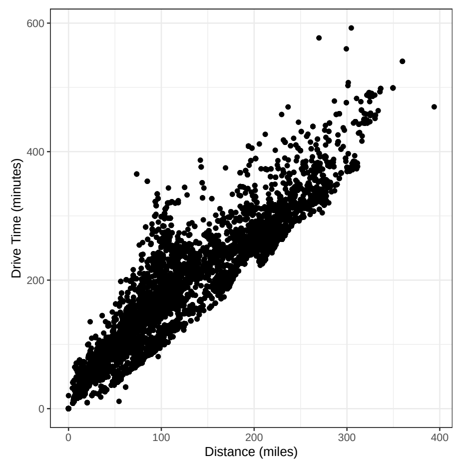


Figure A1: Distance vs. Drive-Time

Notes: This figure plots the correlation between Euclidean distance drive-time. Drive times are calculated using Google Maps API. Distance is on the x-axis and drive-time is on the y-axis. Each dot represents how long the estimated drive-time is for the given distance.

Table A1: Testing For When Distance Starts to Matter

	Readmit in 1 year (1)	Readmit in 3 years (2)
Distance > 30 miles	0.0078	0.0097
	(0.0063)	(0.0095)
Distance > 50 miles	0.0057	0.0086
	(0.0050)	(0.0073)
Distance > 60 miles	0.0081*	0.0093
	(0.0048)	(0.0070)
Distance > 70 miles	0.0087*	0.0102
	(0.0047)	(0.0069)
Distance > 80 miles	0.0109**	0.0164**
	(0.0046)	(0.0068)
Distance > 90 miles	0.0132***	0.0198***
	(0.0046)	(0.0068)
Controls	Yes	Yes
Fixed-effects	Yes	Yes
Observations	24,338	24,338

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the individual level. This table tables when distance starts to impact recidivism. Each cell is an estimate from OLS regressions of a binary indicator for prison readmittance on binary indicators for whether prison distance is greater than indicated. Each cell is a separate regression. All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

Table A2: Distance Results, Seattle Metropolitan Area Excluded

	Readmit in 1 year	Readmit in 3 years
Distance (100)	0.0076**	0.0108**
	(0.0039)	(0.0055)
Controls	Yes	Yes
Fixed effects	Yes	Yes
Observations	14,718	14,718

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the individual level. This table tables when distance starts to impact recidivism. Each cell is an estimate from OLS regressions of a binary indicator for prison readmittance on binary indicators for whether prison distance is greater than indicated. Each cell is a separate regression. All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

Table A3: First Stage, Logit and Poisson

	Visit Received Logit (1)	N Visits per Mo. Poisson (2)
Distance (100 miles)	-0.5429^{***}	-0.7831
	(0.0269)	(0.0354)
Marginal Effect	-0.1125	-0.5430
Controls	Yes	Yes
Fixed-effects	Yes	Yes
Observations	24,413	24,413

Notes: ***: 0.01, **: 0.05, *: 0.1. This table presents first stage results for the effect of distance on visitation using alternative standard error clusters. Visitation is measured as a binary indicator in Column (1) and estimation is done using logistical regression. Visitation is measured as the count of visits per month incarcerated in Column (2) and estimation is done using a Poisson regression. The marginal effect for Column (1) is the average marginal effect. For a continuous regressor x_k: $AME = \frac{1}{n}\sum_i \beta_k p_i(1-p_i)$ where $p_i = \Lambda(x_i'\beta)$. The marginal effect for Column (2) is calculated as $e^{\beta} - 1$. All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

Table A4: The Effect of Distance Rank on Visitation

	Visit Received (1)	Visit Count (per Mo.) (2)
Second Closest Facility	-0.0670***	-0.5913***
	(0.0116)	(0.0697)
Third Closest Facility	-0.0781***	-0.6912***
	(0.0123)	(0.0700)
Fourth Closest Facility	-0.1104***	-1.062***
	(0.0173)	(0.0646)
Fifth Closest Facility	-0.1783***	-1.195***
	(0.0116)	(0.0609)
Sixth Closest Facility	-0.2170***	-1.300***
	(0.0132)	(0.0585)
Seventh Closest Facility	-0.2293***	-1.329***
	(0.0146)	(0.0628)
Controls	Yes	Yes
Fixed-effects	Yes	Yes
Observations	16,371	16,371
F-stat	83.30	107.10

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. Estimates are from OLS regressions of visitation on indicators for an individual's placement facility's distance rank. Each individual has a set of facilities they can be placed in, which are ranked from closest to furthest. This is the facility distance rank. The omitted category is the first closest facility. The outcome variable for Column (1) is a binary indicator for whether a prisoner received any visits. The outcome variable for Column (2) is the count of visits received in a given spell normalized by the number of in-prison months for a given prisoner-spell. Controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility are included. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code. The sample is all men predicted to be medium security level using sentence length and history of prison admissions.

Table A5: First Stage, Alternate Clusters

	Visit Received		N Visits per Mo.	
	ZIP	County	ZIP	County
	(1)	(2)	(3)	(4)
Distance (100 miles)	-0.1071***	-0.1071***	-0.5963***	-0.5963***
	(0.0057)	(0.0068)	(0.0355)	(0.0431)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,413	24,413	24,413	24,413
F-test	443.07	570.58	443.76	571.48

Notes: ***: 0.01, **: 0.05, *: 0.1. This table presents first stage results for the effect of distance on visitation using alternative standard error clusters. Visitation is measured as a binary indicator in Columns (1) and (2). Visitation is measured as the count of visits per month incarcerated in Columns (3) and (4). In Columns (1) and (3) standard-errors are clustered at the ZIP-code level and are in parentheses. In Columns (2) and (4) standard-errors are clustered at the county level and are in parentheses. Counties are the relevant jurisdictions. All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

Table A6: Visitation Results, ZIP Code Clusters

	Readmit in 1 year		Readmit in 3 years	
	(1)	(2)	(3)	(4)
Visit Received	-0.0834**		-0.1107**	
	(0.0343)		(0.0474)	
Visit Count per Mo.		-0.0150**		-0.0199**
		(0.0060)		(0.0084)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,413	24,413	24,413	24,413

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the ZIP-code level and are in parentheses. Visitation is measured as a binary indicator in Columns (1) and (3). Visitation is measured as the count of visits per month incarcerated in Columns (2) and (4). All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

Table A7: Visitation Results, Jurisdiction Clusters

	Readmit in 1 year		Readmit in 3 years	
	(1)	(2)	(3)	(4)
Visit Received	-0.0834**		-0.1107**	
	(0.0321)		(0.0508)	
Visit Count per Mo.		-0.0150**		-0.0199**
		(0.0057)		(0.0094)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,413	24,413	24,413	24,413

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the county level and are in parentheses. Counties are the relevant sentencing jurisdiction. Visitation is measured as a binary indicator in Columns (1) and (3). Visitation is measured as the count of visits per month incarcerated in Columns (2) and (4). All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code.

Table A8: Visitation Results, Incarcerated Individuals Only in One Facility

	Readmit in 1 year		Readmit in 3 years	
	(1)	(2)	(3)	(4)
Visit Received	-0.0597		-0.0782	
	(0.0398)		(0.0552)	
N Visits per Mo.		-0.0107		-0.0140
		(0.0071)		(0.0098)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	13,819	13,819	13,819	13,819
F-test (1st stage)	320.07	366.13	320.07	366.13

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors are clustered at the individual level and are in parentheses. Visitation is measured as a binary indicator in Columns (1) and (3). Visitation is measured as the count of visits per month incarcerated in Columns (2) and (4). All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

Table A9: Visitation Results, More Than 1 Visit

	Readmit in 1 year		Readmit in 3 years	
Visit Received	-0.0944***		-0.1389***	
	(0.0321)		(0.0444)	
N Visits per Mo.		-0.0174***		-0.0256***
		(0.0059)		(0.0082)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,413	24,413	24,413	24,413
F-test (1st stage)		432.30		448.33

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. Anyone who only received 1 visit is recoded as being not visited and their visit count is set to 0. Visitation is measured as a binary indicator in Columns (1) and (3). Visitation is measured as the count of visits per month incarcerated in Columns (2) and (4). All models include controls for sentence length, crime type, and race, as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

Table A10: Visitation Results, Seattle Metropolitan Area Excluded

	Readmit in 1 year		Readmit in 3 years	
Visit Received	-0.0681**		-0.0970**	
	(0.0347)		(0.0492)	
Visit Count per Mo.		-0.0131**		-0.0186**
		(0.0067)		(0.0094)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	14,718	14,718	14,718	14,718
F-stat (1st stage)	448.4	591.1	448.4	591.1

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. Visitation is measured as a binary indicator in Columns (1) and (3). Visitation is measured as the count of visits per month incarcerated in Columns (2) and (4).All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted on or after January 1, 2010 to Washington state prisons excluding those with a home county of King County, Snohomish County or Pierce County.

Table A11: Visitation Results, Airway Heights Corrections Center Excluded

	Readmit in 1 year		Readmit in 3 years	
Visit Received	-0.0910**		-0.1377**	
	(0.0402)		(0.0571)	
Visit Count (per Mo.)		-0.0177**		-0.0268**
		(0.0078)		(0.0111)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	20,855	20,855	20,855	120,855
F-stat (1st stage)	310.8	378.2	310.8	378.2

Note: ***: 0.01, **: 0.05, *: 0.1. Standard-errors clustered at the individual level are in parentheses. Visitation is measured as a binary indicator in Columns (1) and (3). Visitation is measured as the count of visits per month incarcerated in Columns (2) and (4). All models include controls for sentence length, crime type, incarcerated individual race, and criminal history as well as fixed effects for admit year, placement facility, and home county. The sample consists of all prison spells for men admitted on or after January 1, 2010 to Washington state prisons excluding those placed in Airway Heights Correctional Center.

Table A12: The Effect of Visitation on Recidivism, Binary Instrument

	Readmit in 1 year		**Readmit in 3 years**	
	Main Results	$>$ 99 miles	Main Results	$>$ 99 miles
	(1)	(2)	(3)	(4)
Visit Received	-0.0781**	-0.0519	-0.1036**	-0.0988*
	(0.0318)	(0.0358)	(0.0451)	(0.0524)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,338	24,338	24,338	24,338

Note: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. The outcome variable for Columns (1) and (2) is a binary indicator for whether an incarcerated individual is re-admitted within 1 year of release, and the outcome variable for Columns (3) and (4) is a binary indicator for re-admit within 3 years of release for the given spell. All specifications include controls of the individual's race, spell length, offense type, and previous prison admissions as well as fixed effects for admit year, placement facility, and home county. The untreated mean is the rate of recidivism of non-visited incarcerated individuals. The median placement distance is 99 miles from home. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

Table A13: The Effect of Visitation on Recidivism, EFV Recipients Removed

	Readmit in 1 year		Readmit in 3 years	
	(1)	(2)	(3)	(4)
Visit Received	-0.0827**		-0.1165**	
	(0.0324)		(0.0460)	
Visit Count (per Month)		-0.0155**		-0.0219**
		(0.0061)		(0.0086)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,046	24,046	24,046	24,046

Note: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. The outcome variable for Columns (1) and (2) is a binary indicator for whether an incarcerated individual is re-admitted within 1 year of release, and the outcome variable for Columns (3) and (4) is a binary indicator for re-admit within 3 years of release for the given spell. All specifications include controls of the individual's race, spell length, offense type, and previous prison admissions as well as fixed effects for admit year, placement facility, and home county. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility. An incarcerated individual received at least one Extended Family Visit in 292 spells and those are dropped.

Readmissions

Although the modal individual in the sample serves one sentence, there are 23% of individuals who serve more than one sentence. I use these individuals to see whether distance has an effect even within the same individual. 39% of readmitted individuals are placed closer to home in their second admit, 39% are placed further from home, and 22% are placed in the same facility. For those placed further from home the second time, they are placed about 90 miles further. For those placed closer the second time, they are placed about 90 miles closer. There are some individuals who serve more than 2 spells during the sample time window but I focus on just the first two spells. Individuals placed closer versus further appear similar on observables. Visitation rates and intensity of visit both increase in the second spell when placed closer and decrease in the second spell when placed further. Notably, visitation probability does not change for same placements but intensity does decrease a bit.

OLS Regression of binary indicator for receiving visits in the second spell on a binary indicator for whether the individual received visits in their first spell and an indicator for whether the individual is placed closer in the second spell and their interaction.

OLS Regression of binary indicator for receiving visits in the second spell on a binary indicator for whether the individual received visits in their first spell and an indicator for whether the individual is placed further in the second spell and their interaction.

Table A14: Individuals Serving Two Full Sentences During Sample Window

	Same Placement		Closer Placement		Further Placement	
	Spell 1	Spell 2	Spell 1	Spell 2	Spell 1	Spell 2
Median placement distance (miles)	86.70	86.70	176.70	65.92	63.81	172.96
Median admit age	30	31	30	30	30	30
% Non-white	0.40	0.40	0.35	0.35	0.37	0.37
% property crime	0.45	0.45	0.48	0.47	0.46	0.46
% violent crime	0.09	0.09	0.09	0.09	0.08	0.09
% visited	0.40	0.40	0.34	0.36	0.42	0.35
N visits per month	0.70	0.67	0.39	0.71	0.73	0.45
N Individuals	535		955		956	

Notes: The sample consists of all men admitted to Washington state prisons more than once on or after January 1, 2010 and released as of December 31, 2016 for all spells. It is limited to individuals who were placed in a standard facility and had a non-missing home ZIP code. Individuals can enter prison more than twice in the sample window, but attention is restricted to the first two spells, as admissions beyond there are exceedingly rare.

Table A15: Visits in Second Spell

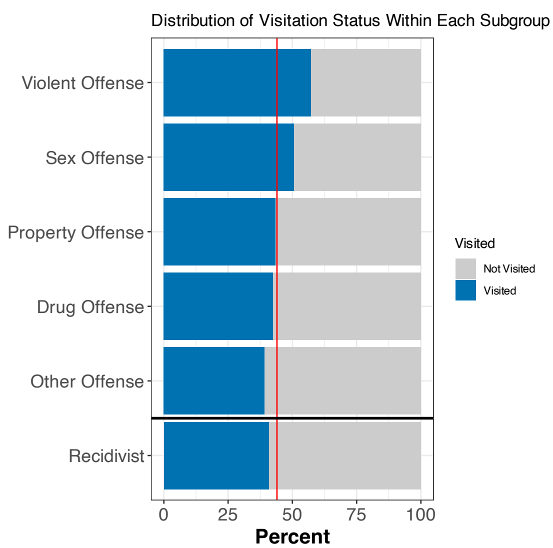
	Visited in Second Spell
Closer second placement	0.0351*
	(0.0206)
Visited in first spell	0.3830***
	(0.0231)
Closer second placement × Visited in first spell	-0.0193
	(0.0384)
Further second placement	-0.0444**
	(0.0205)
Visited in first spell	0.3914***
	(0.0239)
Further second placement × Visited in first spell	-0.0356
	(0.0374)
Observations	2,689

Notes: ***: 0.01, **: 0.05, *: 0.1. Each panel represents a separate OLS regression. *Closer second placement* is an indicator for whether the individual was placed in a facility that was closer to their home in their second prison spell in the sample relative to their first prison spell in the sample. The excluded category is individuals placed at the same distance or closer. *Visited in first spell* is an indicator for whether an individual received at least one visit in their first spell in the sample. The sample consists of all men admitted to Washington state prisons more than once on or after January 1, 2010 and released as of December 31, 2016 for all spells. It is limited to individuals who were placed in a standard facility and had a non-missing home ZIP code. Individuals can enter prison more than twice in the sample window, but attention is restricted to the first two spells, as admissions beyond there are exceedingly rare.

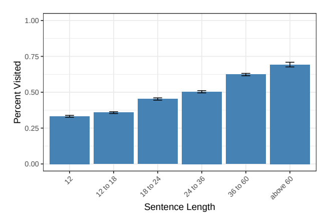
B Descriptives

Figure A2 highlights sharp differences in visitation across baseline characteristics. Panel (a) reports visitation rates by offense type and recidivism status. Offense types are classified by the most serious offense, with violent offenses ranked above sex offenses, followed by property and drug offenses. The red line marks the population average visitation rate of 44 percent. Individuals convicted of violent and sex offenses exhibit the highest visitation rates. Panels (b) and (c) show patterns by sentence length: while the likelihood of receiving any visit rises with sentence length, the frequency of visits per month actually declines. Panels (d) and (e) present visitation by age quartile, indicating that younger individuals are substantially more likely to be visited and to receive more frequent visits.

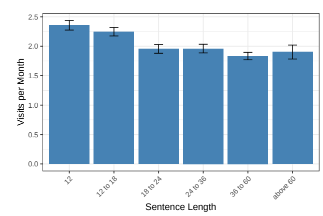
Figure A2: Selection into Visitation



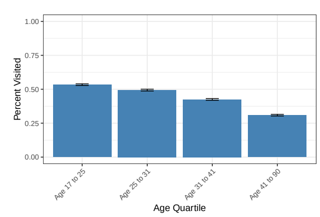
(a) Binary characteristics by visitation status



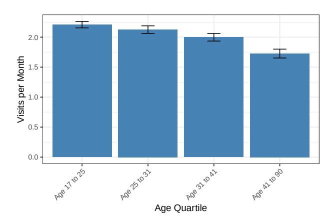
(b) Any visit by sentence length



(c) Visits/month by sentence length



(d) Any visit by age at admit



(e) Visits/month by age at admit

Note: This figure shows patterns of selection into visitation across observable characteristics. Panel (a) shows the share of individuals who ever received a visit (blue) versus those who never did (gray) by baseline offense type and recidivism history. Panels (b) and (c) display the probability of any visit and the average monthly number of visits, respectively, by sentence length quartile. Panels (d) and (e) show the same outcomes by quartiles of age at admission. The red vertical line in panel (a) indicates the overall visitation rate in the sample. The sample consists of all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016 who were placed in a standard facility and had a non-missing home ZIP code. Underlying data comes from merged Washington Department of Corrections admissions and visitation records.

B.1 Supplementary Sample

Table A16: Supplementary Sample Descriptive Statistics

	Overall	Not visited	Visited
N People	585	295	293
N Spells	590	297	293
Earliest admit	2000-03-28	2000-03-28	2002-11-08
Latest admit	2019-11-01	2019-11-01	2019-07-19
Median days served	570	406	968
Median days sentenced	815	669	1247
Avg age at admit	37.23	40.05	34.36
% white	0.62	0.60	0.63
% Black	0.17	0.18	0.16
% Hispanic	0.10	0.10	0.10
% Native American	0.07	0.08	0.06
% Asian	0.04	0.04	0.04
% Drug crime	0.19	0.15	0.22
% Violent crime	0.22	0.16	0.28
% Property crime	0.42	0.42	0.41
% Sex crime	0.04	0.02	0.06
% Visited	0.50	0	1
Avg visits per month	0	0	0.52
Median placement distance	118.08	125.35	109.57
% Low risk	0.21	0.16	0.26
% Moderate risk	0.10	0.10	0.10
% High drug crime risk	0.07	0.07	0.07
% High property crime risk	0.16	0.19	0.14
% High violent crime risk	0.22	0.22	0.21
% High risk all crimes	0.24	0.26	0.22
% Mental health or substance abuse issue	0.88	0.92	0.83
% Married or with long-term partner	0.41	0.32	0.50
% with good family relationship	0.71	0.67	0.75
% with children	0.51	0.49	0.54
% with 1 child	0.21	0.19	0.24
% with 2 or more children	0.30	0.30	0.30
Avg monthly income in 6mo prior to admit			
No legal income	0.34	0.34	0.33
<\$1,000	0.18	0.21	0.15
\$1,000-1,999	0.22	0.25	0.20
\$2,000-3,999	0.19	0.16	0.22
$\geq$ \$4,000	0.08	0.05	0.10

Notes: The sample is all men already incarcerated as of 2018 or who were incarcerated after 2018 and were placed in a standard facility without a life sentence. Data is from the first risk assessment done for each individual in a given spell. Risk score classifications come from Washington's classification system based on discrete cuts of continuous numeric scores for property crime, drug crime and violent crime re-offense risk. Scores are determined by the responses to interview questions, criminal history, and past incarceration behavior (if applicable). Relationship status, number of children, family relationships and substance abuse issues are self-reported. Mental health issues refer to a documented diagnosis. Average monthly income is self-reported for the last 6 months in the community prior to incarceration. "Under the table" income is considered illegal and is not counted.

Table A17: Balance on Distance to Initial Placement

Panel A: Main Sample

Variable	**Coefficient**	**Standard Error**
Demographics		
Non-white	-0.7578	(0.8708)
Violent crime	-2.4832	(1.4055)
Property crime	-0.8260	(0.9354)
Age at admit	0.0415	(0.0393)
Programming Participation		
Parenting program	0.0011	(0.0010)
Education	0.0002	(0.0009)
Work crew	0.0003	(0.0014)
Prison job	0.0057	(0.0039)
Reentry planning	0.0025*	(0.0010)
Undisclosed	-0.0080	(0.0041)
Observations	24,338	

Panel B: Supplementary Sample

Variable	**Coefficient**	**Standard Error**
Demographics		
Non-white	0.4766	(0.6486)
Violent crime	0.6124	(0.6791)
Property crime	0.7953	(0.6447)
Age at admit	-0.0118	(0.0241)
Programming Participation		
Parenting program	-0.7462	(1.2018)
Education	0.6665	(0.8678)
Work crew	-1.9472	(1.0065)
Prison job	1.5469*	(0.6351)
Reentry planning	-1.9440	(1.1306)
Undisclosed	-0.4223	(0.6344)
Family and Risk		
Long-term partner	-0.2000	(0.6351)
Children	0.4550	(0.6295)
Good family relationship	0.4478	(0.6866)
Low-risk	-0.8620	(0.7038)
Moderate-risk	-0.7910	(0.9932)
High-risk	1.0037	(0.6300)
Observations	590	

Note: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. Panel A presents statistics for the main sample. Each row is a regression of distance (in 1-mile units) on the given pre-determined characteristic or programming indicator, controlling for sentence length and first admit status, with fixed effects for admit year, placement facility, and home county. Panel B shows results for a supplementary sample incarcerated between 2018–2020 with intake records. Risk is WADOC's recidivism classification. High-risk combines high drug, property, violent, and diverse risk. No controls or fixed effects included in Panel B.

B.2 Post-release Housing

Table A18: Descriptive Statistics by Housing Assistance Status

	Overall	No Voucher	Voucher
Number of Spells	20,199	16,377	3,822
Median Sent. Length (months)	20	20	20
Median Time Served (days)	362	364	353
Median Age at Admit	31	31	34
% with prior admit	0.49	0.50	0.54
% drug crime	0.25	0.25	0.26
% sex crime	0.05	0.04	0.11
% violent crime	0.17	0.17	0.16
% property crime	0.42	0.46	0.28
Median Placement Distance (miles)	101.77	100.55	110.14
% Visited	0.45	0.49	0.26
Mean N Visits/month	0.88	1.01	0.29
% readmitted in 1 year	0.09	0.08	0.11
% drugs	0.02	0.02	0.03
% sex crime	< 0.01	< 0.01	< 0.01
% violent crime	0.01	0.01	0.01
% property crime	0.05	0.05	0.05
% readmitted in 3 years	0.25	0.24	0.29
% drugs	0.06	0.05	0.06
% sex crime	< 0.01	< 0.01	0.01
% violent crime	0.02	0.02	0.02
% property crime	0.13	0.13	0.13

Notes: This table presents descriptive statistics for the sample split by housing voucher status. Voucher use data comes from Washington Department of Corrections records. Spells are categorized as receiving housing assistance if the incarcerated individual received a housing voucher in that spell. All statistics are at the incarcerated individual-spell level. Offense types are not mutually exclusive and are binary indicators for if any of the crimes associated with the current spell fall in the given category. Distance is calculated as the Euclidean distance from the geographic centroid of a prisoner's home ZIP code to the geographic centroid of their placement facility's ZIP code. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility. Six percent of spells in the main sample are missing housing voucher information and are excluded.

Table A19: Descriptive Statistics of Voucher Recipients by Visitation Status

	Overall	Not Visited	Visited
Number of Spells	3,822	2,810	1,012
% Voucher Receipt	1	0.74	0.26
Median sent. length (months)	19	18	25
Median time served (days)	353	311.5	510.5
Median age at admit	34	36	31
% with prior admit	0.54	0.57	0.48
% drug crime	0.26	0.27	0.22
% sex crime	0.11	0.08	0.18
% violent crime	0.16	0.15	0.21
% property crime	0.28	0.27	0.31
Median placement distance	110.14	115.49	96.61
% visited	0.26	0	1
Mean N Visits/month	0.29	0	1.09
% readmitted in 1 year	0.11	0.13	0.08
% drugs	0.03	0.03	0.02
% sex crime	< 0.01	< 0.01	0.01
% violent crime	0.01	0.01	0.01
% property crime	0.05	0.06	0.04
% readmitted in 3 years	0.29	0.31	0.24
% drugs	0.06	0.07	0.05
% sex crime	0.01	< 0.01	0.01
% violent crime	0.02	0.02	0.02
% property crime	0.13	0.13	0.11

Note: This table presents descriptive statistics for all visited individuals, split by housing voucher status. Spells are categorized as receiving housing assistance if the incarcerated individual received a housing voucher in that spell. All statistics are at the incarcerated individual-spell level. Offense types are not mutually exclusive and are binary indicators for if any of the crimes associated with the current spell fall in the given category. Distance is calculated as the Euclidean distance from the geographic centroid of a prisoner's home ZIP code to the geographic centroid of their placement facility's ZIP code. The sample includes all prison spells for visited men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

Table A20: Supplementary Sample Descriptive Statistics by Housing Assistance Status

	Overall	No Voucher	Voucher
Number of Spells	563	457	106
% Visited	0.49	0.53	0.32
% Low risk	0.17	0.17	0.18
% Moderate risk	0.09	0.09	0.11
% High drug crime risk	0.07	0.07	0.09
% High property crime risk	0.18	0.19	0.12
% High violent crime risk	0.23	0.23	0.22
% High risk all crimes	0.26	0.25	0.29
% Mental health or substance abuse issue	0.92	0.92	0.92
% Married or with long-term partner	0.41	0.44	0.31
% with good family relationship	0.72	0.74	0.60
% with children	0.52	0.53	0.47
% with 1 child	0.22	0.23	0.15
% with 2 or more children	0.30	0.29	0.32
Avg monthly income bucket in 6mo prior to admit			
No legal income	0.36	0.37	0.32
<\$1,000	0.19	0.17	0.25
\$1,000-1,999	0.21	0.20	0.23
\$2,000-3,999	0.19	0.20	0.15
$\geq$ \$4,000	0.05	0.05	0.05

Notes: This table presents descriptive statistics for the supplementary sample split by housing voucher status. Voucher use data comes from Washington Department of Corrections records. Spells are categorized as receiving housing assistance if the incarcerated individual received a housing voucher in that spell. The sample is all men already incarcerated as of 2018 or who were incarcerated after 2018 and were placed in a standard facility without a life sentence. Data is from the first risk assessment done for each individual in a given spell. Risk score classifications come from Washington's classification system based on discrete cuts of continuous numeric scores for property crime, drug crime and violent crime re-offense risk. Scores are determined by the responses to interview questions, criminal history, and past incarceration behavior (if applicable). Relationship status, number of children, family relationships and substance abuse issues are self-reported. Mental health issues refer to a documented diagnosis. Average monthly income is self-reported for the last 6 months in the community prior to incarceration. "Under the table" income is considered illegal and is counter as no legal income. Ten percent of spells in the sample are missing housing voucher information and are excluded.

Table A21: Supplementary Sample, Sub-group Use of Voucher

	% Voucher Use
Within Visited	0.12
Within Non-visited	0.25
Within Married/long-term partner	0.14
Within Non-Married/long-term partner	0.22
Within good family relationship	0.16
Within not good family relationship	0.26
Within parents	0.17
Within non-parents	0.21
Within avg monthly income bucket	
No legal income	0.17
<$1,000	0.25
$1,000-1,999	0.21
$2,000-3,999	0.15
$\geq$ $4,000	0.17

Notes: This table presents what percent of each sub-group within the supplementary sample used a housing voucher. Voucher use data comes from Washington Department of Corrections records. Spells are categorized as receiving housing assistance if the incarcerated individual received a housing voucher in that spell. The sample is all men already incarcerated as of 2018 or who were incarcerated after 2018 and were placed in a standard facility without a life sentence. Data is from the first risk assessment done for each individual in a given spell. Relationship status, number of children, and family relationships are self-reported. Average monthly income is self-reported for the last 6 months in the community prior to incarceration. "Under the table" income is considered illegal and is counter as no legal income. Ten percent of spells in the sample are missing housing voucher information and are excluded.

B.3 Security Level Proxy

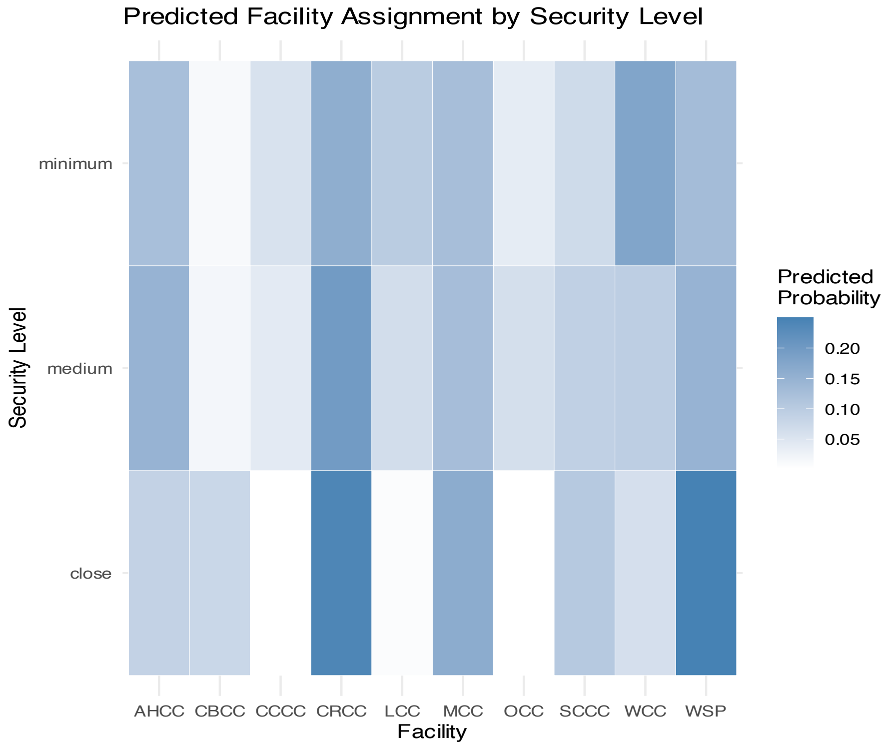


Figure A3: Predicted Facility Placement by Security Level

Note: This figure illustrates the average predicted probability an individual is placed in each facility given the proxy security level I create. OCC, LCC, and CCCC are minimum only facilities. CBCC and WCC house only incarcerated individuals medium and above. AHCC and CRCC house minimum and medium. MCC, WSP, and SCCC house all three security levels. OCC and CCCC are the smallest facilities.

B.4 Prison Population Maps

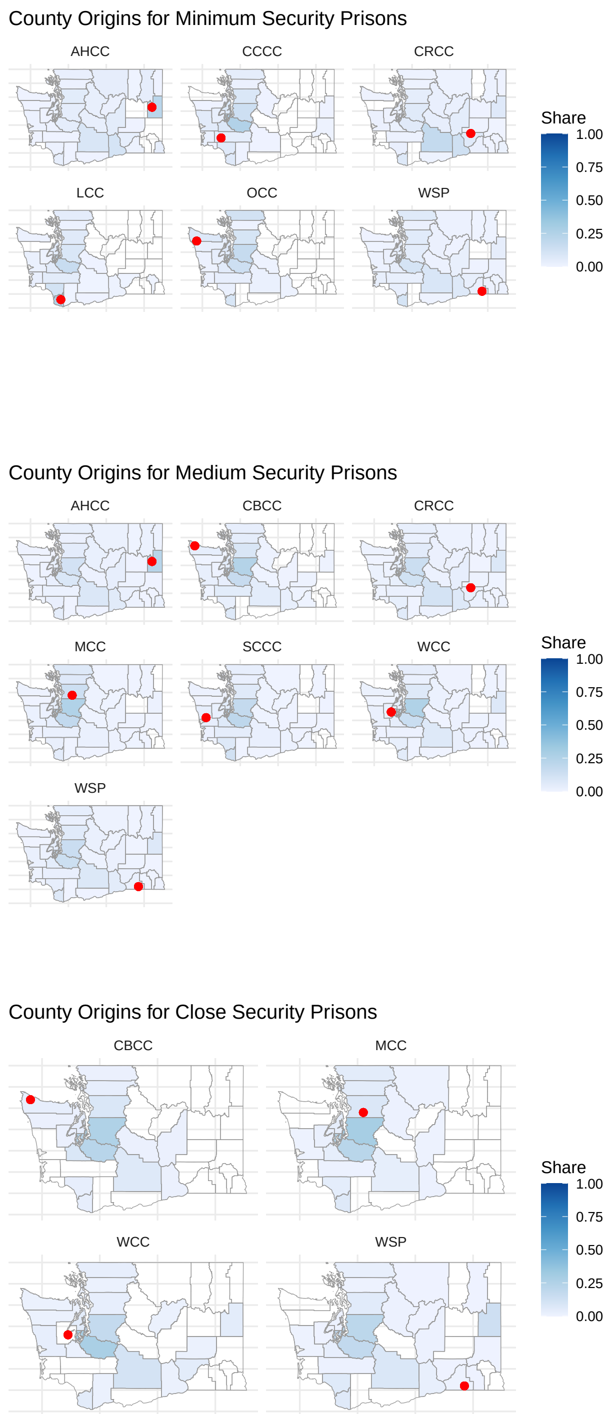


Figure A4: Heatmap of Home County of Each Prison's Population

Note: This figure is a heatmap of the state of Washington's counties depicting the home counties of each prison population from 2010-2016. Each Washington map corresponds to one prison. Darker colors indicate a higher share of individuals placed in the given prison were from the indicated county.

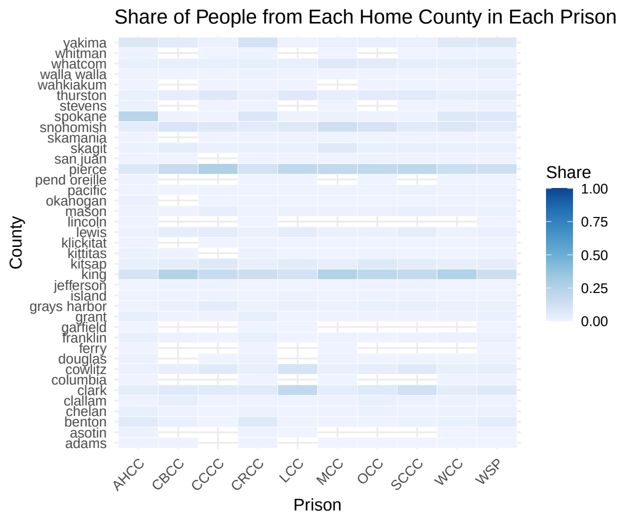


Figure A5: Heatmap of Share of Each County in Each Prison's Population

Note: This figure is a heatmap showing the share of each county's incarcerated population that was sent to each facility. Each row is one county. Each column is one prison. The cells across a row sum to one. Darker colors indicate a higher share of the given county's incarcerated population was placed in the given prison.

C Heterogeneity and Non-Linearities

C.1 Non-linearties in Visitation

The main analysis assumes that visitation has a linear effect on recidivism—that is, the difference between receiving 0 and 1 visit is assumed to have the same impact as the difference between 30 and 31 visits. If the effect of visitation instead exhibits diminishing or increasing returns, this linearity assumption would be violated. In Table A22, I explore several specifications that allow for nonlinear treatment effects.

Column (1) replicates the baseline linear specification, using the count of visits per month instrumented by distance, and shows a statistically significant negative effect of visitation on recidivism. Column (2) adds a squared term for visit count and instruments using both distance and distance squared to capture possible curvature. While the coefficient on the squared term is positive, suggesting possible diminishing returns, the estimate is imprecise and not statistically significant. Column (3) includes both the continuous visit count and an indicator for any visitation, attempting to separate extensive and intensive margin effects. Here too, neither estimate is significant, and standard errors are large. Finally, Column (4) splits the visit rate into discrete buckets: no visits (reference), low visitation (below the median among those visited), and high visitation (above the median). While the effect of low visitation is imprecisely estimated, the effect of higher visitation is large and statistically significant, indicating that sustained or repeated contact may be especially important.

Overall, these results suggest some evidence of nonlinearity, particularly that the extensive margin of visitation may matter more. However, the estimates across specifications are generally noisy, and wide confidence intervals reflect the limited power to detect precise nonlinear effects. This imprecision cautions against strong conclusions but does not rule out meaningful nonlinear dynamics in the effect of visitation on recidivism.

Table A22: Nonlinear Visitation Effects

	Readmit in 3 years			
	(1)	(2)	(3)	(4)
Visit Count (per Mo.)	-0.0199**	-0.1234	0.0128	
	(0.0082)	(0.0953)	(0.0309)	
Visit Count^2		0.0096		
		(0.0090)		
Visit Received			-0.2152	
			(0.1901)	
$0 < visits <= med.$				-0.2725
				(0.3285)
$visits > med.$				-0.1486***
				(0.0515)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	24,413	24,413	24,413	24,413

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. The outcome variable is a binary indicator for whether an incarcerated individual is readmitted to prison within 3 years of release. The complete set of controls described in Section 3 are included as well as fixed effects for admit year, placement facility, and home county. Column (1) uses only distance as an instrument while Columns (2)-(4) use distance and distance squared. Conditional on receiving at least one visits, the median number of visits per month is 0.91. Column (4) splits visitation into 0 visits, 0 to median, and above median. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

C.2 Heterogeneity by observable characteristics

Table A23 presents results for the sample split below and above the median age at admit of 33, by whether the individual's current conviction is for a violent crime, and by race. Effects are noisy, but suggestive that older individuals, those convicted of non-violent crime, and non-white individuals benefit the most from visitation.

Table A23: Treatment Effect Heterogeneity by Observable Characteristics

	Readmit in 3 Years					
	Age		Crime Type		Race	
	young	old	violent	non-violent	white	non-white
	(1)	(2)	(3)	(4)	(5)	(6)
Visit Received	-0.1053*	-0.1603**	-0.1565	-0.1445***	-0.0977*	-0.2833***
	(0.0603)	(0.0699)	(0.0958)	(0.0504)	(0.0524)	(0.0906)
Visit Count (per Mo.)	-0.0178*	-0.0315**	-0.0174*	-0.0298***	-0.0181*	-0.0475***
	(0.0102)	(0.0137)	(0.0105)	(0.0104)	(0.0097)	(0.0152)
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	12,353	11,985	4,063	20,275	15,212	9,126
Untreated mean	0.33	0.25	0.16	0.29	0.29	0.27

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. This table presents 2SLS estimates of the effect of visitation on readmission to prison within 3 years of release for splits of the sample. Visit count (per mo.) is the count of visits received in a given spell normalized by the number of in-prison months for a given prisoner-spell. The outcome variable is a binary indicator for whether an incarcerated individual is readmitted to prison within 3 years of release. The young sub-sample is men who were age 33 or young at time of admission, and the old sub-sample is men who were age 34 or older at the time of admissions. The violent sample consists of individuals convicted of a violent crime in the given spell. The non-violent sample consists of individuals who were only convicted for non-violent crimes in the given spell. Controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility are included. The untreated mean is the readmit rate for non-visited incarcerated men in the relevant sample.

C.3 Subsequent Crime

Instead of examining whether an individual is readmitted to prison at all, I now explore whether visitation affects the type of offense for which an individual is readmitted. Specifically, I estimate separate regressions using binary indicators for whether a person is readmitted for a violent, drug, sex, or property crime. Property crimes are the most common: about 10 percent of the full sample is readmitted for a property crime, and among those who are reincarcerated, 36 percent committed a property offense. Drug crimes follow, with a 6 percent overall readmission rate and comprising 23 percent of recidivism events. Violent and sex crime readmissions are far less common.

Results for the effect of visitation on subsequent crime are shown in Table A24. Columns (1), (3), (5), and (7) show the unconditional effects, while columns (2), (4), (6), and (8) include controls for the individual's current offense type. The results show that visitation has no statistically significant effect on violent crime recidivism, even after controlling for offense type. For drug crime, visitation reduces the probability of recidivism by about 4.8 percentage points (column 4). For sex offenses, the effect of visitation is small but negative. The largest and most robust effect is for property crime: visitation reduces the likelihood of being readmitted for a property crime by approximately 10 percentage points, a substantial and highly statistically significant effect, even after adjusting for current offense type. Small sample sizes for violent crimes and sex crimes make it difficult to detect results for these crimes, but results are suggestive that visitation may be particularly effective at reducing recidivism related to property and drug crimes, which are often economically motivated and potentially more responsive to social and logistical support.

Table A24: Treatment Effect Heterogeneity by New Crime Type

	Readmit in 3 years							
	New Violent Crime		New Drug Crime		New Sex Crime		New Property Crime	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Visit Received	0.0042	0.0013	-0.0385	-0.0476*	-0.0122*	-0.0120*	-0.1083***	-0.1019***
	(0.0122)	(0.0122)	(0.0279)	(0.0276)	(0.0063)	(0.0063)	(0.0323)	(0.0310)
Current drug offense		-0.0011		0.0985***		-0.0015**		-0.0163***
		(0.0017)		(0.0048)		(0.0007)		(0.0042)
Current violent offense		0.0539***		-0.0294***		0.0006		-0.0777***
		(0.0052)		(0.0045)		(0.0017)		(0.0071)
Current sex offense		-0.0040		-0.0244***		0.0444***		-0.0445***
		(0.0036)		(0.0040)		(0.0061)		(0.0046)
Current property crime		0.0043**		0.0227***		-0.0023***		0.1732***
		(0.0019)		(0.0037)		(0.0007)		(0.0056)
Current Crime	No	Yes	No	Yes	No	Yes	No	Yes
Other Controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,413	24,413	24,413	24,413	24,413	24,413	24,413	24,413
Untreated mean	0.02	0.02	0.07	0.07	0.004	0.004	0.10	0.10

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. This table presents 2SLS regression results for the effect of visitation on subsequent crime. The outcome variable is a binary indicator for whether an incarcerated individual is readmitted to prison within 3 years of release for the given crime type. Columns (2), (4), (6), and (8) add controls for the current conviction. Controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility are included. The untreated mean is the readmit rate for the given crime type for non-visited incarcerated individuals. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

C.4 Visitors

Incarcerated individuals receive visits from parents, spouses, friends, children, and other relatives. Up to this point I have treated "visit" as a single object, but the visitor's relationship to the incarcerated person may matter in its impact on recidivism. To asses this, I next split visitation up by relationship of the visitor and investigate heterogeneous effects by visitor type.

I first examine whether the composition of visitors changes across distance. In other words, does who visits change as individuals are placed farther from home? Figure A6 shows that visitor types remain remarkably stable across distance. While the likelihood of receiving a visit declines, it declines proportionally for all visitor types. Further, among those who are visited the mix of visitors (parents, spouses, children, friends, and other family members) changes little as distance increases.[48] However, visitor composition does change across the length of the spell. Figure A7 shows that visitor types remains stable until the last 3 months of the spell: in the last 3 months of the spell extended family members drop out and parents make up a larger share of the visitor pool.

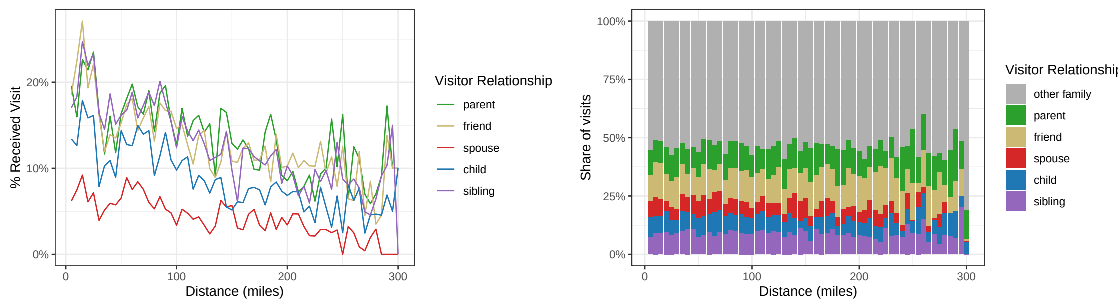


Figure A6: Visitor Composition by Distance

Note: This figure presents the composition of visitors by their relationship to the incarcerated individual across distance. The left panel displays the percent of individuals who receive at least one visit from the given visitor type. The right panel displays the total composition of visitor types within visited individuals. *Other family* includes grandparents, cousins, uncles, aunts, and in-laws.

[48]There is a drop-off in spousal visits at the very tail end of distance, but as spousal visits are relatively rare this is likely noise.

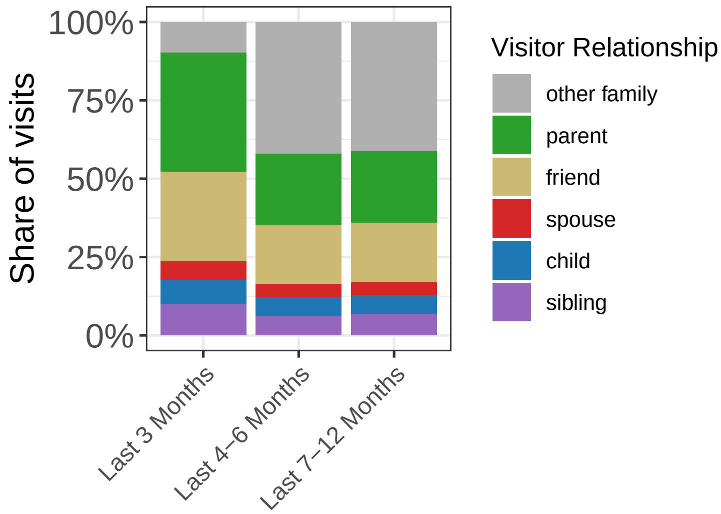


Figure A7: Visitor Composition Over Spell

Note: This figure presents the composition of visitors by their relationship to the incarcerated individual across the spell. The sample is limited to individuals who served at least 14 months and received at least 1 visit in the last year of the spell. Visits are grouped into mutually exclusive timing groups. *Other family* includes grandparents, cousins, uncles, aunts, and in-laws.

One avenue to investigate the differential effects of visitor-type would be to look at individuals who only ever receive visits from one type of visitor. However, nearly 70 percent of visited individuals receive visits from a mix of types of visitors, whether it be their parents and their spouse or friends, a grandparent and their children, or many other combination.[49] Therefore, I instead divide the visited population into groups based on the modal relationship of their visitors: (i) children or spouse, (ii) parents, and (iii) friends or other family.[50]

To assess the causal impact of visitor relationship, I decompose the overall effect of distance on visitation and recidivism into sub-effects defined by the dominant type of visitor. The main results estimate the LATE of distance, $LATE_{dist}$. This can be decomposed into a weighted average of sub-LATEs measuring the effects of visitation for individuals with different visitor compositions.[51]

$$LATE_{dist} = S_{child,spouse} LATE_{child,spouse} + S_{parent} LATE_{parent} + S_{friend,other} LATE_{friend,other}$$

[49]See Appendix Table A25.

[50]Appendix Table A26 reports descriptive statistics for each visitor-group.

[51]This decomposition follows the approach in Kline and Walters (2016).

where $LATE_{relationship}$ is the average treatment effect for compliers who move from receiving no visits to receiving visits from mostly visitor type $relationship \in \{child/spouse, parent, friend/otherfamily\}$ when they are placed closer to home. The weights $S_{relationship}$ give the fraction of compliers from each visitor-group.

It is important to clarify how these visitor groups should be interpreted. Individuals have predetermined sets of potential visitors (parents, spouses, children, friends), and distance shifts whether those visitors are able to visit, not which type of visitor they have. The estimated effects for each visitor group therefore capture the causal impact of visitation for the subset of compliers whose marginal visits come from that relationship type, rather than substitution between visitor types.

To estimate these sub-LATEs, I decompose visitation into separate endogenous variables for each visitor group. To generate instruments, I interact covariates with distance to create multiple instruments. I create quartiles of both sentence length and age and interact those with quartiles of distance. This approach requires a constant effects assumption (see Kline and Walters (2016)). This rules out the possibility that, for example, spouse visits reduce recidivism more for older individuals than for younger ones, or that parent visits have larger effects for those with shorter sentences than for those with longer ones. The visitor-type sub-LATEs are presented in Table A27. The estimates indicate that compliers whose marginal visitors are spouses or children may benefit the most from visitation. However, these estimates should be interpreted with caution given the relative weakness of the instruments and the noisiness of the effects.

Table A25: Visits from Only One Visitor Type

Visitor Relationship	N	Percent	Visitor Relationship	N	Percent
Only Children	53	< 0.01	Most Children	670	0.06
Only Spouse	225	0.02	Most Spouse	702	0.06
Only Friends	1,777	0.16	Most Friends	3,577	0.33
Only Parents	1,497	0.14	Most Parents	4,839	0.45
Mix or Other	7,286	0.67	Most Other Family	1,059	0.10
Total	10,775	1	Total	10,775	1

Notes: This table presents counts and percentages of incarcerated individuals who only receive visits from one type of visitor as well as by dominant visitor groups. The visited sample is split into groups by their visitors relationships, which is determined by the relationship of their visitor recorded at time of visit. The left panel presents the count and percent of visited individuals who only ever received visits from one type of visitor. The right panel splits the group by their dominant visitor-type.

Table A26: Descriptive Statistics by Dominant-Visitor Group

Most Visits from:	Child	Spouse	Parents	Friend	Other Family	No Visits
N	667	696	4,800	3,558	1,054	13,563
Age at Admit	36.93	36.65	29.25	32.30	32.42	35.06
Sentence Length (mos.)	24	25	22	22	22	17
% with prior admit	0.45	0.55	0.37	0.52	0.46	0.51
% violent offense	0.22	0.21	0.23	0.20	0.20	0.13
% drug offense	0.28	0.26	0.24	0.25	0.23	0.26
% sex offense	0.04	0.09	0.06	0.05	0.05	0.04
% property offense	0.35	0.37	0.48	0.39	0.44	0.40
% readmitted within 1 year	0.04	0.03	0.08	0.06	0.09	0.10
% readmitted within 3 years	0.16	0.15	0.24	0.22	0.25	0.28

Notes: This table presents descriptive statistics for the sample split by their dominant visitor. The sample is split into groups by their dominant visitor type, which is determined by the relationship of their visitor recorded at time of visit. "No Visits" is the group that did not receive any visits in the given spell. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

Table A27: Visitation Effects by Visitor Type

	Readmit in 1 year		Readmit in 3 years	
	Dist × Age	Dist × Sent.	Dist × Age	Dist × Sent.
	(1)	(2)	(3)	(4)
Most Visits: spouse or child	-0.2963***	-0.4244	-0.4003***	-0.1615
	(0.1111)	(0.2602)	(0.1554)	(0.3808)
Most Visits: parents	-0.2107**	0.0136	-0.2163	0.1272
	(0.1000)	(0.1837)	(0.1399)	(0.2721)
Most Visits: other family or friend	0.2206	0.0580	0.1575	-0.1962
	(0.1368)	(0.1713)	(0.1929)	(0.2587)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
F-stat (spouse, child)	12.70	6.04	12.70	6.04
F-stat (parents)	11.00	11.4	11.00	11.4
F-stat (other)	7.05	9.77	7.05	9.77
Observations	24,413	24,413	24,413	24,413

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. The outcome variable for Columns (1) and (2) is a binary indicator for whether an incarcerated individual is readmitted to prison within 1 year of release. The outcome variable for Columns (3) and (4) is a binary indicator for whether an incarcerated individual is readmitted to prison within 3 years of release. The complete set of controls described in Section 3 are included as well as fixed effects for admit year, placement facility, and home county. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

D LATE and Complier Characteristics

D.1 LATE Result

Binary instrument.
Consider the case of binary treatment and binary instrument. Let V_i be visitation treatment: $V_i \in \{0, 1\}$. Let Z_i be the distance instrument such that placement below the median indicates $Z_i = 1$ and placement above indicates $Z_i = 0$. Let $R_i(1)$ be the potential recidivism outcome for $V_i = 1$ and let $R_i(0)$ be the potential recidivism outcome for $V_i = 0$.

Suppose independence $(R(1), R(0), V_1, V_0) \perp\!\!\!\perp Z$, exclusion $R(z, v) = R(v)$, relevance $\mathbb{E}[V_1 - V_0] \neq 0$, and monotonicity such that closer distance makes visitation weakly more likely $V_1 \geq V_0$.

The IV (Wald) estimand is given by:

$$\beta_{IV} = \frac{\mathbb{E}[R|Z = 1] - \mathbb{E}[R|Z = 0]}{\mathbb{E}[V|Z = 1] - \mathbb{E}[V|Z = 0]}$$

Consider the first half of the numerator $\mathbb{E}[R|Z = 1]$. Using the exclusion restriction this can be written as:

$$\begin{aligned}\mathbb{E}[R|Z = 1] &= \mathbb{E}[R(1) \cdot V + R(0) \cdot (1 - V)|Z = 1] \\ &= \mathbb{E}[R(0) + (R(1) - R(0))V|Z = 1]\end{aligned}$$

And by independence:

$$= \mathbb{E}[R(0) + (R(1) - R(0))V_1]$$

And equivalently $\mathbb{E}[R|Z = 0] = \mathbb{E}[R(0) + (R(1) - R(0))V_0]$. This means the numerator of the Wald estimand becomes:

$$\mathbb{E}[R|Z = 1] - \mathbb{E}[R|Z = 0] = \mathbb{E}[(R(1) - R(0))(V_1 - V_0)]$$

by monotonicity:

$$= \mathbb{E}[R(1) - R(0)|V_0 < V_1]\mathbb{E}[V_1 - V_0] \quad = \mathbb{E}[R(1) - R(0)|V_0 < V_1]\mathbb{P}[V_1 > V_0]$$

Similarly, the denominator is then:

$$\mathbb{E}[V|Z=1] - \mathbb{E}[V|Z=0] = \mathbb{E}[V_1 - V_0] = \mathbb{P}[V_1 > V_0]$$

The Wald estimand can then be written:

$$\begin{aligned}\beta_{IV} &= \frac{\mathbb{E}[R|Z=1] - \mathbb{E}[R|Z=0]}{\mathbb{E}[D|Z=1] - \mathbb{E}[D|Z=0]} \\ &= \frac{\mathbb{E}[R(1) - R(0)|V_0 < V_1]\mathbb{P}[V_1 > V_0]}{\mathbb{P}[V_1 > V_0]} \\ &= \mathbb{E}[R(1) - R(0)|V_1 > V_0]\end{aligned}$$

$V_1 > V_0$ defines a complier, and so this is the treatment effect for compliers.

Multi-valued or continuous instrument.
I following a Roy (1951)/Heckman (1976) selection framework (Vytlacil (2002) shows this is equivalent to the Imbens-Angrist LATE model under monotonicity).

Let R be the recidivism outcome, and $V \in \{0,1\}$ be binary treatment. Let $Z \in [0, z_{max}]$ be distance, such that further distance discourages visitation.

Let $U \sim Unif[0,1]$ be latent resistance to treatment. Define the first-stage visitation propensity as $p(z) = \mathbb{P}[V=1|Z=z]$ and $p'(z) \leq 0$. Individuals only receive visits when their resistance to visitation is lower than the instrument-induced threshold $p(Z)$: $V = 1\{U \leq p(Z)\}$.

Further assume exclusion $R(z,v) = R(v)$ and independence $R(1), R(0), U) \perp\!\!\!\perp Z$.

Define the marginal treatment effect as:

$$MTE(u) = \mathbb{E}[R(1) - R(0)|U=u].$$

This is the causal treatment effect for individuals at resistance quantile u.

Consider two values of Z: $z < z'$ with $p(z) > p(z')$. There is a set of compliers for those two values of Z just as there are when $Z \in \{0,1\}$. The IV/wald estimand for z to z' is given by:

$$\beta_{IV} = \frac{\mathbb{E}[R|Z=z] - \mathbb{E}[R|Z=z']}{\mathbb{E}[V|Z=z] - \mathbb{E}[V|Z=z']}$$

Using the latent-index notation and exclusion the numerator is:

$$\begin{aligned}
\mathbb{E}[R|Z=z] - \mathbb{E}[R|Z=z'] &= \int_{p(z')}^{p(z)} \mathbb{E}[R(1)|U=u]du - \int_{p(z')}^{p(z)} \mathbb{E}[R(0)|U=u]du \\
&= \int_{p(z')}^{p(z)} MTE(u)du \\
&= \int_{0}^{1} MTE(u)1[u \in [p(z'), p(z)]]du
\end{aligned}$$

And the denominator is:

$$\mathbb{E}[V|Z=z] - \mathbb{E}[V|Z=z'] = p(z) - p(z')$$

Therefore, $\text{LATE}_{z'}^{z}$ is:

$$\text{LATE}_{z'}^{z} = \int_{0}^{1} MTE(u) \frac{1[u \in [p(z'), p(z)]]}{p(z) - p(z')} du$$

This identifies the average treatment effect for the compliers whose resistance lies between the two propensity cutoffs. Intuitively, these are exactly the individuals whose visiting status changes when moving from distance z to the closer distance z'. Aggregating such local contrasts gives a weighted average of MTEs, with weights concentrating where distance most strongly shifts visitation.

D.2 Selection Test Under Heterogeneity

The instrumental variables approach is motivated by potential unobserved selection and by the goal of identifying a policy-relevant local effect. With heterogeneous treatment effects, however, OLS and 2SLS target different parameters, so the traditional Wu–Hausman test for endogeneity is not informative about selection. For that reason, I turn to the heterogeneity-robust test in Black et al. (2022), which compares mean outcomes for treated compliers to always-takers and for untreated compliers to never-takers. Under no selection in levels, these means coincide. Essentially, I estimate the regression in Eq. (1) separately within the treated and untreated samples. The coefficient on the instrument is the parameter of interest.

To implement the test I estimate

$$R_{is} = a_0 Dist_{is} + B_0' X_{is}$$

within the sample of non-visited individuals. And I estimate

$$R_{is} = a_1 Dist_{is} + B_1' X_{is}$$

within the sample of visited individuals. R_{is} is a binary indicator for prison re-admission within 1 year and within 3 years of release from prison spell s. X_{is} includes all controls and fixed effects from the main specification. $Dist_{is}$ is the distance from home county to placement facility.

Formally, the null hypothesis is $H_0 : a_j = 0; j \in 0, 1$. Rejection of either coefficient indicates that either the exclusion restriction is violated or selection is present. Under the assumption that the exclusion restriction holds, rejection is evidence of selection. I fail to reject the null for both untreated and treated groups for both one-year and three-year recidivism (see Table A28 below). I also conduct the test using a binary instrument indicating whether an individual is placed more than 99 miles from their home county (the median distance) and I again fail to reject the null for both untreated and treated groups for both time horizons. The 2SLS estimates have large standard errors, so the lack of statistical significance is not necessarily strong evidence of no selection, but is rather inconclusive given limited precision.

Table A28: Selection Test

	Readmit in 3 years	
	Untreated Sample (1)	Treated Sample (2)
Above median distance	0.0103 (0.0079)	-0.0042 (0.0081)
Controls	Yes	Yes
Fixed Effects	Yes	Yes
Observations	13,563	10,775

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. This table presents results from the Black et al. (2022) test for selection with heterogeneous treatment effects. The dependent variable is an indicator for whether an individual is readmitted to prison within 3 years of release. The independent variable is an indicator for whether an individual is placed above the median distance of 99 miles. The untreated sample consists of individuals who did not receive any visits in the given spell. The treated sample consists of individuals who received one or more visits in the given spell. Controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility are included. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and whose placement facility is the same as their release facility.

D.3 OLS Estimate with LATE-groups

Consider an outcome Y and binary treatment D. Then β_{OLS} gives:

$$\beta_{OLS} = \mathbb{E}[Y|D=1] - \mathbb{E}[Y|D=0]$$

Let G be an individual's compliance group such that $G \in \{AT, C, NT\}$ with shares in the population of p_{AT}, p_C, p_{NT} that sum to 1.

The treated group $D = 1$ consists of always-takers and compliers with $Z = 1$ and the untreated group $D = 0$ consists of never-takers and compliers with $Z = 0$.

The share of always-takers among the treated is:

$$s_{AT}^{T} = \mathbb{P}(G = AT|D = 1) \\ = \frac{p_{AT}}{p_{AT} + p_C \cdot \mathbb{P}(Z = 1)}$$

The share of compliers among the treated is:

$$s_{C}^{T} = \mathbb{P}(G = C|D = 1) \\ = \frac{p_C \cdot \mathbb{P}(Z = 1)}{p_{AT} + p_C \cdot \mathbb{P}(Z = 1)}$$

The share of never-takers among the untreated is:

$$s_{NT}^{U} = \mathbb{P}(G = NT|D = 0) \\ = \frac{p_{NT}}{p_{NT} + p_C \cdot (1 - \mathbb{P}(Z = 1))}$$

And the share of compliers among the untreated is:

$$s_{C}^{U} = \mathbb{P}(G = C|D = 0) \\ = \frac{p_C \cdot (1 - \mathbb{P}(Z = 1))}{p_{NT} + p_C \cdot (1 - \mathbb{P}(Z = 1))}$$

Let μ_G^1 be the treated mean among group G and let μ_G^0 be the untreated mean among group G. Let τ_G be the treatment effect for group G. We can then write β_{OLS} as:

$$\begin{aligned} \beta_{OLS} &= \mathbb{E}[Y|D = 1] - \mathbb{E}[Y|D = 0] \\ &= \left(s_{AT}^{T}\mu_{AT}^{1} + s_{C}^{T}\mu_{C}^{1}\right) - \left(s_{NT}^{U}\mu_{NT}^{0} + s_{C}^{U}\mu_{C}^{0}\right) \\ &= s_{AT}^{T}(\mu_{AT}^{1} - \mu_{AT}^{0}) + s_{C}^{T}(\mu_{C}^{1} - \mu_{C}^{0}) + \left[\left(s_{AT}^{T}\mu_{AT}^{0} - s_{NT}^{U}\mu_{NT}^{0}\right) + \left(s_{C}^{T}\mu_{C}^{0} - s_{C}^{U}\mu_{C}^{0}\right)\right] \\ &= \underbrace{s_{AT}^{T}\tau_{AT} + s_{C}^{T}\tau_{C}}_{\text{weighted treatment effects of the treated}} + \underbrace{\left(s_{AT}^{T}\mu_{AT}^{0} - s_{NT}^{U}\mu_{NT}^{0}\right) + \left(s_{C}^{T}\mu_{C}^{0} - s_{C}^{U}\mu_{C}^{0}\right)}_{\text{selection in levels}} \end{aligned}$$

Comparatively, within the LATE-framework IV estimates τ_C, the treatment effect for the compliers. I can then use this to see when IV will be larger in magnitude than OLS.

$$
\begin{aligned}
\beta_{IV} - \beta_{OLS} &= \tau_C - \left(s^T_{AT}\tau_{AT} + s^T_C\tau_C + \left(s^T_{AT}\mu^0_{AT} - s^U_{NT}\mu^0_{NT}\right) + \left(s^T_C\mu^0_C - s^U_C\mu^0_C\right)\right) \\
&= s^T_{AT}(\tau_C - \tau_{AT}) - \left(\left(s^T_{AT}\mu^0_{AT} - s^U_{NT}\mu^0_{NT}\right) + \left(s^T_C\mu^0_C - s^U_C\mu^0_C\right)\right)
\end{aligned}
$$

Assuming same sign for β_{OLS} and β_{IV} :

$$
\begin{aligned}
\mid \beta_{IV} \mid - \mid \beta_{OLS} \mid > 0 &\Leftrightarrow s^T_{AT}(\tau_C - \tau_{AT}) - \left(\left(s^T_{AT}\mu^0_{AT} - s^U_{NT}\mu^0_{NT}\right) + \left(s^T_C\mu^0_C - s^U_C\mu^0_C\right)\right) > 0 \\
\mid \beta_{IV} \mid > \mid \beta_{OLS} \mid &\Leftrightarrow \underbrace{s^T_{AT}(\tau_C - \tau_{AT})}_{\text{difference in treatment effects}} < \underbrace{\left(s^T_{AT}\mu^0_{AT} - s^U_{NT}\mu^0_{NT}\right) + \left(s^T_C\mu^0_C - s^U_C\mu^0_C\right)}_{\text{selection}}
\end{aligned}
$$

This tells us that in order for the IV estimate to be larger in magnitude than the OLS estimate if i) there is no selection in levels and compliers have larger treatment effects than always-takers, ii) treated individuals have a higher baseline risk of recidivism (negative selection), or iii) treated individuals have lower baseline risk of recidivism (positive selection) and compliers have a much larger treatment effect than always-takers.

While the null result from the Black et al. (2022) possibly indicates no selection in levels, it has low power due to the imprecision of the IV estimates. Descriptive statistics do show that visited individuals seem positively selected relative to non-visited individuals, specifically, they are more likely to report positive family relationships and have a higher self-reported income (see Tables 1 and A32). This points to positive selection, which requires $\mid \tau_C \mid > \mid \tau_{AT} \mid$ (compliers have a larger treatment effect relative to always-takers) for IV to be larger in magnitude than OLS.

D.4 Complier Characteristics

Consider the following instrumental variables specification where endogenous regressor x_i is a binary indicator for visitation, y_i is the recidivism outcome, z_i is individual i's distance from home, and w_i collects fixed effects for placement facility, home county, and security level:

$$
\begin{aligned}
y_i &= \beta x_i + w_i'\gamma + \varepsilon_i, \\
x_i &= \pi z_i + w_i'\mu + u_i.
\end{aligned}
$$

Let the true causal model have linear heterogeneous treatment effects:

$$
y_i = x_i\beta_i + \varepsilon_i.
$$

Then β is the IV estimand of β_i.

Following Borusyak and Hull (2024), under the following two assumptions β can be expressed as a convex combination (non-negative weights that sum to one) of heterogeneous treatment effects:

Assumption 1 (Exogeneity): $\mathbb{E}[z_i \mid y_i(x), w_i] = w_i'\lambda$, conditional on w_i, the instrument is as-good-as randomly assigned and its expectation is linear in w_i.

Assumption 2 (Monotonicity): z_i moves x_i in a single direction (with no defiers).

Under these assumptions, and assuming the IV estimator consistently estimates β, the estimand can be written as:

$$\beta = \mathbb{E}\left[\int \phi_i(x)\beta_i(x)dx\right] / \mathbb{E}\left[\int \phi_i(x)dx\right]$$

$$\beta = \mathbb{E}\left[\int \omega_i(x) \quad \underbrace{\frac{\partial y_i}{\partial x}(x)}_{\text{hetero effects } \beta_i} \quad dx\right]$$

$$\text{for binary } x_i : \beta = \mathbb{E}\left[\omega_i(y_i(1) - y_i(0))\right]$$

Hull (2025) shows how to use this result to characterize the population contributing to an OLS and 2SLS estimand. Specifically, summary statistics on pre-determined characteristics can be calculated by replacing the outcome variable with the interaction of the pre-determined characteristic, c_i, and treatment x_i. This is similar to the well-known Abadie (2003) result for characterizing compliers except that here the instrument does not need to be binary.

$$x_i c_i = \tilde{\beta} x_i + w_i'\tilde{\gamma} + \epsilon_i$$

$$x_i = \pi z_i + w_i'\mu + \nu_i$$

Using the convex expression of treatment effects above, we can then write $\tilde{\beta}$:

$$\tilde{\beta} = \mathbb{E}\left[\int \omega_i(x)\frac{\partial x_i c_i}{\partial x}(x)dx\right]$$

$$= \mathbb{E}\left[\int \omega_i(x)c_i dx\right]$$

which gives you the weighted mean of characteristic c_i using the weights used in the estimand.

To illustrate this procedure I provide an example of how to estimate the mean age of admit of compliers contributing to the 2SLS estimate in my main results. I run the following 2SLS regression (S_i are controls/FEs required for exogeneity, namely security level):

$$age_i \times visit_i = \alpha_0 + S_i'\alpha_2 + \rho visit_i + \epsilon_i$$

$$visit_i = \pi distance_i + S_i'\mu + \nu_i$$

The estimated coefficient ρ gives the sample mean for the effective population.

Table A29 reports summary statistics for pre-determined characteristics. Column (1) shows unadjusted sample means. Column (2) presents estimates obtained using the method of Hull (2025) for OLS estimation of the effect of visitation on three-year readmission rates. Column (3) applies the same method to the 2SLS estimates, instrumenting visitation with distance. The population characterized in Column (3) is the complier population. Overall, the effective sample for 2SLS is similar to that for OLS, with two notable differences: the 2SLS complier population is much whiter and includes more property crime offenders. Non-violent offenders tend to have larger treatment effects while whites have smaller treatment effects than non-white individuals. The combined effect could help explain a 2SLS estimate that is modestly larger than OLS but statistically indistinguishable from it.

Table A29: Effective Population Characteristics

	Sample (1)	OLS (2)	2SLS (3)
Admit age	33.5	31.6	31.9
	(0.07)	(0.10)	(0.60)
% Above median admit age	0.49	0.41	0.42
	(0.004)	(0.005)	(0.03)
% Non-white	0.37	0.33	0.26
	(0.003)	(0.005)	(0.03)
% Violent crime conviction	0.17	0.19	0.18
	(0.002)	(0.004)	(0.02)
% Drug crime conviction	0.25	0.25	0.26
	(0.003)	(0.004)	(0.03)
% Property crime conviction	0.41	0.43	0.46
	(0.003)	(0.005)	(0.03)

Notes: Standard errors in parentheses. "Above median admit age" is a binary indicator whether an individual was above age 33 at admit and is used for comparison to the heterogeneous treatment effect estimates that use this binary split. In Column (1) means and standard errors are calculated directly from the sample. In Column (2) means and standard errors are for the coefficient on treatment from an OLS regression with the interaction of treatment and the given characteristics as the outcome variable and treatment as the independent variable with controls for sentence length, recidivist status, home county and placement facility. In Column (3) means and standard errors are for the coefficient on treatment from a 2SLS regression with the interaction of treatment and the given characteristics as the outcome variable and treatment as the independent variable, distance as the instrument and with controls for sentence length, recidivist status, home county and placement facility. Sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and who were placed in a standard placement facility.

E Extended Family Visits

Washington state is one of the four states, along with California, New York and Connecticut, that offer multi-day private visitation with immediate family members. In Washington this program is called Extended Family Visits (EFV). Visits take place in trailer units set up on prison facilities but outside on the main buildings and are unsupervised. Eligibility is limited to visitors who are immediate family (spouses, children, parents), and the relationship must be verified with legal documentation such as birth certificates and marriage licenses. Visitors are also required to maintain regular visitation schedules with the incarcerated individual in order to be eligible for EFV participation. Visitors must bring all food they wish to consume or cook during the visit and both visitors and all their belongings are screened and searched upon entry and exit.

Due to the stringent requirements, there is relatively little program take-up. Less than 1 percent of the sample (only 290 individuals) who receive an EFV in my sample. The selectivity of participation makes distance a weak instrument for EFV participation and for regular visitation within the EFV recipient pool. Table A30 presents the first stage effects of distance on EFV participation. Effects for visitation within EFV participants cannot be estimated as all EFV recipients also received regular visitation. Although point estimates are statistically significant, F-tests reveal a weak relationship between distance and EFV participation.

Anecdotal evidence from WADOC staff suggests that EFV participants are highly motivated and extremely committed to their incarcerated loved one. Combined with their relative insensitivity to travel costs, this makes EFV recipients conceptually similar to"always-takers" (those who receive visit regardless of distance). Abadie (2003) shows how to directly identify and characterize always-takers, compliers and never-takers in settings with a binary treatment and binary instrument and Hull (2025) shows how to describe the complier population with a continuous treatment, but I can only do this in my main sample, which does not contain the particularly salient characteristics such as family support, self-reported income and risk. I therefore use EFV recipients as a proxy for always-takers to distinguish them from compliers within the visited population.[52]

Table A31 displays descriptive statistics for the incarcerated individuals who receive EFVs relative to those who only receive regular visitation and relative to those who do not receive any visitation. Unsurprisingly given both the program requirements of regular visitation and the hypothesized strong family ties, EFV recipients receive almost 2.5 times more visits per month of incarceration than those who only receive receive standard visitation. EFV recipients also have much longer spells, are more likely to have committed a violent crime, are older and notably, have much lower rates of recidivism than those who receive standard visitation.

Table A32 reports descriptive statistics for EFV recipients in the supplementary sample. Although the group is small, EFV recipients clearly differ from individuals who receive standard visitation. EFV recipients are much more likely to be rated low risk of recidivism, to report being in a long-term relationship, to describe their family relationships as good, and to report having children. They are also less likely to have a documented mental health diagnosis. Notably, EFV recipients are also disproportionately in the highest income bracket, which is consistent with the time and financial resources required for visitation and especially for multi-day visitation (taking several days off work and travel costs). It is unsurprising that EFV receipt is correlated with a low risk score because the WADOC risk score incorporates interview information on stability and social support. The positive correlation with family is also expected.

[52]This is not to say that EFVs themselves have no effect. It is quite possible they help strengthen family support. However, I am unable to speak to their causal effect in this setting.

This pattern matters because positive selection into visitation among those with strong support is the standard critique of correlational studies – the estimated benefits of visitation might reflect preexisting support rather than the effect of visitation itself. While visited-no-EFV recipients are more positively selected than never visited people, they are much less so than the EFV recipients. This is important because always-takers do not receive weight in a 2SLS specification since they are not moved by the instrument. If the IV compliers are more "at-risk" than the always-takers, this is a plausible reason the 2SLS estimate could be larger in magnitude than the OLS estimate. Compliers actually benefit more from visitation and have larger effects.

Table A30: EFV First Stage

	EFV Received		EFV Count (per Mo.)	
	Full Sample	Visited Sample	Full Sample	Visited Sample
	(1)	(2)	(3)	(4)
	-0.0057***	-0.0086***	-0.0012***	-0.0017**
	(0.0011)	(0.0031)	(0.0003)	(0.0080)
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
F-stat	27.7	7.95	16.70	4.34
Observations	24,413	10,775	24,413	10,775

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. This table presents the first stage effect of distance on likelihood and intensity of Extended Family Visits. Columns 1-2 present results for a binary indicator of EFV-receipt. Columns 3-4 present results for the count of EFVs received in a spell normalized by the number of months served for that spell. Columns (1) and (3) use the full sample. Columns (2) and (4) use the visited sample and show the effect of distance on receiving an EFV and the number of EFVs given already receiving regular visitation. Controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility are included. The sample includes all prison spells for men admitted to Washington state prisons on or after January 1, 2010 and released as of December 31, 2016, had a non-missing home ZIP code and who were placed in a standard facility.

Table A31: Sample Descriptives by EFV Status

	Overall	Never Visited	Visited, No EFV	EFV
N Incarceration Spells	24,338	13,563	10,483	292
N Incarcerated Individuals	21,389	12,090	9,840	290
% First admit	0.52	0.49	0.55	0.52
Median time served (days)	329	270	412	960
Median sentence length (days)	578	517	669	1,369
% Property crime	0.34	0.34	0.43	0.46
% Drug offense	0.25	0.26	0.25	0.29
% Violent offense	0.17	0.13	0.21	0.30
% Sex offense	0.05	0.04	0.06	0.08
% White	0.62	0.59	0.67	0.72
% Black	0.15	0.17	0.13	0.12
% Hispanic	0.13	0.14	0.12	0.10
% Native American	0.05	0.06	0.04	0.02
% Asian	0.03	0.04	0.03	0.04
Mean Age at admit	33.5	35.06	31.47	33.24
% Visited	0.44	0.00	1.00	1.00
Mean No. visits per month	0.91	0.00	1.97	4.80
% EFV participant	0.01	0	0	1
Mean No. EFVs per month	0.002	0	0	0.21
Median placement distance (miles)	98.65	111.94	86.70	79.12
% Use housing voucher	0.19	0.25	0.11	0.05
% Readmitted within 1 year	0.09	0.10	0.07	0.02
% Readmitted within 3 years	0.26	0.28	0.23	0.12

Notes: This table presents summary statistics for all men incarcerated in Washington state prisons admitted on or after January 1, 2010 and released by December 31, 2016. Data is at the prison spell level. Incarcerated individuals are categorized as "visited, No EFV" if they received one or more visits during the given spell but did not receive an Extended Family visit in the given spell. Incarcerated individuals are categorized as EFV recipients if they received one or more Extended Family visits during the given spell. Offense types are not mutually exclusive and are binary indicators for if any of the crimes associated with the current spell fall in the given category. Crime category definitions are taken from the Revised Code of Washington. Distance is calculated as the Euclidean distance from the geographic centroid of a prisoner's home ZIP code to the geographic centroid of their placement facility's ZIP code. Data comes from Washington Department of Corrections records and statistics are calculated by the author.

Table A32: Supplementary Sample EFV Statistics

	Overall	Never Visited	Visited, No EFV	EFV
N People	585	295	264	29
N Spells	590	297	264	29
% low risk	0.21	0.16	0.21	0.76
% moderate risk	0.10	0.10	0.10	0.14
% high drug crime risk	0.07	0.07	0.08	0.00
% high property crime risk	0.16	0.19	0.15	0.03
% high violent crime risk	0.22	0.22	0.23	0.07
% high risk all crimes	0.24	0.26	0.24	0.00
% mental health or substance abuse issue	0.88	0.92	0.87	0.52
% married or with long-term partner	0.41	0.32	0.48	0.76
% with good family relationship	0.71	0.67	0.75	0.79
% with children	0.51	0.49	0.55	0.59
% with 1 child	0.21	0.19	0.24	0.17
% with 2 or more children	0.30	0.30	0.29	0.41
Avg monthly income in 6mo prior to admit				
No legal income	0.34	0.34	0.36	0.07
<\$1,000	0.18	0.21	0.17	0.07
\$1,000-1,999	0.22	0.25	0.19	0.31
\$2,000-3,999	0.19	0.16	0.22	0.17
$\geq$ \$4,000	0.08	0.05	0.08	0.38

Notes: The sample is all men already incarcerated as of 2018 or who were incarcerated after 2018 and were placed in a standard facility without a life sentence. Data is from the first risk assessment done for each individual in a given spell. Risk score classifications come from Washington's classification system based on discrete cuts of continuous numeric scores for property crime, drug crime and violent crime re-offense risk. Scores are determined by the responses to interview questions, criminal history, and past incarceration behavior (if applicable). Relationship status, number of children, family relationships and substance abuse issues are self-reported. Mental health issues refer to a documented diagnosis.

F Housing Stability and Recidivism Joint Outcomes

Table A33: Joint Housing and Prison Readmission Outcomes

	Readmit, Voucher (1)	Readmit, No Voucher (2)	Voucher, No Readmit (3)	No Readmit, No Voucher (4)
Readmit in 1 year				
Visit Received	-0.0356*	-0.0569*	-0.1265***	0.2190***
	(0.0194)	(0.0304)	(0.0405)	(0.0478)
Non-visited outcome mean	0.03	0.07	0.22	0.67
Readmit in 3 years				
Visit Received	-0.0787***	-0.0427	-0.0835**	0.2048***
	(0.0289)	(0.0455)	(0.0366)	(0.0534)
Non-visited outcome mean	0.08	0.17	0.20	0.55
Controls	Yes	Yes	Yes	Yes
Fixed-effects	Yes	Yes	Yes	Yes
Observations	19,953	19,953	19,953	19,953

Notes: ***: 0.01, **: 0.05, *: 0.1. Standard errors clustered at the individual level are in parentheses. This table presents 2SLS estimates of the effect of visits (a binary indicator for receiving any visits) on joint housing voucher use and prison readmission within 1 and 3 years of release. Controls for the individual's race, the individual's age at the time of prison admission, the length of the sentence in months, indicators the type of crime the individual was convicted for in the given spell, and an indicator for if this spell is the individual's first prison spell, as well as fixed effects for year of admission, home county and facility are included. The untreated mean is the readmit rate for non-visited incarcerated men in the relevant sample.

Numerical Example.
Let visits (V) causally reduce both the probability of recidivism (R) and the probability of needing a housing voucher (H) such that (based on data):

$$P(R=1|V=1)=0.18 \quad P(R=1|V=0)=0.28$$

$$P(H=1|V=1)=0.09 \quad P(H=1|V=0)=0.25$$

Further assume unobservable $P(R=1|H=1)=0.50$ and $P(R=1|H=0)=0.10$, and these are unchanged by visits in the sense that conditional recidivism rates are fixed for a given housing status, and visitation operates by shifting people in and out of those states.

Table A34: Joint Outcomes Numerical Example

	Without Visits	With Visits	Change
Full Independence			
No Recidivism, No Voucher	$(1-0.28)\times(1-0.25)=0.54$	$(1-0.18)\times(1-0.09)=0.75$	+0.21
No Recidivism, Voucher	$(1-0.28)\times 0.25=0.18$	$(1-0.18)\times 0.09=0.07$	−0.11
Recidivism, No Voucher	$0.28\times(1-0.25)=0.21$	$0.18\times(1-0.09)=0.16$	−0.05
Recidivism, Voucher	$0.28\times 0.25=0.07$	$0.18\times 0.09=0.02$	−0.05
Full Mediation			
No Recidivism, No Voucher	$(1-0.10)\times(1-0.25)=0.68$	$(1-0.10)\times(1-0.09)=0.82$	+0.14
No Recidivism, Voucher	$(1-0.50)\times 0.25=0.13$	$(1-0.10)\times 0.09=0.05$	−0.08
Recidivism, No Voucher	$0.10\times(1-0.25)=0.08$	$0.18\times(1-0.09)=0.10$	+0.02
Recidivism, Voucher	$0.50\times 0.25=0.13$	$0.18\times 0.09=0.05$	−0.08

G Counterfactual Results

Table A35: Counterfactual Placement Simulations

	Mean Δ_{Dist}	Mean Δ_{visit}	Mean $\Delta_{Readmit1}$	Mean $\Delta_{Readmit3}$	Mean Δ_{Days}
No Constraints	−82 miles	0.087	−0.007	−0.010	12 days
Security & Capacity Constraints	−40 miles	0.040	−0.003	−0.004	4 days
+ Age Priority	−31 miles	0.030	−0.004	−0.005	5 days

Notes: Mean Δ_{dist} is the average change in placement distance from the placement simulation. A negative number indicates individuals were placed closer to home. Mean Δ_{visit} is the change in the probability of visitation given the change in the probability of distance. This is estimated as Mean $\Delta_{dist} \times \gamma_1$ from Equation 3 Equation 2 (first stage estimate of the effect of distance on visitation). Mean $\Delta_{Readmit1}$ is the average change in the probability of readmission within 1 year of release given the change in visitation. This is estimated as Mean $\Delta_{visit} \times \alpha_1$ from Equation 2 (2SLS estimate of the effect of visitation on recidivism), when the outcome variable is a binary indicator for prison readmission within 1 year. Mean $\Delta_{Readmit3}$ is the average change in the probability of readmission within 3 years of release given the change in visitation. This is estimated as Mean $\Delta_{visit} \times \alpha_1$ from Equation 2 (2SLS estimate of the effect of visitation on recidivism), when the outcome variable is a binary indicator for prison readmission within 3 years. Mean Δ_{Days} is the average change in number of days served in prison for the five years following sentencing. This is estimated as Mean $\Delta_{visit} \times \alpha_1$ from Equation 2 (2SLS estimate of the effect of visitation on recidivism), when the outcome variable is the count of days served in prison within 5 years post-sentencing.