WORKING PAPER Nº IDB-WP-1786

Understanding and Predicting Recidivism in Latin America:

A Machine Learning Approach

María Victoria Anauati
María Noelia Romero
Lucía Baraldi
Walter Sosa Escudero
Mariano Tommasi

Inter-American Development Bank
Department of Research and Chief Economist

January 2026

Understanding and Predicting Recidivism in Latin America:

A Machine Learning Approach

María Victoria Anauati*
María Noelia Romero*
Lucía Baraldi*
Walter Sosa Escudero**
Mariano Tommasi*

* Universidad de San Andrés, CEDH
** Universidad de San Andrés, CONICED and CEDH

Inter-American Development Bank
Department of Research and Chief Economist

January 2026

Cataloging-in-Publication data provided by the
Inter-American Development Bank
Felipe Herrera Library

Understanding and predicting recidivism in Latin America: a machine learning approach / María Victoria Anauati, María Noelia Romero, Lucía Baraldi, Walter Sosa Escudero, Mariano Tommasi.
p. cm. — (IDB Working Paper Series; 1786)
Includes bibliographical references.
1. Recidivism-Latin America. 2. Recidivism-Argentina. 3. Prisons-Latin America. 4. Prisons-Argentina. 5. Predictive analytics-Argentina. 6. Machine learning. I. Anauati, María Victoria. II. Romero, María Noelia. III. Baraldi, Lucía. IV. Sosa Escudero, Walter. V. Tommasi, Mariano, 1964- VI. Inter-American Development Bank. Department of Research and Chief Economist. VII. Series.
IDB-WP-1786

http://www.iadb.org

Abstract[1]

Recidivism is a persistent challenge for criminal justice systems worldwide, yet evidence from Latin America remains scarce. This study addresses that gap through three contributions. First, it reviews the individual, institutional, and contextual determinants of recidivism, with special attention to Latin America. Second, it examines the potential use of AI-based prediction tools, discussing the institutional, data-related, and ethical challenges such implementation entails. Third, using two decades of administrative data from Argentina's prison system, it applies six machine learning models to predict reoffending. The analysis identifies economic offenses and age at incarceration as the strongest predictors, while geographic indicators also play a role, reflecting the spatial clustering of repeat offenders across prisons. The findings suggest that routinely collected prison-level information, often underutilized, can enable reasonably accurate risk prediction and guide effective rehabilitation and prison management strategies.

JEL: K4, C5, I3

Keywords: Reoffenders, Predictive Modeling, Prisons, Classification

---

[1] Email contacts: Anauati: vanauati@udesa.edu.ar; Romero: mromero@udesa.edu.ar; Baraldi: lbaraldi@udesa.edu.ar; Sosa Escudero: wsosa@udesa.edu.ar; Tommasi: tommasi@udesa.edu.ar.

We are grateful for the helpful comments of Daron Acemoglu and Santiago Perez Vincent at the first and second Discussion Seminar—Research Network: The Role of AI and Digitalization in LAC. We also thank Daniel Mejía for his valuable insights, and we acknowledge the research assistance of Ignacio Anchorena.

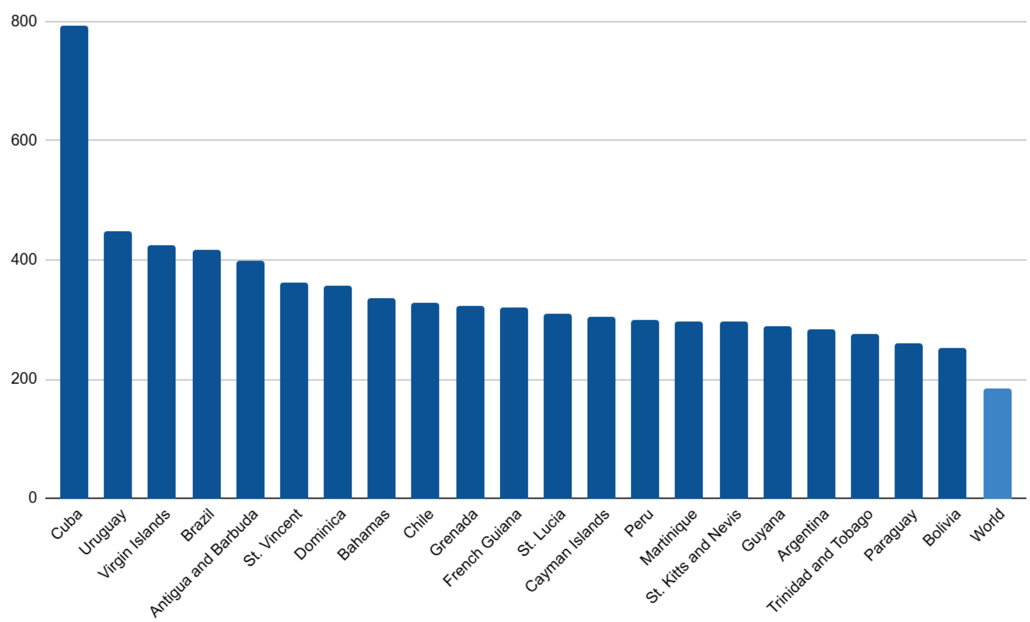
The work was financed with the support of the Latin America and the Caribbean Research Network of the Inter-American Development Bank.

1. Introduction

Recidivism, defined as reoffense after individuals are released from incarceration, remains one of the most persistent and costly challenges confronting criminal justice systems worldwide. In high-income countries like the US, France, and the UK, over half of former inmates are reconvicted within five years (Fazel & Wolf, 2015). The issue may be even more severe in Latin America, a region marked by high violence and incarceration rates. Although it constitutes only 8% of the global population, Latin America accounts for over a third of the world's homicides and hosts 43 of the 50 most dangerous cities (Tobón, 2022). Yet empirical research on the determinants of recidivism in the region remains scarce.

Across Latin America and the Caribbean, incarceration rates are generally well above the world average of 185 prisoners per 100,000 inhabitants. Several countries, such as El Salvador, Cuba, Panama, and Uruguay, show particularly high levels, with El Salvador standing out as an extreme outlier at 1,659 (Figure 1). Many other countries in the region, such as Brazil, Chile, Costa Rica, and Argentina, also exceed the global average by wide margins. Overall, the data suggest that the region faces very high imprisonment rates.

Figure 1. Prison population rate (per 100,000 of national population) for selected Latin American countries and the world



Note: Data correspond to the most recent available figures, though not all originate from the same year.
Source: Own elaboration based on World Prison Brief data.

Despite growing interest in assessing risk, efforts to predict who is most likely to reoffend remain limited in the region. Most research on the determinants of recidivism has focused on the United States and other high-income countries, largely because of greater data availability (Bogliaccini et al., 2024). Whether these findings can be generalized to Latin America and the Caribbean remains an open question. Given the complexity of recidivism and its far-reaching consequences, there is a pressing need for more regionally grounded research. This study seeks to address that gap by examining both the theoretical foundations and empirical predictors of recidivism. To do so, we adopt a two-part approach: (1) we review the academic literature and conduct a case-based analysis of how risk assessment tools have been applied to predict recidivism, and (2) we develop a predictive model using machine learning (ML) techniques applied to digitalized prison administrative data, illustrating how such tools can enhance decision-making within judicial and correctional systems.

First, we review the individual, institutional, and contextual determinants of recidivism. We emphasize factors specific to Latin America and contrast them with patterns in high-income countries, highlighting gaps in the literature and the need for region-specific research. In addition, we review the growing use of ML to predict recidivism and its potential application in criminal justice systems. ML is well suited to this task, uncovering complex relationships among risk factors (Kleinberg et al., 2015, 2018). Following Mullainathan and Obermeyer (2017), our approach is predictive rather than causal—for example, identifying unemployment as a predictor does not mean that job programs reduce reoffending.

We find that ML-based risk assessments are typically used for three purposes: (1) targeting rehabilitation programs, (2) supporting prison management, and (3) informing judicial decisions on detention, sentencing, and parole. The first purpose involves stratifying individuals according to their criminogenic needs and likelihood of reoffending, allowing correctional authorities to direct high-intensity interventions to high-risk individuals while avoiding unnecessary programs for low-risk populations. The second purpose concerns prison management and institutional governance. Risk assessments support more accurate inmate classification, enabling administrators to allocate housing, supervision, and program access proportionately—thereby enhancing safety, institutional stability, and opportunities for rehabilitation—while reducing operational issues that can arise from misclassification. The third purpose relates to judicial decision-making: Structured assessments provide judges and prosecutors with standardized, evidence-based evaluations of recidivism risk to inform pretrial detention, sentencing, and parole decisions. Such tools aim to improve fairness, consistency, and evidence-based decision-making, particularly where case information is fragmented or incomplete. However, their use also raises ethical and legal concerns, as predicted future behavior can be conflated with legal culpability, potentially blurring the line between preventive and retributive justice.

Second, using Argentina as a case study, we analyze two decades of prison census data (2003–23). We apply six ML methods: logistic regression, LASSO, k-nearest neighbors (KNN), decision trees, random forests, and XGBoost. Our analysis indicates that economic offenses and age at incarceration are the strongest predictors of recidivism, while geographic indicators also play a notable role because repeat offenders are clustered in certain prisons. Other factors, such as sentence duration, sanctions, and prison-level conditions, are less potent but still relevant. These findings highlight that both individual and institutional factors matter for reoffending and that prison system data can yield accurate predictions useful for resource allocation and management.

Our model primarily supports the first two purposes of risk assessment: First, it enables authorities to allocate interventions more effectively by directing intensive programs toward high-risk individuals while avoiding over-intervention for low-risk cases. The central challenge is not only determining *what* works, but *for whom* and under what conditions since program outcomes vary by risk level and undifferentiated approaches can be ineffective or even harmful (Doleac, 2023). Second, our model strengthens prison management by informing housing allocation, supervision, and facility placement, all of which affect exposure to violence, rehabilitation opportunities, and institutional security. Misclassification can create cascading problems, but predictive models mitigate this by incorporating more variables, detecting complex patterns, and updating risk estimates over time. More broadly, predictive tools can optimize cell assignments, enable proactive violence prevention, and target disciplinary oversight, thereby improving safety while reducing strain on staff.

Finally, we stress that the value of predictive tools depends not only on technical performance but also on their fit with policy objectives and institutional capacity. Effective adoption requires robust data systems, attention to fairness and transparency, adequate staff training, and strong governance. Drawing on regional experiences and international guidance, we identify six dimensions critical to context-sensitive implementation in Latin America.

The paper proceeds as follows: Section 2 reviews the determinants of recidivism; Section 3 reviews the use of ML to predict recidivism and its potential application in criminal justice systems; Section 4 introduces the dataset; Section 5 presents methods and results; and Section 6 concludes with findings and directions of future research.

2. A Conceptual Framework for Understanding Recidivism from an Economic Perspective

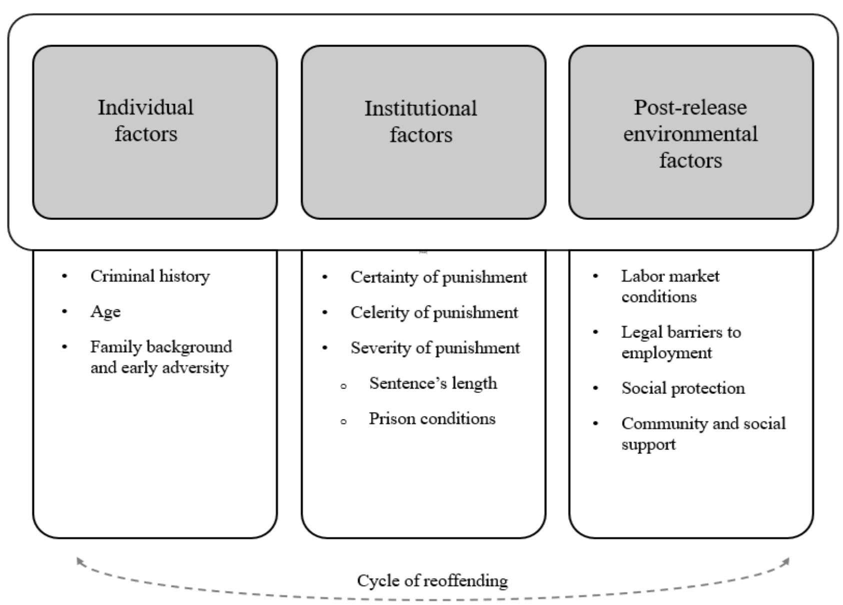
Recidivism is shaped by a complex interplay of individual, institutional, and contextual factors. While some determinants concern personal histories and life-course dynamics, others are about the way criminal justice institutions operate and the broader social and economic environment to which individuals return after incarceration. Understanding these dimensions in an integrated way is crucial since no single factor explains reoffending on its own: Individual disadvantages may increase vulnerability, institutional arrangements can either mitigate or exacerbate these risks, and contextual conditions often determine whether reintegration is feasible. Building on Becker's (1968) economic framework of crime and its extension by Doleac (2023), this section reviews the evidence at these three levels (individual, institutional, and contextual) with particular attention to Latin America, where structural inequalities, punitive penal systems, and fragile social supports create distinctive challenges in reducing recidivism.

Figure 2 depicts our conceptual framework. Among individual factors, criminal history stands out as the most consistent and powerful predictor of both juvenile and adult recidivism (Cottle, Lee, & Heilbrun, 2001; Walters, 2012). Individuals with more extensive criminal records consistently exhibit higher rates of recidivism (Gendreau et al., 1996; Hamilton, 2015). This reoffending pattern, often referred to as the revolving-door effect, is further supported by longitudinal research showing that extensive criminal histories significantly increase the likelihood of repeated incarceration (Farrington et al., 2013; Laub & Sampson, 2001). In Latin America, a study by Molina-Coloma et al. (2021) similarly finds a strong link between prior criminal history, particularly juvenile delinquency, and recidivism in Ecuador. The strength of criminal history as a predictor is often attributed to two reinforcing mechanisms: A history of offending reflects entrenched behavioral patterns, socialization into criminal networks, and reduced deterrence effects over time; and repeated involvement in the justice system worsens employment prospects, stigmatization, and social disconnection, thereby reinforcing the structural conditions that sustain reoffending.

Age is also critical. Crime rates tend to peak around ages 18–20 and decline thereafter (though some individuals continue offending further into adulthood), reflecting life-course desistance processes (Hirschi & Gottfredson, 1983; Landersø, Nielsen, & Simonsen, 2017; Doleac, 2023). Early onset of criminal behavior, particularly during adolescence, increases the likelihood of continued offending into adulthood (Farrington et al., 2007, 2013; Laub & Sampson, 2001). Gender appears less relevant: While men commit more crimes overall, the predictors of recidivism are largely similar across genders (Safranoff & Tiravassi, 2018; Mears et al., 2012).

Family background and socioeconomic status are other factors that influence the decision to commit a crime. Research has shown that individuals who experience multiple adverse events in childhood are more likely to have contact with the criminal justice system later in life (see also Graf et al., 2021; Basto-Pereira et al., 2022; Reavis et al., 2013). For instance, Malvaso et al. (2022) systematically examine the evidence linking childhood trauma to juvenile offending. In addition to these individual disadvantages, poverty-related structural challenges, such as unstable housing and neighborhood disadvantage, further compound the risk of recidivism (Clark, 2016). While socioeconomic factors are important predictors of recidivism globally, their relevance is particularly strong in Latin America, where persistent inequality, weak institutions, and widespread informal labor markets reinforce cycles of crime (Bogliaccini et al., 2024). Low education, unstable employment, and poverty heighten reoffending risks, and women are especially affected. For instance, Safranoff and Tiravassi (2018) document that many incarcerated women come from vulnerable socioeconomic backgrounds marked by economic dependency, caregiving responsibilities, and limited access to work, which increase both their involvement in crime and their likelihood of reoffending in the absence of targeted support.

Figure 2. Conceptual framework: Stages and determinants of recidivism



Source: Own elaboration

Beyond individual factors, institutional dimensions of punishment shape the perceived costs of reengaging in crime and thus influence the decision to reoffend. The literature highlights three key elements: the certainty, celerity, and severity of punishment (Jaitman, 2019). Certainty refers to the likelihood of legal consequences after committing a crime, celerity to the speed of punishment (Nagin, 2013), and severity to the harshness of sanctions, including sentence length, security level, and prison conditions. Among these, severity has been the most extensively studied. Evidence suggests that longer sentences generate mixed effects. They may deter future crimes since imprisonment incapacitates offenders during confinement. But they can also worsen post-release outcomes by disrupting employment and social ties, leading to higher risks of reoffending (Drago et al., 2011). As Doleac (2023) highlights, incarceration can simultaneously raise the returns to crime by fostering prison networks (the crime-school effect) and reduce the returns to legitimate work by eroding skills or causing psychological harm. These competing forces make the net effect of sentence length on recidivism ambiguous.

Importantly, severity is not only about how long individuals are incarcerated but also about the quality of the prison environment in which sentences are served. Prison conditions play a crucial role: Overcrowding, isolation, violence, and lack of access to rehabilitative programs can heighten recidivism risks, while education, vocational training, and behavioral therapy improve reintegration prospects (Drago et al., 2011; Doleac, 2023; Butler et al., 2024). Much research has focused on sentence length, but recent studies highlight that the quality of prison environments is equally important. For instance, Drago et al. (2011), using Italian data, find that harsher conditions, proxied by mortality rates and overcrowding, are linked to higher reoffending, a result echoed by Baggio et al. (2020) and van Ginneken & Palmen (2023).

This issue is especially relevant in developing countries, where prison overcrowding and poor infrastructure are widespread. In Latin America, harsh incarceration policies and limited resources can turn prisons into schools of crime, reinforcing social ties among offenders and eroding post-release opportunities. Evidence remains scarce, but Tobón (2022) provides causal estimates: A large prison construction program in Colombia reduced rearrest by 36% within a year, thanks to improved infrastructure, stricter supervision, and greater access to services. Therefore, overall, prisons are not neutral spaces: Depending on institutional quality and the availability of rehabilitative programs, they can either facilitate reintegration or intensify criminal trajectories. In Latin America, where data limitations and underinvestment hinder evaluation, more evidence is needed to assess how prison conditions and rehabilitation programs affect recidivism.

Beyond individual and institutional factors, contextual factors also shape the decision to reoffend, particularly after release from prison. We categorize these as post-release environmental factors, focusing on four main dimensions: labor market conditions, legal barriers to employment, social protection, and community and social support. Favorable local labor markets, especially in low-skill sectors, raise the opportunity cost of crime by offering both material benefits (income) and symbolic ones (social inclusion). Conversely, weak labor markets leave individuals with few lawful alternatives. Most evidence comes from high-income countries, where stronger labor markets are linked to lower recidivism (Ramakers et al., 2020; Skardhamar & Telle, 2012; Wermink et al., 2018; Yang, 2017). In the US, Yang (2017) shows that higher low-skill wages reduce recidivism, and Schnepel (2016) finds that construction and manufacturing job growth lowers reoffending. Evidence for Latin America is scarce: The only study to date, Bogliaccini et al. (2024), using Uruguayan data, finds that improved low-skill employment opportunities (in construction and domestic services) reduce recidivism, especially among property offenders.

Legal barriers to employment further compound disadvantage. Audit studies show that applicants with records face lower callback rates, even with identical qualifications (Pager, 2003; Agan & Starr, 2018). Some countries use parole systems or Ban the Box policies to mitigate these disadvantages (Seim & Harding, 2020). Yet the evidence is mixed: Ban the Box does not consistently improve outcomes (Rose, 2021; Jackson & Zhao, 2017) and may even worsen racial disparities (Sherrard, 2020). Such initiatives are mostly absent in Latin America. In Uruguay, for instance, individuals with criminal records are legally barred from public employment (18% of jobs), forcing them to rely on private sector opportunities shaped by market conditions (Bogliaccini et al., 2024).

Cash or in-kind transfers can reduce reoffending by alleviating immediate financial pressures and enabling distance from criminal peers (Doleac, 2023). US evidence shows that financial support at release lowers recidivism (Berk & Rauma, 1983; Yang, 2017; Tuttle, 2019; Palmer et al., 2019). In Latin America, where safety nets are weaker, evidence is limited. Munyo and Rossi (2015) find that increasing "gate money" in Uruguay significantly reduced post-release crime, especially property offenses, underscoring the importance of even modest transfers.

Finally, community and social support can help reintegrate reoffenders. Neighborhoods influence life outcomes including crime (Chetty & Hendren, 2018a, 2018b; Ludwig et al., 2013; Kling et al., 2005; Sviatschi, 2022). In Latin America, Barrios Fernández and García Hombrados (2025) show that the opening of evangelical churches in Chile reduced reincarceration among young ex-inmates. They suggest three channels: material and emotional support, promotion of prosocial values, and increased social cohesion and monitoring—all of which raise the costs of reoffending.

3. Leveraging Machine Learning to Predict Recidivism

This section reviews the growing use of ML to predict recidivism and addresses its potential application in criminal justice systems. It first synthesizes the academic literature, outlining how ML techniques have been used to forecast reoffending behavior and highlighting key variables, data sources, and methodological approaches. It then turns to real-world implementations, discussing how algorithmic models are being integrated into structured risk assessment systems to inform correctional, administrative, and judicial decisions.

3.1. Literature Review on Machine Learning and Recidivism Prediction

The conceptual framework in the previous section highlights the multifaceted nature of recidivism, with factors interacting in complex ways to influence reoffending. This complexity makes recidivism prediction well suited for ML, which can handle high-dimensional data, capture nonlinear relationships, and detect interaction effects. By leveraging administrative and justice system datasets, ML can integrate diverse predictors, from early-life adversity and incarceration experiences to post-release socioeconomic conditions, producing individualized risk assessments even when data are noisy, variables are correlated, or many predictors are irrelevant.

The use of ML to predict recidivism in Latin America is very limited, with no peer-reviewed studies in the region.[2] Most research on ML-driven recidivism prediction focuses on high-income countries, particularly the US and European countries, and evaluates whether ML models improve the accuracy of traditional offender risk assessment tools (Travaini et al., 2022). Risk assessment tools are structured instruments used in the criminal justice system to forecast reoffending and support decision-making across the correctional process. ML-based models are increasingly integrated into risk assessment tools to enhance the accuracy of predictions. Finally, because most studies are conducted in high-income countries, researchers often overlook barriers faced by criminal justice institutions in low- and middle-income countries, such as limited technical capacity, restricted access to quality data, and legal or ethical constraints. These challenges are critical for assessing the feasibility of implementing ML-based recidivism prediction tools, yet they remain largely unexplored.

Previous studies employing ML to predict recidivism typically define it in one of three ways: rearrest (an individual is apprehended again after release), reconviction (they are found guilty of a new offense), and readmission (they return to a detention facility). No single definition is universally accepted, and each carries limitations; this lack of standardization complicates cross-study comparisons. For example, reconviction is often considered a more reliable predictor, as it requires confirmation of guilt through the judicial process. However, it tends to understate recidivism in contexts with low conviction rates.

Among these measures, reconviction within a specific period after release is the most frequently applied, followed by rearrest (Ozkan et al., 2019; Lee et al., 2025). Tollenaar and van der Heijden (2013, 2019) and Duwe and Kim (2017), for instance, operationalize recidivism as reconviction within four years of release. In our study, as described in Section 4, we adopt a broader definition that combines reconviction and readmission. Specifically, we include individuals with prior convictions who reoffend, as well as those involved in multiple criminal proceedings, regardless of whether there is a final conviction.

The literature on ML-based recidivism prediction primarily relies on two types of data sources. The first is correctional or justice system records (Tollenaar and van der Heijden, 2013, 2019; Ozkan et al., 2019; Mu et al., 2024). For instance, Liu et al. (2011) analyze a cohort of prisoners in England and Wales using the Prison Service Inmate Information System, and Hamilton et al. (2014) employ a large random sample of Washington State offenders. The second type of source is risk assessment instruments designed to estimate recidivism (Karimi-Haghighi and Castillo, 2021; Ghasemi et al., 2021). Duwe and Kim (2017), for example, rely on data from the Minnesota Screening Tool Assessing Recidivism Risk (MnSTARR), which includes 27,772 cases and assesses the probability of five types of recidivism among offenders released between 2003 and 2006.

While the sample sizes of these data sources vary widely, most datasets are small to medium in size— with fewer than 5,000 observations (Liu et al., 2011; Ozkan et al., 201; and Butsara et al., 2019) or between 5,000 and 35,000 observations (Tollenaar and van der Heijden, 2013, 2019; Duwe and Kim, 2017; Mu et al., 2024). Fewer studies analyze large-scale datasets, with Hamilton et al. (2014) being a notable example, using a database with over 300,000 observations. Our study benefits from access to a very large dataset of more than 1.5 million individuals detained and 700,000 convicted in Argentina

[2] Among peer-reviewed published studies, we consider papers that meet high standards of methodological robustness, validity, and reproducibility in applying ML techniques to predict recidivism.

between 2002 and 2023, covering all types of establishments, allowing us to exploit individual- and prison-level characteristics.

Most studies identify criminal history as the strongest predictor of recidivism, particularly the number and severity of prior convictions and age at release, with younger individuals showing higher reoffending rates (Zeng et al., 2016; Liu et al., 2011; Hamilton et al., 2014; Duwe & Kim, 2017; Tollenaar & van der Heijden, 2019; Mu et al., 2024). Other characteristics, such as sex, education, and nationality, also matter, though their predictive power varies across contexts (Duwe & Kim, 2017; Tollenaar & van der Heijden, 2019; Karimi-Haghighi & Castillo, 2021; Mu et al., 2024). More recent work has incorporated in-prison behavioral and contextual variables, which add explanatory value (Mu et al., 2024). In our case, the Argentine prison census allows us to analyze both individual- and prison-level characteristics, though the absence of criminal history data is a limitation. We find that economic offenses and age at incarceration are the strongest predictors, consistent with prior evidence, while geographic indicators also emerge as relevant—a departure from much of the existing literature.

All the reviewed studies assess multiple models to identify the most effective approach for predicting recidivism, depending on the available data and the target variable. Most commonly, logistic regression is used as a baseline (Tollenaar and van der Heijden, 2013, 2019), including variants such as LogitBoost (Duwe and Kim, 2017) and generalized linear models with ridge or LASSO regularization (Sevigny et al., 2022). These linear models are often contrasted with tree-based algorithms, such as CART, random forests, and gradient boosting, which are valued for their ability to capture complex interactions (Liu et al., 2011; Hamilton et al., 2014; Duwe and Kim, 2017; Tollenaar and van der Heijden, 2019; Ghasemi et al., 2021; Mu et al., 2024). Across studies, performance is typically evaluated with accuracy and the area under the curve. In our case, we compare linear models (logit and logit with LASSO penalty) to nonparametric and nonlinear models (nearest neighbor, classification tree, random forest, and gradient boosting).

Finally, very few of the reviewed studies examine the practical implementation of ML models for predicting recidivism. While studies such as Zeng et al. (2016), Duwe and Kim (2017), and Tollenaar and van der Heijden (2019) highlight ML's potential as a risk assessment tool, they do not explore how these models could be integrated into real-world criminal justice systems or used for specific purposes. An exception is Mu et al. (2024), who incorporate predictive models into a local prisoner assessment system for the release process. Their approach classifies high-risk factors as modifiable or nonmodifiable and proposes targeted interventions with professionals and stakeholders. Interventions focus on modifiable factors such as mental health, education, and family support, using a mapping system that links risk indicators to support services—for instance, counseling for negative psychological test results, educational support for low education levels, or financial aid for limited family support. Samii, Paler, and Daly (2016) extend this logic by combining predictive and causal approaches to estimate the potential impact of different interventions on recidivism risk in Colombia. The authors use ensemble ML methods to simulate the effects of hypothetical policies (such as strengthening trust in government institutions) on the likelihood of reoffending.

3.2. Practical Implementations of Machine Learning for Recidivism Prediction

To the best of our knowledge, the practical application of ML in public decision-making around recidivism remains limited. The closest application that we identified is its integration into structured risk assessment tools. These instruments aim to estimate the likelihood of reoffending and have been adopted in several high-income countries (Dressel, 2021). They are typically grounded in actuarial logic or structured professional judgment and are applied at various stages of the criminal justice process, including sentencing, parole, and allocation of rehabilitative services (Fazel, 2022). While these tools have increasingly incorporated algorithmic models to improve predictive accuracy, the use of ML for broader policy implementation remains limited.

Over time, a wide range of structured risk assessment tools have been developed to support decision-making within criminal justice systems, each tailored to specific operational needs. Although their design and implementation vary across jurisdictions, these instruments tend to serve one or more of three core functions: (1) prioritizing access to targeted rehabilitation programs, (2) supporting prison management decisions, and (3) informing judicial processes such as pretrial detention, sentencing, and parole.

The primary challenge facing correctional systems today is not identifying what works, but determining *for whom* and *under what conditions* these interventions are most effective. Thus, the first use of structured risk assessment is targeted rehabilitation relying on risk stratification to match individuals with interventions that correspond to their specific criminogenic needs and likelihood of reoffending. Studies consistently find that program effectiveness is not uniform across risk groups and that applying the same intervention to all individuals can yield suboptimal, or even counterproductive, results (Doleac, 2023). By stratifying individuals based on their level of risk, these tools enable correctional authorities to deliver programs more proportionately, directing high-intensity interventions toward high-risk individuals while avoiding over-intervention with low-risk populations.

A particularly well-developed example is the United Kingdom's Offender Assessment System (OASys), which integrates static factors, such as age at first offense and prior criminal history, with dynamic indicators, including substance use, housing instability, employment status, and cognitive-behavioral patterns. Based on the results, correctional staff generate individualized sentence plans that include behavioral programs, substance abuse treatment, or vocational and educational training. These instruments are typically administered by probation services, correctional case managers, or multidisciplinary teams within ministries of justice or correctional authorities, who are responsible for designing and coordinating rehabilitative responses. This tailored, risk-informed model reflects a broader institutional shift away from reactive, one-size-fits-all strategies and toward preventive, targeted, and evidence-based correctional planning.

The second function, supporting prison management decisions, extends this principle beyond program allocation to core aspects of institutional governance. Within prison and jail systems, structured risk assessment tools are frequently used to determine an inmate's initial security classification levels (Long, 2020). Upon admission, individuals are evaluated using standardized instruments that assign them to minimum, medium, or maximum security categories. These decisions are typically based on a combination of variables, such as offense type, criminal history, and sentence length, and dynamic indicators, including recent misconduct or gang affiliation. Classification affects every dimension of institutional life, from housing location and program access to movement restrictions and levels of supervision (UNODC, 2020). It also shapes the extent to which individuals are exposed to violence, isolation, and opportunities for rehabilitation. This is why, for prison managers and supervisors, accurate classification systems are important for maintaining institutional stability and anticipating risk. A more precise understanding of individual profiles enables facility administrators to distribute inmates strategically, design appropriate supervision plans, and prevent potential conflicts. Classification errors, such as placing high-risk individuals in low-security settings or unduly restricting low-risk individuals, can generate cascading operational problems.

The third and perhaps most controversial function relates to judicial decision-making. Structured tools are increasingly used to inform pretrial detention, sentencing, and parole. They also facilitate access to standardized information for key actors, such as judges and prosecutors, ensuring that relevant data, including prior criminal history and dynamic risk factors, are available and used during hearings. In these contexts, they are presented as mechanisms for enhancing consistency and procedural fairness by providing quantifiable, evidence-based assessments of recidivism risk. This is particularly important in systems in which information is fragmented across different databases and prosecutors face heavy workloads that limit their ability to gather complete case information in time. For example, in the United States, risk scores help to guide decisions on sentence length or the appropriateness of noncustodial alternatives; in the United Kingdom, they assist parole boards in evaluating whether a person is ready for release. In theory, these tools reduce subjectivity and promote more proportionate legal outcomes. However, their use at multiple legal stages also raises critical ethical and legal concerns (Dressel, 2021). Foremost among them is the tendency to conflate predicted future behavior with legal culpability, thereby blurring the line between preventive and retributive justice.

In Latin America, where correctional systems often operate under conditions of limited resources, high incarceration rates, and uneven access to rehabilitative services (UNODC, 2011), ML should not be understood merely as a technological upgrade, but as an institutional tool capable of enabling more intelligent allocation of effort and investment. Its value lies not simply in predicting risk with greater accuracy, but in aligning that predictive power with operational needs, such as reducing unnecessary pretrial detention, managing overcrowding, or targeting interventions toward individuals most likely to benefit. In Colombia's experience with the PRISMA system, aligning ML tools with prosecutorial decision-making could rationalize pretrial detention by standardizing how criminal history is used to assess risk.[3] PRISMA applies ML algorithms to administrative data to estimate the likelihood that pretrial detainees will reoffend. The system integrates individual-level records from three institutional databases—SPOA (Prosecutor's Office), SIEDCO (police), and INPEC (prison management agency)—containing information on criminal history, charges, indictments, convictions, and prior detention. Unlike static tools, which often reflect normative assumptions imported from other jurisdictions, ML models can be trained on local data and adapted to specific institutional capacities, legal frameworks, and demographic realities. The rationale behind this technological intervention is twofold: First, it seeks to rationalize the use of preventive detention by reducing type I errors (detaining low-risk individuals); second, it aims to mitigate type II errors (failing to detain high-risk individuals), thereby improving public safety and minimize resource misallocation. This example opens the door to a model of implementation that is not only more responsive to the lived realities of justice systems in Latin America, but also more likely to succeed over time.

[3] The Colombian criminal justice system has tried machine learning tools on a pilot basis to systematize many data sources and evaluate the recidivism risk with PRISMA (which stands for Perfil de Riesgo de Reincidencia para la Solicitud de Medidas de Aseguramiento). See Appendix D.

Latin American countries should consider six key conditions, or institutional requirements, when implementing ML tools in their criminal justice systems: aligning ML with operational needs, ensuring fairness across population groups, building strong data infrastructure, promoting transparency, strengthening staff capacity, and adopting a gradual and monitored implementation strategy.

Aligning ML with operational needs means ensuring that predictive tools are designed to address the concrete challenges faced by criminal justice institutions, not merely to improve accuracy for its own sake. In Latin America, this involves directing ML models toward priorities such as reducing pretrial detention, managing overcrowding, optimizing inmate classification, or identifying individuals who would benefit most from rehabilitative programs. When models are built around these practical objectives and trained on local data, they can help institutions allocate resources more efficiently, support more consistent decision-making, and ultimately improve outcomes across the justice system.

Ensuring fairness across population groups requires evaluating whether ML tools perform equitably for individuals of different genders, ages, ethnic backgrounds, or legal statuses. Even highly accurate models can produce uneven error rates if underlying data reflect historical biases or uneven law enforcement. For this reason, ML systems should be tested with multiple fairness metrics, validated across subgroups, and adjusted when disparities emerge. By doing so, institutions can prevent unintended harm, strengthen legitimacy, and use these tools to uncover and correct deeper systemic inequities.

Building high-quality, interoperable data infrastructure is essential for reliable ML applications. Many justice systems in Latin America rely on fragmented, incomplete, or manually recorded data, which can significantly undermine model performance. ML tools require structured, consistent, and up-to-date information, especially in key areas such as pretrial detention, disciplinary incidents, criminal history, and program participation. Strengthening data infrastructure involves integrating databases across police, courts, and correctional agencies; standardizing variable definitions; and establishing protocols for real-time updates. These investments not only improve the accuracy of ML models but also enhance monitoring, evaluation, and long-term planning across the entire justice system.

Transparency is an equally indispensable consideration. For ML systems to gain legitimacy, they must be explainable, open to external review, and integrated within robust institutional governance structures. In many countries, risk assessment tools currently operate without adequate documentation or public oversight, limiting both public trust and internal accountability. In contrast, ML-based systems should be designed with transparency from the outset: Their architecture, inputs, logic, and validation results should be available to decision-makers and, where appropriate, the public. As seen in the case of Colombia's PRISMA system (see Appendix D), efforts to institutionalize this tool include ex ante constitutional reviews to ensure compliance with due process, as well as preliminary pilots to gather feedback from prosecutors, judges, and public defenders. Individuals subject to risk classification should be informed of the role algorithms play in the decision and be given access to mechanisms for clarification, review, or contestation. This is particularly relevant in a region where public institutions face ongoing challenges related to legitimacy and procedural fairness. As both the US Department of Justice (2024) and Brookings Institution (2023) have underscored, transparency is not merely a safeguard; it is a condition for sustainable trust in automated systems and a prerequisite for democratic governance of AI technologies.

Equally important is investing in the capacity of correctional and judicial staff to effectively engage with ML tools. In many countries across the region, overburdened personnel operate with limited training, time, and technological support—conditions that may hinder the successful integration of algorithmic systems. Even the most advanced models will fail to deliver value if frontline staff lack the skills or institutional incentives to interpret outputs, incorporate them into decision-making, or flag errors. Building capacity requires more than brief technical workshops; it involves continuous training, clear operational protocols, and the development of user-friendly interfaces that translate model insights into actionable guidance. Moreover, engaging staff early in the design and piloting stages can improve uptake, surface practical challenges, and foster a sense of ownership.

Finally, countries in Latin America should approach ML implementation as a gradual, adaptive process, grounded in institutional learning and interagency collaboration. Rather than deploying models system-wide from the outset, agencies could begin with small-scale pilots in targeted areas such as rehabilitation program allocation or internal classification reviews. These pilots can generate valuable data on performance, staff interaction, and user experience, which can inform broader rollouts. Embedding these initiatives within broader criminal justice reforms—for example, efforts to reduce pretrial detention or improve community supervision—can ensure that predictive tools reinforce rather than displace policy priorities. Importantly, this process should be inclusive: Civil society organizations, academic researchers, and affected communities should all have a voice in the design, testing, and governance of these tools. Such collaboration fosters accountability, strengthens institutional legitimacy, and enhances the overall quality of technological adaptation in justice systems.

However, none of this is possible without sustained political will. Meaningful adoption of ML tools requires leadership commitment, resource allocation, and long-term planning. Political actors must prioritize not only technological innovation but also the structural reforms and capacity building needed to support it. Without this, even well-designed tools risk being poorly implemented, misaligned with broader justice goals, or abandoned altogether.

4. Argentina: A Case Study based on Prison Census Data

This section presents the dataset underpinning our analysis of recidivism in Argentina. After briefly introducing the institutional setting, we describe the main features of the data and highlight emerging patterns in inmate profiles, prison characteristics, and recidivism dynamics. These descriptive trends provide a foundation for understanding who is most likely to reoffend and how institutional conditions may affect their reintegration.

4.1. Institutional Background: Argentine Judicial System

A critical feature of the Argentine penal system is its extensive use of preventive detention, under which individuals can be held for long periods before trial or sentencing. Although the Code of Criminal Procedure authorizes its use to prevent flight or interference with investigations, in practice it has often gone beyond these aims, functioning as a form of preemptive punishment (Binder, 2011; Kostenwein, 2017). As a result, Argentina maintains a persistently high share of pretrial detainees, as shown in Section 4.2.

The criminal trajectory to the prison system typically begins with arrest, followed by detention in pre-prison facilities such as police station holding cells, short-term judicial units (*alcaidías*), and transfer hubs. Upon arrest, detainees are generally held at a police station pending judicial review, where a judge decides on release, preventive detention, or transfer to a penitentiary (INECIP, 2006). When preventive detention is ordered, individuals are moved from these short-term facilities into prisons through administrative transfers coordinated between judicial authorities and penitentiary services, sometimes involving interim stays at transfer hubs, depending on capacity and logistics (Decree No. 303/96).

Pre-prison facilities ostensibly serve a transitional function, intended to hold individuals during the investigative phase of criminal proceedings and pending their transfer to a formal prison facility. Despite their temporary designation, the facilities frequently become sites of prolonged detention (INECIP, 2024). Structural delays in judicial processing, chronic saturation of formal prison facilities, and logistically limited interinstitutional coordination often result in individuals' confinement in these units for weeks or even months (PPN, 2024). In many jurisdictions, detainees remain in police custody well beyond legally prescribed limits, even though such facilities are not equipped, either infrastructurally or administratively, for sustained incarceration. Conditions in these spaces are frequently substandard. Many police station cells and short-term holding units lack access to basic health services, sanitary infrastructure, or mechanisms for regular external oversight. Detainees in these settings typically have limited or no contact with legal counsel, usually experience restricted access to family visitation, and are often held in overcrowded and unsanitary conditions (Defensor del Pueblo de la Nación, 2006).

By contrast, formal correctional facilities are legally mandated to house individuals under extended preventive detention or serving final sentences. These prisons range from low-security rehabilitation centers to maximum-security institutions, differentiated by population, security protocols, and services. Unlike pre-prison units, they are expected to offer rehabilitative programs, education and vocational training, and health services, though implementation is uneven (Ley Penitenciaria Nacional: Decreto Ley 412/58).

The Argentine system also distinguishes between processed individuals (those in pretrial detention without a final judgment) and convicted individuals (those who have received an enforceable sentence). This distinction is key for classifying and recording recidivism. In this study, recidivism is defined broadly, as detailed in Table 1. We define *repeat offenders* as individuals who have previously committed a crime for which they were convicted, and who subsequently committed one or more additional crimes, regardless of whether these later offenses resulted in a conviction. This category includes repeat, recidivist,[4] and multiple-recidivist offenders, while others are classified as first-time offenders. Since recidivism data are only available for convicted inmates, our analysis is limited to this group.

[4] A recidivist is a person whose sentence includes a formal declaration of recidivism pursuant to Article 50 of the Argentine Penal Code.

Table 1. Argentina's legal definitions for convicted detainees

Category	Definition
First-time offender	An individual convicted for the first time
Repeat offender	An individual who previously committed a crime for which they were convicted, and who subsequently committed one or more additional crimes, regardless of whether these later offenses have resulted in a conviction

Note: This table summarizes the different legal definitions and types of repeat offenders according to the Argentine Penal Code. Own elaboration.

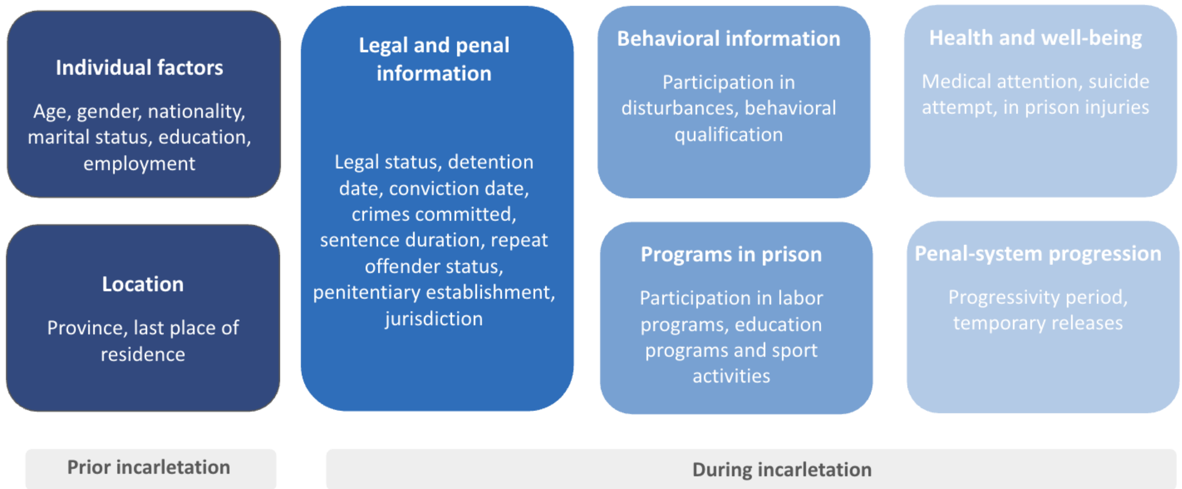
4.2. Data from the National System of Statistics on Sentence Execution

We have access to a comprehensive and virtually unexplored dataset that provides valuable insights into Argentina's prison system. This dataset consists of digitized annual prison censuses from all detention facilities nationwide, systematically collected by the National System of Statistics on Sentence Execution (SNEEP). Covering 2002 to 2023, it offers a consistent and reliable 21-year overview of incarceration trends and patterns. With over 1.5 million inmate observations and 86 variables, the dataset enables detailed analyses of demographic characteristics, sentencing patterns, and institutional conditions across the country. This dataset was developed collaboratively by the National Department of Criminal Policy, academic researchers, and NGOs, and represents the most comprehensive source of prison data in Argentina. Table A.1 in Appendix A presents the variables included in our raw dataset, along with the number of missing observations and the percentage of missing values for each variable out of the total 1,548,475 observations.

Our database includes multiple predictors. In Figure 3, we illustrate how we group all individual and prison characteristics based on a proposed a taxonomy of major factors related to recidivism.

First, we group individual demographic variables such as age, gender, education, employment status, and place of residence. Then, we group legal and penal information related to each detainee's progression within the penal system, such as sentence completion and temporary release (e.g., parole). Third, we group behavioral variables, focusing on in-prison behavior, including participation in disturbances and behavioral evaluations by prison staff. Fourth, the "health and well-being" category covers access to health care, psychological status (e.g., suicide attempts), and in-prison injuries. Finally, the dataset provides information on involvement in educational, labor, and sports programs in prison, which may enhance individuals' prospects of securing employment after release.

Figure 3. Available individual and prison characteristics by group and stage of incarceration



Note: This figure illustrates the available individual and prison characteristics in the National System of Statistics on Sentence Execution data. We present a taxonomy of variables by key factors from our literature review on recidivism. See Section 2 for further detail.

We construct two analytical samples, one for descriptive analysis and another for predictive modeling. For the descriptive sample, we restrict the data to male and female inmates aged 21 and older. Starting from an initial dataset of 1,548,475 observations, this filter leads to the exclusion of 101,143 cases. We aggregate certain categorical variables, such as behavior assessments, at the prison level, generating continuous indicators that capture the percentage of inmates falling into each category to minimize missing information.[5] While this approach reduces individual-level variation, it preserves more observations and retains variation across prisons and over time. We exclude variables missing more than 70% of values (Table A.1 in Appendix A shows the percentage of missing data for each variable). Finally, we drop individuals without recidivism information (38,988 cases). After this procedure, the descriptive analytical sample includes 1,408,344 individuals.

The analysis of reoffending is further restricted to convicted individuals, as legal-recidivism data are only available for this group. Convicted inmates represent 51% of the sample across all years. Within this group, 67% (500,803 individuals) are classified as first-time offenders and 5% lack recidivism status and are excluded from the analysis. After dropping the observations with missing values, the final analytical sample includes 574,409 individuals. This final sample is used for predicting recidivism in Section 5. Appendix A provides a detailed description of these data-cleaning and sample-construction steps.

Our database has certain limitations. First, it includes only individuals serving custodial sentences, excluding those with noncustodial penalties, who represent nearly 40% of all convictions (CELIV, 2022). Moreover, many reoffending individuals are not rearrested, making them invisible to SNEEP. Because the data are collected annually, individuals with short sentences may fall outside the reference period. Second, beyond coverage issues, the database reflects the composition of the prison population, which is shaped by

[5] An examination of patterns of missing data (see Figure A.1 in Appendix A) shows that much of the missing information is concentrated in the early years of SNEEP's implementation, when prison staff were still becoming familiar with the data-collection process.

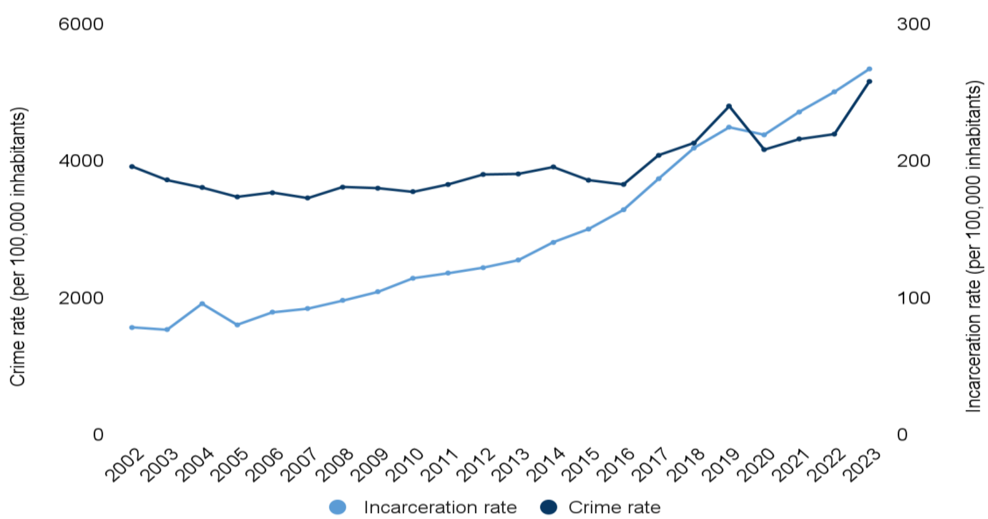
access to legal defense, pretrial detention, and structural inequalities. As noted by Chouldechova and Lum (2020), predictive models trained on such data risk reproducing existing disparities since features associated with disadvantage may appear predictive of recidivism but actually capture systemic bias. Thus, the lack of longitudinal information prevents us from tracking individuals after release or incorporating prior criminal history, a key variable for modeling recidivism. The absence of detailed intrafacility data, such as cell-level interactions, also limits analyses of peer effects and behavioral transmission within prisons (Tobón, 2022).

4.3. Descriptive Statistics of the Argentine Prison System

This subsection examines how Argentina's prison system has evolved over the past two decades, briefly describing the size and distribution of detention facilities and the characteristics of their inmate populations. The analysis highlights the growing heterogeneity of the prison system, offering new insights into how the system has expanded, not only in size but also in complexity.

Analyzing the relationship between incarceration and crime rates in Argentina from 2002 to 2023 reveals shifts over time (Figure 4). Between 2002 and 2005, crime rates declined slightly while incarceration rose modestly. From 2006 to 2016, incarceration continued to grow steadily despite stable crime levels, with the gap widening sharply after 2010. Finally, between 2017 and 2023, both crime and incarceration rates increased.

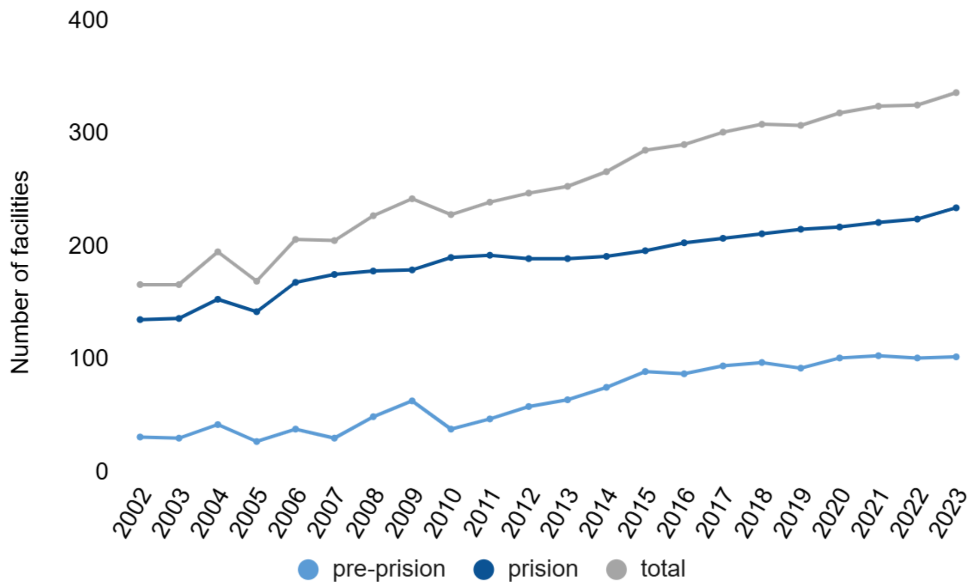
Figure 4: Trends in crime and incarceration rate (per 100,000 inhabitants, 2002–23)



Note: This figure shows the trends in crime and incarceration rates per 100,000 inhabitants between 2002 and 2023.
Source: Own elaboration using the National System of Statistics on Sentence Execution and National Criminal Information System (Sistema Nacional de Información Criminal).

From 2000 to 2023, Argentina's prison population increased steadily and without interruption. In the early 2000s, inmate records ranged between 30,000 and 40,000; by 2010, they had surpassed 60,000, and by 2023 they approached 100,000—more than doubling over the period. This growth was accompanied by an expansion in detention infrastructure. Throughout the period, prisons accounted for the vast majority of incarcerated individuals (around 93% on average), with the remainder held in pre-prison facilities. Both types of establishments expanded substantially between 2002 and 2023, with particularly rapid growth in pre-prison facilities after 2010, consistent with efforts to accommodate the rising inmate population

Figure 5. Evolution of the raw number of detention facilities in Argentina (2002–23)



Source: Own elaboration using the National System of Statistics on Sentence Execution.

The infrastructure efforts were insufficient because the average number of inmates per facility increased over time. Table 2 reports descriptive statistics on facility size for 2003, 2013, and 2023. For the full sample (Panel A), average facility size rises markedly, particularly between 2013 and 2023, along with increases in dispersion, as measured by the standard deviation and interquartile range, indicating growing heterogeneity across facilities.

Disaggregating by facility type reveals diverging patterns. Pre-prison facilities (Panel B) experienced a decline in average size, while prison facilities (Panel C) show a continuous increase in average occupancy, from 267 inmates in 2003 to 297 in 2013 and 425 in 2023. Overall, the expansion in the number of facilities did not keep pace with the growth of the incarcerated population, resulting in higher inmate density and suggesting a worsening overcrowding problem.

Distributional evidence further qualifies these patterns. While average pre-prison facility size declined, the distribution became more dispersed over time, reflecting a growing presence of both small and large establishments. In contrast, the distribution of prison sizes shifted steadily toward larger units, with an increasingly pronounced right tail by 2023, indicating the emergence of larger prisons. Additional distributional evidence is presented in Appendix B.

Table 2. Descriptive statistics on prison size in Argentina in 2003, 2013, and 2023

	Mean	S.D.	p25	Median	p75
Panel A. Whole sample					
2003	240	415	18	84	247
2013	236	335	18	88	318
2023	323	505	19	104	392
Panel B. Pre-prison sample					
2003	112	388	7	12	34
2013	49	139	3	9	26
2023	85	225	4	10	48
Panel C. Prison sample					
2003	267	417	27	127	292
2013	297	356	45	168	427
2023	425	556	47	201	498

Note: This table shows the summary statistics on prison size by year and sample. We show the mean, the standard deviation (S.D.), and the 25th, 50th, and 75th percentiles. See text for definition of prison size.

Facilities are heterogeneous not only in size but also in their inmate composition. To illustrate this heterogeneity, we compare characteristics of smaller and larger facilities in 2023, defined using thresholds based on the 2003 facility-size distribution. Mean differences between smaller and larger pre-prison facilities and prisons are reported in Appendix Tables B.2 and B.3, respectively.

Overall, the results point to systematic differences both across facility types and by size within each type, suggesting that facility size and institutional setting are jointly associated with inmate profiles and institutional dynamics. In pre-prison facilities, larger establishments tend to house individuals with higher educational attainment and stronger prior labor market attachment, while smaller centers exhibit greater participation in education programs. Larger pre-prison facilities also show lower rates of temporary leave and higher incidence of disruptive behavior, consistent with greater management challenges. Additional descriptive evidence on program participation over time is reported in Appendix B.

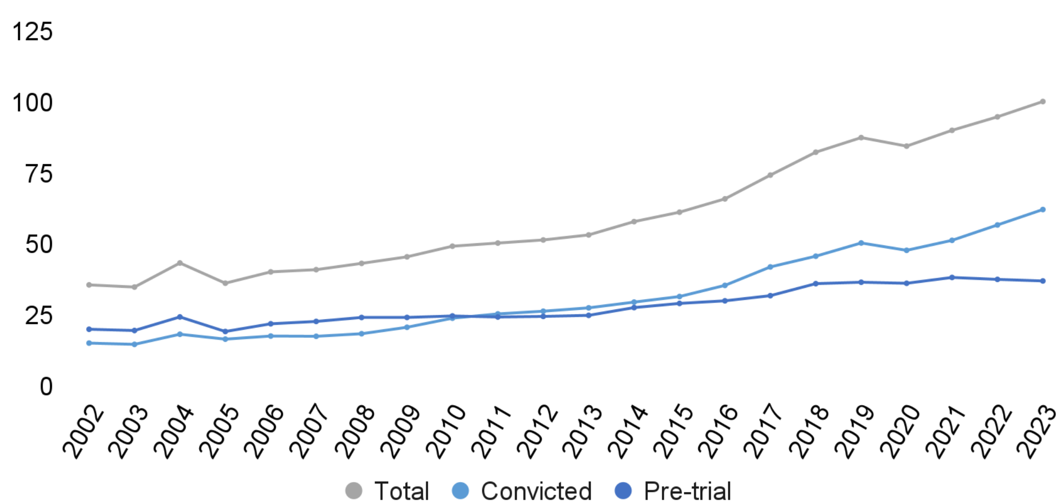
For prison facilities, larger institutions tend to house younger, less educated, and more frequently single inmates. In contrast, inmates in smaller prisons are more likely to engage in paid work and to receive parole benefits. While smaller prisons display better average behavioral indicators, they also experience higher rates of internal disruptions, escapes, and poorer health outcomes during incarceration. Participation in labor and educational programs is systematically lower in larger prisons, consistent with capacity constraints or reduced program effectiveness in more crowded settings. Descriptive evidence on program participation is reported in Appendix B.

Differences by facility size also extend to the composition of offenses. Descriptive statistics for 2023 indicate that sexual offenses are the most frequent crimes in pre-prison facilities regardless of size, followed by property crimes in smaller centers and homicides in larger ones. In prisons, property crimes dominate in larger facilities, while sexual offenses and homicides are relatively more prevalent in smaller ones. Taken together, these patterns suggest that smaller pre-prison facilities and prisons are more likely to house individuals convicted of more serious or violent crimes, whereas larger prisons concentrate inmates convicted of property-related offenses. Supporting evidence is presented in Appendix Tables B.3 and B.4.

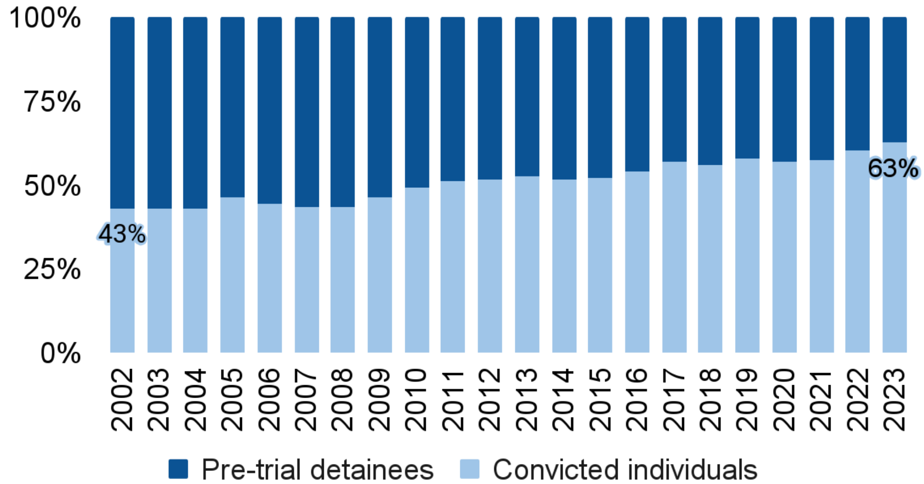
Further insights into the prison system emerge when examining inmate populations by legal status. Figure 6 shows that both pretrial detainees and convicted prisoners increased over time, although from 2015 onward the growth in the convicted population accelerated markedly. Consistent with this pattern, the share of convicted inmates rose from 43% in 2002 to 63% in 2023. This shift coincides with the legislative reforms introduced in 2017, which tightened sentencing rules and limited early release, contributing to longer incarceration spells and a sustained increase in the convicted prison population. As expected, prisons primarily house convicted individuals, while pre-prison centers predominantly accommodate pretrial detainees (see Appendix B for complementary evidence).

Figure 6. Evolution of total, convicted, and pretrial detainees in Argentina (2002–23)

Panel A. Raw trends of incarcerated population (in thousands) by legal status



Panel B. Percent of incarcerated population by legal status



Sources: Own elaboration using the National System of Statistics on Sentence Execution.

In conclusion, the evidence highlights institutional sorting in Argentina's prison system by facility size, type, and legal status. Argentina has experienced a surge in incarceration rates together with an expansion of large prison facilities, which increasingly house convicted individuals for nonviolent crimes such as property offenses. Larger prisons face greater challenges in managing inmate behavior and program delivery, suggesting that scale comes at a cost. Conversely, smaller prisons show higher program engagement, more paid work, and better individual-level outcomes (like parole access). Smaller facilities are more likely to detain individuals accused or convicted of more serious and violent offenses, such as sexual crimes and crimes against persons. These characteristics reveal a system that has become more heterogeneous.

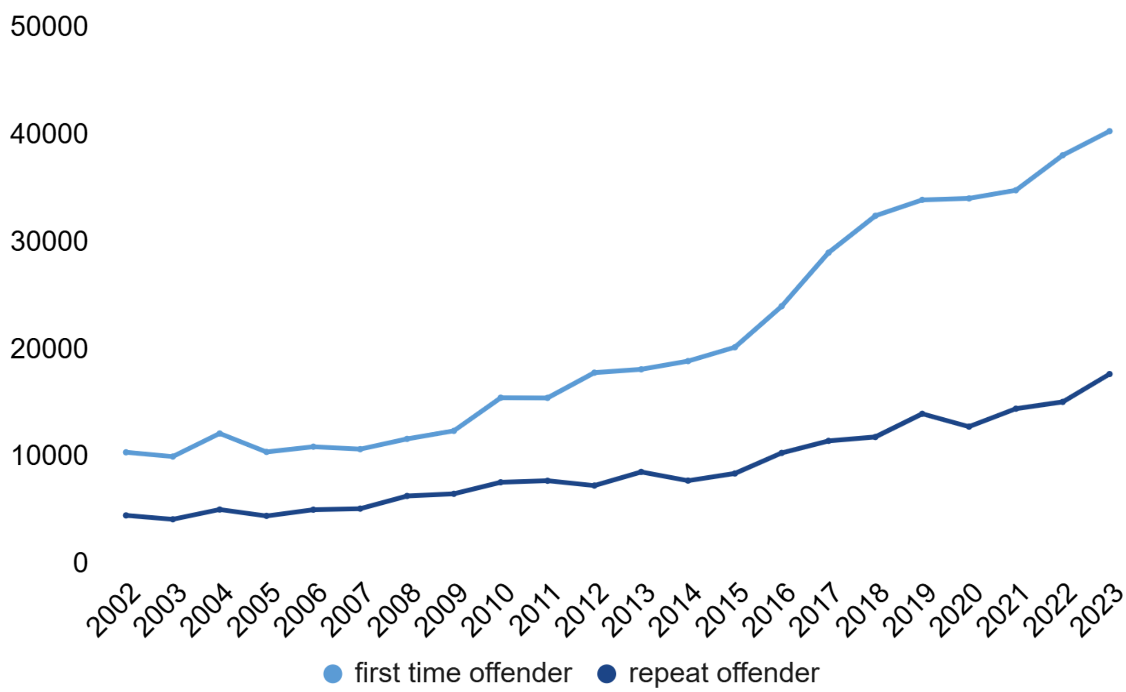
4.3.1 Stylized Facts for Repeat Offenders in Argentina

In this subsection, we document the patterns and characteristics of recidivism in Argentina between 2002 and 2023. First, recall that we define legal recidivists as individuals convicted of a new crime and reincarcerated after release; therefore, they are *repeat offenders*. This category includes repeat, recidivist, and multiple-recidivist offenders, while others are classified as first-time offenders.

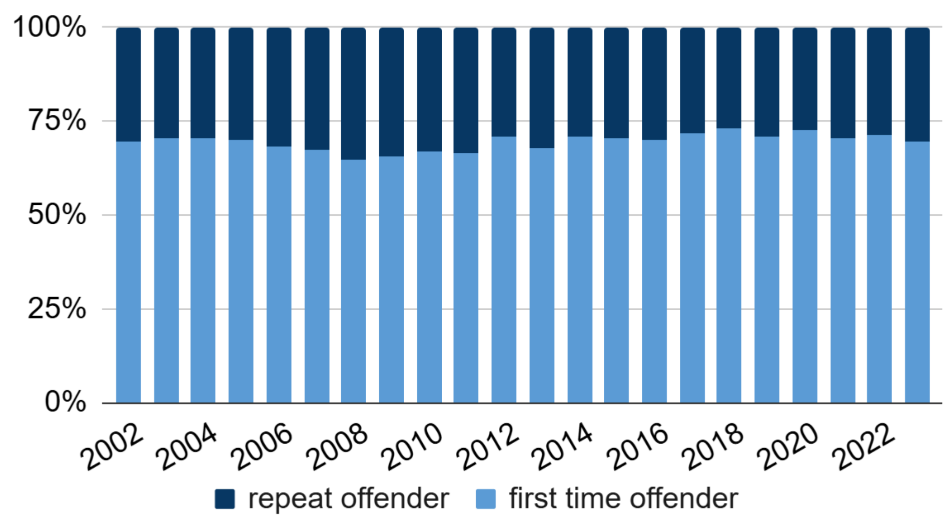
Figure 7 shows the evolution of first-time and repeat offenders. Both groups have grown since the early 2000s. First-time offenders represented 69.6% of convicted inmates in 2002, peaked at 73.2% in 2018, and declined slightly to 69.5% by 2023, indicating that the share of repeat offenders has remained relatively stable.

Figure 7. Evolution of raw trends in first-time offenders and repeat offenders in Argentina among the total convicted population (2002–23)

Panel A. Population of repeat and first-time offenders



Panel B. Percent of repeat and first-time offenders

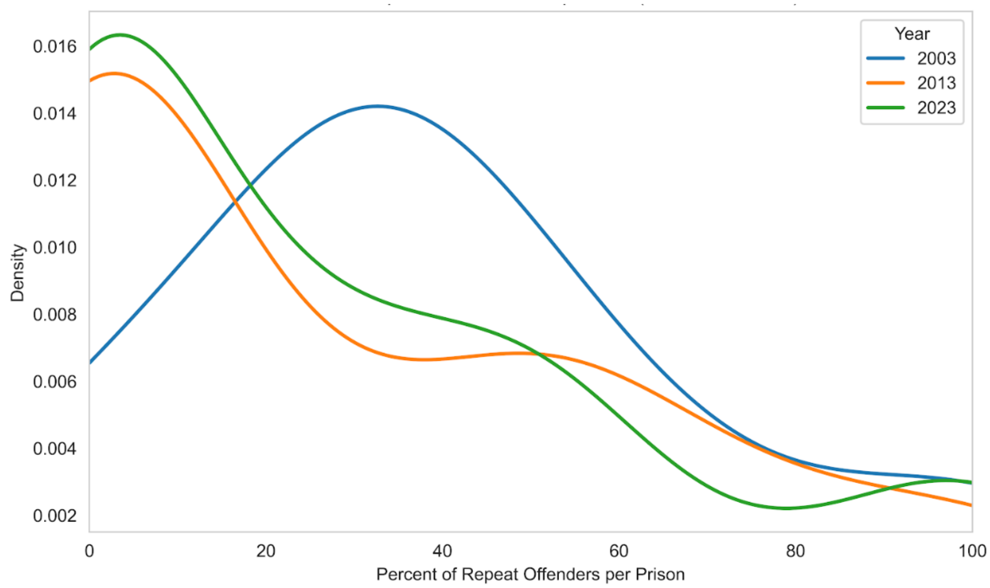


Source: Own elaboration using the National System of Statistics on Sentence Execution.

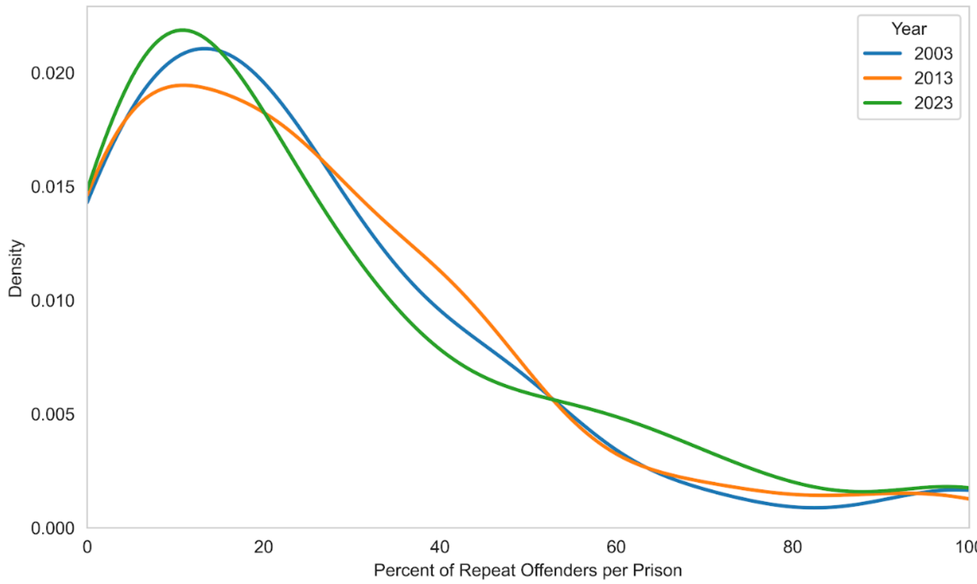
Figure 8 examines the distribution of repeat offenders across facilities. The distribution changes substantially over time in both pre-prison and prison centers. For pre-prison facilities (Panel A), the distribution in 2023 shifts leftward relative to earlier years, indicating that a larger share of centers now admit a lower proportion of repeat offenders. This contrasts with the 2003 distribution, which was more concentrated around intermediate repeat-offender rates, with relatively few facilities exhibiting very low or very high shares. For prisons (Panel B), the distribution in 2023 becomes more polarized relative to earlier years. On the one hand, a larger group of facilities concentrates very low shares of repeat offenders; on the other, an increasing number of prisons exhibit very high repeat-offender rates. This pattern suggests a growing separation between prisons that predominantly host first-time offenders and those that increasingly concentrate repeat offenders. Additional distributional evidence is provided in Appendix B.

Figure 8. Distribution of the percentage of repeat offenders per detention center in Argentina

Panel A. Pre-prison (1%–99 % trimmed)



Panel B. Prison (1%–99 % trimmed)



Note: This figure shows the kernel estimates of the percentage of repeat offenders (among convicted inmates) per detention center, disaggregated into pre-prison and prison facilities, for 2003, 2013, and 2023. To better visualize the distribution, we trimmed the top and bottom 1% of the distribution. See Table A.1. in Appendix A for further details about these distributions. Source: Own elaboration using the National System of Statistics on Sentence Execution.

We also examine the characteristics of repeat offenders in 2023 across facilities with high and low concentrations of recidivism. Compared to repeat offenders housed in facilities with low recidivism rates, those in facilities with high concentrations of repeat offenders tend to be younger, less educated, and more frequently convicted of property crimes. They also exhibit worse behavioral indicators and distinct patterns of progression through the penal system, including differences in access to sentence reductions, temporary leaves, and progressive regimes. Program participation also differs across facilities, with lower engagement in educational programs in high-recidivism prisons. Detailed descriptive evidence is reported in Appendix B.

4.3.2 Reoffenders' Characteristics: Predictor Variables Availability

Using our taxonomy of pre-incarceration and incarceration variables, Table 3 presents a comparison between first-time offenders and repeat offenders in 2023 across individual, legal, behavioral, health, and program-participation variables. In terms of individual characteristics, both groups have a similar average age. Most inmates are Argentine nationals, with a marginally higher proportion among repeat offenders. Educational attainment is low across both groups, although there are small but significant differences in secondary and higher education completion, with first-time offenders showing slightly higher levels. Employment rates prior to incarceration are similar, but a higher percentage of repeat offenders hold professional qualifications. Marital-status distributions also show minor differences, with repeat offenders being slightly less likely to be separated and more likely to be single.

A larger share of repeat offenders have committed property crimes, which are typically associated with shorter sentences and a faster return to the penal system, while first-time offenders are more often involved in sexual and homicide offenses, which usually carry longer sentences. Repeat offenders also show higher involvement in crimes against public safety and administration, while drug-related offenses are more prevalent among first-time offenders. Regarding penal system progression, repeat offenders are somewhat more likely to access progressive regimes and benefit from sentence reductions. However, these differences, while statistically significant, are relatively small. In terms of prison regimes, repeat offenders are slightly overrepresented in semi-freedom, discontinuous-imprisonment, and semi-detention schemes.

In behavioral terms, repeat offenders exhibit worse disciplinary outcomes, with higher rates of infractions, sanctions, and order disruptions. Differences in exemplary or good behavior are negligible, and escape attempts are rare for both groups. In terms of health and well-being, suicide attempts are more frequent among first-time offenders, while repeat offenders experience higher rates of injuries during incarceration.

Program participation is widespread among both groups, but first-time offenders are more engaged in labor, recreational, and sports activities. Overall participation in education programs is similar across groups; however, first-time offenders are more likely to enroll in secondary education, whereas repeat offenders participate relatively more in primary education, consistent with their lower levels of educational attainment upon entry.

Table 3. Means of difference between first-time offenders and repeat offenders among the convicted in 2023

		First-time offenders			Repeat offenders			
	Variable	**N**	**Mean**	**S.D.**	**N**	**Mean**	**S.D.**	**t-test p-value**
Individual factors	Age	42835	36.98	11.82	18703	36.02	9.96	0
	Argentine nationality	42835	0.94	0.23	18703	0.95	0.21	0
	Completed primary education	42835	0.31	0.46	18703	0.29	0.46	0.003
	Incomplete secondary education	42835	0.24	0.43	18703	0.24	0.43	0.475
	Completed secondary education	42835	0.11	0.31	18703	0.08	0.27	0
	Higher education	42835	0.01	0.11	18703	0.01	0.09	0
	Employed	42835	0.64	0.48	18703	0.63	0.48	0.149
	Has a professional qualification	41490	0.57	0.49	18324	0.61	0.49	0
	Married	42835	0.14	0.35	18703	0.14	0.35	0.907
	Separated	42835	0.05	0.21	18703	0.02	0.14	0
	Single	42835	0.79	0.41	18703	0.82	0.39	0

Legal and penal information	Received visits last year	42092	0.86	0.34	18640	0.87	0.34	0.061
	Homicide offense	42835	0.19	0.39	18703	0.16	0.37	0
	Crimes against persons	42835	0.08	0.27	18703	0.13	0.33	0
	Property crimes	42835	0.31	0.46	18703	0.48	0.5	0
	Sexual offenses	42835	0.26	0.44	18703	0.11	0.31	0
	Crimes against freedom	42835	0.01	0.12	18703	0.02	0.13	0.068
	Crimes against public administration	42835	0.01	0.1	18703	0.02	0.12	0
	Crimes against public safety	42835	0.01	0.11	18703	0.02	0.13	0
	Drug offenses	42835	0.11	0.32	18703	0.07	0.25	0
	Economic offenses	42835	0.00	0.02	18703	0.00	0.01	0.046
	Minor offenses	42835	0.00	0.06	18703	0.00	0.03	0
	Crimes against humanity	42835	0.00	0.03	18703	0.00	0.02	0.076
	Percent in discontinuous prison*	42835	0.682	0.2466	18703	0.718	0.27	0
	Percent in semi-detention*	42835	0.681	0.246	18703	0.730	0.248	0
	Works paid job in prison	42835	0.995	0.07	18703	0.997	0.06	0.005
Penal-system progression	Sentence reduction	40685	0.05	0.22	18094	0.06	0.23	0
	Percent with progressive regime*	42835	0.587	0.329	18703	0.636	0.329	0
	Percent with temporary leaves*	42835	0.643	0.231	18703	0.667	0.257	0
Behavioral information	Percent with disciplinary infraction*	42835	0.159	0.155	18703	0.175	0.132	0
	Order disruption dummy	42422	0.10	0.3	17880	0.13	0.34	0
	Percent with sanction applied*	42835	0.156	0.1642	18703	0.179	0.156	0
	Percent with exemplary behavior**	42835	0.627	0.483	18703	0.620	0.483	0.094
	Percent with very good/good behavior**	42835	0.120	0.325	18703	0.177	0.322	0.159
	Percent with fair behavior**	42835	0.298	0.170	18703	0.405	0.197	0

	Percent with bad/very bad behavior**	42835	0.166	0.128	18703	0.232	0.150	0
	Escape or evasion attempt	42835	0.000	0.03	18703	0.00	0.04	0.076
Health and well-being	Suicide attempt	42835	0.02	0.17	18703	0.01	0.09	0
	Percent received medical attention*	42835	0.945	0.207	18703	0.981	0.129	0
	Percent injured*	42835	0.582	0.700	18703	0.625	0.605	0
Programs in prison	Percent in labor program*	41285	0.206	0.239	17633	0.199	0.213	0.002
	Percent in education program	42835	0.493	0.312	18703	0.488	0.271	0.041
	Percent in primary education program*	42835	0.175	0.174	18703	0.184	0.182	0
	Percent in secondary education program*	42835	0.173	0.166	18703	0.152	0.145	0
	Percent in recreational or sport activities*	42240	0.721	0.335	18207	0.657	0.305	0

Note: This table includes only the convicted population and presents the average differences between first-time and repeat offenders in 2023, disaggregated by groups of individual characteristics. Variables marked with * are at the prison level, while those without * are at the individual level. Values marked with ** do not add up to 1 because they represent averages calculated within each correctional facility, which are then averaged across all facilities. The last column shows the p-values from t-tests, which test whether the differences between the two groups are statistically significant.

To assess how the profile of repeat offenders has evolved over time, we compare individual- and facility-level characteristics in 2003, 2013, and 2023. While property crimes remain the most common offense among repeat offenders, their share declined markedly between 2003 and 2023. In contrast, convictions for more serious crimes (including homicide, sexual offenses, and other crimes against persons) increased steadily over time. At the same time, repeat offenders are increasingly held under less restrictive detention regimes, with higher prevalence of discontinuous incarceration and semi-detention, alongside a sustained rise in access to temporary leave.

Conditions within prison also improved along several dimensions. Behavioral indicators show a clear decline in disciplinary infractions and disruptive behavior, accompanied by a rise in exemplary conduct. Participation in labor and education programs increased sharply between 2003 and 2013 and then stabilized or declined slightly by 2023, particularly in nonformal and recreational activities. Finally, health and well-being outcomes improved, with lower rates of injuries and suicide attempts and consistently high access to medical care. Detailed descriptive evidence is provided in Appendix B.

Simple partial correlations for 2023 indicate that recidivism is only weakly associated with both individual- and prison-level characteristics. At the individual level, no single factor shows a strong linear relationship with reoffending. Economic offenses display the strongest positive association, while violent offenses are weakly negatively correlated with recidivism; correlations with age, education, marital status, and employment are close to zero. At the institutional level, associations between prison characteristics and recidivism rates are also modest. Larger facilities are slightly more likely to exhibit higher shares of repeat offenders, and program availability is weakly correlated with better behavioral outcomes. At the same time, prison size is negatively associated with the availability of labor and recreational programs, suggesting capacity constraints in larger institutions. Overall, the low magnitude of these correlations underscores the limited explanatory power of single characteristics and motivates the use of multivariate and predictive approaches. Supporting evidence is provided in Appendix B.

Finally, we document substantial geographic heterogeneity in recidivism rates across Argentine provinces in 2023. A group of provinces (including Mendoza, San Juan, Tucumán, and Córdoba) exhibits consistently high shares of repeat offenders among convicted inmates, often exceeding 50%. In contrast, several northern provinces, as well as Neuquén, display markedly lower recidivism rates, generally below 20%.

These geographic patterns vary by type of offense. Recidivism in economic crimes is high in most provinces, frequently surpassing 60%, though some northeastern provinces show substantially lower rates. For violent crimes, the spatial distribution closely mirrors overall recidivism, with the highest rates concentrated in Mendoza, San Juan, Tucumán, and Córdoba, and the lowest in northern provinces and parts of central Argentina. For other offenses (including drug-related and public-order crimes) high recidivism rates are more geographically dispersed, though still concentrated in a subset of provinces. Complementary geographic evidence by crime type is reported in Appendix B.

5. Machine Learning Applications for Predicting Recidivism in Argentina

In the context of recidivism prediction, we compare the traditional statistical methods and the ML techniques using the prison census data in Argentina. First, we employ the traditional approach of logistic regression to classify individuals as either repeat or first-time offenders based on a set of individual and prison characteristics (James et al. 2023). Formally, following James et al.'s (p. 139) notation, let $Pr(Y_i = 1)$ be the probability that convicted inmate i is a repeat reoffender. We estimate the risk of reoffending with the logit model in equation (1):

$$Pr(Y_i = 1) = e^{\beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p} / (1 + e^{\beta_0 + \beta_1 X_1 + \ldots + \beta_p X_p}) \qquad (1)$$

Here, X_j is the j-th predictor in our dataset. The logistic regression is well suited for identifying general linear relationships between the probability of each class of the dependent variable and the predictors. Yet since we count with more than 100 variables (after creating dummies for key categorical variables), the logit model may have limitations in handling this type of large-dimension dataset. For these reasons, we also use the regularization model adding the LASSO penalty. This penalty term has the benefit of selecting predictor variables (reducing the dimensionality) while decreasing the variance of the classification error with respect to logit (James et al. 2023, p. 244).

The classification linear models and regularization techniques have poor performance when using complex datasets with high nonlinearity between predictors. To address this challenge, we also use the nonlinear prediction models k-nearest neighbors (KNN), decision-tree classifier (CART), random forest (an ensemble method), and XGBoosting (adaptative tree-base model) to enhance predictive accuracy. While KNN accounts for a nonlinear Bayes decision boundary to identify repeat offenders, it also has limitations under a high-dimensional predictor matrix like ours (James et al. 2023, p. 36).

Regarding CART and random forest, both have the advantage of better classification when there are nonlinear relationships between predictor variables. More importantly, the graphical nature of CART allows for a more intuitive interpretation of the decision rules used to differentiate between first-time and recidivist offenders. However, CART models suffer from high variance predictions out of the sample, limiting their use for policy orientation (James et al. 2023, p. 342). Random forest aggregates predictions from multiple decision trees using bootstrapped samples and a subset of random predictors to reduce overfitting and handle datasets with numerous predictors as in our context. In contrast, XGBoosting is an ensemble type of algorithm that learns from previous model error rates and aims to minimize a loss function with one final tree (Chen & Guestrin, 2016; James et al. 2023, p. 321). Overall, there is no a priori model that dominates in a context of relatively low correlations among predictor variables in our dataset (such as age and economic offenses in Figure B.8). But considering that high-dimensional datasets containing numerous dummy variables create a complex predictor matrix, the nonlinear models might have an advantage in predicting recidivism using the annual prison census data.

To evaluate the performance of these five preliminary models, we use standard classification metrics. First, *Accuracy* measures the correct prediction of first-time and repeat offenders among all the observations. Formally, it is the proportion (*TP*+*TN*) / (*P*+*N*), where *TP* and *TN* are predictions of the true positives and negatives respectively, and *P* and *N* are the total positive and negative observations. Then, we show the *AUC* measure, which is the area under the ROC (receiver operating characteristic) curve, where the ROC curve shows the combination of true and false positive rates for different thresholds of the Bayes classifier (James et al. 2023, p. 154). *Sensitivity* (true positive rate) and *Specificity* (false positive rate) are the percentage of correctly predicted repeat offenders and the correct rate of predicted first-time offenders among all first-time offenders, respectively (p. 155). We also calculate the *type I error* ($1 -$ *Specificity*), which provides the error rate in predicting repeat offenders when they are first-time offenders (p. 156). Finally, we show *type II error* ($1 -$ *Sensitivity*), which counts how many individuals we predict to be first-time offenders when they are in fact repeat offenders.

Predicting recidivism in Argentina is challenging because recidivists are the minority class, representing 30% of the incarcerated population during the observation period as shown in Figure 6. While the accuracy and area-under-the-curve metrics are easy to interpret (like R^2), they might hide poor performance because they measure the trivial null prediction of identifying everyone as first-time offenders with an accuracy of 70% of the time (James et al. 2023, p. 152). Thus, to evaluate the performance of the five ML methods, we focus on the true and false positive rates.

Finally, since recidivism is a policy prediction problem, we consider the performance of these models using a validation-set approach (James et al. 2023, p. 202). We perform a random sample split of the sample, stratified by census year, where we separate 30% of the year-level sample as the test sample and the remaining 70% as the train sample. We document the balance of each sample in Table C.1. Intuitively, the out-of-the-sample metrics reported above provide a measure of the model's predictive performance in assessing the risk that an individual will reoffend, based on their observed characteristics. Additionally, to mitigate overfitting in models such as CART, we perform a fivefold cross-validation approach in our train sample to select the tuning parameter of each model. This approach means that we select the penalty weight in the logit with LASSO, the number of neighbor observations, the size of the tree, the number of predictors for the random subset in random forest, and the error-rate penalization in XGBoosting. Overall, by comparing traditional performance and ML performance out of the sample, this application aims to identify the most effective tools for understanding and predicting recidivism, ultimately supporting evidence-based policy interventions.

5.1. Results: Reoffender Risk Assessment

Table 4 shows the performance metrics in our test sample for each of the six models applied to assess the risk of being a repeat offender. As mentioned before, the trivial null prediction with repeat offenders as the minority class is that all individuals are first-time offenders with an accuracy of 70%. Overall, the accuracy rates are similar and slightly above 70% across all the models, with CART (around 0.72) and KNN (close to 0.76) having the lowest and highest accuracy rates, respectively. These performance metrics reflect a common challenge in recidivism prediction: The class imbalance leads to strong performance in identifying first-time offenders but significant difficulties in correctly classifying repeat offenders. Finally, even though we lack data on criminal-record history, our six models perform in the range of previous studies. Kleinberg et al. (2018) have a performance of 0.707, while Mejía (2025) obtained an area under the curve of 0.773 in his recidivism-prediction pilot in Colombia using criminal-record history, as mentioned in Section 3.2.

Comparing the models, three perform in unexpected ways. First, the logit with LASSO penalty does not significantly improve the prediction of repeat offenders relative to the traditional logistic regression, regardless of the classification metric in the test sample. To better inspect the coefficient differences between logit and logit with LASSO penalty, Table C.2 in Appendix C shows that the logit with LASSO does not actually select a smaller sample of predictors and slightly shrinks the logit coefficients. Taking these comparisons together, the LASSO penalty to reduce the model variance does not sufficiently improve the prediction of a linear model relative to logistic regression.

Second, among the nonlinear methods, KNN classification performs better than logistic regression in identifying repeat offenders with new data in a context of high dimensionality (with more than 100 predictors). This model shows the highest sensitivity, as it correctly predicts 37% of repeat offenders among this minority class in the sample. This true positive rate is followed by XGBoosting with 27% and logit with 25%. Third, the decision tree for classifying first-time and repeat offenders performs the worst of all five models. In particular, we illustrate in Figure C.2 (in Appendix C) that the decision tree makes the trivial prediction that regardless of individual and prison characteristics, every observation is a first-time offender. Using the sensitivity measure, CART and random forest are the worst models for identifying repeat offenders.

Table 4. Machine learning performance out of the sample for reoffender classification

		Model performance out of the sample					
Measures	**Formula**	*Logit*	*Logit with LASSO penalty*	*KNN*	*CART*	*Random forest*	*XGBoosting*
Accuracy	$(TP+TN)$ / $(P+N)$	0.733	0.733	0.760	0.728	0.747	0.756
AUC	Area under ROC	0.712	0.711	0.759	0.680	0.759	0.755

Sensitivity	*TP/P*	0.250	0.237	0.373	0.129	0.187	0.271
Specificity	*TN/N*	0.931	0.936	0.918	0.973	0.976	0.954
Type I Error	*FP/P*	0.069	0.064	0.082	0.027	0.024	0.046
Type II Error	*FN/N*	0.750	0.763	0.627	0.871	0.813	0.729

Note: This table shows the classification metrics out of the sample for each of five machine learning methods. Our test sample used to evaluate each model estimated with new data consisted of 172,332 observations. AUC=area under the curve.

These three striking results, obtained across both linear and nonlinear models, highlight the importance of understanding the nature and structure of prison data. In Argentina, the prison census includes a large number of individual- and institution-level variables that are categorical and have multiple categories. This type of information needs to be transformed into binary variables, except for one category, meaning that the resulting set of predictors for models has a nonlinear structure. In this data context, KNN does a better job identifying repeat offenders using these sets of variables than the rest of the ML algorithms. Further refinement, including rebalancing techniques or adjusting decision thresholds, could improve the model's ability to correctly identify repeat offenders, addressing the current limitations in sensitivity.

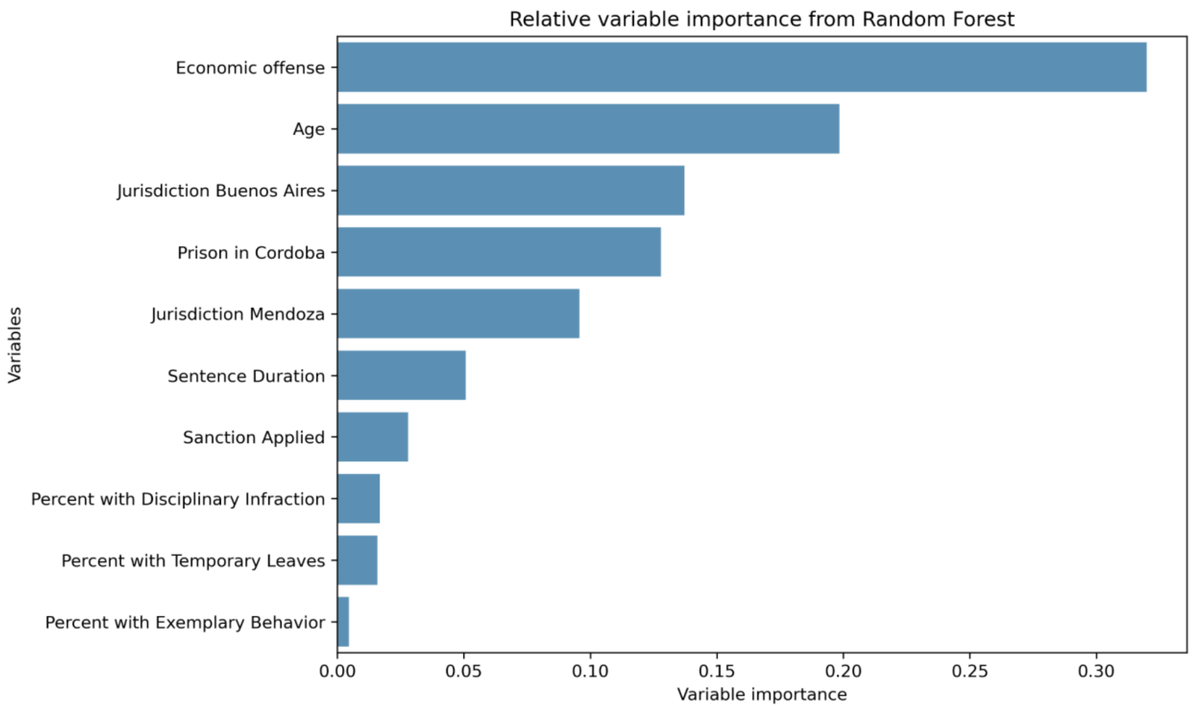
Finally, in any classification problem, there is a trade-off between type I and type II errors. Intuitively, when we try to increase our prediction of repeat offenders (true positives), we also increase the error of classifying individuals as repeat offenders when they are really first-time offenders (type I error, or false positive rate). Figure C.1, in Appendix C, shows the ROC curve of each of these models using the test sample as an additional visualization of this trade-off between true and false positive rates and as a further comparison across the six models. Similar to the metrics above, the ROC curve for CART lies close to the 45-degree line, indicating that its predictions are barely better than random guessing. This reflects poor performance across all classification thresholds, with a rapid increase in the type I error rate as sensitivity rises. In contrast, KNN, random forest, and XGBoosting have the ROC curve closest to the ideal scenario of perfect identification of reoffenders (true positive rate = 1) and no type I error (false positive = 0).

The nature of the prison census data facilitates an economic interpretation of the model's error trade-offs, particularly from the perspective of a prison manager facing resource constraints. We frame this as a decision problem in which interventions such as educational programs are allocated to inmates that the model classifies as likely reoffenders. Within this simple framework, the two error types have distinct costs. A type I error (false positive rate) occurs when resources are allocated to a first-time offender mistakenly classified as a reoffender. This error results in the inefficient allocation of limited resources to an individual who, by this measure, is low risk and does not require intervention. A type II error means a true reoffender is incorrectly classified as a first-time offender and thus excluded from receiving potential support when they are at high risk of recidivism. Therefore, from a managerial or policy perspective, the cost of type II error (failing to intervene with a true reoffender) may be considered substantially greater than the cost of type I error (misallocating resources to a first-time offender). Consequently, given that the KNN model achieved the lowest type II error rate among the alternatives, it represents the most suitable potential implementation to guide and complement decisions regarding resource allocation.

5.2. Key Factors Predicting Recidivism in Argentina

A key question for policymakers and correctional authorities is how to identify individuals at higher risk of recidivism so that interventions can be targeted effectively. To address this concern, Figure 9 shows the top 10 most important predictors of recidivism using random forest. The horizontal axis measures the improvement of the Gini index, attributed to the splitting variable using the Gini index for each node as the split criterion (Friedman et al., 2003, p. 593). The variables with the highest-importance measure are predictors that contribute more to improving the purity of nodes in each split across all the decision trees in the random forest. Intuitively, the top 10 most important predictors help classify individuals as first-time and repeat offenders.

Figure 9. Top 10 most important predictors of repeat reoffenders using random forest



Note: This figure shows the relative importance of each predictor variable after using the random forest algorithm to predict repeat offenders in Argentina. This figure uses the train and test samples of 402,077 and 172,332 observations, respectively.

Economic offense and age stand out as the two main predictors of repeat offenders, followed by the geographic-location indicators, such as jurisdiction in Buenos Aires, prison in Córdoba, or jurisdiction in Mendoza. Prison-location indicators capture the physical location of the facility where the individual is held, while jurisdiction indicators reflect whether the case is prosecuted in the provincial or federal system. That is, *Prison in Córdoba* is a dummy variable equal to 1 if the facility is located in the province of Córdoba (the second most populous province in Argentina). In contrast, *Jurisdiction in Buenos Aires* is a dummy equal to 1 when the crime is prosecuted under the provincial justice system, as opposed to the federal system. For example, drug-related offenses typically fall under federal jurisdiction, while crimes such as theft are often handled by provincial courts. Therefore, jurisdiction dummies depend on the type of crime and prosecuting authority, whereas prison-location dummies capture the geographic location where the inmate is being held. Although jurisdiction is formally an institutional variable, it often correlates with territorial patterns of crime and prosecution. For example, federal jurisdiction is more common in provinces where drug-related offenses or cross-border crimes are concentrated, whereas provincial jurisdiction is typical for high-recidivism offenses such as theft. Thus, jurisdiction dummies may behave similarly to geographic indicators in predictive models because they reflect both the institutional authority overseeing the case and the territorial context in which different types of crimes occur. Taken together, both types of indicators help identify geographic and institutional dynamics that shape recidivism patterns across the country.

Other, less important predictors involve sentence duration, sanction applied, and prison-level characteristics—specifically, the proportions of inmates with disciplinary infractions, temporary leave, and exemplary behavior. This suggests that both individual-level factors (like type of crime and age) and contextual factors (such as prison management and location) are associated with reoffending. The prominence of geographic and prison-level variables highlights the potential role of institutional practices and regional differences in influencing recidivism rates.

With the caveat that the decision tree performs poorly in identifying repeat offenders, the CART decision tree in Figure C.2 in Appendix C has some overlap with these relatively important predictors from random forest. At the top of the tree, economic offense (which means charges such as "Theft and/or attempted theft," "Other property crimes") is the most important predictor of first-time offenders. This selection of economic crime as the main predictor is consistent with the random forest model, which shows it is the most important. Additionally, as shown in Table 2, repeat offenders have a proportion of 0.48 inmates involved in property crimes as a first charge, in contrast to the 0.31 among first-time offenders. Age also plays a role in the prediction of first-time offenders, according to CART in the second level of splits, and is consistent with the top two predictors according to random forest.

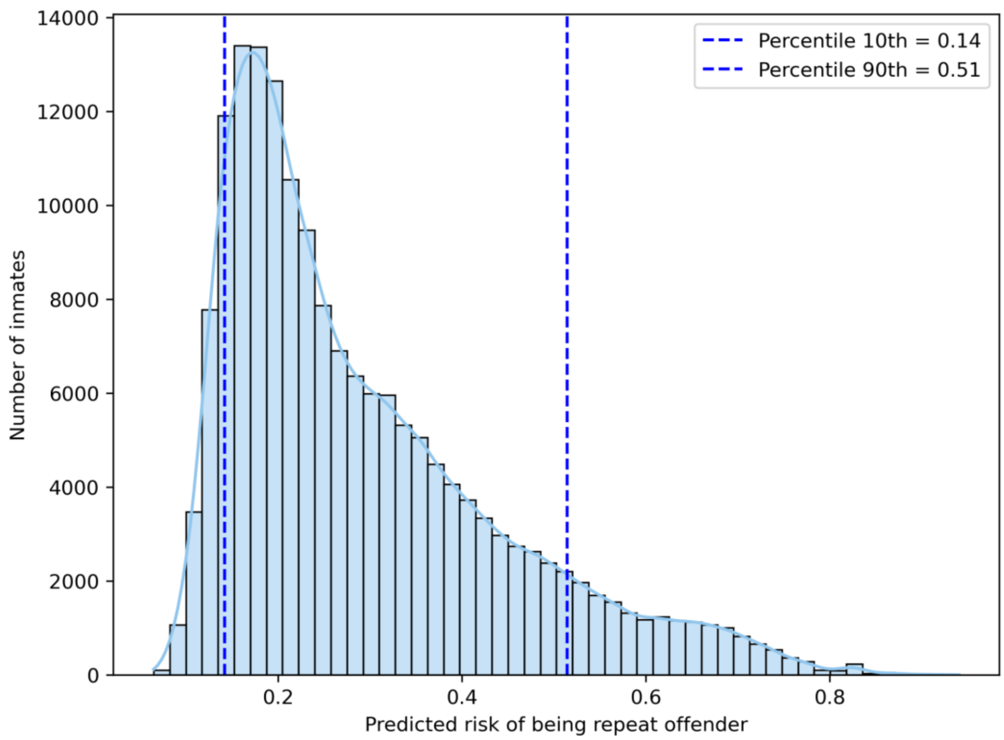
The geographic location of either the prison or jurisdiction plays an important role as a predictor of repeat offenders across the models. Random forest ranked these geographic dummies between the top three and top five most important predictors. CART also considers the prison location in Córdoba an important predictor of first-time offenders. Looking at the coefficients of logit and logit with LASSO penalty in Table C.2 in Appendix C, the largest magnitude of estimates is for jurisdiction in Ciudad de Buenos Aires, Córdoba, Mendoza, Tucumán, and San Juan. These findings regarding the importance of geographic dummies are also consistent with the patterns observed in Figure B.9 in Appendix B. This suggests that geographic factors play a role in shaping reoffending outcomes.

Overall, the main predictors across models are consistent with the literature review on ML methods for recidivism prediction (Section 3). Despite limitations in our prison census data—particularly the lack of individual criminal histories—age and property crimes emerge as two key and commonly identified predictors of recidivism. Additionally, sentence-related variables such as sentence duration and sanctions applied are relevant predictors, as shown by Zeng, Ustun, and Rudin (2017) and Mu et al. (2024). However, unlike in most studies, geographic variables appear as significant predictors in our models. We hypothesize that this difference arises from our data source and context. Since the data come from prisons, the assignment of inmates to specific facilities tends to concentrate repeat offenders unevenly across locations. As discussed in Section 4.3.1, some prisons have disproportionately high shares of repeat offenders, while others have lower shares. This spatial clustering likely explains why geographic location strongly predicts recidivism in our setting.

5.3. Characteristics of Individuals at High and Low Risk of Being Repeat Offenders

To guide decision-making with limited resources, the next question to ask is how different high- and low-risk recidivist profiles are. Using the XGBoost model's predictions of repeat-offender risk, we identify and characterize detained individuals with low- and high-risk profiles following Mejía's (2025) approach with PRISMA (more information about our approach is provided in Appendix D). Figure 10 illustrates the distribution of predicted probability of being reoffenders, with the number of convicted inmates on the y-axis. We define low-risk individuals as those with predicted risk scores below 0.14 (10th percentile), marked by the first vertical blue line. High-risk individuals are those with a predicted risk of being repeat offenders above 0.51 (90th percentile). The distribution is notably skewed to the right, with a long tail indicating few individuals have high predicted risk scores (e.g., 0.8). Most observations cluster around a predicted risk score of 0.2, suggesting a relatively low likelihood of reoffending. This visualization underscores the challenge of identifying repeat offenders, a minority class, as most test observations are assigned low predicted probabilities, consistent with the likelihood of being first-time offenders.

Figure 10. Predicted risk of being repeat offenders: Distribution out of the sample



Note: This figure shows the histogram and kernel distribution of the predicted probability of being a repeat offender after using the XGBoosting algorithm (best predictive model) in Argentina. The two vertical lines denote the 10th and 90th percentiles of the distribution of predicted risk. This figure uses the test sample of 172,332 observations.

We now turn to understanding the profiles of those at highest and lowest risk of recidivism in prison. Table 5 shows the individual, legal, penal-progression, and other grouped variables for the test sample. In terms of socioeconomic characteristics, individuals at low and high predicted risk of recidivism are similar in average age (around 35). However, 98% of high-risk individuals are Argentine nationals, compared to 88% in the low-risk group. Educational attainment is low in both groups, though those at lower risk are slightly more likely to have completed secondary or higher education. Pre-incarceration employment is also somewhat more common among low-risk individuals (65% vs. 61%). High-risk individuals are also more likely to have received sentence reductions and to be incarcerated in facilities with higher proportions of inmates in semi-detention or discontinuous-imprisonment regimes, suggesting possible institutional clustering of high-risk profiles across some prisons. High-risk reoffenders are associated with higher rates of part-time paid jobs in prison (35% of them work less than 40 hours per week), while low-risk repeat offenders engage more in full-time jobs in prison (17% vs. 13%).

Table 5. Mean difference between the lowest- and highest-predicted-risk reoffenders in the test sample

	Variable	Low Risk			High Risk			t-test p-value
		N	Mean	S.D.	N	Mean	S.D.	
Individual Factor	Age	34467	35.32	13.26	34467	35.01	8.23	0.0003
	Argentine nationality	34467	0.88	0.32	34467	0.98	0.15	0
	Completed primary education	34467	0.34	0.47	34467	0.34	0.47	0.088
	Incomplete secondary education	34467	0.19	0.39	34467	0.23	0.42	0
	Completed secondary education	34467	0.09	0.29	34467	0.07	0.25	0
	Higher education	34467	0.01	0.10	34467	0.00	0.07	0
	Employed	34467	0.65	0.48	34467	0.61	0.49	0
	Professional qualification	34467	0.55	0.50	34467	0.56	0.50	0.011
	Married	34467	0.20	0.40	34467	0.21	0.41	0.027
	Separated	34467	0.05	0.22	34467	0.03	0.17	0
	Single	34467	0.74	0.44	34467	0.76	0.43	0
Legal and penal information	Received visits last year	34467	0.87	0.33	34467	0.87	0.34	0.020
	Economic offense	34467	0.14	0.34	34467	0.80	0.40	0
	Violent offenses	34467	0.68	0.47	34467	0.28	0.45	0
	Others offense	34467	0.22	0.41	34467	0.14	0.35	0
	Percent in discontinuous prison*	34467	0.64	0.26	34467	0.72	0.28	0

	Percent in semi-detention*	34467	0.65	0.26	34467	0.73	0.27	0
	Full-time job in prison	34467	0.17	0.38	34467	0.13	0.34	0
	Part-time job in prison	34467	0.26	0.44	34467	0.35	0.48	0
Penal-system progression	Sentence reduction	34467	0.03	0.18	34467	0.06	0.23	0
	Sentence duration	34467	0.08	0.05	34467	0.07	0.06	)
	Percent with progressive regime*	34467	0.58	0.32	34467	0.70	0.30	0
	Percent with temporary leave*	34467	0.62	0.20	34467	0.61	0.31	0.058
Behavioral information	Percent with disciplinary infraction*	34467	0.12	0.21	34467	0.26	0.19	0
	Order disruption dummy	34467	0.07	0.26	34467	0.23	0.42	0
	Percent with sanction applied*	34467	0.12	0.13	34467	0.29	0.24	0
	Percent with exemplary behavior*	34467	0.52	0.50	34467	0.55	0.50	0
	Percent with very good behavior*	34467	0.18	0.38	34467	0.13	0.34	0
	Percent with good behavior*	34467	0.21	0.41	34467	0.11	0.31	0
	Percent with fair behavior*	34467	0.03	0.16	34467	0.07	0.26	0
	Percent with bad behavior*	34467	0.01	0.11	34467	0.05	0.21	0
	Percent with very bad behavior*	34467	0.01	0.10	34467	0.04	0.19	0
	Escape or evasion attempt*	34467	0.00	0.06	34467	0.01	0.11	0
Health and well-being	Received medical attention dummy*	34467	0.98	0.14	34467	0.99	0.11	0
	Injured dummy	34467	0.04	0.19	34467	0.16	0.36	0
Programs in prison	Percent in labor program*	34467	0.22	0.26	34467	0.23	0.25	0
	Percent in any educational program*	34467	0.08	0.15	34467	0.14	0.15	0
	Percent in secondary education program*	34467	0.14	0.13	34467	0.14	0.14	0
	Percent in primary education program*	34467	0.19	0.18	34467	0.19	0.18	0.143
	Percent in recreational or sport activities*	34467	0.78	0.33	34467	0.68	0.33	0

Note: This table shows the average differences between the lowest- and highest-predicted-risk reoffenders in the test sample, disaggregated by groups of characteristics. Variables marked with * are at the prison level, while those without * are at the individual level. We define the lowest-predicted-risk reoffenders as inmates below the 20th percentile of the predicted-risk distribution, and the highest-risk reoffenders as those above the 80th percentile. The last column shows the p-values from t-tests, which test whether the differences between the two groups are statistically significant. This table uses the test sample of 172,332 observations.

The most notable differences between groups are observed in the types of offenses committed, yet these results must be interpreted with caution. Economic (property-related) offenses are significantly more prevalent among high-risk individuals (80%) than among their low-risk counterparts (14%). In contrast, violent offenses are much more frequent among the low-risk group (68% vs. 28%). A key caveat when interpreting these differences is that they may partly reflect differences in release opportunities rather than underlying propensities to reoffend. For instance, while it makes sense that someone who committed robbery or theft has a high risk of reoffending if released, those detained for sex crimes are generally less likely to enter parole or temporary-release programs. Therefore, they have less chance of reoffending simply because they remain incarcerated. So these results do not necessarily indicate that someone convicted of a sex or violent crime actually has a low risk of reoffending; rather, this prediction arises from the very nature of the detention-center data and the comparison of who remains incarcerated versus those who had a chance to be released at least once and reoffend.

Finally, in-prison behavior further differentiates the groups. High-risk individuals exhibit more disciplinary issues, including more infractions, sanctions, and negative behavioral evaluations. Injuries are also more common in this group (16% vs. 4%), potentially indicating greater exposure to violence or self-harm. Regarding participation in prison educational programs, high-risk individuals are more likely to engage in any educational program (which includes some short-term courses, such as ceramics courses). Yet the differences in primary and secondary educational participation rates between the two types of risk offenders are negligible. While both types participate more in recreational and sport activities than in educational programs, low-risk individuals have a 10 percentage point participation rate higher than high-risk inmates. This self-selection of the least and most risky repeat offenders to educational and other rehabilitation programs within prison is not trivial when considering prisoners' time horizon. High-risk individuals have slightly shorter average sentences (7.0 years) compared to low-risk individuals (7.78 years), reducing their expected time imprisoned. With a shorter horizon, high-risk individuals may be less inclined (or less eligible) to commit to longer-term programs and instead select shorter activities. This helps understand why they may participate less in sports and somewhat more in short-course educational activities.

6. Conclusions

This study contributes to the still-limited research on recidivism in Latin America and the Caribbean by combining empirical evidence and policy-oriented analysis in a unified framework. While predictive tools are increasingly used in high-income countries, their application in the region remains scarce. We help fill this gap by examining the use of machine-learning methods for recidivism prediction and by applying these tools to a novel, large-scale prison dataset from Argentina. Beyond prediction, the paper highlights how these methods can support specific stages of the criminal justice policy process when embedded in appropriate institutional settings.

Our analysis shows that predictive models can generate actionable insights for judicial and correctional systems by identifying heterogeneity in recidivism risk. This allows policymakers to move from "what works on average" toward "for whom and under what conditions interventions are most effective," supporting more targeted rehabilitation, improved prison management, and more efficient allocation of scarce resources. Predictive tools can also inform operational decisions such as housing, supervision, and facility placement, enhancing inmate safety, institutional security, and access to programs.

The paper documents substantial heterogeneity within the prison system. Differences across facilities in size, population composition, and access to programs shape incarceration experiences and condition the feasibility of risk-based interventions. These institutional features underscore that predictive tools do not operate in isolation: their usefulness depends on organizational capacity and the broader governance environment in which they are deployed.

Several limitations remain. The prison census captures only a subset of reoffending behaviors and lacks complete information for some facilities. While we address these constraints pragmatically, future research would benefit from more comprehensive longitudinal data linking prison, court, and post-release outcomes.

Looking ahead, we identify three promising directions for future research in the region. First, comparative studies examining how justice institutions, labor markets, social protection systems, and prison conditions shape criminal trajectories would deepen understanding of recidivism dynamics. Second, more systematic evidence is needed on how in-prison experiences—such as overcrowding, violence, rehabilitation access, and peer effects—influence reoffending. Third, the role of nonstate actors in reintegration, including community organizations, churches, and mentoring programs, remains underexplored despite its potential importance.

Finally, effective use of predictive tools in Latin America requires more than technical sophistication. Drawing on international experience, we highlight six institutional conditions for successful implementation: fairness across groups, reliable and interoperable data systems, transparency and governance, staff capacity and training, ongoing monitoring, and sustained political commitment. When these conditions are met, machine-learning tools can contribute to more strategic, evidence-based, and equitable criminal justice policies. The central challenge is therefore not whether these tools can be useful, but how to embed them within institutions capable of using them responsibly and consistently.

References

Agan, A., & Starr, S. (2017). El efecto de los antecedentes penales en el acceso al empleo. American Economic Review, 107(5), 560–564. https://doi.org/10.1257/aer.p20171028

Baggio, S., Peigné, N., Heller, P., Gétaz, L., Liebrenz, M., & Wolff, H. (2020). Do overcrowding and turnover cause violence in prison?. *Frontiers in Psychiatry*, *10*, 1015.

Balnco, N. (2019). Inteligencia artificial y reincidencia: Control inteligente del delito. ¿Efectivización de los cupos carcelarios?: Aproximación al Sistema Prisma de la Fiscalía General de la Nación. Retrieved from: https://repositorio.uniandes.edu.co/server/api/core/bitstreams/8f222f35-d11e-4469-bd53-dfe2426a57d5/content

Bogliaccini, Juan A. & Flores-Macías, Gustavo A. & Tealde, Emiliano, 2024. "Recidivism, Labor Markets, and Prison Conditions: Evidence from Uruguay," World Development, Elsevier, vol. 183(C).

Barrios-Fernández, A., & García-Hombrados, J. (2025). Recidivism and neighborhood institutions: Evidence from the rise of the evangelical church in Chile. *Journal of Labor Economics*, *43*(3), 000–000.

Basto-Pereira, M., Gouveia-Pereira, M., Pereira, C. R., Barrett, E. L., Lawler, S., Newton, N., & Sakulku, J. (2022). The global impact of adverse childhood experiences on criminal behavior: A cross-continental study. *Child Abuse & Neglect*, *124*, 105459.

Becker, G. S. (1968). Crime and Punishment: An Economic Approach. Journal of Political Economy, 76(2), 169–217. http://www.jstor.org/stable/1830482

Berk, R. A., & Rauma, D. (1983). Capitalizing on Nonrandom Assignment to Treatments: A Regression-Discontinuity Evaluation of a Crime-Control Program. Journal of the American Statistical Association, 78(381), 21–27. https://doi.org/10.2307/2287095

Binder, A. (2011). La intolerabilidad de la prisión preventiva. *Revista Pensamiento Penal*. https://www.pensamientopenal.com.ar/system/files/2011/07/doctrina29870.pdf

Butler, M., McNamee, C. B., & Kelly, D. (2024). Exploring the factors influencing prison incentive scheme status among adult males: A prospective longitudinal study. *European Journal of Criminology*, *21*(6), 887–907.

Butsara, N., Athonthitichot, P., & Jodpimai, P. (2019). Predicting recidivism to drug distribution using machine learning techniques. In 2019 17th International Conference on ICT and Knowledge Engineering (ICT&KE) (pp. 1–5). IEEE. https://doi.org/10.1109/ICTKE47035.2019.8966834

Chen, T., & Guestrin, C. (2016, August). XGBoost: A scalable tree boosting system. In Proceedings of the 22nd ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (pp. 785–794). ACM.

Chetty, R. and N. Hendren (2018a). The Impacts of Neighborhoods on Intergenerational Mobility I: Childhood Exposure Effects. *The Quarterly Journal of Economics*, *133*(3), 1107– 1162.

Chetty, R. and N. Hendren (2018b). The Impacts of Neighborhoods on Intergenerational Mobility II: County-Level Estimates. *The Quarterly Journal of Economics*, *133*(3), 1163–1228.

Chouldechova, A., & Lum, K. (2020, June). *The present and future of AI in pre-trial risk assessment instruments*. John D. and Catherine T. MacArthur Foundation. https://www.safetyandjusticechallenge.org/media/documents/AI-Risk-Assessment-Instruments-Report.pdf

Clark, V. A. (2016). Predicting two types of recidivism among newly released prisoners: First addresses as "launch pads" for recidivism or reentry success. *Crime & Delinquency*, *62*(10), 1364–1400.

Cottle, C. C., Lee, R. J., & Heilbrun, K. (2001). The prediction of criminal recidivism in juveniles: A meta-analysis. Criminal Justice and Behavior, 28(3), 367–394. https://doi.org/10.1177/0093854801028003005

Defensor del Pueblo de la Nación. (2006). *Las cárceles en Argentina*.

Doleac, J. L. (2023). Encouraging desistance from crime. *Journal of Economic Literature*, *61*(2), 383–427.

Drago, F. and R. Galbiati (2011). Indirect Effects of a Policy Altering Criminal Behavior: Evidence from the Italian Prison Experiment. *American Economic Journal: Applied Economics*, *4*(2), 199–218.

Dressel, J., & Farid, H. (2018). The accuracy, fairness, and limits of predicting recidivism. *Science Advances*, *4*(1), eaao5580. https://doi.org/10.1126/sciadv.aao5580

Duwe, G., & Kim, K. (2017). Out with the old and in with the new? An empirical comparison of supervised learning algorithms to predict recidivism. *Criminal Justice Policy Review*, *28*(6), 570–600. https://doi.org/10.1177/0887403415604899

Farrington, D. P. (2007). Origins of violent behavior over the life span. In D. J. Flannery, A. T. Vazsonyi, & I. D. Waldman (Eds.), The Cambridge handbook of violent behavior and aggression (pp. 19–48). Cambridge University Press. https://doi.org/10.1017/CBO9780511816840.003

Farrington D., Piquero A. y Jennings W (2013) Offending from Childhood to Late Middle Age: Recent Results from the Cambridge Study in Delinquent Development. SpringerBriefs in Criminology.

Fazel, S., Burghart, M., Fanshawe, T., Gil, S. D., Monahan, J., & Yu, R. (2022). The predictive performance of criminal risk assessment tools used at sentencing: Systematic review of validation studies. *Journal of Criminal Justice*, *81*, 101902. https://doi.org/10.1016/j.jcrimjus.2022.101902

Fazel S, Wolf A (2015) A Systematic Review of Criminal Recidivism Rates Worldwide: Current Difficulties and Recommendations for Best Practice. PLoS ONE 10(6): e0130390. https://doi.org/10.1371/journal.pone.0130390

Fiscalía General de la Nación (n.d.) *Risk profile of recidivism for pretrial detention requests*. Retrieved from: https://www.fiscalia.gov.co/colombia/wp-content/uploads/Perfil-de-riesgo-de-reincidencia-para-solicitudes-de-medida-de-aseguramiento.pdf

Friedman, J., Hastie, T., & Tibshirani, R. (2003). *The elements of statistical learning* (Vol. 1). Springer, Berlin: Springer series in statistics. Chap. 15

Gendreau, P., Little, T., & Goggin, C. (1996). A meta-analysis of the predictors of adult offender recidivism: What works!. Criminology, 34(4), 575–608. https://doi.org/10.1111/j.1745-9125.1996.tb01220.x

Ghasemi, M., Anvari, D., Atapour, M., Wormith, J. S., Stockdale, K. C., & Spiteri, R. J. (2021). The application of machine learning to a general risk–need assessment instrument in the prediction of criminal recidivism. *Criminal Justice and Behavior*, *48*(4), 518–538. https://doi.org/10.1177/0093854820969753

Graf, G. H. J., Chihuri, S., Blow, M., & Li, G. (2021). Adverse childhood experiences and justice system contact: A systematic review. *Pediatrics*, *147*(1).

Hamilton, Z., Neuilly, M. A., Lee, S., & Barnoski, R. (2015). Isolating modeling effects in offender risk assessment. *Journal of Experimental Criminology*, *11*(2), 299–318. https://doi.org/10.1007/s1129-014-9221-8

Heller, S. B., Shah, A. K., Guryan, J., Ludwig, J., Mullainathan, S., & Pollack, H. A. (2017). Thinking, fast and slow? Some field experiments to reduce crime and dropout in Chicago. *The Quarterly Journal of Economics*, *132*(1), 1–54. https://doi.org/10.1093/qje/qjw033

Hirschi, T., & Gottfredson, M. (1983). Age and the explanation of crime. American Journal of Sociology, 89(3), 552–584. https://doi.org/10.1086/227905

INECIP. (2006). *Manual práctico para defenderse de la cárcel*. Instituto de Estudios Comparados en Ciencias Penales y Sociales.

Jackson, O., & Zhao, B. (2017). The effect of changing employers' access to criminal histories on ex-offenders' labor market outcomes: Evidence from the 2010–2012 Massachusetts CORI Reform (Working Paper No. 16–30). Federal Reserve Bank of Boston. https://www.bostonfed.org/economic/wp/index.htm

Jaitman, L., Caprirolo, D., Ochoa, R. G., Keefer, P., Leggett, T., Lewis, J. A., . . . & Torre, I. (2019). *The costs of crime and violence: New evidence and insights in Latin America and the Caribbean*.

James, G., Witten, D., Hastie, T., Tibshirani, R., & Taylor, J. (2023). *An introduction to statistical learning: With applications in Python*. Springer Nature. Chap. 4, 6, and 8.

Karimi-Haghighi, M., & Castillo, C. (2021). Enhancing a recidivism prediction tool with machine learning: Effectiveness and algorithmic fairness. In *Proceedings of the Eighteenth International Conference on Artificial Intelligence and Law (ICAIL '21)* (pp. 210–214). ACM. https://doi.org/10.1145/3462757.3466150

Kleinberg, Jon, Jens Ludwig, Sendhil Mullainathan, and Ziad Obermeyer. 2015. "Prediction Policy Problems." American Economic Review 105 (5): 491–95.

Kling, J. R., J. Ludwig, and L. F. Katz (2005). Neighborhood Effects on Crime for Female and Male Youth: Evidence from a Randomized Housing Voucher Experiment. *The Quarterly Journal of Economics*, *120*(1), 87–130.

Kostenwein, E. (2017). Pre-trial detention in plural. *Revista Direito e Práxis*, *8*(2), 601–626. https://doi.org/10.12957/dep.2017.25019

Rasmus Landersø & Helena Skyt Nielsen & Marianne Simonsen, 2017. "School Starting Age and the Crime-age Profile," Economic Journal, Royal Economic Society, vol. 127(602), pages 1096–1118, June.

Laub, J. y Sampson, J. (2001) "Understanding distance from crime," en *Crime and Justice: a Review of Research*, *Vol. 28*, pp. 1–69.

Lee, Y., O, S., & Eck, J. E. (2025). Improving recidivism forecasting with a relaxed Naïve Bayes classifier. *Crime & Delinquency*, *71*(1), 89–117.

Liu, Y. Y., Yang, M., Ramsay, M., Li, X. S., & Coid, J. W. (2011). A comparison of logistic regression, classification and regression tree, and neural networks models in predicting violent re-offending. *Journal of Quantitative Criminology*, *27*(4), 547–573. https://doi.org/10.1007/s10940-011-9137-7

Lochner, L., & Moretti, E. (2004). The effect of education on crime: Evidence from prison inmates, arrests, and self-reports. *American Economic Review*, *94*(1), 155–189.

Long, J. S. (2020). Appropriate classification of prisoners: Balancing prison safety with the least restrictive placements of Ohio inmates [Doctoral dissertation, University of Cincinnati].

Ludwig, J., G. J. Duncan, L. A. Gennetian, L. F. Katz, R. C. Kessler, J. R. Kling, and L. Sanbonmatsu (2013, May). Long-Term Neighborhood Effects on Low-Income Families: Evidence from Moving to Opportunity. *American Economic Review*, *103*(3), 226–231.

Malvaso, C. G., Cale, J., Whitten, T., Day, A., Singh, S., Hackett, L., . . . & Ross, S. (2022). Associations between adverse childhood experiences and trauma among young people who offend: A systematic literature review. *Trauma, Violence, & Abuse*, *23*(5), 1677–1694.

Mears, D. P., Cochran, J. C., Siennick, S. E., & Bales, W. D. (2012). Prison Visitation and Recidivism. Justice Quarterly, 29(6), 888–918. https://doi.org/10.1080/07418825.2011.583932

Ministry of Justice. (2019, July 18). *Identified needs of offenders in custody and the community from OASys*. https://www.gov.uk/government/statistics/identified-needs-of-offenders-in-custody-and-the-community-from-oasys

Molina-Coloma, M., Salaberría, K., & Pérez, J. (2021). Factores de riesgo de reincidencia en personas privadas de libertad en Ecuador. *Revista Criminalidad*, *63*(1), 89–104. https://doi.org/10.47745/rc.vi63n1.488

Moore, K. E., Stuewig, J. B., & Tangney, J. P. (2016). The effect of stigma on criminal offenders' functioning: A longitudinal mediational model. *Deviant Behavior*, *37*(2), 196–218.

Mu, D., Xiang, S., Zhou, T., Zhou, Y., & Zhang, W. (2024). Prediction of recidivism and detection of risk factors under different time windows using machine learning techniques. *Social Science Computer Review*, *42*(6), 1379–1402. https://doi.org/10.1177/08944393241234607

Munyo, I., & Rossi, M. A. (2015). First-day criminal recidivism. Journal of Public Economics, 124, 81–90. https://doi.org/10.1016/j.jpubeco.2014.12.002

Murton, T. (1976). *The Dilemma of Prison Reform*. New York: Holt, Rinehart and Winston.

Ozkan, T., Clipper, S. J., Piquero, A. R., Baglivio, M., & Wolff, K. (2020). Predicting sexual recidivism. *Sex Abuse*, *32*(4), 375–399. https://doi.org/10.1177/1079063219852944

Pager, D. (2003). The mark of a criminal record. American Journal of Sociology, 108(5), 937–975. https://doi.org/10.1086/374403

Palmer, C., Phillips, D. C., & Sullivan, J. X. (2019). Does emergency financial assistance reduce crime? Journal of Public Economics, 169, 34–51. https://doi.org/10.1016/j.jpubeco.2018.10.012

Pew Charitable Trusts. (2011). *Risk/needs assessment 101: Science reveals new tools to manage offenders*. https://www.pew.org/-/media/legacy/uploadedfiles/pcs_assets/2011/pewriskassessmentbriefpdf.pdf

Ramakers, A., Aaltonen, M., & Martikainen, P. (2020). A closer look at labour market status and crime among a general population sample of young men and women. Advances in Life Course Research, 43, 100322. https://doi.org/10.1016/j.alcr.2019.100322

Reavis, J. A., Looman, J., Franco, K. A., & Rojas, B. (2013). Adverse childhood experiences and adult criminality: How long must we live before we possess our own lives?. *The Permanente Journal*, *17*(2), 44.

República Argentina. (1958, 14 de enero). *Ley Penitenciaria Nacional: Decreto Ley 412/58* (B. O. 24 de enero de 1958).

Safranoff, A., & Tiravassi, A. (2018). Mujeres en contextos de encierro en América Latina: Características y factores de riesgo asociados a determinados comportamientos delictivos. Olson, E. L., Pantzer, R., Bastien-Olvera, G. M., & Dolezal, J. (Eds.). https://doi.org/10.18235/0001113

Sherrard, R. (2020). "Ban the Box" policies and criminal recidivism (Working paper). SSRN. https://doi.org/10.2139/ssrn.3515048

Skardhamar, T., & Telle, K. (2012). Post-release Employment and Recidivism in Norway. Journal of Quantitative Criminology, 28(4), 629–649. http://www.jstor.org/stable/43551948

Salo, B., Laaksonen, T., & Santtila, P. (2019). Predictive power of dynamic (vs. static) risk factors in the Finnish Risk and Needs Assessment Form. *Criminal Justice and Behavior*, *46*(7), 939–960.

Samii, C., Paler, L., & Daly, S. Z. (2016). Retrospective causal inference with machine learning ensembles: An application to anti-recidivism policies in colombia. Political Analysis, 24(4), 434–456.

Saridakis, G., and H. Spengler. (2012). "Crime, Deterrence and Unemployment in Greece: A Panel Data Approach."

Schnepel, K. T. (2018). "Good Jobs and Recidivism." *Economic Journal*, *128*(608): 447–69.

Seim, J., & Harding, D. J. (2020). Parolefare: Post-prison supervision and low-wage work. RSF: The Russell Sage Foundation Journal of the Social Sciences, 6(1), 173–195. https://doi.org/10.7758/rsf.2020.6.1.08

Seroczynski, A. D., Marzano, L., Debellis, M., Rogers, K., & Klein, S. (2016). Treating high-risk youth with MDT: Toward effective rehabilitation. *Psychological Services*, *13*(3), 239–249. https://doi.org/10.1037/ser0000071

Sevigny, E. L., Johnson, T. L., & Greathouse, J. A. (2022). *Predicting recidivism fairly: A machine learning application using contextual and individual data* (Document No. 305036). National Institute of Justice. https://nij.ojp.gov/library/publications/predicting-recidivism-fairly-machine-learning-application-using-contextual-and

Sviatschi, M. M. (2022). Making a narco: Childhood exposure to illegal labor markets and criminal life paths. *Econometrica*, forthcoming.

Travaini, G. V., Pacchioni, F., Bellumore, S., Bosia, M., & De Micco, F. (2022). Machine Learning and Criminal Justice: A Systematic Review of Advanced Methodology for Recidivism Risk Prediction. International Journal of Environmental Research and Public Health, 19(17), 10594. https://doi.org/10.3390/ijerph191710594

Tobón, S. (2017). "Condiciones de Reclusión y Reincidencia: Evidencia de Una Expansión de Cupos Carcelario (Conditions of Confinement and Recidivism: Evidence of Prison Capacity Expansion)." https://ssrn.com/abstract=2921477.

Tobón, S. (2022). Do better prisons reduce recidivism? Evidence from a prison construction program. *Review of Economics and Statistics*, *104*(6), 1256–1272.

Tollenaar, N., & van der Heijden, P. G. M. (2013). Which method predicts recidivism best?: A comparison of statistical, machine learning and data mining predictive models. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *176*(2), 565–584. https://doi.org/10.1111/j.1467-985X.2012.01065.x

Tuttle, C. (2019). Snapping back: Food stamp bans and criminal recidivism. *American Economic Journal: Economic Policy*, *11*(2), 301–327.

United Nations Office on Drugs and Crime. (2020). *Handbook on the classification of prisoners* (Criminal Justice Handbook Series). United Nations.

U.S. Department of Justice. (2024, December 3). Artificial intelligence and criminal justice: Final report.

van Ginneken, E. F., & Palmen, H. (2023). Is there a relationship between prison conditions and recidivism?. *Justice Quarterly*, *40*(1), 106–128.

Venkatesh, S. A., & Levitt, S. D. (2000). "Are we a family or a business?" History and disjuncture in the urban American street gang. *Theory and Society*, *29*(4), 427–462. https://doi.org/10.1023/A:1007032503470

Viljoen, J. L., Goossens, I., Monjazeb, S., Cochrane, D. M., Vargen, L. M., Jonnson, M. R., Blanchard, A. J. E., Li, S. M. Y., & Jackson, J. R. (2024). Are risk assessment tools more accurate than unstructured judgments in predicting violent, any, and sexual offending? A meta-analysis of direct comparison studies. *Behavioral Sciences & the Law*, *43*(1), 75–113. https://doi.org/10.1002/bsl.2698

Walters, G. D. (2012). Criminal thinking and recidivism: Meta-analytic evidence on the predictive and incremental validity of the Psychological Inventory of Criminal Thinking Styles (PICTS). Aggression and Violent Behavior, 17(3), 272–278. https://doi.org/10.1016/j.avb.2012.02.010

Walk, M., Wang, Y., & Hagedorn, J. (2021). Prison education programs and recidivism: A systematic review and meta-analysis. *Journal of Experimental Criminology*, *17*(3), 353–385. https://doi.org/10.1007/s11292-020-09427-z

Wermink, H., Nieuwbeerta, P., Ramakers, A. A. T., de Keijser, J. W., & Dirkzwager, A. J. E. (2018). Short-term effects of imprisonment length on recidivism in the Netherlands. Crime & Delinquency, 64(8), 1057–1093. https://doi.org/10.1177/0011128716687290

Western, B., Kling, J. R., & Weiman, D. F. (2001). The labor market consequences of incarceration. *Crime & Delinquency*, *47*(3), 410–427.

Wilson, A. B., Draine, J., Hadley, T., Metraux, S., & Evans, A. (2011). Examining the impact of mental illness and substance use on recidivism in a county jail. *International Journal of Law and Psychiatry*, *34*(4), 264–268.

Wilson, D. B., Gallagher, C. A., & MacKenzie, D. L. (2000). A meta-analysis of corrections-based education, vocation, and work programs for adult offenders. *Journal of Research in Crime and Delinquency*, *37*(4), 347–368. https://doi.org/10.1177/0022427800037004001

Winnick, T. A., & Bodkin, M. (2008). Anticipated stigma and stigma management among those to be labeled “ex-con.” *Deviant Behavior*, *29*(4), 295–333.

Yang, C. S. (2017). “Local Labor Markets and Criminal Recidivism.” *Journal of Public Economics*, *147*: 16–29.

Yang, Crystal S. (2017b). “Local Labor Markets and Criminal Recidivism.” *Journal of Public Economics*, *147*: 16–29.

Zeng, J., Ustun, B., & Rudin, C. (2017). Interpretable classification models for recidivism prediction. *Journal of the Royal Statistical Society: Series A (Statistics in Society)*, *180*(3), 689–722. https://doi.org/10.1111/rssa.12227

Appendix A: Data Appendix

This appendix documents the process of cleaning the prison census data in Argentina (from SNEEP) used in the paper "Understanding and Predicting Recidivism in Latin America: Insights from Machine Learning and Policy-Oriented Research." The production of these national prison statistics is overseen by the National Department of Criminal Policy within the Ministry of Justice and Human Rights, established under Law 25,266. This department is responsible for generating official statistics on crime and the functioning of the criminal justice system. To fulfill this mandate, it created the National Criminal Statistics System, which compiles data from various institutional sources. A key component of this system is SNEEP, introduced in 2002 to focus specifically on individuals deprived of liberty because of criminal offenses. The census data-collection process follows a methodology aligned with Law 24,660 on the execution of sentences. Each detention facility completes two distinct forms: one at the facility level, reporting aggregated indicators such as legal status, admissions, releases, disciplinary incidents, deaths, escapes, and structural data; and one at the individual level, which captures information on each person deprived of liberty as of December 31 each year. The two forms by the detention facility are also used as a data-collection check so that the aggregated indicators calculated from the individual forms correspond with the facility-level form.

This original dataset has 86 variables and 1,548,475 observations. Most variables (48) in the data are categorical variables, while only a few, such as age, are numerical. Additionally, while the original dataset contains 86 variables, most of them have repeated information since they are just an encoding of categorical variables. For example, we have the legal-status information description of whether the individual is convicted or waiting for trial (original name in Spanish: *situacion_legal_descripcion*) and the encoding variable with a number for each described categorical variable (original name in Spanish: *situacion_legal_id*). Thus, we drop many variables with just the code of the string variable. Our general objective is to keep as many observations as possible. In the next two subsections, we explain in detail our process of creating variables and dropping observations with the goal of maximizing observations.

Sample for the Descriptive Analysis

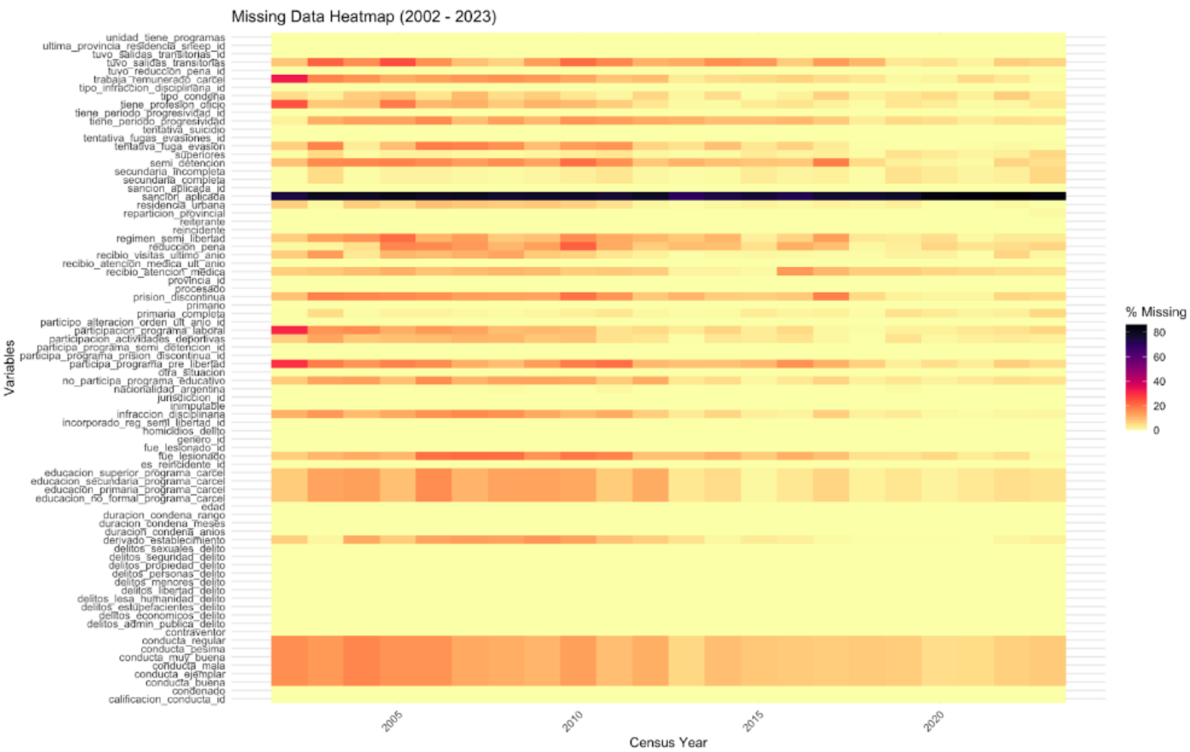
A first general rule to minimize dropping observations is to create a continuous variable at the prison level with the percentage of inmates with certain categorical variables. To clarify the rationale behind constructing variables at the prison level, Figure A presents the evolution of missing values for each variable over time using the raw data.. This figure shows the variable name in Spanish in the original dataset for transparency and replication purposes, as it was obtained from the National Department of Criminal Policy within the Ministry of Justice and Human Rights upon request.[6] Light yellow represents the variables with almost-complete information in a certain year, while dark violet represents variables with a high percentage of missing values in that year. Overall, most variables exhibit a very high share of missing values during the first decade (up to 2010), which corresponds to the initial years in which prison managers were required to complete and familiarise themselves with the two reporting forms. As a result, data availability largely

[6] We will happily share our codes in Jupyter Notebook upon request.

reflects the data collection process itself, which required greater training and coordination between the National Department of Criminal Policy and the prison managers responsible for completing the forms.

The behavioral-information variables illustrate the application of this rule. Individual-level behavior assessments (classified as exemplary, very good, good, fair, bad, or very bad) contain a large number of missing values within prisons, as shown in Figure D.2. To minimize the loss of observations, we therefore aggregate this information at the prison level by computing the percentage of inmates in each prison falling into each behavior category. This transformation sacrifices individual-level variation but preserves a substantially larger number of observations and meaningful variation across prisons over time.

Figure A.1. Evolution of the percentage of NAs in the raw prison census data (SNEEP)



Note: This figure shows the percentage of missing observations for each variable between 2002 and 2023 in the raw data. This figure is produced before keeping the individuals 21 years and older and before dropping anything else.

In Table A.1, we show the raw number of missing observations and the percentage of missing observations in the SNEEP raw data. Columns (1) and (4) show the variable names in Spanish. Next, we show the total number of individuals with missing values in the listed variable in columns (2) and (5). Last, columns (3) and (4) display the percentage of the missing values over the total of 1,548,475 observations.

As shown in column (3), the top five variables include more than 60% of missing values. In particular, the variables *delito#_descripcion* contain information about the second, third, fourth, and fifth charges. Yet most detained individuals are charged with committing one type of offense (*delito1_descripcion*), and fewer have two or more charges. So we keep only the first and second charges.

Table A.1. Raw number and percentage of missing-value observations in descending order by variable in the SNEEP data, 2003 to 2023

Variable (1)	Count (2)	Percentage of NAs (3)	Variable (4)	Count (5)	Percentage of NAs (6)
delito5_descripcion	1541687	99.56%	fue_lesionado_id	0	0.00%
delito4_descripcion	1532388	98.96%	tentativa_suicidio	0	0.00%
delito3_descripcion	1488973	96.16%	establecimiento_es_prision	0	0.00%
mujer_tiene_hijos_intramuro	1478172	95.46%	tuvo_reduccion_pena_id	0	0.00%
delito2_descripcion	1282162	82.80%	duracion_condena_meses	0	0.00%
sancion_aplicada_descripcion	1215824	78.52%	duracion_condena_rango	0	0.00%
fecha_condenado	876637	56.61%	provincia_id	0	0.00%
tuvo_salidas_transitorias_descripcion	851629	55.00%	es_reincidente_id	0	0.00%
participa_programa_pre_libertad	848571	54.80%	participa_programa_semi_detencion_id	0	0.00%
participa_programa_semi_detencion_descripcion	841813	54.36%	tiene_periodo_progresividad_id	0	0.00%
participa_programa_prision_discontinua_descripcion	840307	54.27%	participa_programa_prision_discontinua_id	0	0.00%
tiene_periodo_progresividad_descripcion	833787	53.85%	tuvo_salidas_transitorias_id	0	0.00%
tuvo_reduccion_pena_descripcion	830929	53.66%	censo_anio	0	0.00%
incorporado_reg_semi_libertad_descripcion	828335	53.49%	tentativa_fugas_evasiones_id	0	0.00%
es_reincidente_descripcion	816243	52.71%	situacion_legal_id	0	0.00%
tipo_condena	804712	51.97%	provincia_descripcion	0	0.00%
fue_lesionado_descripcion	158273	10.22%	establecimiento_id	0	0.00%
fecha_detencion	146085	9.43%	edad	0	0.00%
horas_trabajo_remunerado_descripcion	115349	7.45%	genero_id	0	0.00%
recibio_atencion_medica_ult_anio_descripcion	100228	6.47%	genero_descripcion	0	0.00%

participacion_programa_laboral	96859	6.26%	nacionalidad_id	0	0.00%
participacion_programa_educativo_descripcion	95244	6.15%	estado_civil_id	0	0.00%
tentativa_fugas_evasiones_descripcion	94536	6.11%	nivel_instruccion_id	0	0.00%
tipo_infraccion_disciplinaria_descripcion	90890	5.87%	ultima_situacion_laboral_id	0	0.00%
calificacion_conducta_descripcion	87658	5.66%	capacitacion_laboral_al_ingresar_id	0	0.00%
participo_alteracion_orden_ult_anio_descripcion	84173	5.44%	ultimo_lugar_residencia_id	0	0.00%
ultima_situacion_laboral_descripcion	79488	5.13%	ultima_provincia_residencia_sneep_id	0	0.00%
capacitacion_laboral_al_ingresar_descripcion	77108	4.98%	jurisdiccion_id	0	0.00%
establecimiento_procedencia_descripcion	66831	4.32%	situacion_legal_descripcion	0	0.00%
participacion_actividades_deportivas	62093	4.01%	calificacion_conducta_id	0	0.00%
recibio_visitas_ultimo_anio	55249	3.57%	establecimiento_procedencia_id	0	0.00%
delito1_descripcion	43265	2.79%	delito1_id	0	0.00%
ultima_provincia_residencia_id	42438	2.74%	delito2_id	0	0.00%
ultima_provincia_residencia_descripcion	42438	2.74%	delito3_id	0	0.00%
nivel_instruccion_descripcion	40882	2.64%	delito4_id	0	0.00%
ultimo_lugar_residencia_descripcion	39848	2.57%	delito5_id	0	0.00%
estado_civil_descripcion	25436	1.64%	horas_trabajo_remunerado_id	0	0.00%
jurisdiccion_descripcion	19597	1.27%	participacion_programa_educativo_id	0	0.00%
nacionalidad_descripcion	6596	0.43%	provincia_sneep_id	0	0.00%
establecimiento_descripcion	3012	0.19%	recibio_atencion_medica_ult_anio	0	0.00%
reparticion_id	3012	0.19%	participo_alteracion_orden_ult_anio_id	0	0.00%

reparticion_descripcion	3012	0.19%	tipo_infraccion_disciplinaria_id	0	0.00%
duracion_condena_anios	0	0.00%	sancion_aplicada_id	0	0.00%
incorporado_reg_semi_libertad_id	0	0.00%	establecimiento_es_preprision	0	0.00%
establecimiento_categoria	0	0.00%			

Note: This preliminary table shows the raw number of missing values and the percentage of the whole sample of SNEEP data in Argentina. Variable names are shown in Spanish. The original sample size is 1,548,475.

The first restriction on the raw SNEEP data is keeping individuals 21 years of age or older and only male and female inmates.[7] This decision leads us to drop 101,143 observations. We also merge the information regarding the duration of the sentence served in the detention center. Originally, this information was distributed in three variables with one variable for the years, months, and range. We combined this information into a continuous total duration in years. Then, we dropped those original variables to avoid redundancy of predictors.

As described in Section 4.1, we use a broad definition of repeat offenders including all the legal definitions different to first-time offenders for the condemned inmates. From Table C.1, the key variable of interest with this legal-recidivism information is the variable *es_reincidente_descripcion*. This variable has 816,243 missing values, representing 52% of the sample. As mentioned in Section 4.1, this is because the recidivism information is only available for convicted individuals. The variable on legal status (*situacion_legal_descripcion*) distinguishes between those convicted, awaiting trial, and with other legal status.

Table A.2 illustrates the distribution of observations depending on legal status and the recidivism definitions. First, notice that the convicted sample represents 51% of the observations. Among this sample with information on legal recidivism, 500,803 observations, or 67% of the sample, are first-time offenders. More importantly, 38,988 convicted inmates (5% of the sample) do not have information on whether they are repeat offenders.

Table A.2. Raw SNEEP sample by legal status and definitions of recidivism

	Legal definition of recidivism					
	Missing	First-time offender	Repeat offender	Recidivist	Multiple recidivist	**All**
Legal status	(1)	(2)	(3)	(4)	(5)	**(6)**
Convicted	389,88	500,803	130,507	12,351	63,297	**745,946**
Offender	62	0	0	0	0	**62**

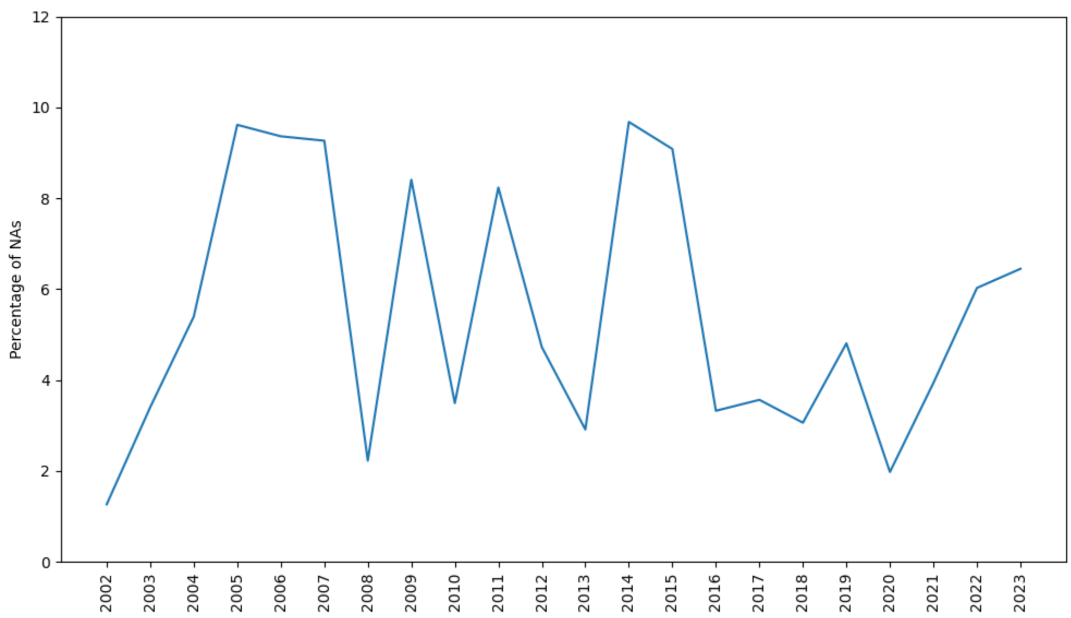
[7] Since 2015 the National Department of Criminal Policy has included the trangender label in the gender-identity question.

Unaccountable	8,179	0	0	0	0	**8,179**
Other situation	6,068	0	0	0	0	**60,68**
Waiting for trial	687,077	0	0	0	0	**687,077**
All	**740,374**	**500,803**	**130,507**	**12,351**	**63,297**	**1,447,332**

Note: This table shows the number of observations depending on legal status and recidivism information. This table was produced after keeping the individuals 21 years and older and before dropping anything else.

Before dropping the observations without this legal-recidivism information, we describe these 38,988 observations. Figure D.2 shows the raw percentage of observations with missing recidivism information among convicted individuals between 2002 and 2023. Overall, observations without the recidivism information ranged from 2% to 10% from 2002 and 2016 and from 3% to 6% between 2016 and 2023.

Figure A.2. Evolution of the percent of NAs in recidivism information among the convicted



Note: This figure shows the percentage of missing observations without recidivism information among convicted individuals. This figure was produced after keeping individuals 21 years and older and before dropping anything else.

To understand who the individuals without recidivism information among the convicted are, we present selected characteristics in Table D.3. These individuals without information on their recidivism status are mostly in prisons and have an average age of around 34, which is younger than both first-time and repeat offenders (see Table 4). Most are Argentine nationals, employed at similar rates to first-time offenders (see Table 4), and many are working for a salary in prison. They tend to commit more economic and violent crimes. Given the absence of recidivism information, we exclude these observations from further analysis. Therefore, the descriptive analysis of first-time and repeat offenders in Section 4.3.2 focuses solely on convicted individuals with available recidivism data.

Table A.3. Selected characteristics of convicted individuals without recidivism status: Information on selected individual and legal characteristics for the missing observations without recidivism information

Variables	count	mean	S.D.	min	25%	50%	75%	max
= 1 if establishment prison vs pre-prison	38988	0.81	0.4	0	1	1	1	1
Age	38988	34.2	11.1	21	26	31	40	86
Argentine nationality	38988	0.96	0.19	0	1	1	1	1
= 1 if higher education	38988	0.01	0.08	0	0	0	0	1
=1 if employed	38988	0.6	0.49	0	0	1	1	1
=1 if professional qualification	31962	0.57	0.49	0	0	1	1	1
=1 if works paid job	38988	0.80	0.4	0	1	1	1	1
=1 if received visits last year	31228	0.91	0.29	0	1	1	1	1
Economic crimes	38988	0.44	0.50	0	0	0	1	1
Violent crimes	38988	0.45	0.50	0	0	0	1	1
Other offenses	38988	0.22	0.41	0	0	0	0	1

Note: This table shows selected characteristics of observations without the recidivism information. This table was produced after keeping individuals 21 years and older and before dropping anything else.

For the individual and prison characteristics in tables and figures, we create all the necessary variables as dummies from the categorical variables. For example, the education-level variable is grouped conveniently in four dummies instead of creating nine dummies from the original nine categories. We follow this second general rule to minimize the increasing dimension of our matrix for two reasons: first, to simplify the descriptive analysis; and second, to minimize the memory used when running the predictive models (since it takes longer with a larger-dimension matrix).

Summary of Raw Sample to obtain the Descriptive Analytical Sample

1. After checking the raw data evolution of NAs, we create continuous variables at the prison level.
2. We keep individuals 21 years and older and keep only male and female individuals, dropping 101,143 observations.
3. We drop variables with more than 70% of NAs.
4. We drop 38,988 individuals without legal-recidivism information.
5. We drop the original categorical variables to avoid redundancy and keep convenient dummy variables.
6. We keep convicted individuals for the repeat-offender descriptives.

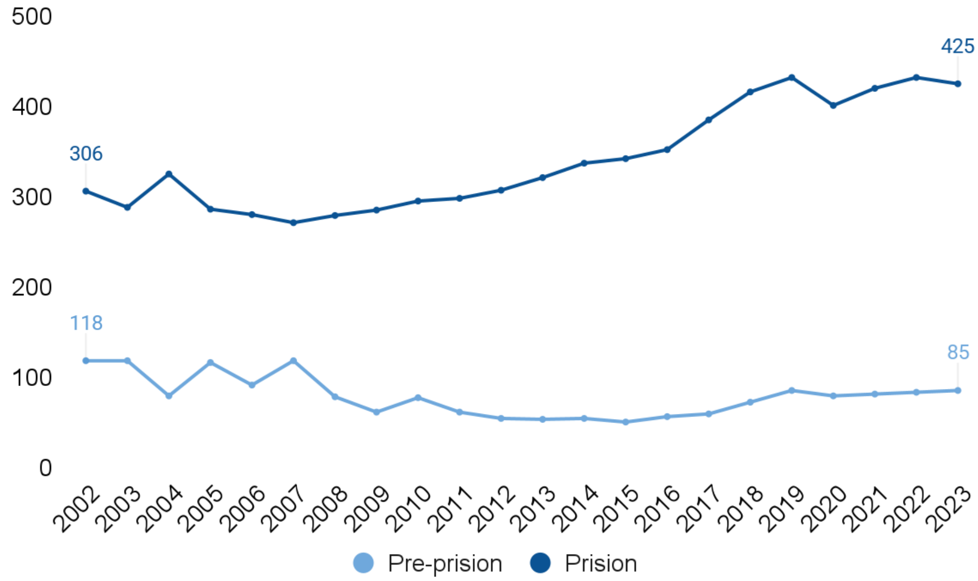
Sample for the Predictive Analysis

To minimize the number of dropped observations, we follow the general rule of checking each original variable with the highest percentage of missing values and dropping missing values if only if it represents less than 10% of the current sample. This general rule implies that when there was a risk of losing many observations, we created convenient dummy variables that indicate when the variable has missing values instead of dropping so many observations.[8] With this sequential checking and dropping, we reach a final analytical sample for the predictive model of 574,409 observations.

[8] Our second Jupyter notebook code, "Predictive_Models_Recidivism_Arg.ipynb," contains detailed checking data step by step before dropping any missing values. For more detail, refer to this replication code.

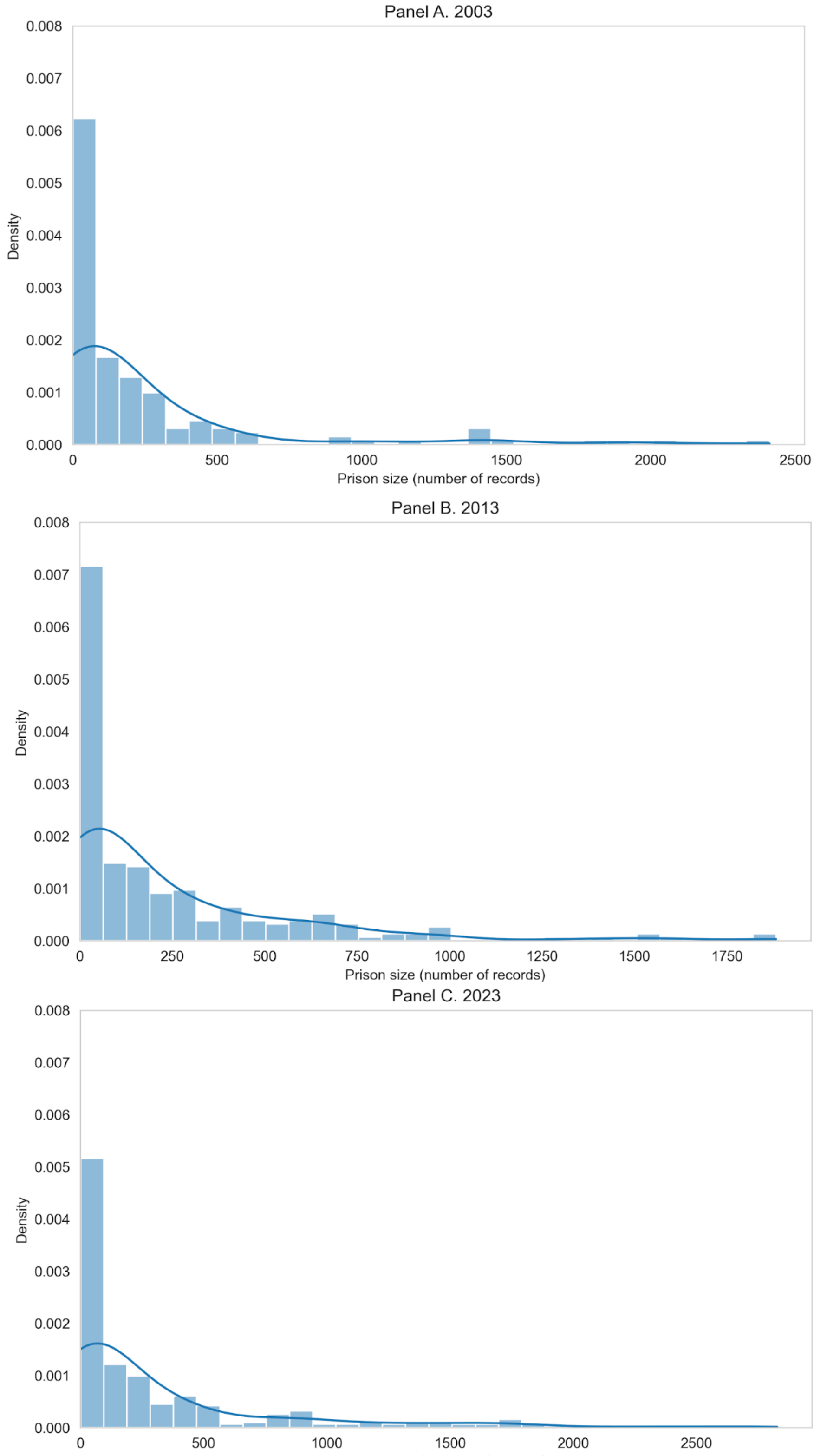
Appendix B: More Detailed Information About SNEEP Data

Figure B.1. Raw average number of prisoners per facility by type of establishment in Argentina (2002–23)



Source: Own elaboration using the National System of Statistics on Penal Execution.

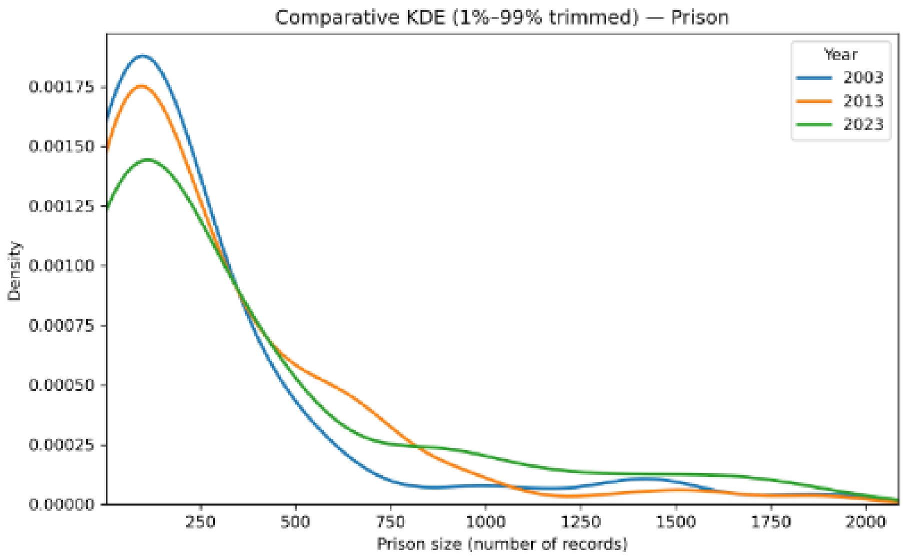
Figure B.2. Overall distribution of raw prison size in Argentina in 2003, 2013, and 2023

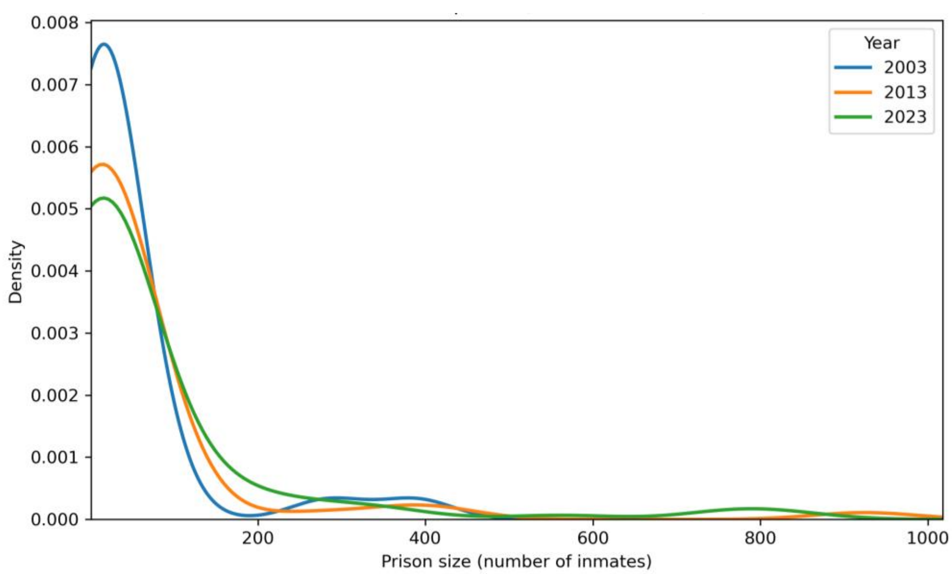


Note: These figures show the histogram and kernel densities of prison size in 2003, 2013, and 2023.
Source: Own elaboration using the National System of Statistics on Penal Execution.

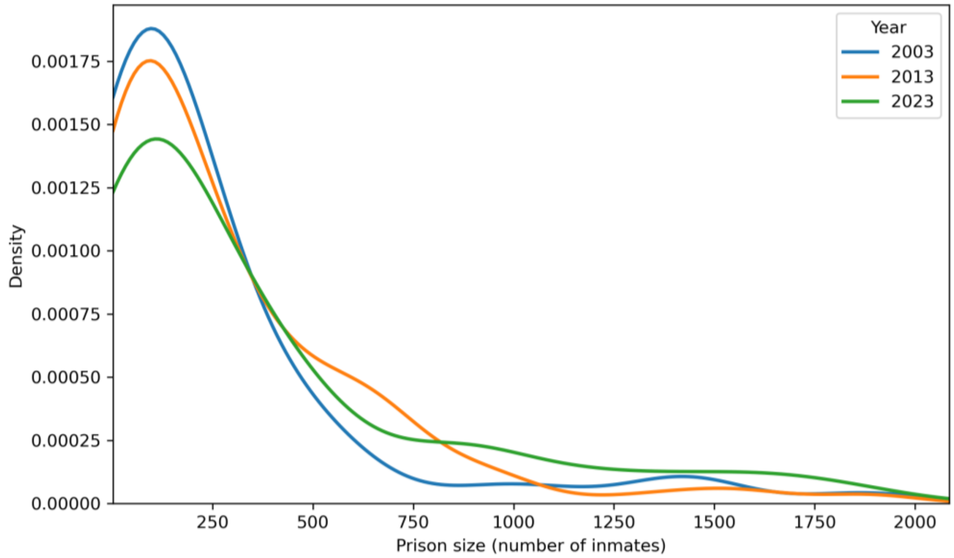
Figure B.3. Distribution of prison size by type of establishment in Argentina: 2003, 2013, and 2023

Panel A. Pre-prison (1%–99% trimmed)



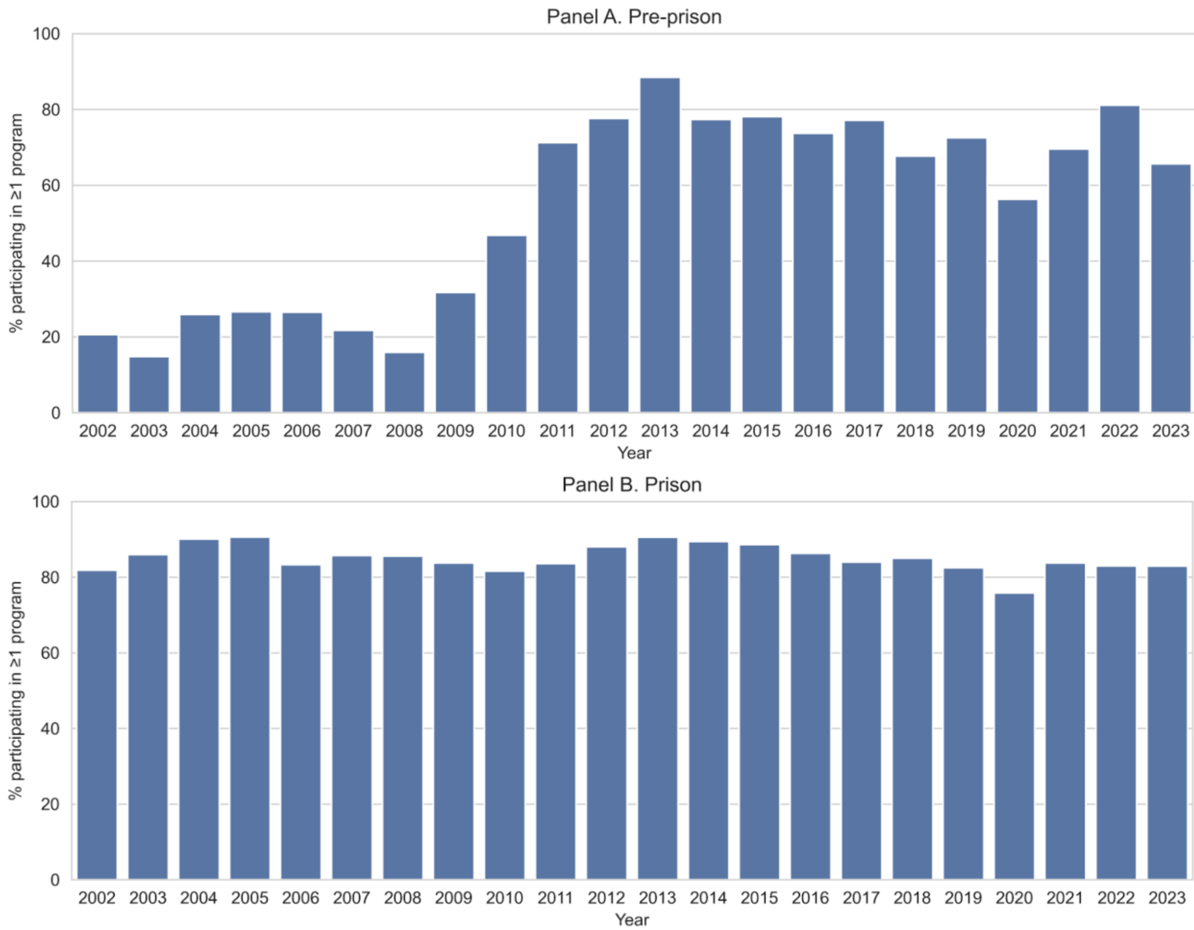


Panel B. Prison (1%–99% trimmed)



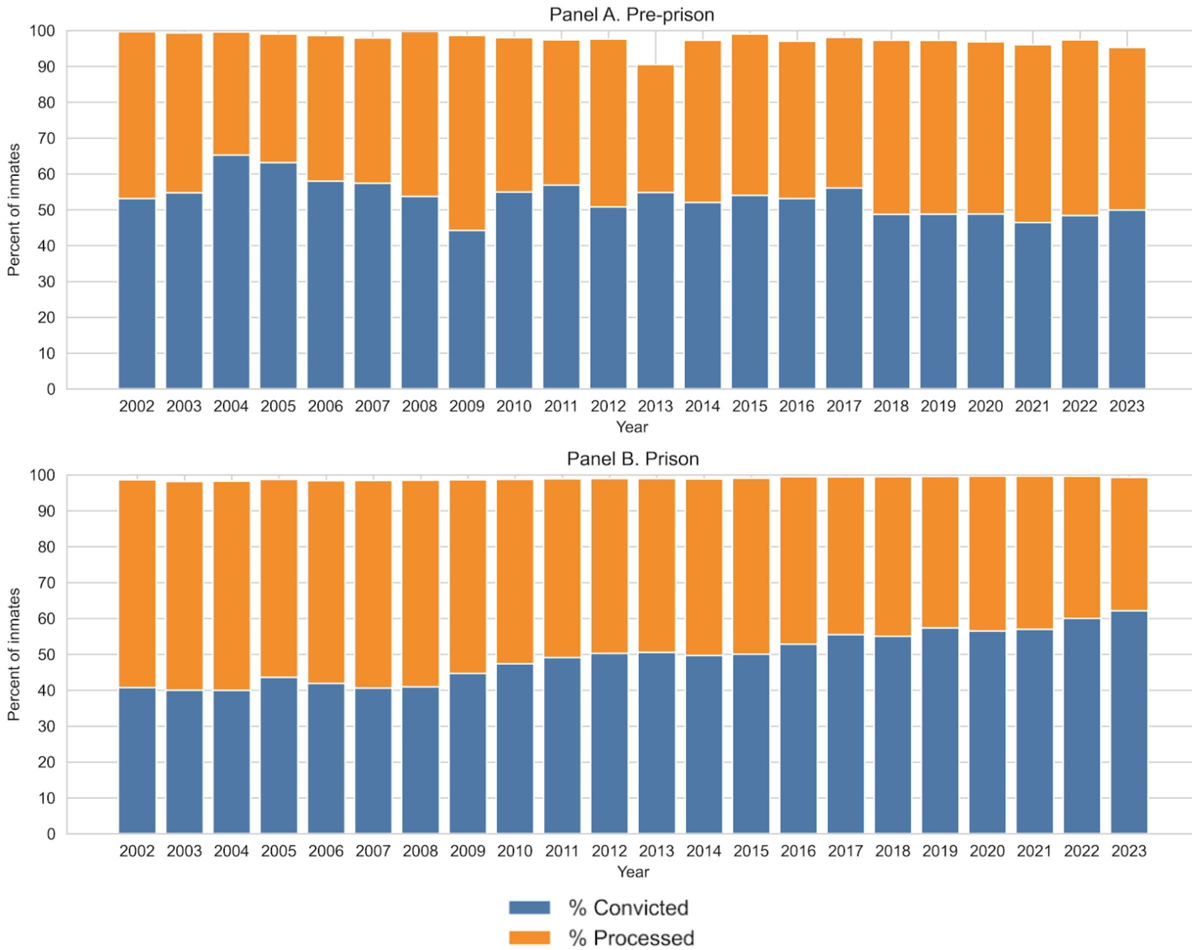
Note: This figure shows the kernel densities of prison size by type of establishment in 2003, 2013, and 2023. To better visualize the distribution, we trimmed the top and bottom 1% of the distribution. Source: Own elaboration using the National System of Statistics on Penal Execution.

Figure B.4. Evolution of average inmate participation in different types of programs from 2002 to 2023



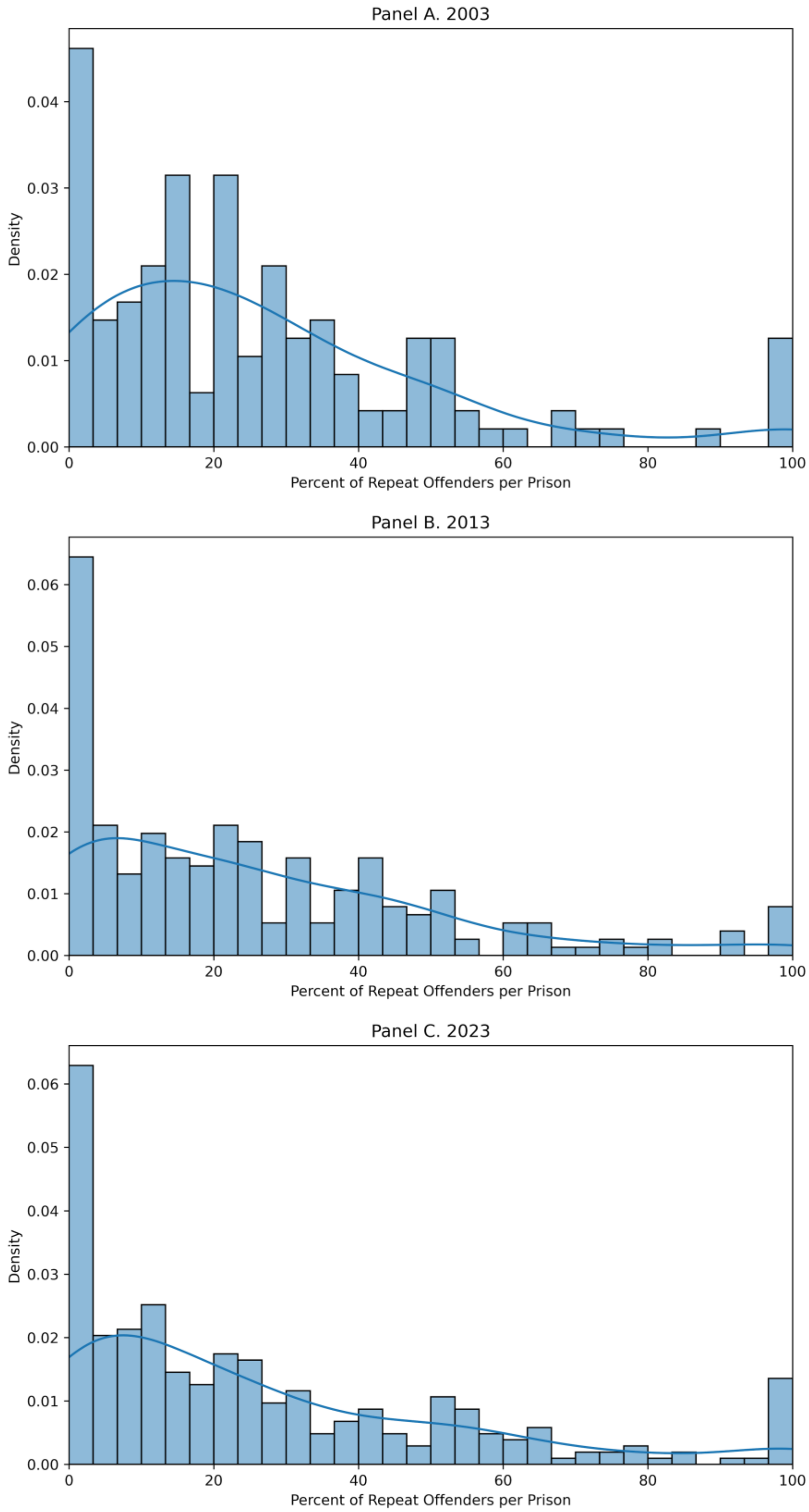
Source: Own elaboration using the National System of Statistics on Penal Execution. The sample includes both pretrial and convicted inmates.

Figure B.5. Evolution of the average percentage of convicted and processed inmates per establishment from 2002 to 2023



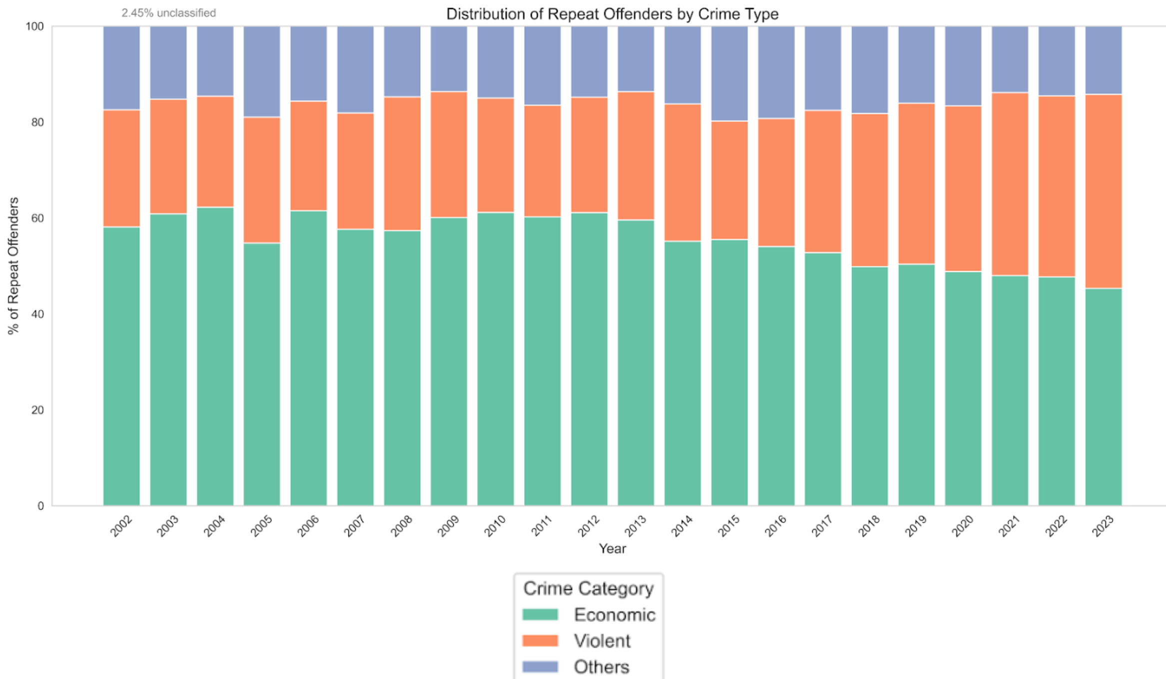
Source: Own elaboration using the National System of Statistics on Penal Execution.

Figure B.6. Overall distribution of the percentage of repeat offenders across detention centers (both prison and pre-prison facilities) in 2003, 2013, and 2023



Note: These figures show the histogram and kernel densities of the percentage of repeat offenders per prison in 2003, 2013, and 2023. Source: Own elaboration using the National System of Statistics on Penal Execution.

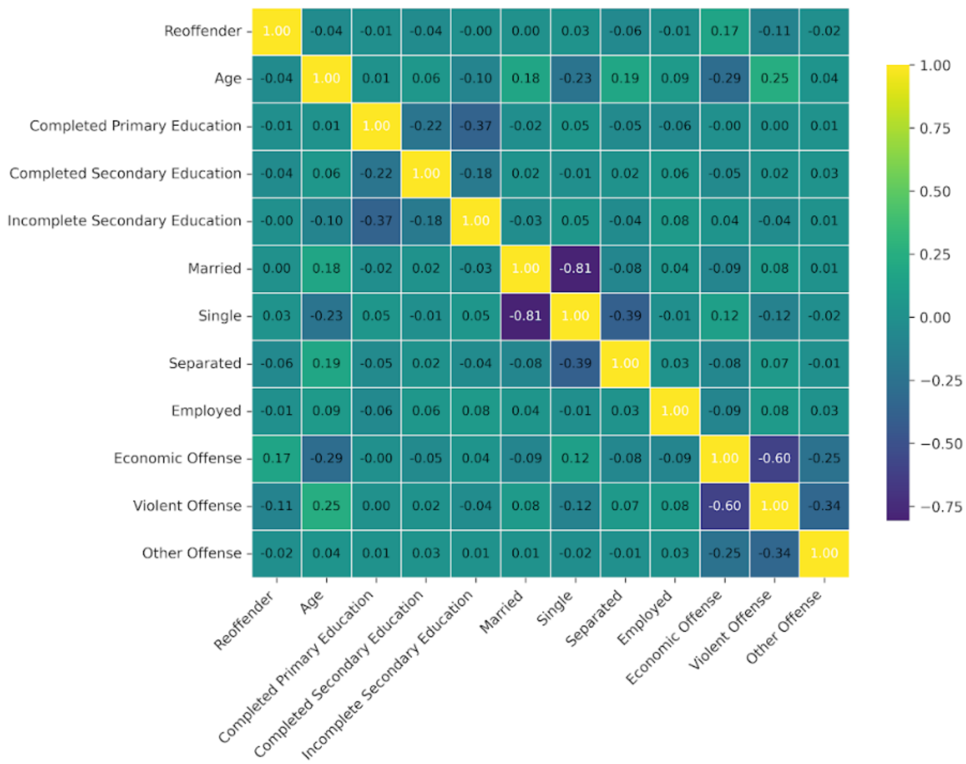
Figure B.7. Evolution of the average percentage of repeat offenders by type of crime over time



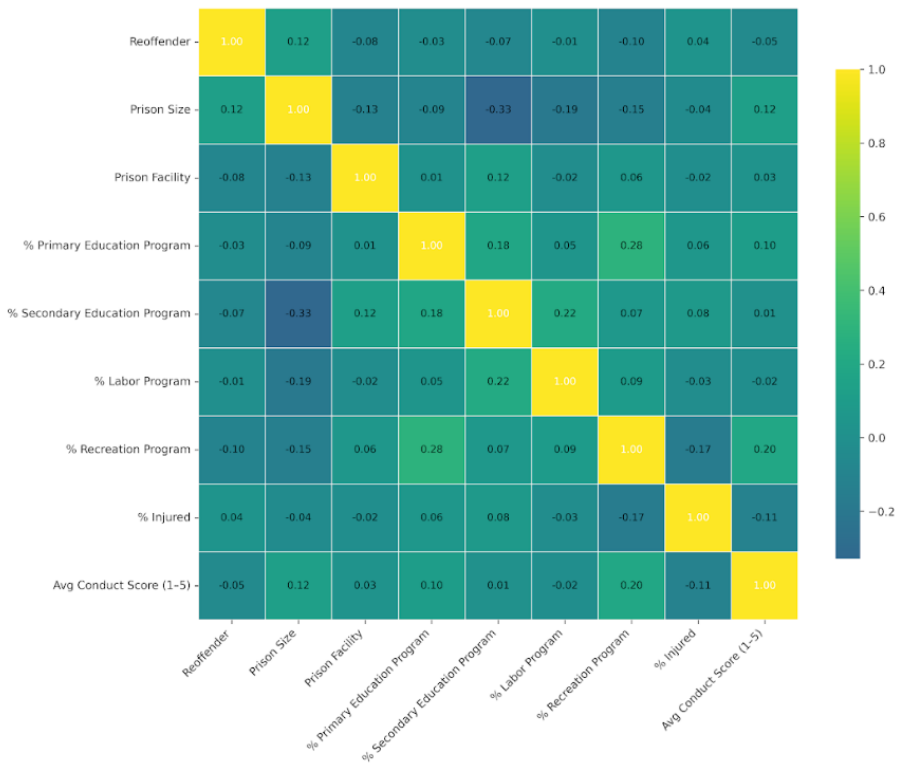
Source: Own elaboration using the National System of Statistics on Penal Execution.

Figure B.8. Partial correlation heatmap between repeat offenders and individual and prison characteristics in 2023

Panel A. Individual characteristics



Panel B. Prison characteristics



Note: *Prison facility* is a binary variable equal to 1 for prison establishments and 0 for pre-prison facilities. *Avg. conduct score* ranges from 1 (very bad behavior) to 5 (exemplary behavior). Source: Own elaboration based on SNPEE dataset.

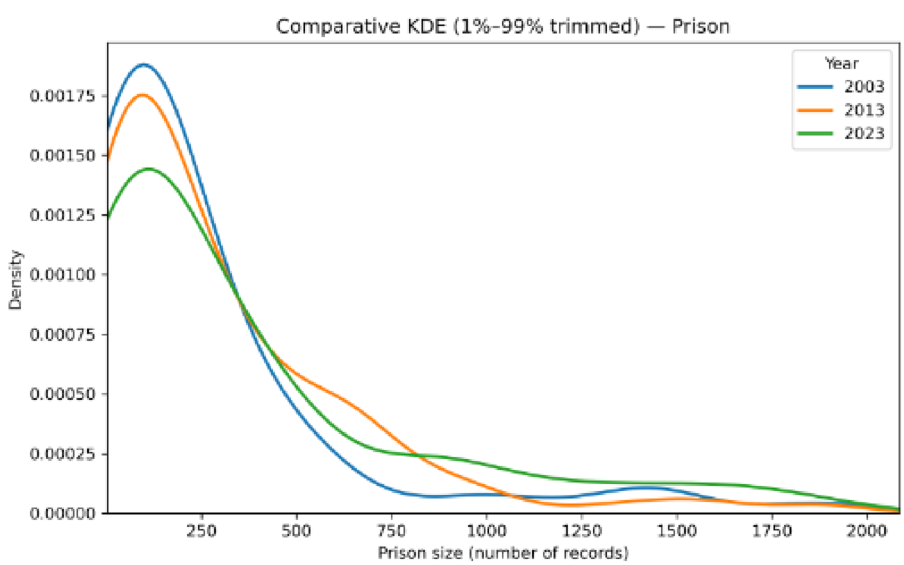
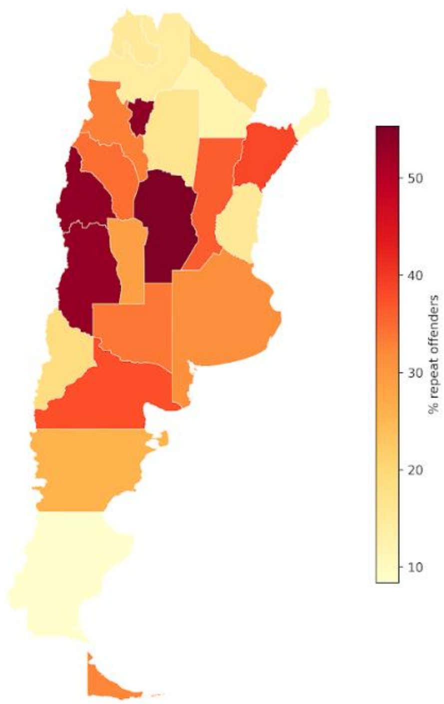
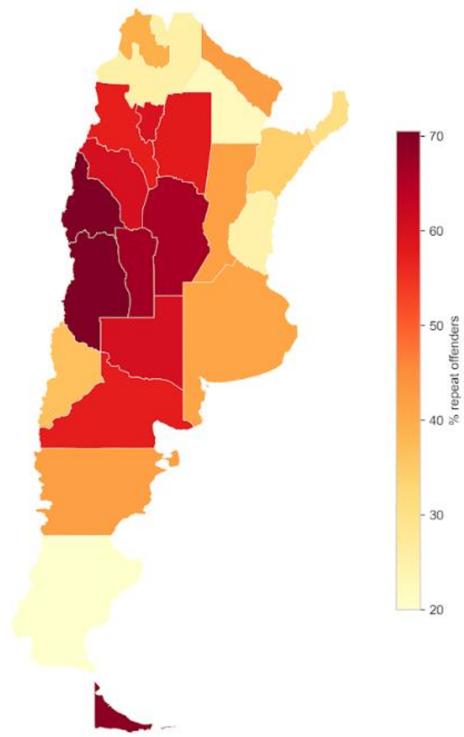


Figure B.9. Percentage of reoffenders by type of offense across Argentina provinces in 2023

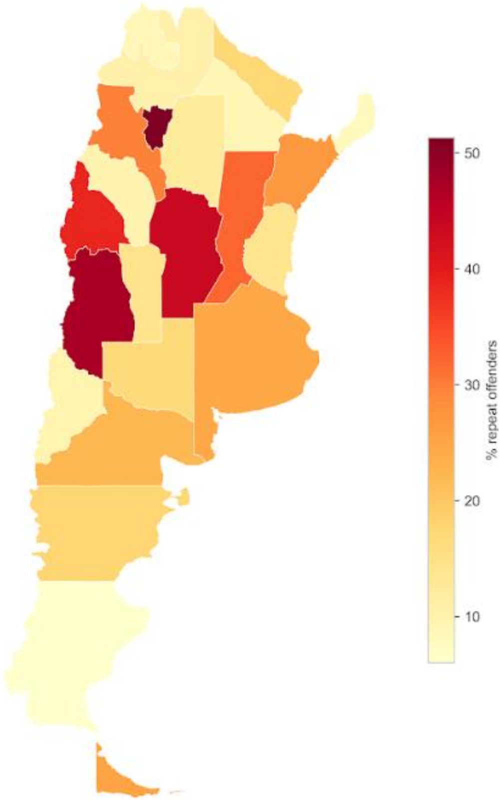
Panel A. All crimes



Panel B. Economic crimes



Panel C. Violent crimes



Panel D. Other types of crimes

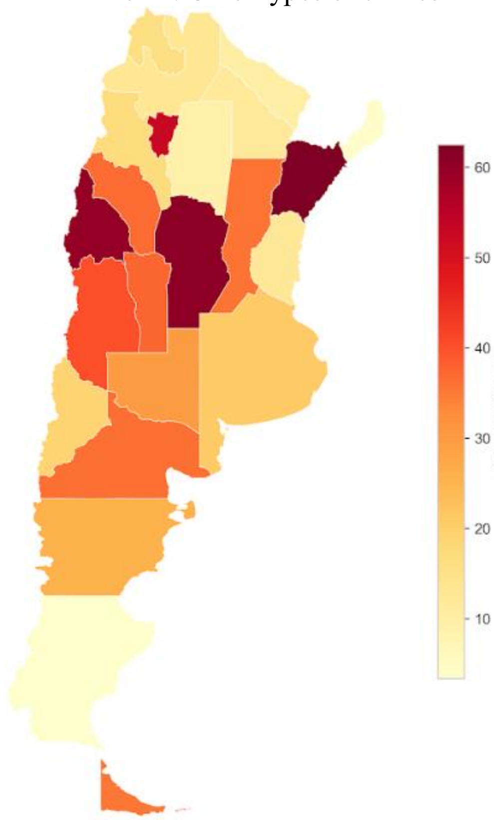


Table B.1. Descriptive statistics on prison size in Argentina in 2003, 2013, and 2023

	Mean	S.D.	min	p1	p25	Median	p75	p99	max
Panel A. Whole sample									
2003	240	415	1	1	18	84	247	1974	2411
2013	236	335	1	1	18	88	318	1579	1883
2023	323	505	1	1	19	104	392	2307	2827
Panel B. Pre-prison sample									
2003	112	388	1	1	7	12	34	1607	2080
2013	49	139	1	1	3	9	26	613	925
2023	85	225	1	1	4	10	48	843	1697

Panel C. Prison sample

2003	267	417	1	1	27	127	292	1888	2411
2013	297	356	2	5	45	168	427	1650	1883
2023	425	556	1	2	47	201	498	2512	2827

Note: This table shows the summary statistics on prison size by year and sample. We show the mean; standard deviation (S.D.); minimum value; 1st, 25th, 50th, 75th, and 99th percentiles; and maximum values. See text for definition of prison size.

Table B.2. Mean difference between the smallest and the largest Argentine pre-prison facilities in 2023

	Variable	Smallest prison (≤p20)			Largest prison (≥p80)			
		N	Mean	S.D	N	Mean	S.D	T-test p-value
Individual factors	Age	40	35.425	12.2	7418	35.951	10.9	0.787
	Argentine nationality	40	0.975	0.16	7418	0.949	0.22	0.301
	Completed primary education	40	0.175	0.38	7418	0.341	0.47	0.01
	Incomplete secondary education	40	0.375	0.49	7418	0.236	0.42	0.081
	Completed secondary education	40	0.25	0.44	7418	0.083	0.28	0.021
	Higher education	40	0	0	7418	0.013	0.11	0
	Employed	40	0.575	0.5	7418	0.847	0.36	0.001
	Has a professional qualification	39	0.667	0.48	6829	0.654	0.48	0.871
	Married	40	0.3	0.46	7418	0.136	0.34	0.031
	Separated	40	0.05	0.22	7418	0.031	0.17	0.59
	Single	40	0.65	0.48	7418	0.786	0.41	0.083
Legal and penal information	Received visits last year	40	0.9	0.3	7396	0.902	0.3	0.972
	Homicide offense	40	0.175	0.38	7418	0.161	0.37	0.821
	Crimes against persons	40	0.275	0.45	7418	0.149	0.36	0.087
	Property crimes	40	0.125	0.33	7418	0.331	0.47	0
	Sexual offenses	40	0.325	0.47	7418	0.222	0.42	0.179
	Crimes against freedom	40	0	0	7418	0.015	0.12	0
	Crimes against public administration	40	0	0	7418	0.009	0.09	0
	Crimes against public safety	40	0	0	7418	0.011	0.11	0
	Drug offenses	40	0.05	0.22	7418	0.086	0.28	0.305
	Economic offenses	40	0	0	7418	0.002	0.04	0.001
	Minor offenses	40	0	0	7418	0.004	0.06	0
	Crimes against humanity	40	0	0	7418	0	0	

	Percent in discontinuous prison*	40	75	34.59	7418	43.583	38.88	0
	Percent in semi-detention*	40	77.5	35.11	7418	44.001	38.98	0
	Works paid job in prison	40	1	0	7418	1	0	
Penal-system progression	Sentence reduction	31	0	0	3361	0.007	0.08	0
	Percent with progressive regime*	40	7.5	20.31	7418	38.393	41.03	0
	Percent with temporary leave*	40	67.5	37.35	7418	44.446	38.2	0
Behavioral information	Percent with disciplinary infraction*	40	2.5	11.04	7418	11.85	8.56	0
	Order disruption dummy	40	0	0	7415	0.086	0.28	0
	Percent with sanction applied*	40	2.5	11.04	7418	11.216	8.18	0
	Percent with very good behavior*	40	25	43.85	7418	6.686	24.98	0.012
	Percent with exemplary behavior*	40	10	30.38	7418	41.17	49.22	0
	Percent with good behavior*	40	27.5	45.22	7418	21.502	41.09	0.408
	Percent with fair behavior*	40	7.5	26.67	7418	5.918	23.6	0.71
	Percent with bad behavior*	40	0	0	7418	1.914	13.7	0
	Percent with very bad behavior*	40	0	0	7418	1.105	10.46	0
	Escape or evasion attempt	40	5	22.07	7418	0.148	3.85	0.172
Health and well-being	Suicide attempt	40	0.025	0.16	7418	0.001	0.03	0.337
	Percent received medical attention*	40	100	0	7418	99.757	0.8	0
	Percent injured*	40	7.5	20.31	7418	6.255	4.9	0.7
Programs in prison	Percent in labor program*	40	10	21.28	6659	14.861	15.14	0.157
	Percent_in_education_program*	40	37.5	35.95	7418	27.622	23.33	0.09
	Percent in secondary education program*	40	22.5	26.03	7418	6.511	6.04	0
	Percent in primary education program*	40	10	30.38	7418	9.517	10.1	0.921
	Percent in recreational or other activities*	40	12.5	30.84	7418	52.24	33.39	0

Note: This table shows the mean difference between the largest and smallest pre-prison facilities in Argentina in 2003. We define the smallest prisons as detention centers with a number of inmates below the 20th percentile, and the largest prisons as those above the 80th percentile in the 2003 prison-size distribution. Variables marked with * are at the prison level, while those without * are at the individual level.

Table B.3. Mean difference between the smallest and largest Argentine prison facilities in 2023

		Smallest prison (≤p20)			Largest prison (≥p80)			
	Variable	N	Mean	S.D	N	Mean	S.D	T-test p-value
Individual factors	Age	950	40.131	12.57	64514	36.028	10.81	0
	Argentine nationality	950	0.948	0.22	64514	0.929	0.26	0.008
	Completed primary education	950	0.187	0.39	64514	0.316	0.47	0
	Incomplete secondary education	950	0.303	0.46	64514	0.216	0.41	0
	Completed secondary education	950	0.241	0.43	64514	0.093	0.29	0
	Higher education	950	0.025	0.16	64514	0.009	0.09	0.001
	Employed	950	0.613	0.49	64514	0.612	0.49	0.987
	Has a professional qualification	938	0.543	0.5	61247	0.621	0.49	0
	Married	950	0.214	0.41	64514	0.092	0.29	0
	Separated	950	0.079	0.27	64514	0.053	0.22	0.004
	Single	950	0.701	0.46	64514	0.818	0.39	0
Legal and penal information	Received visits last year	939	0.855	0.35	61804	0.879	0.33	0.036
	Homicide offense	950	0.273	0.45	64514	0.163	0.37	0
	Crimes against persons	950	0.077	0.27	64514	0.098	0.3	0.013
	Property crimes	950	0.16	0.37	64514	0.387	0.49	0
	Sexual offenses	950	0.352	0.48	64514	0.182	0.39	0
	Crimes against freedom	950	0.018	0.13	64514	0.019	0.14	0.807
	Crimes against public administration	950	0.001	0.03	64514	0.018	0.13	0
	Crimes against public safety	950	0.005	0.07	64514	0.016	0.12	0
	Drug offenses	950	0.104	0.31	64514	0.097	0.3	0.457
	Economic offenses	950	0	0	64514	0	0.02	0
	Minor offenses	950	0.004	0.06	64514	0.003	0.06	0.716
	Crimes against humanity	950	0	0	64514	0	0.01	0.002
	Percent in discontinuous prison*	950	67.895	32.72	64514	53.288	25.14	0
	Percent in semi-detention*	950	66.947	33.29	64514	54.103	24.26	0
	Works paid job in prison	950	0.973	0.16	64514	1	0.01	0
Penal system progression	Sentence_reduction	647	0.198	0.4	33841	0.013	0.11	0
	Percent_with_progressive_regime*	950	62.421	35.88	64514	43.718	31.61	0
	Percent_with_temporary_leaves*	950	53.474	30.34	64514	51.589	24.94	0.057
Behavioral information	Percent_with_disciplinary_infraction*	950	11.684	14.18	64514	14.081	13.6	0
	Order_disruption_dummy	940	0.101	0.3	63017	0.081	0.27	0.045
	Percent_with_sanction_applied*	950	12.421	14.06	64514	13.857	14.91	0.002
	Very_good_behavior	950	19.579	39.7	64514	13.158	33.8	0

	Exemplary_behavior	950	33.684	47.29	645143	62.557	48.4	0
	Good_behavior	950	22.737	41.94	64514	9.742	29.65	0
	Fair_behavior	950	5.579	22.96	64514	1.559	12.39	0
	Bad_behavior	950	0.842	9.14	64514	1.234	11.04	0.192
	Very_bad_behavior	950	0.526	7.24	64514	1.533	12.29	0
	Escape_attempt	950	0.421	6.48	64514	0.028	1.67	0.062
Health and well-being	Suicide_attempt	950	0.109	0.45	64514	0.009	0.13	0
	Percent_received_medical_attention*	950	99.158	5.31	64514	95.438	18.6	0
	Percent_injured	950	5.579	17.31	64514	4.303	4.77	0.023
Programs in prison	Percent_in_labor_program*	925	37.267	30.24	61748	12.735	15.95	0
	Percent_nonmissing_labor_program*	950	96.842	16.03	64514	95.624	20.25	0.021
	Percent_in_education_program*	950	53.474	28.91	64514	43.544	30.99	0
	Percent_in_secondary_education_program*	950	24.421	23.21	64514	12.873	12.91	0
	Percent_in_primary_education_program*	950	11.579	13.02	64514	16.537	17.04	0
	Percent_in_recreational_or_other_activities*	925	70.279	33.62	62971	68.463	32.07	0.103
	Percent_nonmissing_recreational_or_other_activities*	950	96.421	16.16	64514	97.391	15.3	0.066

Note: This table shows the mean difference between the largest and smallest prison facilities in Argentina in 2003. We define the smallest prisons as prisons with a number of inmates below the 20th percentile, and the largest prisons as those above the 80th percentile in the 2003 prison-size distribution. Variables marked with * are at the prison level, while those without * are at the individual level.

Table B.4. Top five crimes among the largest and smallest facilities by type of establishment in 2023

Crime category	Small-facilities ranking	Large-facilities ranking
Panel A. Pre-prison		
Drug crimes	5	5
Homicide offenses	3	3
Crimes against persons	2	4
Property crimes	4	1
Sexual offenses	1	2
Panel B. Prison		
Drug crimes	4	5
Homicide offenses	2	3
Crimes against persons	5	4
Property crimes	3	1
Sexual offenses	1	2

Note: This table shows the top five crimes among the smallest and largest detention facilities in 2023. For this table, we define the smallest and largest facilities using the 10th and 90th percentiles, respectively. Panels A and B show this ranking by pre-prison and prison establishments. Property crimes include "Robo y/o tentativa de robo," "Hurto y/o tentativa de hurto," "Otros delitos contra la propiedad." Sexual offenses are the first criminal charges that include "Violaciones/Abuso sexual," "Otros delitos contra la integridad sexual." We define homicide offenses when the first criminal charge is "Homicidios dolosos," "Homicidios dolosos (tent.)," "Homicidios Culposos." Crimes against persons include charges such as "Lesiones Dolosas," "Lesiones Culposas," "Amenazas," and "Otros delitos contra las personas." Finally, drug crimes are first charged with "Infracción ley n° 23.737 (estupefacientes)" and "Contrabando de estupefacientes."

Table B.5. Mean difference between the lowest and highest concentrations of repeat offenders among detention facilities in Argentina in 2023

Type of variable	Variable	Bottom 20% N	Bottom 20% Mean/SE	Top 20% N	Top 20% Mean/SE	Diff (Top - Bot)
Individual factors	Age	62	40.016 [1.282]	62	35.421 [0.566]	-4.595***
	Argentine nationality	62	0.979 [0.006]	62	0.932 [0.011]	-0.047***
	Completed primary education	62	0.231 [0.034]	62	0.282 [0.024]	0.052
	Incomplete secondary education	62	0.295 [0.037]	62	0.303 [0.026]	0.008
	Completed secondary education	62	0.202 [0.031]	62	0.112 [0.015]	-0.090**
	Higher education	62	0.028 [0.011]	62	0.005 [0.001]	
	Employed	62	0.659 [0.049]	62	0.656 [0.038]	
	Professional qualification	62	0.673 [0.042]	62	0.542 [0.045]	
	Married	62	0.211 [0.030]	62	0.174 [0.022]	-0.037
	Separated	62	0.068 [0.015]	62	0.024 [0.004]	-0.043***
	Single	62	0.721 [0.035]	62	0.797 [0.023]	0.076*
Legal and penal information	Received visits last year	62	0.887 [0.028]	62	0.896 [0.019]	
	Homicide offense	62	0.193 [0.031]	62	0.153 [0.016]	-0.040
	Crimes against persons	62	0.102 [0.025]	62	0.131 [0.017]	0.029
	Property crimes	62	0.141 [0.025]	62	0.364 [0.021]	0.224***
	Sexual offenses	62	0.439 [0.048]	62	0.169 [0.024]	-0.270***
	Crimes against freedom	62	0.011 [0.004]	62	0.016 [0.004]	0.005
	Crimes against public administration	62	0.005 [0.002]	62	0.016 [0.003]	0.011***
	Crimes against public safety	62	0.002 [0.001]	62	0.019 [0.005]	0.016***
	Drug offenses	62	0.073 [0.026]	62	0.107 [0.021]	0.034
	Economic offenses	62	0.000 [0.000]	62	0.000 [0.000]	0.000
	Minor offenses	62	0.005 [0.003]	62	0.003 [0.003]	-0.002

	Crimes against humanity	62	0.016 [0.016]	62	0.000 [0.000]	-0.016
	Percent in discontinuous prison*	62	71.469 [4.191]	62	61.337 [4.254]	
	Percent in semi-detention*	62	72.009 [4.215]	62	62.223 [4.131]	
	Works paid job in prison	62	0.981 [0.016]	62	0.986 [0.012]	
Penal-system progression	Sentence reduction	60	0.017 [0.007]	62	0.126 [0.033]	
	Percent with progressive regime*	62	28.912 [4.934]	62	44.362 [4.900]	
	Percent with temporary leave*	62	63.270 [4.370]	62	51.246 [3.946]	
Behavioral information	Percent with disciplinary infraction*	62	7.264 [2.066]	62	15.329 [2.394]	
	Order-disruption dummy	62	0.037 [0.012]	61	0.117 [0.023]	
	Percent with sanction applied*	62	6.065 [1.471]	62	14.956 [2.382]	
	Very good behavior	62	0.211 [0.044]	62	0.085 [0.012]	
	Exemplary behavior	62	0.186 [0.044]	62	0.355 [0.045]	
	Good behavior	62	0.311 [0.048]	62	0.259 [0.043]	
	Fair behavior	62	0.057 [0.024]	62	0.102 [0.031]	
	Bad behavior	62	0.004 [0.002]	62	0.020 [0.005]	
	Very bad behavior	62	0.003 [0.002]	62	0.026 [0.012]	
	Escape attempt	62	0.016 [0.016]	62	0.003 [0.002]	
Health and well-being	Suicide attempt	62	0.074 [0.045]	62	0.012 [0.006]	
	Percent received medical attention*	62	99.036 [0.819]	62	99.829 [0.110]	
	Percent injured	62	2.344 [0.924]	62	6.375 [1.304]	
Programs in prison	Percent in labor program*	61	15.821 [3.563]	60	18.680 [3.189]	
	Percent in education program*	62	46.159 [4.562]	62	38.723 [3.980]	
	Percent in secondary education program*	62	25.879 [3.707]	62	15.657 [2.453]	
	Percent in primary education program*	62	9.489 [2.109]	62	10.665 [1.718]	

Percent in recreational or other activities*	61	40.685 [5.821]	62	46.762 [4.762]

Note: This table shows the mean difference between prison facilities with the highest and lowest concentrations of repeat offenders in Argentina in 2023. Standard deviations are shown in brackets. ***, **, and * stand for p-values under 0.01, 0.05, and 0.1, respectively.

Table B.6. Mean differences between repeat offenders in 2003, 2013, and 2023

Type of variable	Variable	(1) N	(1) Mean [SE]	(2) N	(2) Mean [SE]	(3) N	(3) Mean [SE]	t (1)-(2)	t (1)-(3)	t (2)-(3)	F-test p
Individual factors	Age	4472	34.171 [0.146]	8976	34.342 [0.103]	18703	36.023 [0.073]	0.171	1.852***	1.681***	0.000
	Argentine nationality	4472	94.969 [0.327]	8976	97.449 [0.166]	18703	95.151 [0.157]	2.480***	0.182	-2.298***	0.000
	Completed primary education	4472	43.090 [0.741]	8976	41.299 [0.520]	18703	29.268 [0.333]	-1.791**	-13.822***	-12.031***	0.000
	Incomplete secondary education	4472	11.225 [0.472]	8976	16.477 [0.392]	18703	23.772 [0.311]	5.252***	12.546***	7.294***	0.000
	Completed secondary education	4472	2.818 [0.247]	8976	5.793 [0.247]	18703	7.758 [0.196]	2.976***	4.941***	1.965***	0.000
	Higher education	4472	0.470 [0.102]	8976	0.323 [0.060]	18703	0.765 [0.064]	-0.147	0.295**	0.441***	0.000
	Employed	4472	62.232 [0.725]	8976	64.873 [0.504]	18703	62.963 [0.353]	2.641***	0.731	-1.910***	0.002
	Has a professional qualification	3977	51.119 [0.793]	8939	57.557 [0.523]	18324	60.833 [0.361]	6.438***	9.714***	3.276***	0.000
	Married	4472	24.016 [0.639]	8976	21.535 [0.434]	18703	14.281 [0.256]	-2.481***	-9.735***	-7.254***	0.000
	Separated	4472	3.600 [0.279]	8976	1.649 [0.134]	18703	2.139 [0.106]	-1.951***	-1.461***	0.490***	0.000
	Single	4472	72.272 [0.669]	8976	76.627 [0.447]	18703	81.650 [0.283]	4.355***	9.378***	5.023***	0.000
Legal and penal informatio n	Received visits last year	3847	82.974 [0.606]	8962	86.811 [0.357]	18640	86.921 [0.247]	3.837***	3.947***	0.110	0.000
	Homicide offense	4472	11.069 [0.469]	8976	12.556 [0.350]	18703	16.115 [0.269]	1.487**	5.046***	3.559***	0.000
	Crimes against persons	4472	6.865 [0.378]	8976	5.704 [0.245]	18703	12.538 [0.242]	-1.161***	5.673***	6.834***	0.000
	Property crimes	4472	62.880 [0.723]	8976	61.419 [0.514]	18703	47.613 [0.365]	-1.461	-15.267***	-13.807***	0.000

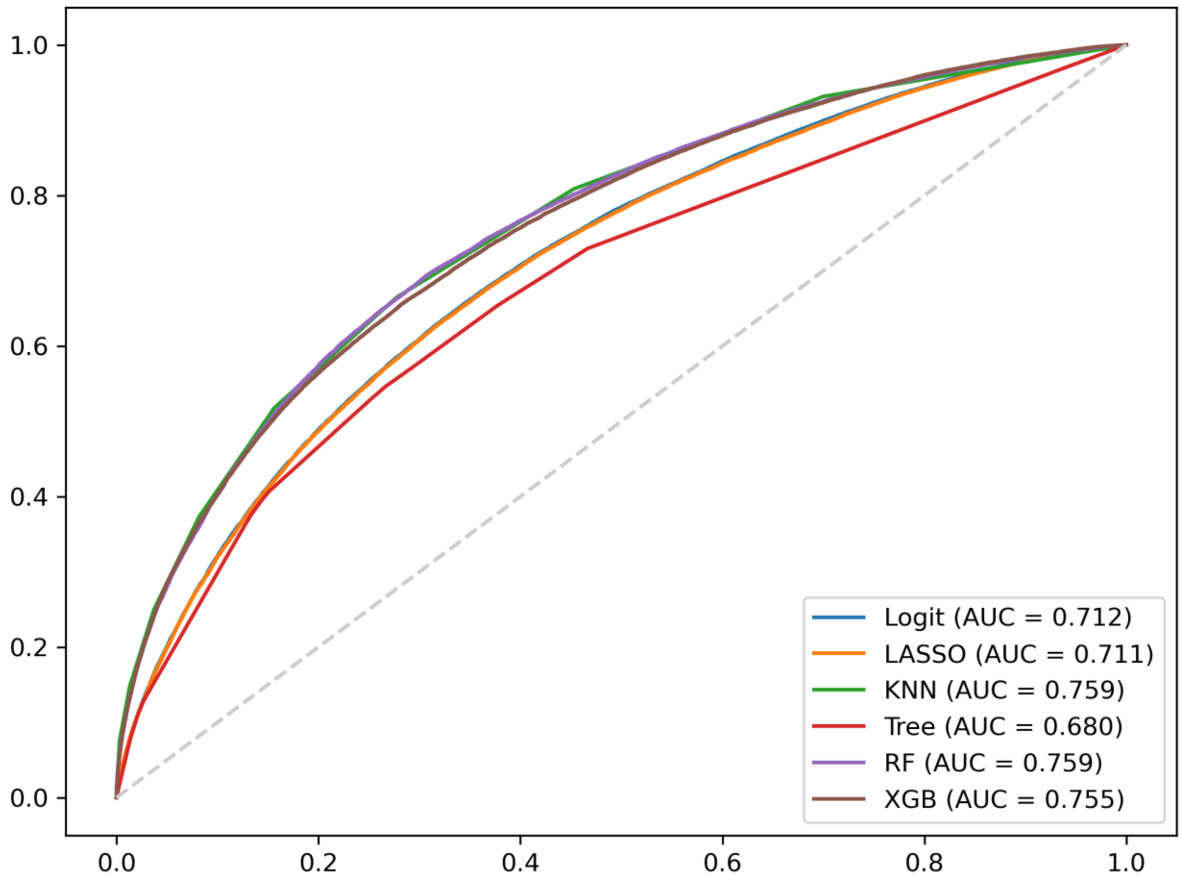
	Sexual offenses	4472	5.590 [0.344]	8976	7.631 [0.280]	18703	10.528 [0.224]	2.041***	4.937***	2.896***	0.000
	Crimes against freedom	4472	1.565 [0.186]	8976	1.615 [0.133]	18703	1.620 [0.092]	0.050	0.055	0.005	0.966
	Crimes against public administration	4472	2.482 [0.233]	8976	0.891 [0.099]	18703	1.513 [0.089]	-1.591***	-0.969***	0.622***	0.000
	Crimes against public safety	4472	1.878 [0.203]	8976	2.685 [0.171]	18703	1.839 [0.098]	0.807***	-0.039	-0.846***	0.000
	Drug offenses	4472	5.859 [0.351]	8976	4.445 [0.218]	18703	6.737 [0.183]	-1.413***	0.878**	2.292***	0.000
	Economic offenses	4472	0.000 [0.000]	8976	0.000 [0.000]	18703	0.005 [0.005]	0.000	0.005	0.005	
	Minor offenses	4472	0.157 [0.059]	8976	0.891 [0.099]	18703	0.091 [0.022]	0.735***	-0.066	-0.800***	0.000
	Crimes against humanity	4472	0.000 [0.000]	8976	0.000 [0.000]	18703	0.037 [0.014]	0.000	0.037	0.037	
	Percent in discontinuous prison*	4472	60.939 [0.521]	8976	63.227 [0.302]	18703	71.788 [0.197]	2.288***	10.850***	8.561***	0.000
	Percent in semi-detention*	4472	62.058 [0.516]	8976	63.180 [0.303]	18703	73.046 [0.181]	1.122*	10.988***	9.866***	0.000
	Works paid job in prison	4472	84.369 [0.543]	8976	97.471 [0.166]	18703	99.652 [0.043]	13.102***	15.283***	2.181***	0.000
Penal-system progression	Sentence reduction	4437	7.933 [0.406]	8320	1.190 [0.119]	18094	5.654 [0.172]	-6.743***	-2.279***	4.464***	0.000
	Percent with progressive regime*	4472	61.021 [0.521]	8976	56.626 [0.347]	18703	63.624 [0.241]	-4.395***	2.602***	6.998***	0.000
	Percent with temporary leave*	4472	50.370 [0.529]	8976	52.806 [0.288]	18703	66.689 [0.188]	2.436***	16.319***	13.883***	0.000
Behavioral information	Percent with disciplinary infraction*	4472	20.706 [0.253]	8976	25.757 [0.197]	18703	17.491 [0.097]	5.050***	-3.216***	-8.266***	0.000
	Order-disruption dummy	4246	19.289 [0.606]	8683	25.072 [0.465]	17880	13.037 [0.252]	5.783***	-6.252***	-12.035***	0.000
	Percent with sanction applied*	4472	23.123 [0.295]	8976	41.315 [0.377]	18703	17.885 [0.114]	18.192***	-5.238***	-23.430***	0.000

	Percent with very good behavior*	4472	14.222 [0.522]	8976	13.915 [0.365]	18703	11.752 [0.235]	-0.307	-2.470***	-2.163***	0.000
	Percent with exemplary behavior*	4472	38.663 [0.728]	8976	54.222 [0.526]	18703	62.027 [0.355]	15.560***	23.365***	7.805***	0.000
	Percent with good behavior*	4472	19.030 [0.587]	8976	11.041 [0.331]	18703	11.720 [0.235]	-7.989***	-7.309***	0.679*	0.000
	Percent with fair behavior*	4472	6.932 [0.380]	8976	7.542 [0.279]	18703	4.047 [0.144]	0.610	-2.885***	-3.495***	0.000
	Percent with bad behavior*	4472	4.562 [0.312]	8976	4.122 [0.210]	18703	2.315 [0.110]	-0.440	-2.247***	-1.807***	0.000
	Percent with very bad behavior*	4472	3.533 [0.276]	8976	4.311 [0.214]	18703	2.342 [0.111]	0.778**	-1.191***	-1.970***	0.000
	Escape or evasion attempt	4472	1.722 [0.195]	8976	1.872 [0.143]	18703	0.176 [0.031]	0.150	-1.545***	-1.695***	0.000
Health and well-being	Suicide attempt	4472	0.109 [0.007]	8976	0.013 [0.002]	18703	0.006 [0.001]	-0.096***	-0.103***	-0.007***	0.000
	Percent received medical attention*	4472	95.604 [0.296]	8976	98.503 [0.124]	18703	98.022 [0.094]	2.899***	2.418***	-0.480***	0.000
	Percent injured*	4472	12.112 [0.235]	8976	10.460 [0.207]	18703	6.245 [0.044]	-1.652***	-5.867***	-4.214***	0.000
Programs in prison	Percent in labor program*	3949	9.487 [0.246]	8886	38.013 [0.380]	17633	19.953 [0.160]	28.526***	10.466***	-18.060***	0.000
	Percent in any education program*	4472	35.040 [0.418]	8976	44.692 [0.313]	18703	48.792 [0.198]	9.652***	13.753***	4.100***	0.000
	Percent in secondary education program*	4472	8.344 [0.139]	8976	17.461 [0.155]	18703	15.247 [0.106]	9.117***	6.904***	-2.214***	0.000
	Percent in primary education program*	4472	18.842 [0.292]	8976	14.683 [0.178]	18703	18.358 [0.133]	-4.159***	-0.484	3.675***	0.000
	Percent in recreational or other activities*	3957	80.612 [0.470]	8976	74.524 [0.364]	18207	65.697 [0.226]	-6.087***	-14.915***	-8.827***	0.000

Note: This table shows the mean difference between the largest and smallest prison facilities in Argentina in 2003. We define the smallest prisons as prisons with a number of inmates below the 20th percentile, and the largest prisons as those above the 80th percentile in the 2003 prison-size distribution. For more information on the variable grouping, see Section 4.3.2. Variables marked with * are at the prison level, while those without * are at the individual level.

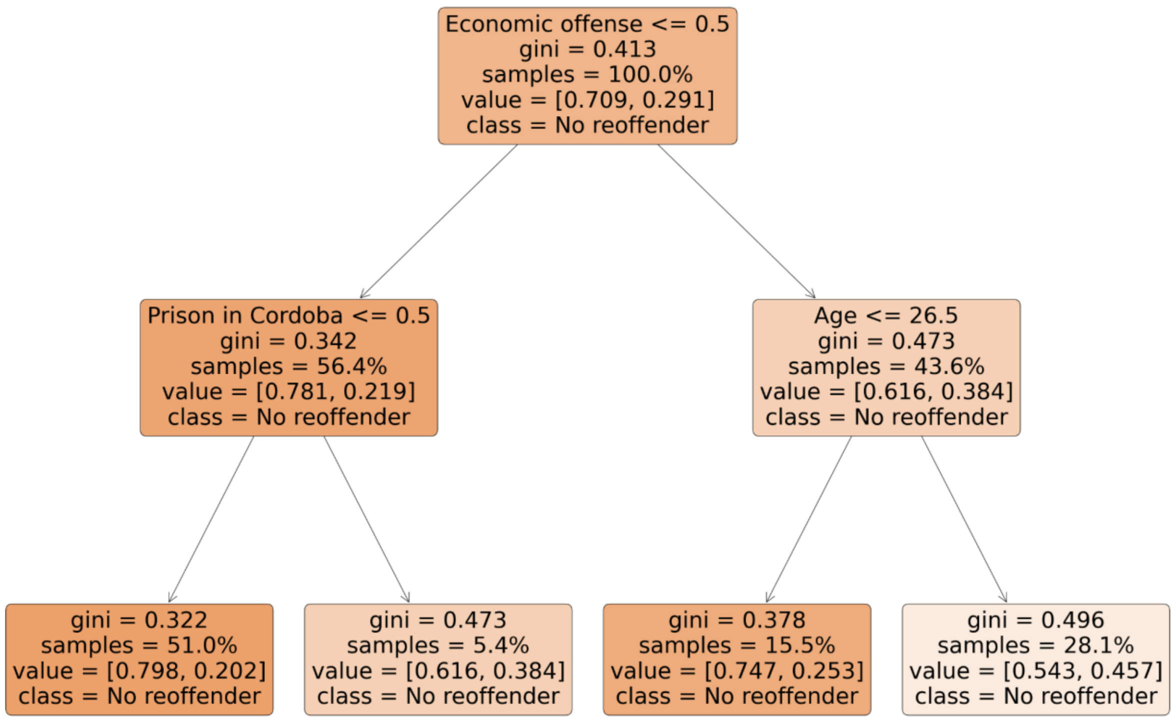
Appendix C: More Detailed Information About the Machine Learning Application

Figure C.1. ROC curve out of the-sample by predictive model



Note: This figure shows the ROC curves in different colors for each of the six models: logit, logit with LASSO penalty, nearest neighbor (KNN), classification tree, random forest (RF), and XGBoosting (XGB). The 45-degree line is displayed in gray, and the area-under-the-curve (AUC) performance metrics by model are measured out of the sample. Our train and test samples consist of 402,077 and 172,332 observations, respectively.

Figure C.2. Prediction of repeat offenders using classification decision tree (CART) in Argentina



Note: This figure shows the decision-tree classification of repeat offenders and non-offenders (first-time offenders in the text). Our train and test samples consist of 402,077 and 172,332 observations, respectively. "Gini" refers to the Gini index, "sample" represents the percentage of observations in each node, "value" shows the proportion of each class (in this context, first-time and repeat offenders), and "class" shows the type of offender in each terminal node of the tree. "Economic offense" is a dummy that takes the value 1 if the first charge of the convicted individual is an offense related to "Theft and/or attempted theft," "Other property crimes." "Prison in Cordoba" is a dummy that indicates whether the inmate is located in a facility in Córdoba, the second-largest province in Argentina. Finally, "age" is the incarcerated individual's age at the moment of the census.

Table C.1. T-statistic and p-values of the mean difference between the test and train samples

Variable	t-statistic	p-value	Variable	t-statistic	p value
census year	0.02	0.99	Completed secondary education	0.41	0.68
state sneep id	2.2	0.03	Married	0.28	0.78
prison id	6.2	0	Separated	0.15	0.88
age	0.81	0.42	Single	0.27	0.79
last residence place id	0.11	0.91	Percent with very good behavior	0.38	0.7
suicide attempt	0.67	0.5	Percent with exemplary behavior	0.85	0.4
state id	2.63	0.01	Percent with good behavior	0.04	0.97
establishment prison	0.2	0.84	Percent with fair behavior	1.8	0.07
nationality description missing	0.35	0.72	Percent with bad behavior	1.08	0.28
nat argentina	1.49	0.14	Percent with very bad behavior	0.12	0.9
sentence duration total years	0.46	0.65	Escape or evasion attempt	1.86	0.06
marital None	0.53	0.6	Percent nonmissing labor program	1.23	0.22
ultima situacion laboral des. missing	1.13	0.26	in primary educ program	0.9	0.37
labor Missing	1.13	0.26	in secondary higher edu program	1.12	0.26
educ Missing	1.16	0.25	economic offense	0.17	0.87
educ Ninguno	1.35	0.18	violent offense	1.11	0.27
crime1 description missing	1.77	0.08	others offense	0.1	0.92
crime2 description missing	0.88	0.38	jurisdiction desc missing	0.83	0.41
received visits last year	0.19	0.85	jurisdiction FEDERAL	1.01	0.31
order disruption	0.03	0.98	jurisdiction Ciudad de Buenos Aires	1.78	0.07
escape attempt missing	1.45	0.15	jurisdiction Missing	0.83	0.41

injured	1.12	0.26	jurisdiction NACIONAL	1.71	0.09
received medical attention	0.53	0.6	jurisdiction PROV Buenos Aires	0.7	0.49
in labor program	0.6	0.55	jurisdiction PROV Catamarca	0.67	0.51
in recreation sport	0	1	jurisdiction PROV Chaco	1.02	0.31
progressive regime	0.27	0.78	jurisdiction PROV Chubut	0.95	0.34
temporary leaves	1.8	0.07	jurisdiction PROV Corrientes	0.63	0.53
disciplinary infraction	0.46	0.65	jurisdiction PROV Córdoba	4.17	0
sanction applied	0.38	0.71	jurisdiction PROV Entre Rios	0.9	0.37
sentence reduction	0.33	0.74	jurisdiction PROV Formosa	0.75	0.45
behavior missing	1.26	0.21	jurisdiction PROV Jujuy	1.75	0.08
exemplary behavior	0.85	0.4	jurisdiction PROV La Pampa	0.23	0.82
very good behavior	0.38	0.7	jurisdiction PROV La Rioja	0.65	0.52
good behavior	0.04	0.97	jurisdiction PROV Mendoza	2.23	0.03
fair behavior	1.8	0.07	jurisdiction PROV Misiones	2.6	0.01
bad behavior	1.08	0.28	jurisdiction PROV Neuquén	0.55	0.59
very bad behavior	0.12	0.9	jurisdiction PROV Rio Negro	0.41	0.68
higher education	0.11	0.91	jurisdiction PROV Salta	1.25	0.21
employed	0.42	0.68	jurisdiction PROV San Juan	0.41	0.68
professional qualification	0.9	0.37	jurisdiction PROV San Luis	0.34	0.74
in semi-detention	0.51	0.61	jurisdiction PROV Santa Cruz	1.68	0.09
in discontinuous prison	0.31	0.76	jurisdiction PROV Santa Fe	1.87	0.06
in pre-free regime	1.12	0.26	jurisdiction PROV Santiago del Estero	1.43	0.15
Percent with progressive regime	1.04	0.3	jurisdiction PROV Tierra del Fuego	0.74	0.46
Percent with temporary leaves	0.52	0.6	jurisdiction PROV Tucumán	1.63	0.1

Percent with disciplinary infraction	0.21	0.83	origin Deriv. de otro establecimiento	0.44	0.66
Percent with sanction applied	0.55	0.58	origin Deriv. de una instit. Policial	0.87	0.39
Percent in labor program	2.33	0.02	origin Deriv. de una fuerza de seg.	0.2	0.84
Percent in courses edu program	0.98	0.33	origin Ingreso directo	0.79	0.43
Percent in secondary education program	0.1	0.92	origin Missing	0.38	0.71
Percent in primary education program	0.75	0.45	out of province	2.83	0
Percent in recreational activities	0.04	0.97	male	0.91	0.36
Percent in discontinuous prison	1.3	0.19	condemned date missing	0.66	0.51
Percent in semi-detention	1.87	0.06	detention date missing	0.06	0.95
percent injured	1.54	0.12	full time job in prison	0.83	0.41
Completed primary education	0.28	0.78	part time job in prison	0.12	0.9
Incomplete secondary education	1.26	0.21	last prov missing	0.04	0.96

Note: This table shows t-statistics and p-values of the mean difference of each predictor between the train and test samples for the machine learning prediction and performance metrics out of the sample. Our train and test sample consisted of 402,077 and 172,332 observations, respectively.

Table C.2. Coefficient estimates by linear classification models of logit and logit with LASSO

Variable	Logit	Logit with LASSO	Variable	Logit	Logit with LASSO
census year	7.1E-04	9.9E-04	Completed secondary education	0.081	0.084
state sneep id	0.006	0.010	Married	0.039	0.135
prison id	0.000	0.000	Separated	0.427	0.316
age	0.021	0.021	Single	0.035	0.128
last residence place id	0.146	0.171	Percent with very good behavior	0.085	0.038
suicide attempt	0.133	0.128	Percent with exemplary behavior	0.087	0.027
state id	0.004	0.001	Percent with good behavior	0.044	0.006
establishment prison	0.082	0.117	Percent with fair behavior	0.044	0.080
nationality description missing	0.587	0.019	Percent with bad behavior	0.001	0.040
nat argentina	0.484	0.469	Percent with very bad behavior	0.044	0.000
sentence duration total years	0.004	0.003	Escape or evasion attempt	0.391	0.147
marital None	0.011	0.013	Percent nonmissing labor program	0.003	0.003
ıltima situacion laboral descripción missing	0.111	0.037	in primary educ program	0.098	0.094
labor Missing	0.111	0.037	in secondary higher edu program	0.146	0.141
educ Missing	1.259	0.420	economic offense	0.316	0.372
educ Ninguno	0.020	0.030	violent offense	0.649	0.592
crime1 description missing	0.252	0.073	others offense	0.309	0.256
crime2 description missing	0.546	0.508	jurisdiction desc missing	0.104	0.000
received visits last year	0.026	0.019	jurisdiction FEDERAL	0.055	0.083
order disruption	0.047	0.040	jurisdiction Ciudad de Buenos Aires	0.672	0.029
escape attempt missing	0.103	0.021	jurisdiction Missing	0.104	0.000

injured	0.161	0.161	jurisdiction NACIONAL	0.234	0.270
received medical attention	0.265	0.221	jurisdiction PROV Buenos Aires	0.334	0.213
in labor program	0.080	0.081	jurisdiction PROV Catamarca	0.445	0.167
in recreation sport	0.017	0.013	jurisdiction PROV Chaco	0.722	0.516
progressive regime	0.019	0.028	jurisdiction PROV Chubut	0.121	0.028
temporary leaves	0.184	0.172	jurisdiction PROV Corrientes	0.823	0.429
disciplinary infraction	0.138	0.135	jurisdiction PROV Córdoba	0.659	0.751
sanction applied	0.061	0.076	jurisdiction PROV Entre Rios	0.251	0.179
sentence reduction	0.350	0.359	jurisdiction PROV Formosa	0.354	0.123
behavior missing	0.150	0.051	jurisdiction PROV Jujuy	0.773	0.470
exemplary behavior	0.087	0.027	jurisdiction PROV La Pampa	0.351	0.192
very good behavior	0.085	0.038	jurisdiction PROV La Rioja	0.272	0.089
good behavior	0.044	0.006	jurisdiction PROV Mendoza	1.121	1.046
fair behavior	0.044	0.080	jurisdiction PROV Misiones	0.605	0.505
bad behavior	0.001	0.040	jurisdiction PROV Neuquén	0.112	0.141
very bad behavior	0.044	0.000	jurisdiction PROV Rio Negro	0.389	0.292
higher education	0.587	0.271	jurisdiction PROV Salta	0.385	0.420
employed	0.137	0.137	jurisdiction PROV San Juan	0.791	0.630
professional qualification	0.042	0.045	jurisdiction PROV San Luis	0.004	0.050
in semi-detention	0.164	0.084	jurisdiction PROV Santa Cruz	0.244	0.156
in discontinuous prison	0.020	0.046	jurisdiction PROV Santa Fe	0.273	0.122
in pre-free regime	0.054	0.040	jurisdiction PROV Santiago del Estero	0.931	0.414
Percent with progressive regime	0.001	0.001	jurisdiction PROV Tierra del Fuego	0.522	0.061
Percent with temporary leaves	0.003	0.003	jurisdiction PROV Tucumán	0.951	0.659

Percent with disciplinary infraction	0.001	0.002	origin Deriv. de otro establecimiento	0.088	0.161
Percent with sanction applied	0.004	0.004	origin Deriv. de una instit. Policial	0.070	0.033
Percent in labor program	0.000	0.000	origin Deriv. de fuerza de seg.	0.496	0.312
Percent in courses edu program	0.000	0.000	origin Ingreso directo	0.047	0.023
Percent in secondary education program	0.001	0.001	origin Missing	0.160	0.135
Percent in primary education program	0.002	0.002	out of province	0.037	0.019
Percent in recreational or other activities	0.000	0.000	male	0.296	0.269
Percent in discontinuous prison	0.006	0.005	condemned date missing	0.003	0.017
Percent in semi-detention	0.008	0.008	detention date missing	0.183	0.176
percent injured	0.002	0.002	full time job in prison	0.127	0.132
Completed primary education	0.049	0.047	part time job in prison	0.063	0.065
Incomplete secondary education	0.018	0.014	last prov missing	0.617	0.387

Note: This table shows coefficients of the logistic regression and logit with LASSO penalty in the prediction of repeat offenders. Our train sample consists of 402,077 observations.

Appendix D: PRISMA

Drawing on insights from an interview with the economist Daniel Mejía, this appendix explores the use of AI in the Colombian criminal justice system through the Perfil de Riesgo de Reincidencia para la Solicitud de Medidas de Aseguramiento (PRISMA). Developed by the Fiscalía General de la Nación (Attorney General's Office), in collaboration with the Policía Nacional (SIEDCO) and the Instituto Nacional Penitenciario y Carcelario (INPEC), PRISMA applies machine learning algorithms to administrative data to estimate the likelihood pretrial detainees will reoffend. The system integrates individual-level records from three institutional databases—SPOA (Prosecutor's Office), SIEDCO, and INPEC—containing information on criminal history, charges, indictments, convictions, and prior detention.

The primary objective of PRISMA is to support prosecutorial requests for preventive detention by providing structured risk assessments based on prior criminal behavior. The system does not rely on isolated indicators; rather, it detects nonlinear associations across variables such as the number and nature of prior arrests, imputations, and convictions, enabling a probabilistic classification of individuals into low-, medium-, or high-risk categories. Prosecutors input the individual's name, ID number, age, sex, and current charges, and the system outputs a summary of the accused's criminal background, highlighting both the current offense and historical data, alongside a risk score (0–100) disaggregated by crime type (violent offense, property crime, and other).

The rationale behind this technological intervention is twofold: First, it seeks to rationalize the use of preventive detention by reducing type I errors (detaining low-risk individuals); second, it aims to mitigate type II errors (failing to detain high-risk individuals), thereby improving public safety and minimizing resource misallocation. Official data from the Fiscalía General de la Nación highlight inconsistencies between assessed risk and actual judicial outcomes: Over one-third of individuals in the lowest-risk decile were nevertheless subjected to preventive detention, while fewer than half of the highest-risk individuals were detained. PRISMA was designed to reduce these imbalances by standardizing the use of criminal history across detention hearings, promoting equality and impartiality, and streamlining prosecutorial access to fragmented records dispersed across multiple databases.

Before implementation, the constitutional validity of PRISMA was reviewed to ensure compliance with due process and proportionality principles. A preliminary qualitative pilot was also conducted to analyze perceptions of the tool among judges, prosecutors, and public defenders, identifying both opportunities and institutional concerns ahead of broader deployment.

From a legal perspective, the tool enables a more proportionate use of preventive detention, limiting arbitrariness and reducing both false positives and false negatives. From an economic standpoint, PRISMA promotes a more efficient allocation of prison capacity, an increasingly scarce resource. Empirical estimates offer a powerful illustration of PRISMA's potential impact (Fiscalía General de la Nación n.d. and Balnco, 2019). If applied systematically (100% adherence) while maintaining the current volume of individuals under pretrial detention (approximately 24,000 per year), the tool could reduce recidivism in any type of crime by 25%; property-crime recidivism by 45%; violent-crime recidivism by 21%; and recidivism in drug, weapons, and conspiracy offenses by 22%. Alternatively, if the level of recidivism remained constant, PRISMA could reduce the number of individuals held in pretrial detention by 36% overall; 52% for property crimes; 32% for violent crimes; and 31% for drug, weapons, and conspiracy offenses. These projections assume full implementation; lower levels of adherence would proportionally reduce the expected impacts.

Nonetheless, PRISMA's implementation has been limited. A 2019 pilot involving 10 prosecutors across five regions tested its usability and institutional fit, but national deployment was suspended following a leadership change at the Ministry of Justice. Technical concerns around algorithmic opacity and accountability, as well as ethical concerns related to the use of historically biased criminal data, further complicate the path forward. A rigorous randomized evaluation to assess the tool's causal impact on recidivism, detention practices, and judicial efficiency has been proposed. While this evaluation is still pending, PRISMA underscores the governance dilemmas inherent to AI in criminal justice: The identification and operationalization of risk is not merely technical, but normative, demanding careful oversight, systematic validation, and ongoing public scrutiny.