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Inequality of Opportunity and Juvenile Crime*

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Abstract

To what extent should young people be normatively held responsible for committing a crime? To contribute to this ongoing debate, our study explores the influence of inequality of opportunity on the behavior of juvenile crime. By drawing upon Roemer's theoretical framework and employing administrative data from Chile, we conduct an empirical analysis to assess the degree to which the responsibility for committing a crime can be attributed to structural factors (termed circumstances) versus decisions made by the perpetrator (termed agency). Our findings reveal compelling evidence of significant inequality of opportunity within this context. Specifically, when explaining crime among males, the contribution of circumstances varies between 46.44% and 39.58%. In contrast, the role of circumstances in high school completion appears to be less relevant, with levels ranging from 34.80% to 26.01%. Importantly, our study challenges previous literature, suggesting that an alternative conceptualization of equality of opportunity yields a distinct understanding regarding the relative contributions of agency versus circumstances.

Keywords: Equal opportunities, Crime.

JEL Classification: D63, I24, K14.

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1 Introduction

Examining the normative responsibility of young individuals in relation to committing a crime presents empirical challenges, as it hinges on determining the extent to which the responsibility for the crime can be attributed to structural factors, referred to as circumstances, versus the decisions made by the perpetrator, denoted as individual agency. Resolving this research question satisfactorily holds crucial implications, particularly in defining the severity of punishment for individuals convicted of crimes. In this context, it becomes essential to consider the degree to which the criminal act can be attributed to an individual's autonomous decisions (i.e., agency), as opposed to circumstances beyond their control.[1]

To contribute to the ongoing debate surrounding equality of opportunity, and based on the seminal work by Roemer (1998), our paper empirically evaluates the extent to which delinquency can be explained by circumstances and individual agency. The advantage of applying this empirical approach is that it allows us to quantitatively measure inequality of opportunity within the context of criminal justice. According to Roemer, equality of opportunity is achieved when individuals, regardless of circumstances beyond their control, have an equal probability of attaining advantageous outcomes based on their individual agency.

One approach employed in Roemer (1998) to capture this idea is to classify the population under study into different types based on their vector of circumstances. For example, a group of students can be divided into two types based on their mother's education level, distinguishing between completion of secondary education and non-completion. Equality of opportunity is attained when the distribution of academic achievement across these student types is equalized. In our study, this would imply that the probability of being prosecuted for a crime should be the same for a student whose mother completed secondary education as it is for a student whose mother did not complete secondary education.

The validity of Roemer's conception of equality of opportunity remains a subject of debate. Defining the set of circumstances that may influence an individual's outcome, as well as the variables of agency for which they can be held responsible, is a critical aspect of this discussion. Moreover, it is unlikely that an individual's decisions are entirely independent of their circumstances. For

[1] In related literature what we call individual agency has been labeled as effort, as the related outcomes are normally positive. Our focus is on negative outcomes and we have therefore chosen to use the word agency.

instance, high school students from privileged backgrounds may be more inclined to engage in additional hours of studying outside the classroom (a factor considered as individual agency) due to parental pressure. Consequently, the treatment of the correlation between circumstances and agency has led to the development of two distinct conceptions of equality of opportunity: one espoused by Roemer, as outlined above, and another by Barry.

Empirically evaluating these two conceptions of equality of opportunity follows a similar econometric structure. In all cases, an outcome of interest, such as a measure of criminal behavior in our specific setting, is regressed on various indicators of circumstances and individual agency. Inequality of opportunity is then quantified by decomposing the variance explained by the model into two sources: circumstances and agency. To illustrate the divergence between the two conceptions, we will examine each approach separately and summarize their implications for analyzing our criminal justice context.

The distinction between the conceptions of Roemer and Barry lies in their respective approaches to measuring the two sets of variables that constitute circumstances and agency. Roemer contends that individual behavior should be considered as agency only in relation to others within the same category, wherein the categorization is based on similar socioeconomic status. This emphasis on grouping individuals with resembling characteristics highlights the importance of relative individual behavior. To capture this argument within an econometric analysis, we estimate auxiliary regressions of agency variables on circumstances, yielding residuals that represent individual agency purged of any influence from circumstances. We then regress the crime outcomes on circumstances and the residuals of behavior.

In contrast, Barry argues that agency should be rewarded regardless of the correlation between circumstances and individual agency, as explained in Barry (2017) (p.230), and (Roemer, 1998) (p.22). Empirically, to align with Barry's paradigm, we regress criminal outcomes on both circumstances and agency variables.[2]

[2] Jusot et al. (2013), drawing on Swift (2005), investigate what they called the Swift normative vision in the context of inequality of opportunity in health. This vision involves estimating auxiliary regressions of circumstances on agency variables, whose residuals are the circumstances cleaned of any correlation with agency. Then, they regress outcomes on residual circumstances and agency variables. However, (Swift (2005), p.272) says: "Intergenerational transmission of advantage that occurs through processes directly involving the fact that some parents are economically better off than others is, in principle, least worthy of respect. The bequeathing of money, the purchasing of expensive education, or of access to superior health care, are things that we might be willing to disallow. Contrast this with personality, and other "culture" variables. Suppose that well-off parents tend to produce well-off children because such parents take an unusual personal interest in their children's development, they read bedtime stories, they talk about things at the table, they instill, by their example, a positive attitude toward work, and so on. Here prevention in the name of equality of

To examine inequality of opportunity in criminal behavior within the framework of these two normative conceptions, we utilize administrative data from the Ministry of Education in Chile. Specifically, the dataset comprises information on all Chilean students who commenced their first-grade studies in 2003. This dataset is then merged with administrative records from the Public Defender's Office (PDO), enabling us to identify individuals within the sample who have been prosecuted for any criminal offense until 2018, which, for most students, corresponds to the age of 22.

Our analysis focuses exclusively on male students, given that they exhibit a threefold higher likelihood of being prosecuted for criminal activities compared to their female counterparts. This gender-specific approach allows us to concentrate our attention on a population segment that is particularly susceptible to involvement in criminal behavior.

We observe that for males, the relative contribution of circumstances to the likelihood of being prosecuted for committing a crime before the age of 22[3] is 46.44% based on Roemer's conception of equality of opportunity, and 39.58% according to Barry's conception. Similarly, the corresponding percentages for *juvenile crime* are 48.27% using Roemer's perspective and 40.62% using Barry's. This indicates that the relative influence of circumstances and agency on the outcome is contingent upon the normative viewpoint.

As a benchmark analysis, employing the same set of variables for circumstances and agency, we examine outcomes related to educational attainment. Among males, we find that the relative contribution of circumstances to the likelihood of *nongraduation* is 34.80% under Roemer's conception and 26.01% under Barry's (similar percentages are obtained when the outcome is *dropout*). Therefore, we contend that inequality of opportunity manifests more prominently in crime-related outcomes compared to educational outcomes. Importantly, our results are robust to changes in both the circumstances and agency variables employed.

Furthermore, our findings indicate that equalizing individual variables, such as *standardized test*

opportunity looks much more problematic." Hence, despite the technical feasibility of adopting the Swift approach, we made the decision to refrain from its implementation. This choice stems from the lack of clarity surrounding the differentiation between circumstances that are inherently integral to a meaningful familial bond and, thus, considered legitimate, versus circumstances provided by parents that may not be essential components of such a relationship.

[3] We consider two criminal outcome variables: *all crime* and *juvenile crime*. The majority of students in our sample were born in 1996, and our database of criminal prosecutions covers information up to 2018. Thus, the reference to *all crime* pertains to individuals prosecuted until approximately 22 years old. *Juvenile crime* refers to prosecutions occurring when the individual was under 18 years old, which for most students implies occurrences before 2014.

score in language - school, can substantially impact the reduction of the P90 - P10 metric. This demonstrates the significance of considering specific variables when formulating policies aimed at addressing inequality of opportunity in both criminal behavior and educational outcomes. Moreover, our analysis reveals that socioeconomic characteristics at the school level exert three times more influence than those at the family level in explaining crime outcomes.

Our article belongs to the broad literature that stems from the seminal work of Roemer (1998) and measures inequality of opportunity in different contexts, such as income and wealth, education, and health.[4] Although the empirical strategies in these studies vary, in general they examine how the distribution of a relevant outcome varies across different individual backgrounds. We contribute to the literature by being, to the best of our knowledge, the first paper to measure inequality of opportunity in the context of criminal justice. This context is highly relevant because normative support for punishment is based on the idea that people receive the punishment *they deserve* and, ultimately, convictions are based on that principle (Robinson and Cahill, 2005). In comparison, the implications of inequality of opportunity in other contexts, such as education, wages, and health are less dramatic as they only impact an individual's chances when competing for resources.

In a closely related paper, Jusot et al. (2013) study inequality of opportunity and explore the normative conceptions proposed by Roemer and Barry, while also introducing a third vision in honor of Adam Swift within the context of health. We adopt the empirical strategy they employ to implement the first two conceptions. In contrast to the findings presented in Jusot et al. (2013), our analysis reveals a significant influence of the normative principle on the relative contribution of circumstances and agency to outcomes. This indicates that the specific context under investigation plays a substantial role in determining whether the applied normative principle yields disparate results.[5]

[4]**Income and wealth**: theoretical models, have been developed by Bourguignon et al. (2007b), Peragine (2004), and Ramos and Van de Gaer (2016), among others; empirical research has mainly focused on developed countries, as in Chetty et al. (2014), Roemer (2013), Lefranc et al. (2008), Aaberge et al. (2011), Bourguignon et al. (2007b) , Pistolesi (2007), Almås et al. (2008), and Checchi and Peragine (2010); for research on developing countries, see Cogneau and Mesplé-Somps (2008), Ferreira and Gignoux (2011), Bourguignon et al. (2007a), and Adamczyk and Fochezatto (2020). For studies looking at Chile, see Contreras et al. (2014) and Núñez and Tartakowsky (2011). **Education**: in developed countries empirical research has been carried out by Betts and Roemer (2005), Checchi and Peragine (2010), Peragine and Serlenga (2007), Martins and Veiga (2010), and Oppedisano and Turati (2015); see Gamboa and Waltenberg (2012) for a study on six Latin American countries, Asadullah et al. (2021) inspects studies schools located in rural Bangladesh, and Contreras and Puentes (2017) look at inequality of opportunity in an education context in Chile. **Health**: see Fleurbaey and Schokkaert (2009), Trannoy et al. (2010), Jusot et al. (2013), Dias (2010), and Balia and Jones (2011). Carranza and Hojman (2015) find that health inequality is higher in Chile than in European countries.

[5]In support of our conclusion, Asadullah et al. (2021) reaches a similar finding in the context of education outcomes.

The second body of literature related to this paper is on youth crime, particularly studies on the relationship between socioeconomic and schooling circumstances and crime. Freeman (1996) analyses the surge in imprisonment rates in the US, particularly affecting Black people, between the mid-1970s and mid-1990s, and finds that high school dropouts have a disproportionate chance of being imprisoned. Lochner and Moretti (2004) find that schooling significantly reduces the probability of incarceration and arrest. Jacob and Lefgren (2003) report that property crime carried out by juveniles decreases on days when school is in session but that violent crime increases.[6] We contribute to this literature by looking at the relationship between socioeconomic background and school characteristics and crime from a different perspective, using different conceptions of inequality of opportunity.

Section 2 describes the two normative approaches used in this study, drawing on Roemer, and Barry. Section 3 describes the judiciary and educational scenario in Chile. Section 4 describes the data. Section 5 presents our results, and Section 6 provides some robustness checks. Finally, Section 7 concludes the paper.

[6]Several studies explore the extensions of mandatory schooling age or birth date cutoffs for enrollment in order to study the effect of education on crime, including Machin et al. (2011), Clay et al. (2012), Anderson (2014), Hjalmarsson (2008), and Cook and Kang (2016), among others. Lochner (2004) develops a model of crime in which human capital increases the opportunity cost of crime and in a later paper (Lochner, 2010) argues that school programs emphasizing social and emotional development are effective in reducing crime. Fu et al. (2021) construct a dynamic model to estimate teenage choices between schooling and crime using Chilean data to calibrate the model.

2 Two Normative Visions of Equality of Opportunity and Empirical Strategy

Roemer (1998) presents the argument that outcomes for any individual are determined by circumstances beyond the person's control, such as family characteristics, neighborhood, school, as well as by agency, which is under control of the individual. According to Roemer, individuals should be only held responsible for the latter.

Achieving equality of opportunity in education, such as ensuring similar access to tertiary education across socioeconomic classes, entails not only equal total investment (the sum of public and private) in primary and secondary education per child (which is the conventional notion of equality of opportunity), but in fact providing higher investment per child to students from disadvantaged backgrounds in order to compensate for the inequality in family conditions between different groups[7].

Even if the objective of achieving equality of opportunity is accepted, disentangling circumstances from agency poses challenges when assessing the relative significance of each factor, as behavior can be influenced by one's circumstances. Therefore, the way to treat the possible correlations between circumstances and agency variables is relevant when assessing the relative importance of each factor. In Roemer (1998), the author illustrates this issue through the example of Asian children's educational outcomes, contrasting it with Barry's viewpoint. Roemer contends that Asian students often excel academically due to familial pressure, and including ”Asian” as a circumstance would diminish the role of agency in their educational achievements. Roemer argues that if an Asian child perceives no choice regarding the exertion of effort, as it is simply expected by their family, their moral deservingness, according to the equal-opportunity perspective, would be lower compared to someone who voluntarily exerts effort despite feeling no obligation to do so (Roemer (1998), p.22). Consequently, Roemer would likely include ”Asian” as a circumstance while asserting that efforts arising from the child's Asian identity should not be rewarded with greater educational attainment.

Barry gives Roemer's response, stating: ”granted, the Asian students have worked hard because

[7]For a more comprehensive understanding of how educational finance reform can help equalize opportunities among racial and socioeconomic groups, see Betts and Roemer (2005).

of familial pressure, an aspect of the environment beyond their control but, nevertheless, if reward is due to effort then they should receive more reward than the academic children, for they really tried harder" (Roemer (1998), p.22). Thus, Barry is inclined not to specifically mention or emphasize the "Asian" aspect within the set of circumstances. This omission arises from the concern that incorporating ethnic or cultural backgrounds may foster a perception of unfairness, despite the fact that differential outcomes are attributable to disparities in exerted effort. [8]

The ongoing discussion can be readily applied to the realm of justice, where questions arise regarding the fairness of attributing differing levels of responsibility to individuals based on their background. A pertinent example pertains to the consideration of a juvenile hailing from a dysfunctional family and residing in a low-income neighborhood, factors commonly associated with adverse circumstances. In this scenario, the issue emerges as to whether this juvenile should bear less responsibility for engaging in activities such as joining a gang, developing substance abuse problems, or dropping out of school. Such actions, which possess the potential to lead to future criminal behavior and can be categorized as acts of agency, prompt deliberation on the appropriateness of accounting for the individual's circumstances as a mitigating factor in evaluating their culpability. It is plausible to posit that Roemer would deem the juvenile's circumstances as warranting mitigation, whereas Barry would be disinclined to acknowledge any elements of the juvenile's circumstances as influential in determining their level of culpability.

An essential component of the work carried out by Roemer and the relevant literature is the empirical testing of the theoretical propositions put forward. In line with this tradition, we adopt the methodology introduced by Jusot et al. (2013) with the aim of quantifying the impact of circumstances and agency on delinquency and educational achievement, in accordance with the two normative perspectives that have been delineated. This approach involves a two-step methodology. In the initial step, we estimate a reduced model to gauge the relationship between circumstances and agency. Subsequently, in the second step, we utilize the model predictions as inputs to derive the respective contributions of each component, thereby obtaining a measure of the inequality of opportunity present within the studied context.

[8] Andre (2021) conducted a series of experiments involving approximately 4,000 participants from the general US population, which yielded evidence supporting the preference for Barry's viewpoint over Roemer's. The findings indicate that individuals tend to reward or penalize workers based on their effort choices, even when those choices are significantly influenced by external circumstances.

2.1 First Step: Estimation

The objective of our study is to comprehensively analyze the statistical associations among the outcome, circumstances, and agency variables. Each of these factors is represented by vectors encompassing a diverse range of variables, which are elucidated in Subsections 4.1, 4.2, and 4.3.

Let us consider that an individual's outcome, denoted as O, can be expressed as a function of a vector of circumstances, denoted as C, a vector of agency variables (referred to as effort in existing literature), denoted as A, and a residual term denoted as μ. Thus, the relationship can be formulated as follows:

$$O = f(C, A, \mu). \tag{1}$$

Within this framework, disparities in outcomes that can be attributed to circumstances are considered illegitimate, with the recognition that certain biological factors, such as sex, may be inherent differences that should not be subject to compensation efforts. On the other hand, differences stemming from agency variables are regarded as legitimate. The error term encompasses the combined effects of circumstances and individual agency on the outcome, which either remain unaccounted for or are a result of pure chance.

According to Barry's proposition, agency should be rewarded regardless of the correlation between circumstances and agency. Consequently, no correction is made for any potential correlation between circumstances and agency. Going forward, the methodology will be presented under the assumption of linear relationships. Barry's approach for an individual denoted as i can be expressed as: [9]

$$O_i^B = \alpha^B + \beta^B C_i + \gamma^B A_i + \mu_i. \tag{2}$$

Testing for equality of opportunity in Barry's framework therefore amounts to testing the linear hypothesis $H_0 : \beta^B = 0$.

[9] In all subsequent equations the superscript indicates the normative view. B stands for Barry, and R for Roemer.

However, it is plausible that the variables representing circumstances and agency are not independent. In fact, as demonstrated by Larrañaga and Telias (2009), SIMCE test scores, which are utilized in Chile to measure certain subjects in the school curriculum, are influenced by some of the circumstances considered in our study. Additionally, Roemer argues that only relative agency should be rewarded. One approach to incorporate this concept is by considering the residual agencies, which refer to the residuals obtained after regressing each agency variable on circumstances, rather than the original agency variables themselves:

$$A_i = \delta_0 + \delta_1 C_i + a_i. \tag{3}$$

After obtaining the estimated relative agency, denoted as $\hat{a}_i$, it can be substituted into the primary equation in place of the uncorrected agency variable:

$$O_i^R = \alpha^R + \beta^R C_i + \gamma^R \hat{a}_i + \mu_i. \tag{4}$$

The examination of Roemer's concept of equality of opportunity entails testing the hypothesis $H_0 : \beta^R = 0$. It is worth noting that when employing linear specifications, the Frisch-Waugh-Lovell theorem indicates that $\hat{\gamma}^B$ in Equation 2 and $\hat{\gamma}^R$ in Equation 4 are identical. However, $\hat{\beta}^B$ and $\hat{\beta}^R$ are not equivalent. In cases where both circumstances and agency variables contribute to the improvement of the outcome, and there is a positive correlation between circumstances and agency, Roemer's approach leads to a magnification of the coefficient of circumstances compared to Barry's approach.

In summary, our estimation process involves conducting a regression analysis, specifically Equation 2, which captures the relationship between the outcome variable and both circumstances and agency (referred to as the Barry approach). Subsequently, we proceed to calibrate Equation 3, an auxiliary equation associated with the Roemer approach, for each individual agency variable. The residuals obtained from Equation 3 are then incorporated into Equation 4, which represents a regression model that includes the outcome variable, circumstances, and the residual agency variable, thereby capturing Roemer's conception of equality of opportunity. This step-by-step procedure is repeated for each outcome variable under investigation.

2.2 Second Step: Inequality Assessment

We proceed with the computation of the relative contributions of circumstances and agency to the outcome. To achieve this, we employ the predicted variables outlined in Subsection 2.1 for decomposing the estimated outcome value based on two normative foundations, namely Roemer, and Barry.:

$$Roemer : \hat{O}_i^R = \hat{\alpha}^R + \hat{\beta}^R C_i + \hat{\gamma}^R \hat{a}_i = \hat{O}_{i,C}^R + \hat{O}_{i,A}^R. \tag{5}$$

$$Barry : \hat{O}_i^B = \hat{\alpha}^B + \hat{\beta}^B C_i + \hat{\gamma}^B A_i = \hat{O}_{i,C}^B + \hat{O}_{i,A}^B. \tag{6}$$

The decomposition of expected inequality, as evident from Equations 5 and 6, involves two primary sources: circumstances and agency. The natural decomposition of the variance of the predicted outcome can be expressed as follows:

$$\sigma^2(\hat{O}^j) = cov(\hat{O}_C^j, \hat{O}^j) + cov(\hat{O}_A^j, \hat{O}^j) \qquad j = R, B, S. \tag{7}$$

Dividing both sides by $\sigma^2(\hat{O}^j)$ we obtain

$$1 = \frac{cov(\hat{O}_C^j, \hat{O}^j)}{\sigma^2(\hat{O}^j)} + \frac{cov(\hat{O}_A^j, \hat{O}^j)}{\sigma^2(\hat{O}^j)} = RC_C + RC_A \quad j = R, B, S, \tag{8}$$

Here, RC_k denotes the relative contribution of k, where k represents circumstances and agency.

Equation 8 offers an insightful means of comprehending the relative influence of circumstances and agency on the desired outcome. It is important to note that the equation yields a sum of the relative contribution of circumstances and agency equal to 1, irrespective of the explanatory power of the independent variables in relation to the dependent variable. By design, the relative contribution of circumstances to the outcome, which captures inequality of opportunity, is bounded between 0 and 1.

Furthermore, it is crucial to emphasize that the chosen normative conception of inequality of opportunity will impact the relative contribution of each factor. While not guaranteed, it is expected that under Roemer, the relative contribution of circumstances would surpass that under Barry. This tendency generally arises when both high circumstances and high agency exert a positive effect on the outcome, and when high circumstances exhibit a positive correlation with high agency.

To assess the accuracy of our variance decompositions, we employ the bootstrapping percentile method. This involves generating 100 samples, drawn with replacement and of the same size as the original sample. Subsequently, we estimate the relative contribution of circumstances and agency for each sample, reporting the 2.5% and 97.5% percentiles

3 Criminal and Educational System in Chile

3.1 Crime Rates in Chile

In developing countries like Chile, crime rates tend to be higher in comparison to developed countries. Data from the World Prison Brief indicates that as of July 2023, the prison population rate per 100,000 of the national population was 376 in the Americas. Within the Americas, specific rates were 212 in Chile, 243 in Argentina, 381 in Brazil, 193 in Colombia, 169 in Mexico, 259 in Peru, 383 in Uruguay, 629 in the USA, and 113 in Venezuela. In contrast, the prison population rate in Europe was 175 per 100,000.[10] In the context of gender division within Chile's prison population,

[10]World Prison Population List, thirteenth edition, Institute for Crime & Justice Policy Research, (https://www.prisonstudies.org/sites/default/files/resources/downloads/world_prison_population_list_13th_edition.pdf)

as of July 2023, out of a total of 53,600 individuals, 49,478 (92.3%) were male, while 4,122 (7.7%) were female.[11]

The prison population rate, as a measurement of crime prevalence in a country, may not always provide an accurate depiction due to its reliance on active prosecution. Consequently, seemingly violent countries like Venezuela, Mexico, Brazil, or Colombia may not exhibit proportionally high prison population rates due to low rates of active prosecution within these nations. Conversely, homicide rates are often regarded as a preferred measure of crime since they are statistically challenging to conceal. Regarding this metric, Chile demonstrates a lower rate compared to its continental counterparts. In 2018, Chile's homicide rate stood at 4.4 per 100,000, while Argentina reported a rate of 5.3, Brazil had 27.4, Colombia had 25.3, Mexico had 29.1, Peru had 7.9, Uruguay had 12.1, the USA had 5, and Venezuela had 36.7. The average homicide rate for South America was calculated at 21.0 per 100,000.[12] Concerning other categories of crime, such as offenses against individuals, sexual assaults, and property crimes, Chile is generally regarded as a relatively safe country within South America. However, making direct comparisons across countries proves challenging due to potential differences in the reporting of offenses.

3.2 The Juvenile Criminal Justice System in Chile

In 2005, Chile implemented a law reforming its juvenile criminal justice system, known as Act Nº 20084, which took effect in 2007. The primary objective of this reform was to align the national legislative framework with international human rights standards, including the principles outlined in the United Nations Convention on the Rights of the Child. Notably, the reform aimed to ensure an exceptional and proportionate application of criminal law, with confinement only used as a last resort (Langer and Lillo, 2014).

The reform introduced three significant changes to the previous system. First, it lowered the age of criminal liability from 16 to 14 years. Second, it addressed the previous system's ambiguity, where adolescents could be treated as either adults or juveniles based on the judge's discretion. Lastly, for convicted juvenile defendants, the reform reduced the severity of punishment by one grade compared to the corresponding adult sentence (Couso and Duce, 2013).

[11] https://www.gendarmeria.gob.cl/est_general.html, accessed on July 12, 2023)

[12] United Nations Office on Drugs and Crime (https://dataunodc.un.org/content/data/homicide/homicide-rate, accessed on July 12, 2023)

The implementation of the new juvenile criminal justice system occurred within the broader context of a comprehensive criminal justice reform that began in 2000 and was finalized in 2005. This comprehensive reform replaced the long-standing inquisitorial model with an oral, public, and adversarial procedure. As part of this reform, several new institutions were established, including the Public Defender's Office (PDO), the Public Prosecutor's Office, the Guarantee Court (which, among other things, safeguards the rights of all parties during the investigation process), and the Oral Criminal Trial Courts. The PDO provides free legal representation to almost all individuals accused of committing a crime, including both minors and adults. The PDO also collects detailed information about defendants accessing their services, including specific details related to the crimes they are involved in.

Under the new juvenile system, the juvenile criminal procedure involves several stages. Initially, the juvenile is arrested, either apprehended by the police at the scene of the crime or following an investigation conducted by the public prosecutor, leading to an accusation. This stage culminates in an arraignment hearing, conducted in the Guarantee Court, which typically lasts around 15 minutes. During this hearing, the arraignment judge must choose one of three possible outcomes: initiating criminal proceedings, opting for an alternative ending (which may involve compensation agreements or the conditional suspension of proceedings), or dismissing the proceedings altogether. The majority of cases are resolved in the Guarantee Court, either through alternative endings or the dismissal of proceedings. Generally, a criminal procedure is reserved for more serious offenses.

3.3 The Chilean Education System

In Chile, the education system consists of primary education, comprising eight sequential grades for children aged between 6 and 14 years, and secondary education, consisting of four sequential grades for teenagers aged between 15 and 18 years. According to Chilean Law Nº 19.876, primary and secondary education is mandatory for all children, although not all students complete secondary education. The Ministry of Education provides guidelines for grade retention, specifying that students should be retained if their grade point average (GPA) or attendance falls below certain cutoffs. However, the implementation of these rules may vary among schools, and some schools have flexibility in their application (Díaz et al., 2021).

During our sample period from 2003 to 2018, school admissions in Chile were decentralized and the responsibility of individual schools. Some schools began selecting students based not only on primary school GPAs but also on family background, leading to further segregation of students with different socioeconomic statuses (SES) across schools. This segregation, which is highly pronounced, is influenced by various factors, including the selective admission process and differential fees (Valenzuela et al., 2014).

In 1988, a system of national standardized tests known as SIMCE (*Sistema de Medición de Calidad de la Educación*) was introduced in Chile to assess the learning process and academic performance of all students in specific grades. We focus on the language and math SIMCE tests taken by all Chilean students in the 4th grade of primary education. The government utilizes SIMCE results to allocate resources and inform the public about the quality of schools by publishing school-level results. However, due to the stakes involved, educational institutions may have incentives to encourage their lowest-performing students not to participate in the test, which can potentially bias the results upwards.

4 Data

Our dataset is constructed by merging administrative data from the Ministry of Education and the PDO. The Ministry of Education provides an administrative dataset that spans the period from 2003 to 2018. It includes information on each student in primary or secondary education in the country, including the school attended, grade level, educational achievement (such as grade completion and average scores), attendance rate, and basic demographic information such as birth date and sex. We merge this panel with information on students' performance on the SIMCE test, which is obtained through surveys filled out by parents. These surveys provide valuable insights into the students' socioeconomic background. Lastly, we link our sample to PDO records of criminal cases prosecuted between 2010 and 2018. In Chile, the minimum age at which individuals can be charged with a criminal offense is 14 years old. As we do not have information on the verdict for all cases, we define ”crime” as being charged with a crime, regardless of the judicial outcome.

Our initial dataset consists of 239,534 students, with 122,102 males and 117,432 females, who entered 1st grade for the first time in 2003. The majority of students (58.89%) were born in 1996, while 39.62% were born in 1997. In our robustness checks, we work with different samples depending on the availability of variables.[13] Throughout our analysis, we will follow the 2003 cohort of students and examine two criminal outcomes.[14] Our primary objective is to determine the proportion of each outcome that can be attributed to circumstances and individual agency. In the subsequent subsections, we will present the specific outcomes, circumstances, and agency variables that we have considered. A more detailed definition of each variable can be found in Appendix A.

4.1 Outcomes

This paper focuses on two key variables of interest. Firstly, we construct the variable *all crime* as an indicator function that takes the value of 1 if the student was arrested between 2010 and 2018 (for most individuals in the sample, covering up to the age of 22), and 0 if not. The other variable is *juvenile crime*, which takes the value of 1 if the student was charged with a crime before the age of 17, and 0 if not.

As a benchmark, we also define *nongraduation*, which is defined as 1 if the student did not graduate from high school and 0 if not. Furthermore, we define *dropout* as 1 if the student was not registered for any course for at least two consecutive years between 2010 and 2014, or if they did not graduate, and 0 otherwise.

4.2 Circumstances

Circumstances refer to pertinent factors that influence the outcome and are beyond the control of the student. When students participate in the SIMCE test, a parental survey is administered to gather information about the student's socioeconomic status. However, it is important to note that not all students take the SIMCE, and not all parents respond to the survey. Moreover, non-participation in the exam or non-response to the survey, or both, are likely correlated with outcomes. To address the potential loss of students who did not take the exam or complete the survey, we employ socioeconomic variables at the baseline, taking the school-level average. This approach serves as a reliable proxy for family socioeconomic background due to Chile's notable degree of educational segregation (Valenzuela et al., 2014).

[13] We have to drop a significant number of observations due to the unavailability of standardized test scores and variables obtained from the associated parents' survey.

[14] As a benchmark, we will also consider two educational outcomes to compare the relative importance of circumstances in the realms of crime and education, which are both crucial aspects of child development.

Consequently, we group students based on the school they attended in 2006, which typically corresponds to their fourth-grade school. Subsequently, we compute the average socioeconomic variables from the surveys completed by the parents of students who participated in the SIMCE, either in 2006 or subsequently. It is important to note that these averages are only calculated when the data is available. Notably, the only variable at the individual level is genre. In Section 6, we conduct robustness checks by introducing additional variables at the individual level.

Socioeconomic status is assessed using various indicators, including the percentage of students utilizing the public health insurance system, the average monthly household income, the monthly school fee paid, and the average years of mother's schooling. Following the approach of Haveman and Wolfe (1995) and in alignment with conventional wisdom, which suggests that the educational attainment of the mother has a greater impact on children's schooling outcomes, we select mother's years of schooling as a key variable due to its higher predictive power. To account for differences in ethnicity among students, we include the percentage of students who have at least one indigenous parent. Furthermore, we incorporate variables that aim to characterize high-performance schools, such as indicators for whether the attended school is private or rural, as well as the student's average score on the SIMCE language and math tests.

Additionally, we construct three variables: *all crime - old generation*, *juvenile crime - old generation*, and *nongraduation - old generation*. These variables represent the proportions of students, among all fourth graders who attended a specific school in 2003, who were involved in criminal activities, who committed crimes during their juvenile years, or who did not graduate. These variables are then linked to our 2003 school cohort by matching the school attended in 2003. In essence, these variables investigate the outcomes of interest for a cohort three years older than the one under study. They have the potential to capture important aspects at the school level, such as the academic capacity of the faculty, student development through extracurricular activities, and the school's culture and organizational environment (including parent involvement, security, and campus organization). These variables may provide a more comprehensive understanding of school-level characteristics compared to simple indicators such as private school status or monthly fees. A detailed description of all the circumstances incorporated into this study can be found in Appendix A.

4.3 Agency

Individual agency refers to variables that are within the control of the individual. In our baseline model, we include three specific variables to capture individual agency: *percentile grades*, which represents the student's grade percentile in relation to their classmates; *ever repeated*, a binary variable indicating whether the student has repeated a primary school grade at any point; and *percentage attendance*, which measures the average attendance rate of the student between 2003 and 2010 (school years) while enrolled. In Section 6, we explore alternative measures of agency, including the two individual SIMCE grades in language and math. These additional measures allow us to further examine the role of individual agency. For a more detailed definition of each variable, please refer to Appendix A.

4.4 Descriptive Statistics

With respect to outcomes, in our sample, females have better outcomes in terms of crime and education than males. In terms of crime outcomes: males are almost three times as likely to be charged with a crime, 14.7% versus 5.1%. Those differences are even more marked for *juvenile crime*: only 2.3% of females commit crime as a juvenile compared to 7.5% of males. Males underperform females in education: 16.7% of males did not graduate compared to 11.5% of females, and the probability of dropout is 18.4% for boys and 13.3% for girls. Because males are substantially more likely to commit crime, we focus on male criminal and educational behavior.

Table 1 contains descriptive statistics for the sets of variables in circumstances and agency and outcomes for male students. It reveals that 78.7% of students in the sample are in the public health insurance system. The mean monthly household income of the students whose parents answered the SIMCE in 2006 was 352,748 Chilean pesos (CLP) (the mean exchange rate in 2006 was 530 CLP to the dollar, so this equates to USD 666). The data show that most of the schools attended by students in the sample were tuition free or had low fees, and a minority of students attended private schools (6.5%) and rural schools (12.7%). In terms of ethnic background, 10.7% of the students had at least one indigenous parent (the Mapuche account for approximately 85% of the indigenous people in Chile). On average, the mother's of the students had 11.1 years of schooling. Finally, regarding SIMCE test scores, male students scored 251.1 on average in the language test and females scored 258.8; for the math test, males scored 251.4 and females 247.0, again on average.

Table 1: Descriptive statistics for male students

Classification	Variable	Obs	Mean	Std. Dev.	Min	Max
Circumstances	Public Health Insurance System	96,436	0.787	0.409	0	1
Circumstances	Public Health Insurance System - School	122,102	0.797	0.255	0	1
Circumstances	Household Income	94,275	352,748	406,196	50,000	1,800,000
Circumstances	Household Income - School	122,102	339,955	335,369	50,000	1,800,000
Circumstances	School Fee	94,432	14,082	25,941	0	100,000
Circumstances	School Fee - School	122,102	13,215	24,356	0	100,000
Circumstances	One Parent Indigenous	93,827	0.107	0.309	0	1
Circumstances	One Parent Indigenous - School	122,102	0.113	0.144	0	1
Circumstances	Standardized Test Score in Language - School	122,102	255.535	25.001	119.870	355.685
Circumstances	Standardized Test Score in Math - School	122,102	250.877	28.626	98.610	347.580
Circumstances	Years Education Mother	102,125	11.142	3.395	0	20.000
Circumstances	Years Education Mother - School	122,102	11.044	2.215	0	17.200
Circumstances	Rural School	122,102	0.127	0.333	0	1
Circumstances	Private School	122,102	0.065	0.246	0	1
Circumstances	All Crime – Old Generation	122,102	0.124	0.071	0	1
Circumstances	Juvenile Crime – Old Generation	122,102	0.040	0.039	0	1
Circumstances	Nongraduation – Old Generation	122,102	0.174	0.138	0	1
Agency	Percentile Grades	122,102	46.081	28.598	0.101	99.821
Agency	Ever Repeated	122,102	0.267	0.443	0	1
Agency	Percentage Attendance	122,102	93.646	4.359	0	100
Agency	Standardized Test Score in Language	110,482	251.116	54.772	102.730	381.820
Agency	Standardized Test Score in Math	110,433	251.453	56.303	81.130	377.540
Outcomes	All Crime	122,102	0.147	0.355	0	1
Outcomes	Juvenile Crime	122,102	0.075	0.264	0	1
Outcomes	Nongraduation	122,102	0.167	0.373	0	1
Outcomes	Dropout	122,102	0.184	0.388	0	1

Note: This table reports descriptive statistics on circumstances, agency and outcomes variables. The sample is made up of male students who were in 1st grade for the first time in 2003. See Appendix A for the definitions of variables.

Table 2 examines the statistical associations among different categories for male students. Notably, students affiliated with private health insurance providers demonstrate significantly better outcomes, with only 6.6% of individuals committing crime (up to the age of 22) compared to 15.0% among those utilizing the public health insurance system. Similarly, individuals from households with higher monthly income (8.1% commit crime versus 15.0%) and those with mothers who have more years of education (8.5% commit crime versus 16.8%) also exhibit improved performance. Students with indigenous parents exhibit slightly lower performance compared to those without indigenous parents.

Furthermore, attending public schools increases the likelihood of interaction with the justice system threefold compared to attending private schools (15.4% versus 4.7%), particularly in the case of *juvenile crime*. Additionally, there is evidence of school quality persistence, as students attending schools with lower crime rates among the previous generation also display lower crime rates themselves.

Lastly, it is noteworthy that individuals achieving higher scores on both SIMCE tests have better odds of completing school successfully and avoiding involvement with the judicial system. On the other hand, students who did not take the SIMCE test demonstrate the lowest performance across all four outcomes.

Appendix B presents the pairwise correlations among the variables utilized in our study for male students. Tables 9, 10, and 11 demonstrate the substantial correlations observed among various circumstances. Notably, the variable *household income* exemplifies that parents with higher incomes tend to have more years of schooling and can afford to enroll their children in more expensive private schools, where they interact with peers from affluent backgrounds. Consequently, these students are likely to exhibit superior performance in the SIMCE tests, experience lower dropout rates, and have fewer encounters with the judicial system.

Moreover, the correlation tables reveal an important finding: both *all crime* and *juvenile crime* exhibit positive correlations with *nongraduation* and *dropout*. This finding aligns with the well-established research in the economics of crime literature, which suggests that higher levels of education are associated with reduced criminality (Lochner and Moretti, 2004).

Table 2: Means per Category for Male Students

Classification	Observations	All Crime	Juvenile Crime	Nongraduation	Dropout
Private Health	20,516	0.066	0.024	0.045	0.053
Public Health Insurance System	75,920	0.150	0.075	0.155	0.172
Chi-Square Test		999 (0.000)	687 (0.000)	1.7e+03 (0.000)	1.8e+03 (0.000)
High Household Income	31,138	0.081	0.034	0.055	0.065
Low Household Income	63,137	0.150	0.075	0.152	0.170
Chi-Square Test		905 (0.000)	605 (0.000)	1.9e+03 (0.000)	2.0e+03 (0.000)
High School Fee	42,022	0.098	0.044	0.076	0.087
Low School Fee	52,410	0.150	0.075	0.154	0.172
Chi-Square Test		579 (0.000)	379 (0.000)	1.4e+03 (0.000)	1.4e+03 (0.000)
No Parent Indigenous	83,764	0.130	0.064	0.137	0.151
One Parent Indigenous	10,063	0.168	0.082	0.178	0.198
Chi-Square Test		110 (0.000)	51 (0.000)	127 (0.000)	146 (0.000)
High Years Education Mother	39,599	0.085	0.037	0.062	0.073
Low Years Education Mother	62,526	0.168	0.086	0.195	0.213
Chi-Square Test		1.4e+03 (0.000)	926 (0.000)	3.5e+03 (0.000)	3.6e+03 (0.000)
Non Rural School	106,632	0.149	0.078	0.157	0.174
Rural School	15,470	0.139	0.059	0.240	0.255
Chi-Square Test		11 (0.001)	65 (0.000)	679 (0.000)	594 (0.000)
Private School	7,898	0.047	0.015	0.036	0.045
Public School	114,204	0.154	0.080	0.176	0.194
Chi-Square Test		671 (0.000)	446 (0.000)	1.0e+03 (0.000)	1.1e+03 (0.000)
High All Crime – Old Generation	58,971	0.188	0.103	0.214	0.235
Low All Crime – Old Generation	63,131	0.110	0.049	0.124	0.136
Chi-Square Test		1.5e+03 (0.000)	1.3e+03 (0.000)	1.8e+03 (0.000)	2.0e+03 (0.000)
High Juvenile Crime – Old Generation	63,526	0.180	0.098	0.202	0.223
Low Juvenile Crime – Old Generation	58,576	0.112	0.051	0.129	0.142
Chi-Square Test		1.1e+03 (0.000)	958 (0.000)	1.2e+03 (0.000)	1.3e+03 (0.000)
High Nongraduation – Old Generation	61,440	0.191	0.103	0.246	0.268
Low Nongraduation – Old Generation	60,662	0.103	0.047	0.087	0.099
Chi-Square Test		1.9e+03 (0.000)	1.4e+03 (0.000)	5.6e+03 (0.000)	5.8e+03 (0.000)
High Standardized Test Score in Language	52,225	0.088	0.039	0.067	0.078
Low Standardized Test Score in Language	58,257	0.190	0.099	0.222	0.243
Non Standardized Test Score in Language	11,620	0.203	0.118	0.343	0.368
Chi-Square Test		2.6e+03 (0.000)	1.8e+03 (0.000)	7.6e+03 (0.000)	7.8e+03 (0.000)
High Standardized Test Score in Math	57,347	0.094	0.042	0.066	0.077
Low Standardized Test Score in Math	53,086	0.193	0.102	0.237	0.259
No Standardized Test Score in Math	11,669	0.203	0.119	0.346	0.371
Chi-Square Test		2.5e+03 (0.000)	1.8e+03 (0.000)	8.8e+03 (0.000)	9.1e+03 (0.000)

Note: This table reports the mean of different categories in criminal and educational outcomes. It also includes the Pearson Chi-square test to assess if there is a statistically significant difference between frequencies in each category (the p-value is reported in parentheses). The sample is made up of male students who were in 1st grade for the first time in 2003. See Appendix A for the definitions of variables.

5 Results

In this section, we present our findings regarding the influence of circumstances and agency on *all crime* and *juvenile crime*. To facilitate comparison, we also examine the effects on *nongraduation* and *dropout*.

Our baseline specification incorporates individual circumstances represented by the mean circumstances at the school level derived from the SIMCE tests and surveys. These include variables such as *public health insurance system - School*, *household income - school*, *school fee - school*, *one parent indigenous - school*, *standardized test score in language - school*, *standardized test score in math - school*, and *mother's education years - school*. Additionally, we consider school characteristics such as *private school* and *rural school*, as well as variables pertaining to the cohort three years prior to our sample cohort: *all crime - old generation*, *juvenile crime - old generation*, and *nongraduation - old generation*. The agency variables include *percentile grades*, *ever repeated*, and *percentage attendance*. Detailed definitions of all variables can be found in Appendix A.

The results of the main regressions are presented in Appendix D, while the results of auxiliary regressions can be found in Appendix E. Additionally, in Section 6, we conduct a robustness analysis by considering other variables.

5.1 Goodness of Fit

Table 3 presents the goodness of fit measures for our four predicted outcomes among male students. The R-squared values indicate the proportion of variance explained by the model. For *all crime*, the R-squared is 7.38%, and for *juvenile crime*, it is 5.81%, suggesting that there is room for improvement in our model. The R-squared percentages are higher for the educational outcomes, with 24.16% for *nongraduation* and 24.96% for *dropout*, indicating a relatively better fit for these variables.

We also assess how good our model is at correctly classifying outcomes by running our regressions to obtain the predicted probability of outcomes for each student. Then, we draw random numbers from a uniform distribution between 0 and 1. If the random number is smaller than our predicted outcome, then we consider the simulated outcome to be 1, and 0 if the number is larger. An individual is considered correctly classified if the simulated outcome matches the observed

Table 3: Goodness of Fit

Goodness of Fit	All Crime		Juvenile Crime		Nongraduation		Dropout	
	Original	Cross Validation	Original	Cross Validation	Original	Cross Validation	Original	Cross Validation
R-squared	7.38%		5.81%		24.16%		24.96%	
Correctly Classified	76.55%	76.63%	86.73%	86.67%	78.09%	77.96%	76.71%	76.59%
Correctly Classified (Simulated Outcome=1)	20.84%	20.85%	12.48%	12.62%	35.24%	34.96%	37.32%	37.08%
Correctly Classified (Simulated Outcome=0)	86.33%	86.34%	92.87%	92.88%	87.22%	87.17%	86.08%	86.03%
Correctly Classified (Outcome=1)	21.10%	21.01%	12.65%	12.94%	36.99%	36.82%	38.93%	38.80%
Correctly Classified (Outcome=0)	86.14%	86.23%	92.77%	92.68%	86.35%	86.23%	85.24%	85.13%

Note: This table reports the goodness of fit of our baseline estimations. The original sample used consists of 122,102 male individuals which represent our baseline sample. The cross validation methodology is explained in Subsection 5.1. The first row reports the R-squared, the second row the % of individuals who were correctly classified, the third row includes the % of individuals correctly classified when the simulated outcome is equal to 1, the fourth row presents the % when the simulated outcome is 0, the fifth row the % of correct classified students when the outcome is in fact 1, and sixth row when the outcome is 0.

outcome. For *all crime* we correctly classify 76.55% of individuals and for *juvenile crime* 86.73% of individuals are correctly classified. Generally, the model performs better when the outcome is 0 and when the simulated outcome is also 0. This is the case because, for most individuals, the predicted probability of committing crime is closer to 0 than to 1.

To conduct an out-of-sample cross-validation exercise, we randomly select 90% of the estimation sample to estimate the probability model. The remaining 10% is used for validation. We draw a uniformly distributed random number between 0 and 1 and assign a simulated outcome of 1 if the predicted probability exceeds the drawn number, or 0 otherwise. We compute the correctly classified cases and repeat this process 100 times to calculate the averages. The out-of-sample goodness of fit for all four outcomes closely resembles the original sample, indicating that the model is not overfitted and maintains validity beyond the estimation sample.

5.2 Contribution of Circumstances and Agency on *All Crime*, *Juvenile Crime*, *Nongraduation*, and *Dropout*

The primary focus of this paper is to examine the magnitudes of inequality in the explained outcome, which provides insights into the model's accuracy, as well as the respective contributions of circumstances and agency to these magnitudes, offering information about inequality of opportunity. Tables 4 and 5 present the contributions of circumstances and agency to the magnitudes of inequality for male students, reflecting our primary focus on this gender group due to their higher likelihood of committing crimes compared to females. However, we also include the contributions for female students in Tables 6 and 7. The methodology employed for this analysis is outlined in Section 2, while Tables of auxiliary and outcome regressions can be found in Appendix D and Appendix E.

Circumstances play a significant role in determining criminal outcomes. According to the two normative conceptions of equality of opportunity, the contribution of circumstances to *all crime* for male students is 46.44% using Roemer's conception and 39.58% using Barry's conception. For *juvenile crime*, these contributions are slightly higher, with 48.27% using Roemer's approach and 40.62% using Barry's approach. These findings suggest that circumstances, irrespective of the normative perspective adopted, strongly influence the likelihood of individuals interacting with the judicial system. Additionally, it is concerning that students' low-quality circumstances persist into their early adulthood.

The relative contribution of circumstances to educational outcomes for male students, specifically in terms of *nongraduation*, varies. According to Roemer's conception, circumstances account for 34.80% of the variation, while according to Barry's conception, the contribution is 26.01%. Similarly, for *dropout*, the contribution is 34.84% according to Roemer and 26.02% according to Barry. Notably, the relative contribution of circumstances is higher for criminal outcomes compared to educational outcomes, irrespective of the normative perspective considered. Thus, we can infer that circumstances have a more pronounced impact on criminal outcomes than on educational outcomes.

In the case of female students, the contribution of circumstances varies for different outcomes. For *all crime*, the contribution is 44.05% under Roemer's normative perspective and 37.74% under Barry's. For *juvenile crime*, the contribution is 42.65% according to Roemer and 35.76% according to Barry. In terms of *nongraduation*, the contribution is 32.64% under Roemer's normative vision and 25.56% under Barry's. Lastly, for *dropout*, the contribution is 33.21% according to Roemer and 26.06% according to Barry. These findings suggest that, among female students, circumstances have a slightly lesser impact compared to male students in terms of their relative contribution to the outcomes, as measured by both normative views.

Using the bootstrapping percentile method, as described in Subsection 2.2, we calculate confidence intervals for the relative contribution of circumstances and agency under the Roemer and Barry approaches. Notably, the confidence intervals for all four outcomes do not overlap. This finding has significant implications, indicating that the choice of normative perspective influences the assessment of the significance of circumstances and agency. Our results contradict the conclusion reached in Jusot et al. (2013), which suggests that the adopted normative view has little impact on the relative contribution. However, it is important to note that their research focuses on health inequality rather than criminal justice.

The relative contribution of circumstances, particularly in the context of educational outcomes, is lower than initially expected. This finding is consistent with the existing literature. For example, Hufe et al. (2017) highlight that several studies report the effect of circumstances on income acquisition in advanced economies to be around 20%. Two main arguments are often put forward to explain this empirical observation. The first argument suggests that the behaviors and achievements of children, as captured by variables such as *percentile grades* and *ever repeated*, should be considered as consequences of circumstances rather than personal efforts (Hufe et al., 2017). According to this perspective, individuals should not be held responsible for their choices before reaching the age of consent, leading to the assertion that the relative contribution of circumstances is 100% in our framework. The second argument highlights that IQ, which some may consider a circumstance,[15] is often excluded as a variable for various reasons (in fact, we do not include it as a variable in our analysis). These reasons include the difficulty of observation and the potential for downward manipulation. Consequently, the exclusion of IQ as a circumstance variable may introduce an upward bias in the relative weight of agency, as what may appear as agency could be partially influenced by IQ.

Table 4: Relative Contribution of Circumstances and Agency for Male Students (Criminal Outcomes)

		All Crime		Juvenile Crime	
		Circumstances	Agency	Circumstances	Agency
Roemer	Point Estimate	46.44%	53.56%	48.27%	51.73%
	C.I.	[44.39% ; 49.37%]	[50.63% ; 55.61%]	[45.69% ; 51.03%]	[48.97% ; 54.31%]
Barry	Point Estimate	39.58%	60.42%	40.62%	59.38%
	C.I.	[37.41% ; 42.54%]	[57.46% ; 62.59%]	[38.08% ; 43.21%]	[56.79% ; 61.92%]

Note: This table reports the relative contribution of circumstances and agency, as expressed in Equation 8, for *all crime* and *juvenile crime*. In brackets We report the confidence intervals in parentheses, which were constructed using a 95% percentile bootstrap confidence interval. The sample is made up of male students who in 2003 were doing in 1st grade for the first time in 2003, and we used the baseline specification.

5.3 Specific Contribution of Variables

In order to investigate the potential influence of specific variables on our findings, we utilize our initial sample of 122,102 male students as the foundation for conducting calculations. However, in

[15] IQ can be seen as a proxy for talent. Although IQ is not under the child's control and could be considered a circumstance, it may be impossible for a distributive agency to provide educational and technological assistance that fully compensates for inherent differences in talent (Arneson, 1989).

Table 5: Relative Contribution of Circumstances and Agency for Male Students (Educational Outcomes)

		Nongraduation		Dropout	
		Circumstances	Agency	Circumstances	Agency
Roemer	Point Estimate	34.80%	65.20%	34.84%	65.16%
	C.I.	[33.76% ; 35.98%]	[64.02% ; 66.24%]	[33.80% ; 36.13%]	[63.87% ; 66.20%]
Barry	Point Estimate	26.01%	73.99%	26.02%	73.98%
	C.I.	[25.09% ; 27.04%]	[72.96% ; 74.91%]	[25.09% ; 27.13%]	[72.87% ; 74.91%]

Note: This table reports the relative contribution of circumstances and agency, as expressed in Equation 8, for *nongraduation* and *dropout*. We report the confidence intervals in parentheses, which were constructed using a 95% percentile bootstrap confidence interval. The sample is made up of male students who were in the 1st grade for the first time in 2003, and we used the baseline specification.

Table 6: Relative Contribution of Circumstances and Agency for Female Students (Criminal Outcomes)

		All Crime		Juvenile Crime	
		Circumstances	Agency	Circumstances	Agency
Roemer	Point Estimate	44.05%	55.95%	42.65%	57.35%
	C.I.	[40.95% ; 48.06%]	[51.94% ; 59.05%]	[38.04% ; 47.26%]	[52.74% ; 61.96%]
Barry	Point Estimate	37.74%	62.26%	35.76%	64.24%
	C.I.	[34.70% ; 41.80%]	[58.20% ; 65.30%]	[31.22% ; 40.32%]	[59.68% ; 68.78%]

Note: This table reports the relative contribution of circumstances and agency, as expressed in Equation 8, for *all crime* and *juvenile crime*. We report the confidence intervals in parentheses, which were constructed using a 95% percentile bootstrap confidence interval. The sample is made up of female students who were in 1st grade for the first time in 2013, and we use the baseline specification.

Table 7: Relative Contribution of Circumstances and Agency for Female Students (Educational Outcomes)

		Nongraduation		Dropout	
		Circumstances	Agency	Circumstances	Agency
Roemer	Point Estimate	32.64%	67.36%	33.21%	66.79%
	C.I.	[31.39% ; 33.87%]	[66.13% ; 68.61%]	[31.89% ; 34.45%]	[65.55% ; 68.11%]
Barry	Point Estimate	25.56%	74.44%	26.06%	73.94%
	C.I.	[24.42% ; 26.72%]	[73.28% ; 75.58%]	[24.74% ; 27.18%]	[72.82% ; 75.26%]

Note: This table reports the relative contribution of circumstance and agency, as expressed in Equation 8, for *nongraduation* and *dropout*. We report the confidence intervals in parentheses, which were constructed using a 95% percentile bootstrap confidence interval. The sample is made up of female students were in 1st grade for the first time in 2003, and we use the baseline specification.

this particular analysis, we systematically exclude one variable at a time. The outcomes of these computations are presented in Appendices F, G, H, and I.

Based on the analysis depicted in Figures 1, 3, 5, and 7, it can be inferred that the exclusion of individual circumstance variables and subsequent regression analyses generally do not have a substantial impact on the assessment of inequality of opportunity in criminal outcomes using either Roemer or Barry's approach. This observation holds true for both *all crime* and *juvenile crime*. Among the various circumstance variables examined, the attendance of students in *rural schools* emerges as the most influential factor. It is noteworthy that, despite exhibiting negative correlations with significant variables such as *household income* or *years education mother*, as demonstrated in Appendix B, students from rural schools display lower crime rates compared to their urban counterparts (refer to Table 2). Evaluation of educational outcomes, as illustrated in Figures 9, 11, 13, and 15, leads to the conclusion that the exclusion of specific variables has limited relevance to the relative influence of circumstances, except in the case of *nongraduation – old generation*, which confirms our suspicions regarding the persistence of school quality.

The findings demonstrate the robustness of the results to the exclusion of individual circumstance variables, indicating that the relative contribution to inequality remains relatively consistent across different specifications. This suggests that reducing inequality of opportunity requires a comprehensive and multidimensional approach, as no single circumstance variable can fully account for the variation in outcomes.

The impact of dropping one agency variable on criminal outcomes is depicted in Figures 2, 4, 6, and 8. Among the agency variables (*percentile grades*, *ever repeated*, and *percentage attendance*), *percentile grades* emerges as the most influential variable when employing Roemer's normative conception. It is possible that the residual for *percentile grades* produced when using Roemer is similar to the variable itself due to the inability of socioeconomic characteristics at the school level to explain how a student's performance compares to their peers. However, when utilizing Barry's approach, *ever repeated* stands out as the key variable in explaining the relative contribution of agency to both *all crime* and *juvenile crime*.

Regarding educational outcomes, as illustrated in Figures 10, 12, 14, and 16, *ever repeated* assumes the greatest importance for both normative conceptions. The debate surrounding grade retention and its impact on student outcomes presents contrasting perspectives. Some researchers, such as Lochner and Moretti (2004), argue that grade promotion enhances the returns to legitimate work, thereby increasing the opportunity costs of engaging in illicit behaviors. Conversely, other scholars, including Jacob (2005), perceive grade retention as an opportunity for students to enhance their competitiveness within the classroom. This theoretical and empirical controversy, known as the grade retention controversy, has been extensively discussed in Díaz et al. (2021).

Finally, an examination of Figures 1, 3, 5, 7, 11, 13, and 15 suggests a marginally greater prominence of the relative contribution of circumstances in select instances when one circumstance variable is excluded compared to the baseline. This seemingly counterintuitive finding aligns with theoretical possibilities elaborated upon in detail in Appendix J.

5.4 Counterfactual Analysis using P90 – P10

Following Gamboa and Waltenberg (2012) and Carranza and Hojman (2015), an alternative measure of inequality is proposed, aiming to provide a better understanding of the importance of each individual variable. In this approach, the predicted outcome probability is estimated for all individuals using a baseline model. The focus then shifts to the differences in estimated probabilities between the 90th and 10th percentile (P90 – P10). This analysis serves to evaluate the magnitude of the variations in predicted outcomes between individuals characterized by high-quality circumstances and high levels of individual agency (90th percentile), compared to individuals with low-quality circumstances and low levels of individual agency (10th percentile).

In Table 8, we present the differences in the percentiles of the distribution for *all crime* and *juvenile crime*, which are independent of the normative view. As a benchmark, we include our two educational outcomes, namely *nongraduation* and *dropout*. Additionally, we provide details of the counterfactual outcomes obtained by estimating the model with all the data while setting one variable at a time to its highest possible value and estimating the probabilities. For each outcome, we report the distance between P90 and P10. The objective of this analysis is to understand if equalizing one variable at a time, while leaving the other variables fixed, alters the gap between high performers and low performers. This methodological strategy holds significant interest from a policy perspective as it facilitates the identification of variables with the greatest potential to reduce inequality, thereby informing policy interventions more effectively.

An analysis of the results leads to the following conclusions. Firstly, the differences in predicted outcomes between students with high-quality circumstances who exercise high levels of individual agency and students with low-quality circumstances who exert low levels of individual agency are moderate. The differences in the percentiles of distribution at the baseline for *all crime* and *juvenile crime* are 25.25% and 16.53% respectively. For the educational outcomes, the distance between P90 and P10 for *nongraduation* is 48.50%, while for *dropout* it is 51.00%. This difference in magnitude can be attributed to the fact that the unconditional probabilities in the crime variables are much lower compared to the educational variables. Consequently, even individuals with the lowest levels of circumstances and agency have relatively low probabilities of engaging in criminal activities, given that the expected probability of committing a crime or committing a crime as a juvenile at the 10th percentile is approximately 0%.

When considering the set of circumstance variables compared to the set of individual agency variables, equalizing a single circumstance across all individuals typically does not have a significant impact on the P90 - P10 metric. However, the most notable impact on the P90 - P10 metric is observed with differences in *standardized test score in language - school*. If this variable were equalized for all students, it would lead to a reduction of 2.73 percentage points in the P90 - P10 metric for *all crime* and 1.88 percentage points for *juvenile crime*. Moreover, *years of education of the mother - school* appears to contribute to a reduction in inequality of opportunity in educational outcomes. These findings align with the results presented in Subsection 5.3.

However, when it comes to agency, the variable *percentile grades* plays a crucial role in determining the P90 - P10 metric. It is important to note that, by definition, *percentile grades* cannot be equalized due to its nature as a percentile measure. Nonetheless, if hypothetically possible, equalizing this variable at the maximum level would result in a decrease of 5.86 percentage points in the P90 - P10 metric for *all crime* and 3.05 percentage points for *juvenile crime*.

Considering that the set of circumstance variables is more extensive than the set of individual agency variables, equalizing a single circumstance across all individuals typically does not lead to a significant impact on the P90 - P10 metric. The most substantial impact on the P90 - P10 metric is observed with differences in *standardized test score in language - school*. Equalizing this variable for all students would lead to a reduction of 2.73 percentage points in the P90 - P10 metric for *all crime* and 1.88 percentage points for *juvenile crime*. Additionally, *years education mother - school* appears to diminish inequality of opportunity in educational outcomes (5.65 percentage points in *nongraduation* and 5.76 percentage points in *dropout*).

When it comes to agency, the variable *percentile grades* plays a crucial role. Equalizing this variable at the maximum level would result in a decrease of 5.86 percentage points in the P90 - P10 metric for *all crime* and 3.05 percentage points for *juvenile crime*.[16] Furthermore, regarding educational outcomes, equalizing the *ever repeated* variable would result in a significant reduction of 17.49 percentage points in *nongraduation* and 17.83 percentage points in *dropout*. Overall, these results align with the findings presented in Subsection 5.3.

[16]It is important to note that by definition, *percentile grades* cannot be equalized due to its nature as a percentile measure.

Table 8: P90 - P10

	All Crime p90-p10	Juvenile Crime p90-p10	Nongraduation p90-p10	Dropout p90-p10
Baseline Circumstances and Agency	25.25%	16.53%	48.46%	51.00%
Public Health Insurance System – School	23.58%	15.83%	47.62%	50.06%
Household Income – School	27.75%	17.64%	51.97%	54.50%
School Fee - School	24.70%	16.38%	48.47%	51.01%
One Parent Indigenous - School	25.08%	16.53%	48.76%	51.33%
Standardized Test Score in Language – School	22.52%	14.65%	46.05%	48.38%
Standardized Test Score in Math - School	25.91%	17.12%	48.19%	50.66%
Years Education Mother – School	23.07%	15.17%	42.80%	45.24%
Rural School	25.61%	16.63%	48.65%	51.28%
Private School	25.27%	16.55%	48.50%	51.11%
All Crime – Old Generation	24.20%	15.82%	48.27%	50.70%
Juvenile Crime - Old Generation	24.74%	15.90%	48.17%	50.67%
Nongraduation - Old Generation	23.47%	15.23%	44.16%	46.48%
Percentile Grades	19.40%	13.47%	40.32%	42.40%
Ever Repeated	21.08%	13.48%	30.97%	33.17%
Percentage Attendance	23.04%	14.68%	43.93%	45.85%

Note: This table reports the differences in estimated probability between the 90th and 10th percentiles of the distribution of estimated probabilities for *all crime*, *juvenile crime*, *nongraduation* and *dropout*, under the two normative conceptions of inequality of opportunity. We include the baseline results and the counterfactual outcomes, which are obtained by estimating the model using the original data, equalizing one variable at a time to the highest possible value, and predicting the outcomes. The sample is made up of male students who were in the 1st grade for the first time in 2003.

6 Robustness Analysis

As part of our robustness check, we present a series of alternative specifications. The results of these specifications can be found in Appendix C. Table 12 provides an analysis of the relative contributions of circumstances and agency to crime outcomes, while Table 14 presents a similar analysis for education outcomes. Additionally, Tables 13 and 15 compare the differences between the alternative scenarios and the baseline scenarios. The variables used in each specification are listed in Table 16.

In the baseline model, we did not include circumstances at the individual level obtained from the SIMCE parent surveys. This decision was based on the fact that not all students take the SIMCE, and not all parents of participating students complete the survey. Additionally, it is likely that the decision to not take the exam or not fill out the survey, or both, may be related to the outcomes we are studying.

To address this limitation, we conducted a robustness check in which we included all variables at the school level and all circumstances at the individual level. As a result, the relative contribution of circumstances slightly increased: 2.54% in *all crime*, 3.32% in *juvenile crime*, 3.73% in *nongraduation*, and 3.49% in *dropout* when utilizing Barry's conception of equality of opportunity. These findings suggest two possibilities: either individual circumstances do not exert significant influence on crime outcomes, or individual circumstances are relatively homogeneous within schools. This implies that school characteristics already capture individual circumstances to some extent.

By incorporating the individual-level circumstances and observing only a marginal increase in the relative contribution of circumstances, our findings provide evidence supporting the significant role of school-level variables in explaining crime outcomes. Nevertheless, it is crucial to acknowledge that the influence of individual circumstances may still be present. In the baseline model, it is possible that these individual circumstances have already been captured to some extent by the school-level characteristics we have included in our analysis.

The second specification of our analysis includes individual test scores (as agency variables), specifically the results from the SIMCE math and SIMCE language tests. With the incorporation of these test scores, the relative contribution of agency increases by 1.79% in *all crime*, 0.66% in *juvenile crime*, 2.07% in *nongraduation*, and 1.66% in *dropout*, as per Barry's conception. This suggests that variables such as *percentile grades*, *ever repeated*, and *percentage attendance* already capture much of the information conveyed by the test results.

In the third specification, we replace circumstances at the school level with circumstances at the individual level. In comparison to the baseline scenario, the relative contribution of circumstances decreases. Under Barry's conception, the relative contribution of circumstances is 28.28% in *all crime* (11.30 percentage points lower than in the baseline scenario), 25.41% in *juvenile crime* (15.21 percentage points lower than in the main specification), 21.43% in *nongraduation* (4.58 percentage points lower than in the main specification), and 20.71% in *dropout* (5.31 percentage points lower than in the main specification). These results suggest that individual circumstances alone do not fully capture the influence of school and peer characteristics that may contribute to criminal behavior or poor educational performance.

Finally, the fourth specification incorporates both individual circumstances and individual test results. In comparison to the baseline scenario, the differences between Roemer and Barry widen, as indicated in Table 13 and Table 15. In *all crime*, the gap between Roemer and Barry increases to 7.76 percentage points, compared to 6.86 percentage points in the baseline scenario. Similarly, in *juvenile crime*, the gap widens to 7.95 percentage points from 7.65 percentage points in the baseline scenario. For *nongraduation*, the gap expands to 10.73 percentage points, in contrast to 8.79 percentage points in the baseline scenario. Finally, in *dropout*, the gap increases to 10.47 percentage points from 8.82 percentage points in the baseline scenario.

Finally, the fourth specification incorporates both individual circumstances and individual test results. Under this specification, the relative contribution of circumstances under Roemer increases more for all four outcome variables compared to the increase observed under Barry. As a result, the differences between Roemer and Barry widen, as indicated in Table 12 and Table 14. For instance, in *all crime*, the gap between Roemer and Barry is 7.76 percentage points, whereas it is 6.86 percentage points in the baseline scenario, in *juvenile crime*, the gap between Roemer and Barry is 7.95 percentage points, whereas it is 7.65 percentage points in the baseline scenario, in *nongraduation*, the gap between Roemer and Barry is 10.73 percentage points, whereas it is 8.79 percentage points in the baseline scenario, and in *dropout*, the gap between Roemer and Barry is 10.47 percentage points, whereas it is 8.82 percentage points in the baseline scenario.

In summary, while the relative contribution remains largely similar across these alternative scenarios, slight variations in the assessments of equality of opportunity may emerge. This highlights the importance of using the same selection of variables when comparing different countries or contexts. By maintaining consistency in the variables employed, we can ensure comparability and enhance the validity of international comparisons.

6.1 School Effects or Family Influence?

As previously discussed, the inclusion of individual circumstances in specification 1 does not result in a significant change in the relative contribution of circumstances. However, when considering only individual circumstances in specification 3, the relative contribution of circumstances decreases (especially in criminal outcomes). These findings suggest that school circumstances are likely more important than individual circumstances in explaining the outcomes, although there may be some overlap since there is little heterogeneity within schools.

To determine the exact contributions of school circumstances and individual circumstances, we extend Equation 7 and Equation 8 to consider circumstances at the school level, individual circumstances, and agency variables. Table 17 and Table 18 present the relative contribution of each factor under Barry's conception.

In *all crime*, school circumstances account for 31.57% of the relative contribution, individual circumstances contribute only 10.55%, and individual agency has the highest contribution at 57.88%. For *juvenile crime*, school circumstances explain 34.24% of the variance, individual circumstances account for 9.70%, and individual agency contributes 56.06%. In education outcomes, the relative contribution between school circumstances and individual circumstances is not as pronounced. For example, in the case of *nongraduation*, school circumstances explain 20.26% of the variance, individual circumstances contribute 9.48%, and individual agency accounts for 70.26%. Similarly, in *dropout*, school circumstances explain 20.81%, individual circumstances contribute 8.70%, and individual agency accounts for 70.49%.

These results suggest that equalizing school quality and reducing segregation at the school level would have a significant impact on reducing inequality of opportunity in the contexts of criminal justice and, to a lesser extent, education.

7 Conclusion

To the best of our knowledge, this paper represents the first study that examines juvenile criminal behavior using the conception of equality of opportunity developed by Roemer (1998). In this framework, the analysis of the studied outcome, namely criminal behavior and educational achievement, involves the consideration of circumstances and individual agency. Quantifying the relevance of each of these two determinants poses an empirical challenge due to the correlation between them. The treatment of this correlation has given rise to two distinct normative views: Roemer and Barry. Roemer's perspective treats the correlation as a circumstance, while Barry splits the correlation between circumstances and agency according to regression rules.

Using extensive administrative data from Chile, specifically focusing on males who are more prone to criminal behavior than females, we find that circumstances account for 46.44% of the inequality in the likelihood of being prosecuted up to the age of 22, as measured by Roemer's conception. This percentage decreases to 39.58% under Barry's conception. When examining the outcome of being prosecuted as a juvenile, the corresponding percentages are 48.27% for Roemer and 40.62% for Barry. As a benchmark, we apply the same approach to evaluate inequality of opportunity in education outcomes. For the case of not graduating, circumstances contribute 34.80% under Roemer's conception and 26.01% under Barry's conception. In the case of dropout, circumstances account for 34.84% under Roemer and 26.02% under Barry. These findings suggest a relatively lesser contribution of circumstances in the case of educational outcomes compared to criminal outcomes. Furthermore, we also demonstrate that equalizing specific variables, such as the standardized test score in language at the school level, has the potential to significantly reduce inequality in both criminal and educational outcomes, as measured by the P90-P10 metric.

In summary, this paper emphasizes the significant impact of circumstances, which are factors beyond an individual's control, on the criminal behavior and educational performance of young individuals. We also acknowledge the influence of variable classification, particularly in categorizing certain variables as agency rather than circumstances. This classification, such as grade retention in the early primary school grades, may introduce an upward bias in the relative contribution of agency. These findings should be carefully considered when developing policies related to punishment severity for young individuals involved in criminal activities.

The authors declare that they have no relevant or material financial interests that relate to the research described in this paper.

Data availability: The dataset analyzed during the current study is not publicly available due to the fact that it is private information. Information on how to obtain it and reproduce the analysis is available from the corresponding author on request.

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Appendix

A Variables' definition

Circumstances:

Female: This binary variable takes the value of 1 if the student is female and 0 otherwise.

Public Health Insurance System: This binary variable takes the value of 1 if the student was registered with the public health insurance system (*Fondo Nacional de Salud* or FONASA) in the first year they took the SIMCE test, and 0 otherwise.

Public Health Insurance System - School: Proportion of students within each school in 2006 who had the *Public Health Insurance System* variable equal to 1. Students are first grouped according to the school they attended in 2006, and then the proportion of students within each school with *Public Health Insurance System* equal to 1 is calculated. Other variables pertaining to the school level are computed in a similar manner.

Household Income: Household income in the first year of taking the SIMCE test, expressed in 2006 CLP. Categorized as *High* (300,000 CLP per month, approximately 566 USD) or *Low* (¡ 300,000 CLP per month).

Household Income - School: average *Household Income* within each school in 2006.

School Fee: The school fee variable represents the amount of money that students pay monthly to the school. The information is obtained from the 2006 SIMCE surveys. It is categorized as *High* if the fee is greater than or equal to 5,000 CLP per month (approximately 9.43 USD) and *Low* otherwise.

School Fee - School: average *School Fee* within each school in 2006.

One Parent Indigenous: This binary variable takes the value 1 if at least one parent of the student is indigenous, and 0 otherwise.

One Parent Indigenous - School: average *One Parent Indigenous* within each school in 2006.

Standardized Test Score in Language - School: This variable represents the average grade in the lecture exam on the 2006 national standardized test (*Sistema de Medición de Calidad de la*

Educación, SIMCE) within each school in 2006.

Standardized Test Score in Math - School: This variable represents the average grade in the math exam on the 2006 national standardized test (*Sistema de Medición de Calidad de la Educación*, SIMCE) within each school in 2006.

Years Education Mother: This variable represents the number of years of schooling the mother has. It is categorized as *High* if the mother's education is greater than or equal to 13 years, and *Low* otherwise.

Years Education Mother - School: This variable is calculated by averaging *Years Education Mother* within each school in 2006.

Rural School: This binary variable takes the value 1 if the school is classified as rural, and 0 otherwise.

Private School: This binary variable takes the value 1 if the student attended a private school in 2006, and 0 otherwise.

All Crime - Old Generation: This variable represents the fraction of 4th graders, among those who were attending the same school in 2003 as 1st graders, who were criminally prosecuted up to 2018.

Juvenile Crime - Old Generation: This variable represents the fraction of 4th graders, among those who were attending the same school in 2003 as 1st graders, who were criminally prosecuted as juveniles (typically up to 2011 or 2012).

Nongraduation - Old Generation: This variable represents the fraction of 4th graders, among those who were attending the same school in 2003 as 1st graders, who did not graduate from secondary school up to 2018.

Agency:

Percentile Grades: This variable represents the percentile that the student's grades occupy relative to their classmates between 2003 and 2010. It is calculated based on the student's grades compared to the grades of all the classmates they shared school with in 2003. The percentile ranges from 0 to 100%, where 0% indicates the lowest grade performance and 100% indicates the highest.

Ever Repeated: This binary variable takes the value 0 if the student successfully completed the

8 grades of primary school in 8 academic years, and 1 if the student had to repeat a grade or had an extended academic duration beyond 8 years.

Percentage Attendance: This variable represents the average attendance of the student to school during the 8 years from 2003 to 2010. The average is calculated only for the years in which the student was enrolled.

Standardized Test Score in Language: This variable represents grade in the lecture exam on the national standardized test (*Sistema de Medición de Calidad de la Educación*, SIMCE). The score used is from the first available year between 2006 and 2009, inclusive. It is categorized as *High* if the score is greater than or equal to 258.18, and *Low* otherwise.

Standardized Test Score in Math: This variable represents grade in the math exam on the national standardized test (*Sistema de Medición de Calidad de la Educación*, SIMCE). The score used is from the first available year between 2006 and 2009, inclusive. It is categorized as *High* if the score is greater than or equal to 251.92, and *Low* otherwise.

Outcomes:

All Crime: This binary variable takes the value 1 if the student was criminally charged up to 2018, which is typically when most students reach the age of 22 years old, and 0 otherwise.

Juvenile Crime: This binary variable takes the value 1 if the student was criminally charged between the ages of 14 and 17, and 0 otherwise.

Nongraduation: This binary variable takes the value 1 if the student did not graduate from high school between 2003 and 2018, indicating unsuccessful completion of their high school education, and 0 otherwise.

Dropout: This binary variable takes the value 1 if the student was out of school for at least two consecutive years between 2010 and 2014 or did not graduate, and 0 otherwise.

B Correlation Matrix

Table 9: Pairwise correlations for male students (part 1)

Variables	Public Health Insurance System	Public Health Insurance System - School	Household Income	Household Income - School	School Fee	School Fee - School	One Parent Indigenous	One Parent Indigenous - School
Public Health Insurance System	1							
Public Health Insurance System - School	0.6249*	1						
Household Income	-0.6162*	-0.7707*	1					
Household Income - School	-0.5793*	-0.9265*	0.8310*	1				
School Fee	-0.5445*	-0.8566*	0.7788*	0.9171*	1			
School Fee - School	-0.5542*	-0.8889*	0.7899*	0.9523*	0.9628*	1		
One Parent Indigenous	0.1076*	0.1354*	-0.1253*	-0.1292*	-0.1130*	-0.1195*	1	
One Parent Indigenous - School	0.1921*	0.3065*	-0.2467*	-0.2908*	-0.2687*	-0.2686*	0.4467*	1
Standardized Test Score in Language - School	-0.4151*	-0.6552*	0.5273*	0.6236*	0.5827*	0.5928*	-0.1214*	-0.2708*
Standardized Test Score in Math - School	-0.4216*	-0.6682*	0.5298*	0.6309*	0.5834*	0.5970*	-0.1456*	-0.3293*
Years Education Mother	-0.4076*	-0.5299*	0.4965*	0.4899*	0.4326*	0.4520*	-0.1729*	-0.2690*
Years Education Mother - School	-0.5230*	-0.8281*	0.6415*	0.7663*	0.6914*	0.7096*	-0.1889*	-0.4256*
Rural School	0.1447*	0.2251*	-0.1602*	-0.1923*	-0.1435*	-0.1517*	0.1089*	0.2225*
Private School	-0.4348*	-0.7041*	0.7050*	0.8500*	0.8504*	0.8830*	-0.0823*	-0.1850*
All Crime - Old Generation	0.2333*	0.3422*	-0.2829*	-0.3176*	-0.3165*	-0.3179*	0.0763*	0.1506*
Juvenile Crime - Old Generation	0.2005*	0.2926*	-0.2445*	-0.2718*	-0.2683*	-0.2681*	0.0569*	0.1154*
Nongraduation - Old Generation	0.3331*	0.4961*	-0.3757*	-0.4311*	-0.3903*	-0.3993*	0.1259*	0.2624*
Percentile Grades	-0.0530*	-0.0293*	0.0218*	0.0202*	-0.0384*	0.0163*	-0.0160*	-0.0094*
Ever Repeated	0.1011*	0.1495*	-0.0883*	-0.1367*	-0.0583*	-0.1234*	0.0315*	0.0723*
Percentage Attendance	-0.0445*	-0.0744*	0.0448*	0.0746*	0.0356*	0.0726*	-0.0129*	-0.0461*
Standardized Test Score in Language	-0.2314*	-0.3225*	0.2798*	0.3051*	0.2613*	0.2902*	-0.0585*	-0.1313*
Standardized Test Score in Math	-0.2504*	-0.3579*	0.3029*	0.3356*	0.2841*	0.3166*	-0.0797*	-0.1703*
All Crime	0.1018*	0.1300*	-0.1002*	-0.1140*	-0.0914*	-0.1100*	0.0342*	0.0617*
Juvenile Crime	0.0844*	0.1066*	-0.0814*	-0.0940*	-0.0733*	-0.0903*	0.0234*	0.0440*
Nongraduation	0.1339*	0.1936*	-0.1297*	-0.1653*	-0.1132*	-0.1522*	0.0367*	0.0953*
Dropout	0.1377*	0.1969*	-0.1325*	-0.1683*	-0.1161*	-0.1551*	0.0394*	0.0954*

Table 10: Pairwise correlations for male students (part 2)

Variables	Standardized Test Score in Language - School	Standardized Test Score in Math - School	Years Education Mother	Years Education Mother - School	Rural School	Private School	All Crime - Old Generation	Juvenile Crime - Old Generation	Nongraduation - Old Generation
Public Health Insurance System									
Public Health Insurance System - School									
Household Income									
Household Income - School									
School Fee									
School Fee - School									
One Parent Indigenous									
One Parent Indigenous - School									
Standardized Test Score in Language - School	1								
Standardized Test Score in Math - School	0.9193*	1							
Years Education Mother	0.4435*	0.4656*	1						
Years Education Mother - School	0.6882*	0.7245*	0.6405*	1					
Rural School	-0.1303*	-0.2078*	-0.2772*	-0.3930*	1				
Private School	0.4391*	0.4374*	0.3175*	0.5037*	-0.0834*	1			
All Crime - Old Generation	-0.3710*	-0.3373*	-0.2111*	-0.3036*	-0.1309*	-0.2375*	1		
Juvenile Crime - Old Generation	-0.3277*	-0.2968*	-0.1906*	-0.2671*	-0.1318*	-0.1951*	0.6956*	1	
Nongraduation - Old Generation	-0.5160*	-0.5316*	-0.4414*	-0.6264*	0.2882*	-0.2514*	0.3838*	0.3667*	1
Percentile Grades	0.0567*	0.0600*	0.1555*	0.0429*	-0.0123*	0.0066*	0.0137*	0.0104*	0.0067*
Ever Repeated	-0.1764*	-0.1826*	-0.1982*	-0.1791*	0.0473*	-0.0877*	0.0883*	0.0858*	0.1648*
Percentage Attendance	0.1516*	0.1393*	0.0951*	0.1022*	0.0293*	0.0491*	-0.0911*	-0.0904*	-0.1254*
Standardized Test Score in Language	0.4629*	0.4329*	0.3117*	0.3428*	-0.0804*	0.2143*	-0.1868*	-0.1695*	-0.2712*
Standardized Test Score in Math	0.4716*	0.5084*	0.3497*	0.3910*	-0.1305*	0.2321*	-0.1886*	-0.1700*	-0.3035*
All Crime	-0.1556*	-0.1476*	-0.1328*	-0.1421*	-0.0094*	-0.0741*	0.1172*	0.1072*	0.1351*
Juvenile Crime	-0.1350*	-0.1255*	-0.1071*	-0.1172*	-0.0231*	-0.0604*	0.1101*	0.1058*	0.1207*
Nongraduation	-0.2354*	-0.2363*	-0.2431*	-0.2500*	0.0746*	-0.0925*	0.1275*	0.1233*	0.2461*
Dropout	-0.2411*	-0.2412*	-0.2435*	-0.2524*	0.0697*	-0.0942*	0.1340*	0.1289*	0.2496*

Table 11: Pairwise correlations for male students (part 3)

Variables	Percentile Grades	Ever Repeated	Percentage Attendance	Standardized Test Score in Language	Standardized Test Score in Math	All Crime	Juvenile Crime	Nongraduation	Dropout
Public Health Insurance System									
Public Health Insurance System - School									
Household Income									
Household Income - School									
School Fee									
School Fee - School									
One Parent Indigenous									
One Parent Indigenous - School									
Standardized Test Score in Language - School									
Standardized Test Score in Math - School									
Years Education Mother									
Years Education Mother - School									
Rural School									
Private School									
All Crime - Old Generation									
Juvenile Crime - Old Generation									
Nongraduation - Old Generation									
Percentile Grades	1								
Ever Repeated	-0.5233*	1							
Percentage Attendance	0.2969*	-0.3099*	1						
Standardized Test Score in Language	0.5125*	-0.3508*	0.1407*	1					
Standardized Test Score in Math	0.5422*	-0.3910*	0.1660*	0.7651*	1				
All Crime	-0.1831*	0.1838*	-0.1452*	-0.1715*	-0.1722*	1			
Juvenile Crime	-0.1505*	0.1642*	-0.1382*	-0.1407*	-0.1381*	0.6865*	1		
Nongraduation	-0.3193*	0.4020*	-0.2737*	-0.2636*	-0.2955*	0.3193*	0.2918*	1	
Dropout	-0.3242*	0.4049*	-0.2857*	-0.2665*	-0.2985*	0.3263*	0.3010*	0.9431*	1

Note: This table displays the pairwise correlations between circumstances, agency and outcome variables. The sample used consists of 122,102 male individuals which represent our baseline sample. * indicates correlation is significant at the 0.01 level

C Scenario Analysis

Table 12: Scenario Analysis (criminal outcomes)

Specification	Observations	Norm	All Crime		Juvenile Crime	
			Circumstances	Agency	Circumstances	Agency
0. Baseline	122,102	Roemer	46.44%	53.56%	48.27%	51.73%
		Barry	39.58%	60.42%	40.62%	59.38%
1. Baseline + Individual Circumstances	86,091	Roemer	49.14%	50.86%	51.52%	48.48%
		Barry	42.12%	57.88%	43.94%	56.06%
2. Baseline + Individual Test Scores	109,356	Roemer	45.04%	54.96%	47.24%	52.76%
		Barry	37.79%	62.21%	39.96%	60.04%
3. Baseline - School Circ. + Individual Circumstances	86,091	Roemer	36.03%	63.97%	33.14%	66.86%
		Barry	28.28%	71.72%	25.41%	74.59%
4. Baseline + Ind. Circ. + Individual Test Scores	84,679	Roemer	48.83%	51.17%	51.17%	48.83%
		Barry	41.07%	58.93%	43.21%	56.79%

Note: This table recapitulates the share of outcome inequalities explained by circumstances and agency in the two normative frameworks under four robustness scenarios using as sample male students who in 2003 were doing 1st grade for the first time . The first column contains the specification. Table 16 provides a detailed overview of the variables included in each specification. The second column informs the number of observations. The last columns recapitulate the relative contribution of circumstances and agency in the two frameworks for each of the outcomes.

Table 13: Differences with baseline scenario (criminal outcomes)

Specification	Observations	Norm	All Crime		Juvenile Crime	
			Circumstances	Agency	Circumstances	Agency
1. Baseline	86,091	Roemer	2.70%	-2.70%	3.25%	-3.25%
+ Individual Circumstances		Barry	2.54%	-2.54%	3.32%	-3.32%
2. Baseline	109,356	Roemer	-1.40%	1.40%	-1.03%	1.03%
+ Individual Test Scores		Barry	-1.79%	1.79%	-0.66%	0.66%
3. Baseline - School Circ.	86,091	Roemer	-10.41%	10.41%	-15.13%	15.13%
+ Individual Circumstances		Barry	-11.30%	11.30%	-15.21%	15.21%
4. Baseline + Ind. Circ.	84,679	Roemer	2.39%	-2.39%	2.90%	-2.90%
+ Individual Test Scores		Barry	1.49%	-1.49%	2.59%	-2.59%

Note: This table recapitulates the differences in share of outcome inequalities explained by circumstances and agency in the two normative frameworks under four robustness scenarios with respect to the baseline scenario. The population are male students who in 2003 were doing 1st grade for the first time . The first column contains the specification. Table 16 provides a detailed overview of the variables included in each specification. The second column informs the number of observations. The last columns recapitulate the relative contribution of circumstances and agency in the two frameworks for each of the outcomes.

Table 14: Scenario Analysis (educational outcomes)

Specification	Observations	Norm	Nongraduation		Dropout	
			Circumstances	Agency	Circumstances	Agency
0. Baseline	122,102	Roemer	34.80%	65.20%	34.84%	65.16%
		Barry	26.01%	73.99%	26.02%	73.98%
1. Baseline + Individual circumstances	86,091	Roemer	38.55%	61.45%	38.30%	61.70%
		Barry	29.74%	70.26%	29.51%	70.49%
2. Baseline + Individual Test Scores	109,356	Roemer	33.36%	66.64%	33.60%	66.40%
		Barry	23.94%	76.06%	24.36%	75.64%
3. Baseline - School Circ. + Individual Circumstances	86,091	Roemer	29.79%	70.21%	28.92%	71.08%
		Barry	21.43%	78.57%	20.71%	79.29%
4. Baseline + Ind. Circ. + Individual Test Scores	84,679	Roemer	38.07%	61.93%	37.87%	62.13%
		Barry	27.34%	72.66%	27.40%	72.60%

Note: This table recapitulates the share of outcome inequalities explained by circumstances and agency in the two normative frameworks under four robustness scenarios using as population male students who in 2003 were doing 1st grade for the first time . The first column contains the specification. Table 16 provides a detailed overview of the variables included in each specification. The second column informs the number of observations. The last columns recapitulate the relative contribution of circumstances and agency in the two frameworks for each of the outcomes.

Table 15: Differences with baseline scenario (educational outcomes)

Specification	Observations	Norm	Nongraduation		Dropout	
			Circumstances	Agency	Circumstances	Agency
1. Baseline	86,091	Roemer	3.75%	-3.75%	3.46%	-3.46%
+ Individual Circumstances		Barry	3.73%	-3.73%	3.49%	-3.49%
2. Baseline	109,356	Roemer	-1.44%	1.44%	-1.24%	1.24%
+ Individual Test Scores		Barry	-2.07%	2.07%	-1.66%	1.66%
3. Baseline - School Circ.	86,091	Roemer	-5.01%	5.01%	-5.92%	5.92%
+ Individual Circumstances		Barry	-4.58%	4.58%	-5.31%	5.31%
4. Baseline + Ind. Circ.	84,679	Roemer	3.27%	-3.27%	3.03%	-3.03%
+ Individual Test Scores		Barry	1.33%	-1.33%	1.38%	-1.38%

Note: This table recapitulates the differences in share of outcome inequalities explained by circumstances and agency in the two normative frameworks under four robustness scenarios with respect to the baseline scenario. The population are male students who in 2003 were doing 1st grade for the first time. The first column contains the specification. Table 16 provides a detailed overview of the variables included in each specification. The second column informs the number of observations. The last columns recapitulate the relative contribution of circumstances and agency in the two frameworks for each of the outcomes.

Table 16: Variables used on each scenario

Specification	Variables
0. Baseline	**Circumstances:** Public Health Insurance System - School, Household Income - School, School Fee - School, One Parent Indigenous - School, Standardized Test Score in Language - School, Standardized Test Score in Math - School, Years Education Mother - School, Rural School, Private School, All Crime - Old Generation, Juvenile Crime - Old Generation, Nongraduation - Old Generation **Agency:** Percentile Grades, Ever Repeated, Percentage Attendance
1. Baseline + Individual Circumstances	**Circumstances:** Public Health Insurance System, Public Health Insurance System - School, Household Income, Household Income - School, School Fee - School, One Parent Indigenous, One Parent Indigenous - School, Standardized Test Score in Language - School, Standardized Test Score in Math - School, Years Education Mother, Years Education Mother - School, Rural School, Private School, All Crime - Old Generation, Juvenile Crime - Old Generation, Nongraduation - Old Generation **Agency:** Percentile Grades, Ever Repeated, Percentage Attendance
2. Baseline + Individual Test Scores	**Circumstances:** Public Health Insurance System - School, Household Income - School, School Fee - School, One Parent Indigenous - School, Standardized Test Score in Language - School, Standardized Test Score in Math - School, Years Education Mother - School, Rural School, Private School, All Crime - Old Generation, Juvenile Crime - Old Generation, Nongraduation - Old Generation **Agency:** Percentile Grades, Ever Repeated, Percentage Attendance, Standardized Test Score in Language, Standardized Test Score in Math
3. Baseline - School Circumstances + Individual Circumstances	**Circumstances:** Public Health Insurance System, Household Income, One Parent Indigenous, Years Education Mother **Agency:** Percentile Grades, Ever Repeated, Percentage Attendance
4. Baseline + Individual Circumstances + Individual Test Scores	**Circumstances:** Public Health Insurance System, Public Health Insurance System - School, Household Income, Household Income - School, School Fee - School, One Parent Indigenous, One Parent Indigenous - School, Standardized Test Score in Language - School, Standardized Test Score in Math - School, Years Education Mother, Years Education Mother - School, Rural School, Private School, All Crime - Old Generation, Juvenile Crime - Old Generation, Nongraduation - Old Generation **Agency:** Percentile Grades, Ever Repeated, Percentage Attendance, Standardized Test Score in Language, Standardized Test Score in Math

Note: This table provides a comprehensive description of the variables employed in each scenario.

Table 17: Relative contribution of factors under Barry (Specification 1 - criminal outcomes)

Factor	Variables	All Crime	Juvenile Crime
Circumstances - School	Public Health Insurance System - School, Household Income - School, School Fee - School, One Parent Indigenous - School, Standardized Test Score in Language - School, Standardized Test Score in Math - School, Years Education Mother - School, Rural School, Private School, All Crime - Old Generation, Juvenile Crime - Old Generation, Nongraduation - Old Generation	31.57%	34.24%
		[28.00% ; 34.94%]	[30.62% ; 38.00%]
Individual Circumstances	Public Health Insurance System, Household Income, One Parent Indigenous, Years Education Mother	10.55%	9.70%
		[8.35% ; 13.01%]	[7.61% ; 12.40%]
Agency	Percentile Grades, Ever Repeated, Percentage Attendance	57.88%	56.06%
		[55.55% ; 60.32%]	[52.99% ; 59.08%]

Note: This table recapitulates the relative contribution of each factor for *All Crime* and *Juvenile Crime* under Barry. The population are male students who in 2003 were doing 1st grade for the first time. The first column contains the factor, the second column specifies the variables and the last columns summarize the relative contribution of each factor. In brackets we report the 95% bootstrap confidence interval.

Table 18: Relative contribution of factors under Barry (Specification 1 - educational outcomes)

Factor	Variables	Nongraduation	Dropout
Circumstances - School	Public Health Insurance System - School, Household Income - School, School Fee - School, One Parent Indigenous - School, Standardized Test Score in Language - School, Standardized Test Score in Math - School, Years Education Mother - School, Rural School, Private School, All Crime - Old Generation, Juvenile Crime - Old Generation, Nongraduation - Old Generation	20.26%	20.81%
		[18.91% ; 22.37%]	[19.35% ; 22.81%]
Individual Circumstances	Public Health Insurance System, Household Income, One Parent Indigenous, Years Education Mother	9.48%	8.70%
		[8.03% ; 10.98%]	[7.44% ; 9.88%]
Agency	Percentile Grades, Ever Repeated, Percentage Attendance	70.26%	70.49%
		[68.93% ; 71.73%]	[68.84% ; 71.93%]

Note: This table recapitulates the relative contribution of each factor for *Nongraduation* and *Dropout* under Barry. The population are male students who in 2003 were doing 1st grade for the first time. The first column contains the factor, the second column specifies the variables and the last columns summarize the relative contribution of each factor. In brackets we report the 95% bootstrap confidence interval.

D Main regressions (male students)

Table 19: *All Crime* main regressions (male students)

	All Crime	
	Roemer (1)	Barry (2)
Public Health Insurance System - School	0.0547***	0.0593***
	(0.000)	(0.000)
Household Income - School	6.50e-08***	5.98e-08***
	(0.000)	(0.000)
School Fee - School	-0.000000127	-0.000000234
	(0.417)	(0.134)
One Parent Indigenous - School	0.0162*	0.0201**
	(0.033)	(0.008)
Standardized Test School in Language - School	-0.00106***	-0.000875***
	(0.000)	(0.000)
Standardized Test School in Math - School	-0.0000148	0.000154
	(0.873)	(0.097)
Years Education Mother - School	-0.0112***	-0.00832***
	(0.000)	(0.000)
Rural School	-0.0588***	-0.0520***
	(0.000)	(0.000)
Private School	-0.00338	0.00104
	(0.740)	(0.919)
All Crime - Old Generation	0.150***	0.164***
	(0.000)	(0.000)
Juvenile Crime - Old Generation	0.167***	0.154***
	(0.000)	(0.000)
Nongraduation - Old Generation	0.131***	0.126***
	(0.000)	(0.000)
Percentile Grades (Roemer residual)	-0.00154***	
	(0.000)	
Ever Repeated (Roemer residual)	0.0567***	
	(0.000)	
Percentage Attendance (Roemer residual)	-0.00495***	
	(0.000)	
Percentile Grades		-0.00154***
		(0.000)
Ever Repeated		0.0567***
		(0.000)
Percentage Attendance		-0.00495***
		(0.000)
Constant	0.439***	0.835***
	(0.000)	(0.000)
Observations	122,102	122,102
R-squared	0.074	0.074
F	648.4	648.4

Note: This table reports coefficients and standard errors (in parentheses) of the main regressions in Roemer and Barry specifications when the outcome is *all crime* and we are using the baseline scenario. The last three rows contain the number of observations, R-squared of the model and the F-value. The definition of variables is in Appendix A. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 20: *Juvenile Crime* main regressions (male students)

	Juvenile Crime	
	Roemer (1)	Barry (2)
Public Health Insurance System - School	0.0186 (0.051)	0.0239* (0.012)
Household Income - School	3.00e-08** (0.002)	2.77e-08** (0.004)
School Fee - School	6.23e-09 (0.958)	-5.98e-08 (0.610)
One Parent Indigenous - School	-0.00406 (0.478)	-0.00198 (0.730)
Standardized Test School in Language - School	-0.000742*** (0.000)	-0.000611*** (0.000)
Standardized Test School in Math - School	0.0000370 (0.595)	0.000146* (0.036)
Years Education Mother - School	-0.00743*** (0.000)	-0.00549*** (0.000)
Rural School	-0.0481*** (0.000)	-0.0429*** (0.000)
Private School	-0.000927 (0.903)	0.00177 (0.816)
All Crime - Old Generation	0.0935*** (0.000)	0.101*** (0.000)
Juvenile Crime - Old Generation	0.185*** (0.000)	0.174*** (0.000)
Nongraduation - Old Generation	0.102*** (0.000)	0.0934*** (0.000)
Percentile Grades (Roemer residual)	-0.000839*** (0.000)	
Ever Repeated (Roemer residual)	0.0426*** (0.000)	
Percentage Attendance (Roemer residual)	-0.00399*** (0.000)	
Percentile Grades		-0.000839*** (0.000)
Ever Repeated		0.0426*** (0.000)
Percentage Attendance		-0.00399*** (0.000)
Constant	0.283*** (0.000)	0.599*** (0.000)
Observations	122,102	122,102
R-squared	0.058	0.058
F	502.3	502.3

Note: This table reports coefficients and standard errors (in parentheses) of the main regressions in Roemer and Barry specifications when the outcome is *juvenile crime* and we are using the baseline scenario. The last three rows contain the number of observations, R-squared of the model and the F-value. The definition of variables is in Appendix A. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 21: *Nongraduation* main regressions (male students)

	Nongraduation	
	Roemer (1)	Barry (2)
Public Health Insurance System - School	0.0134	0.0280*
	(0.268)	(0.021)
Household Income - School	8.67e-08***	8.46e-08***
	(0.000)	(0.000)
School Fee - School	0.000000283	6.15e-09
	(0.057)	(0.967)
One Parent Indigenous - School	-0.0359***	-0.0296***
	(0.000)	(0.000)
Standardized Test School in Language - School	-0.00114***	-0.000762***
	(0.000)	(0.000)
Standardized Test School in Math - School	-0.000455***	-0.0000728
	(0.000)	(0.410)
Years Education Mother - School	-0.0284***	-0.0219***
	(0.000)	(0.000)
Rural School	-0.0251***	-0.00904**
	(0.000)	(0.007)
Private School	-0.00736	0.00301
	(0.447)	(0.756)
All Crime - Old Generation	0.0173	0.0365
	(0.367)	(0.057)
Juvenile Crime - Old Generation	0.168***	0.124***
	(0.000)	(0.000)
Nongraduation - Old Generation	0.324***	0.278***
	(0.000)	(0.000)
Percentile Grades (Roemer residual)	-0.00195***	
	(0.000)	
Ever Repeated (Roemer residual)	0.205***	
	(0.000)	
Percentage Attendance (Roemer residual)	-0.0105***	
	(0.000)	
Percentile Grades		-0.00195***
		(0.000)
Ever Repeated		0.205***
		(0.000)
Percentage Attendance		-0.0105***
		(0.000)
Constant	0.785***	1.533***
	(0.000)	(0.000)
Observations	122,102	122,102
R-squared	0.242	0.242
F	2593.2	2593.2

Note: This table reports coefficients and standard errors (in parentheses) of the main regressions in Roemer and Barry specifications when the outcome is *Nongraduation* and we are using the baseline scenario. The last three rows contain the number of observations, R-squared of the model and the F-value. The definition of variables is in Appendix A. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

Table 22: *Dropout* main regressions (male students)

	Dropout	
	Roemer (1)	Barry (2)
Public Health Insurance System - School	0.0140	0.0312*
	(0.263)	(0.013)
Household Income - School	8.73e-08***	8.51e-08***
	(0.000)	(0.000)
School Fee - School	0.000000285	4.21e-09
	(0.063)	(0.978)
One Parent Indigenous - School	-0.0392***	-0.0327***
	(0.000)	(0.000)
Standardized Test School in Language - School	-0.00124***	-0.000833***
	(0.000)	(0.000)
Standardized Test School in Math - School	-0.000488***	-0.0000892
	(0.000)	(0.329)
Years Education Mother - School	-0.0292***	-0.0223***
	(0.000)	(0.000)
Rural School	-0.0318***	-0.0142***
	(0.000)	(0.000)
Private School	-0.00308	0.00753
	(0.758)	(0.451)
All Crime - Old Generation	0.0364	0.0564**
	(0.066)	(0.004)
Juvenile Crime - Old Generation	0.182***	0.135***
	(0.000)	(0.000)
Nongraduation - Old Generation	0.341***	0.291***
	(0.000)	(0.000)
Percentile Grades (Roemer residual)	-0.00206***	
	(0.000)	
Ever Repeated (Roemer residual)	0.210***	
	(0.000)	
Percentage Attendance (Roemer residual)	-0.0118***	
	(0.000)	
Percentile Grades		-0.00206***
		(0.000)
Ever Repeated		0.210***
		(0.000)
Percentage Attendance		-0.0118***
		(0.000)
Constant	0.840***	1.703***
	(0.000)	(0.000)
Observations	122,102	122,102
R-squared	0.250	0.250
F	2706.9	2706.9

Note: This table reports coefficients and standard errors (in parentheses) of the main regressions in Roemerand Barry specifications when the outcome is *dropout* and we are using the baseline scenario. The last three rows contain the number of observations, R-squared of the model and the F-value. The definition of variables is in Appendix A. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively.

E Auxiliar regressions (male students)

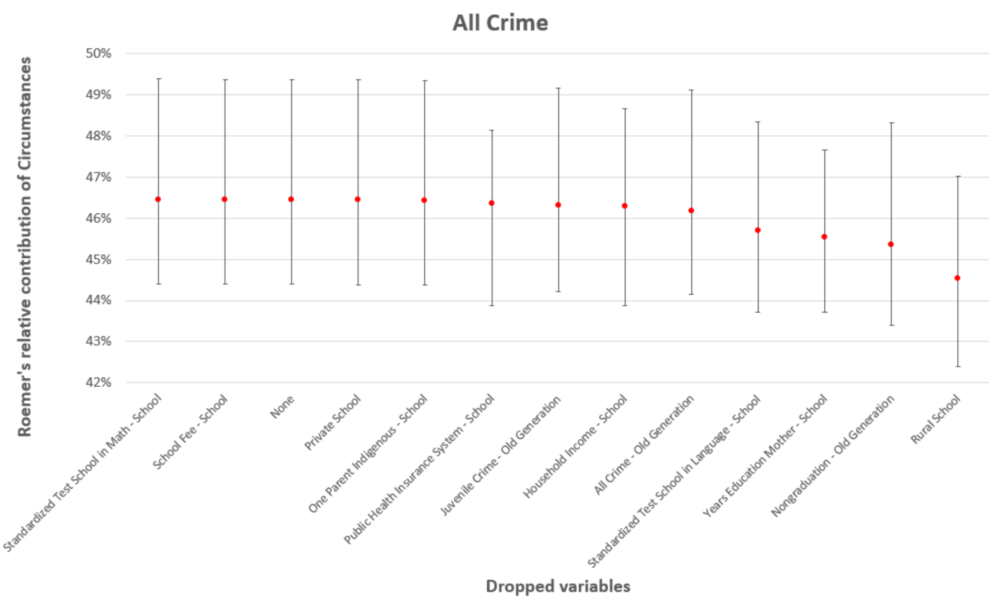
Table 23: Auxiliar Roemer regressions (male students)

All Crime, Juvenile Crime, Nongraduation, Dropout			
	Percentile grades	Ever repeated	Percentage Attendance
	(4)	(5)	(6)
Public Health Insurance System - School	-3.763***	0.00196	2.137***
	(0.000)	(0.903)	(0.000)
Household Income - School	-0.00000510***	-2.69e-08	0.000000219
	(0.000)	(0.097)	(0.174)
School Fee - School	-0.0000413**	0.00000122***	0.00000519**
	(0.002)	(0.000)	(0.008)
One Parent Indigenous - School	2.464***	-0.0163	-0.170
	(0.000)	(0.093)	(0.076)
Standardized Test School in Language - School	0.0354***	-0.000437***	0.0207***
	(0.000)	(0.001)	(0.000)
Standardized Test School in Math - School	0.0582***	-0.00120***	0.00222
	(0.000)	(0.000)	(0.056)
Years Education Mother - School	0.895***	-0.0179***	0.105***
	(0.000)	(0.000)	(0.000)
Rural School	0.497	-0.0279***	0.899***
	(0.088)	(0.000)	(0.000)
Private School	1.815*	-0.0401**	-0.133
	(0.032)	(0.002)	(0.298)
All Crime - Old Generation	9.299***	-0.0169	-0.229
	(0.000)	(0.509)	(0.366)
Juvenile Crime - Old Generation	2.859	0.139**	-1.943***
	(0.330)	(0.002)	(0.000)
Nongraduation - Old Generation	12.98***	0.226***	-2.479***
	(0.000)	(0.000)	(0.000)
Constant	13.85***	0.835***	85.24***
	(0.000)	(0.000)	(0.000)
Observations	122,102	122,102	122,102
R-squared	0.008	0.042	0.033
F	83.27	449.0	349.6

Note: This table reports coefficients and standard errors (in parentheses) of the auxiliary regressions in Roemer specifications for any of the four outcomes. The last three rows contain the number of observations, R-squared of the model and the F-value. The definition of variables is in Appendix A. ***, ** and * indicate statistical significance at 1%, 5% and 10% respectively

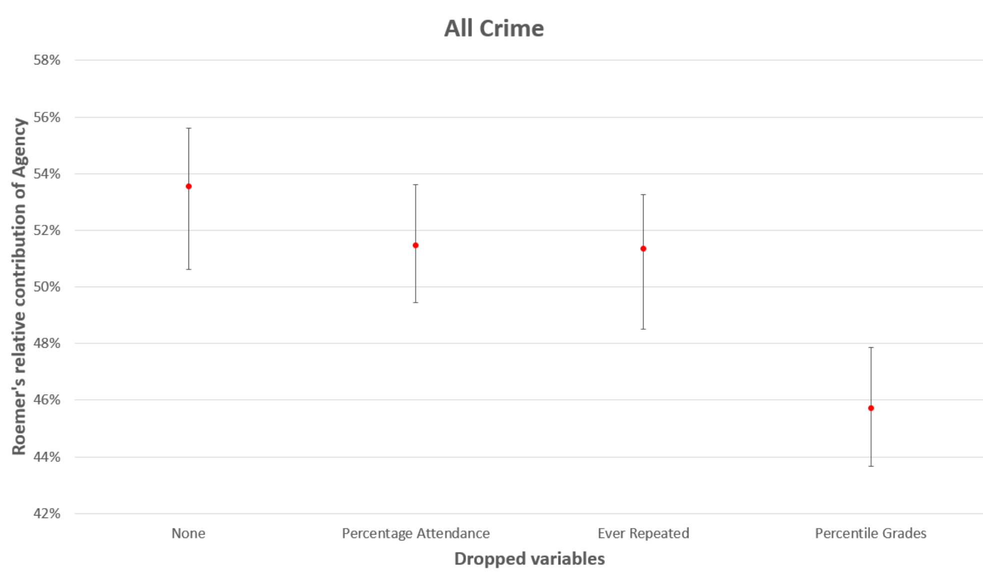
F The impact of variables on *All Crime* (male students)

Figure 1: Effect of dropping one variable on Roemer's relative contribution of circumstances



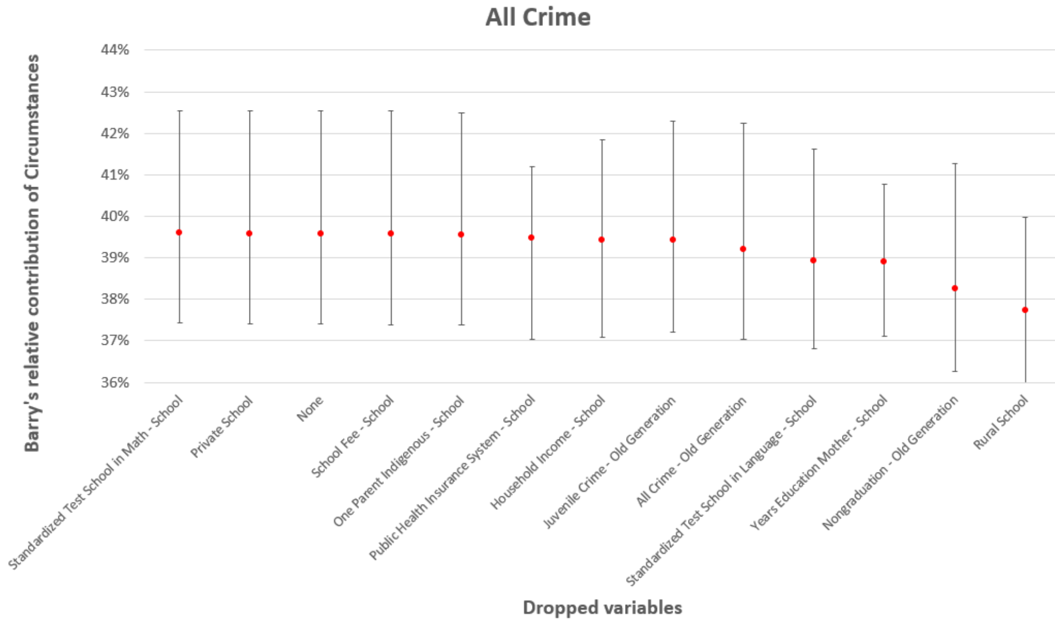
Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}^j_C, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

Figure 2: Effect of dropping one variable on Roemer's relative contribution of agency



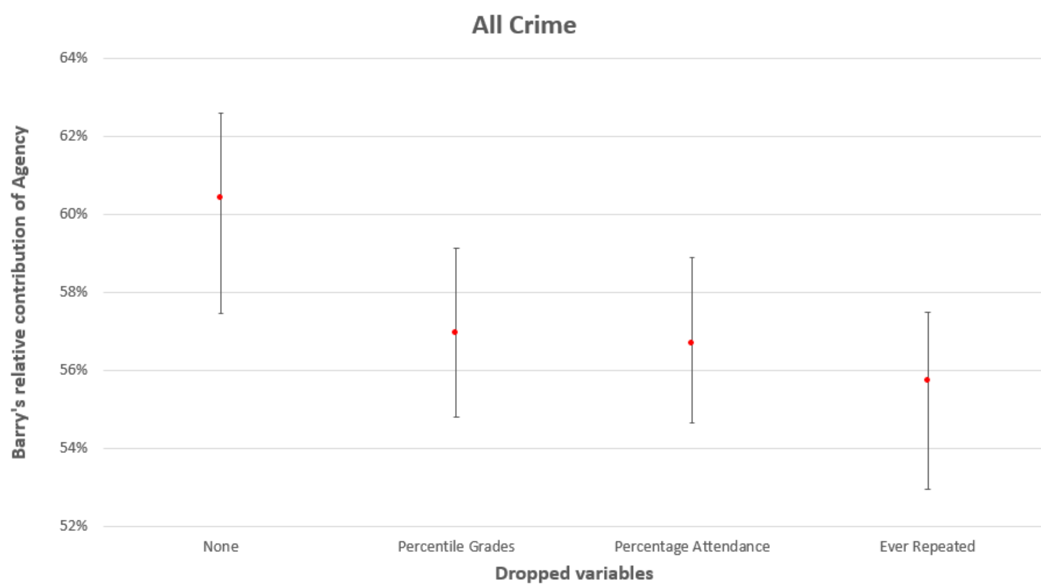
Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}^j_A, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

Figure 3: Effect of dropping one variable on Barry's relative contribution of circumstances



Notes: This table reports the effects of dropping one variable at a time on $\text{cov}\left(\hat{O}^j_C, \hat{O}^j\right) / \text{cov}\left(\hat{O}^j, \hat{O}^j\right)$

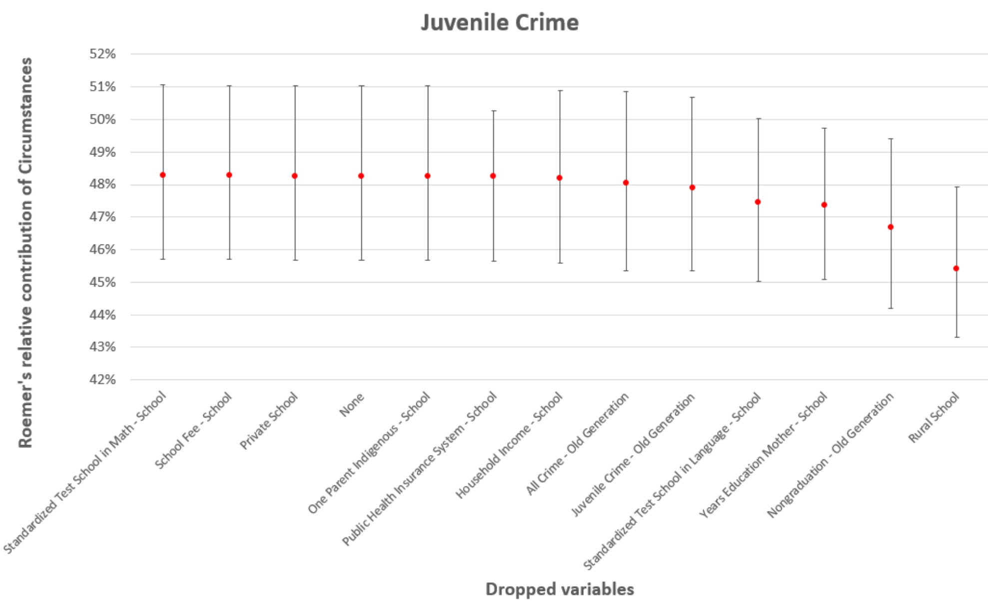
Figure 4: Effect of dropping one variable on Barry's relative contribution of agency



Notes: This table reports the effects of dropping one variable at a time on $\text{cov}\left(\hat{O}^j_A, \hat{O}^j\right) / \text{cov}\left(\hat{O}^j, \hat{O}^j\right)$

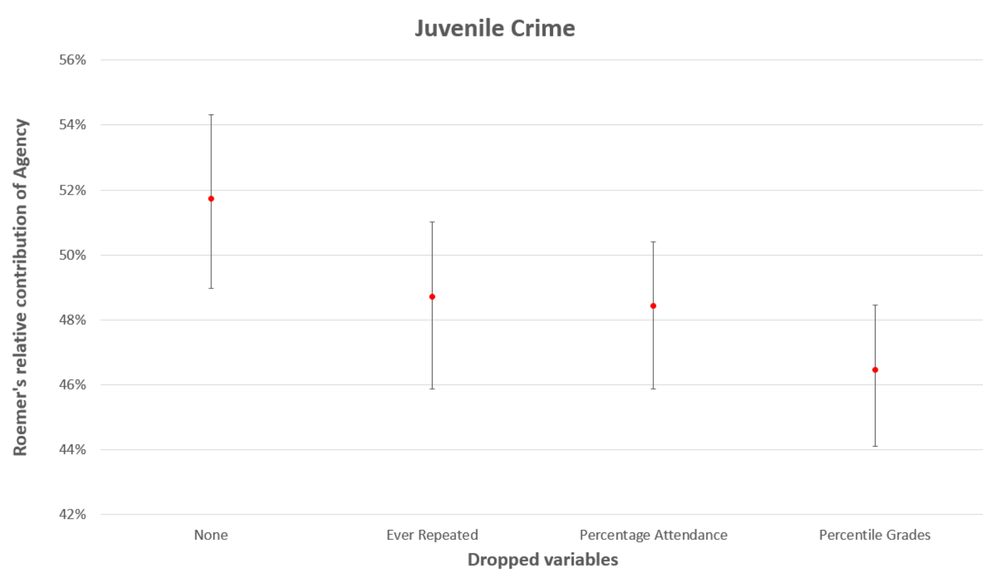
G The impact of variables on *Juvenile Crime*

Figure 5: Effect of dropping one variable on Roemer's relative contribution of circumstances



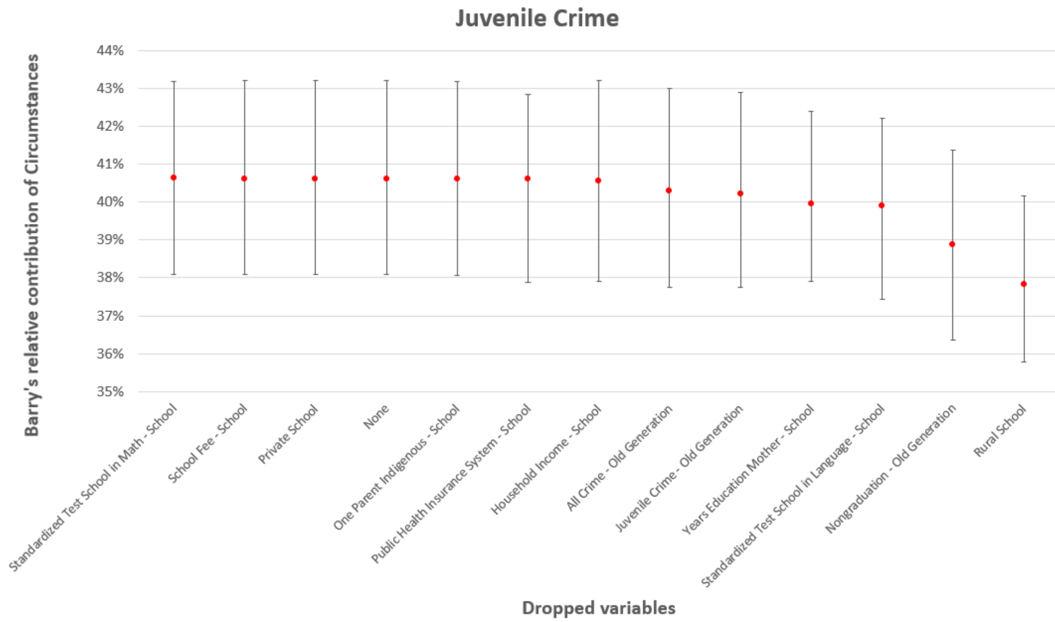
Notes: This table reports the effects of dropping one variable at a time on $\text{cov}\left(\hat{O}^j_C, \hat{O}^j\right) / \text{cov}\left(\hat{O}^j, \hat{O}^j\right)$

Figure 6: Effect of dropping one variable on Roemer's relative contribution of agency



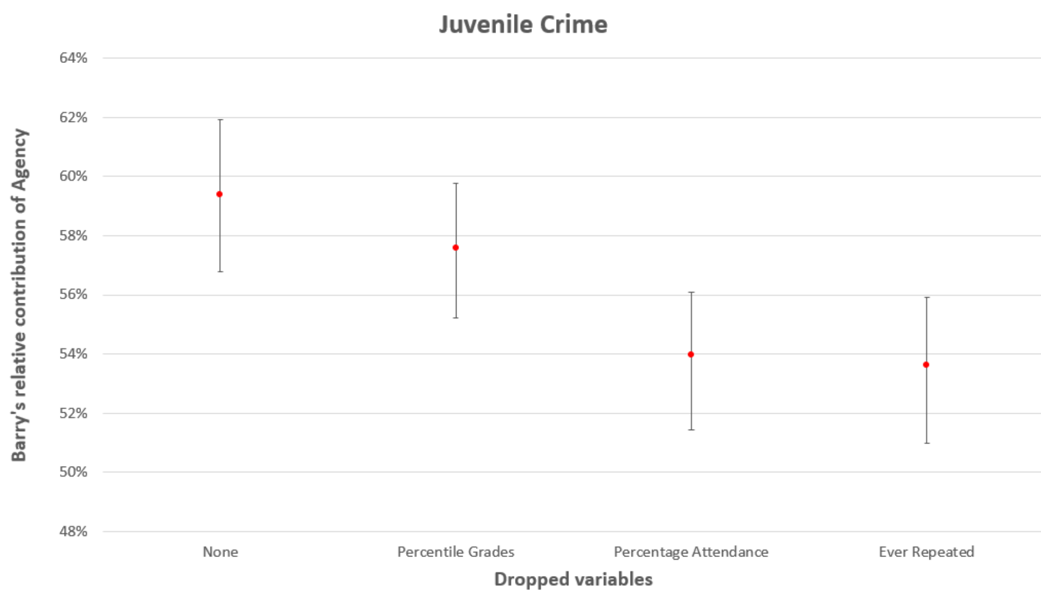
Notes: This table reports the effects of dropping one variable at a time on $\text{cov}\left(\hat{O}^j_A, \hat{O}^j\right) / \text{cov}\left(\hat{O}^j, \hat{O}^j\right)$

Figure 7: Effect of dropping one variable on Barry's relative contribution of circumstances



Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}_C^j, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

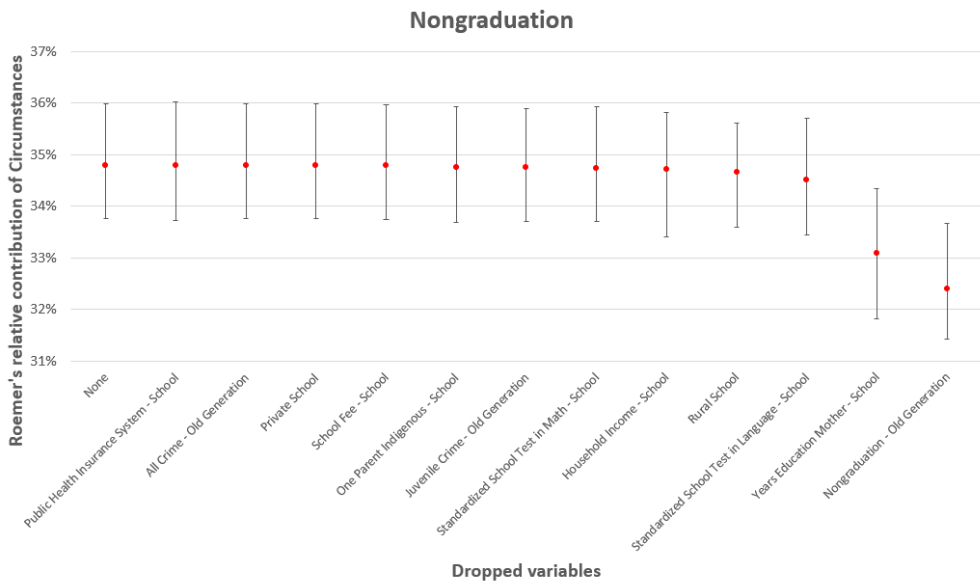
Figure 8: Effect of dropping one variable on Barry's relative contribution of agency



Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}_A^j, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

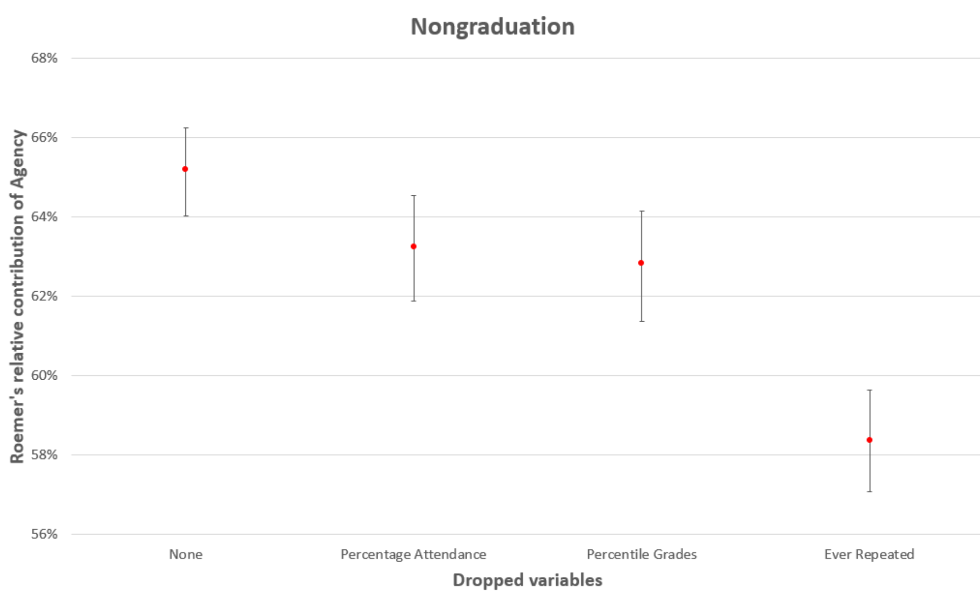
H The impact of variables on *Nongraduation*

Figure 9: Effect of dropping one variable on Roemer's relative contribution of circumstances



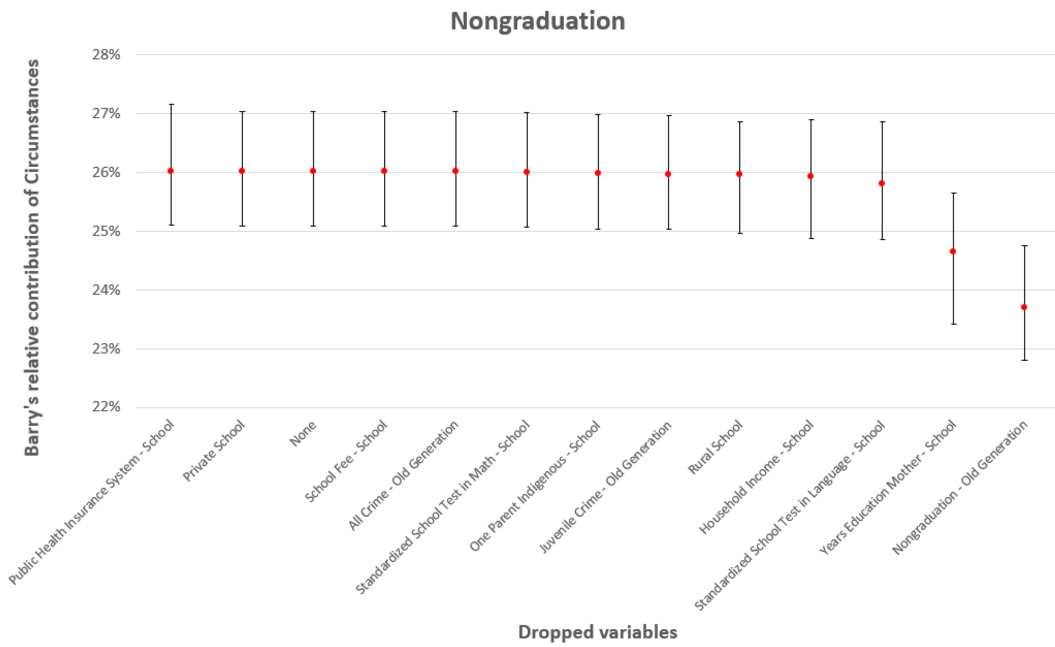
Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}_C^j, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

Figure 10: Effect of dropping one variable on Roemer's relative contribution of agency



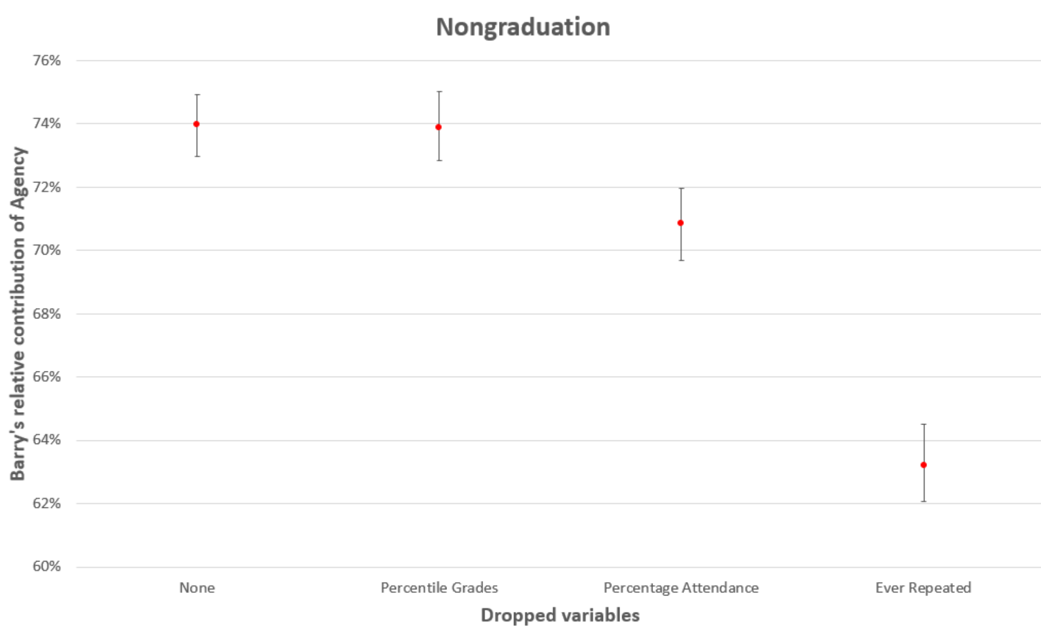
Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}_A^j, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

Figure 11: Effect of dropping one variable on Barry's relative contribution of circumstances



Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}^j_C, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

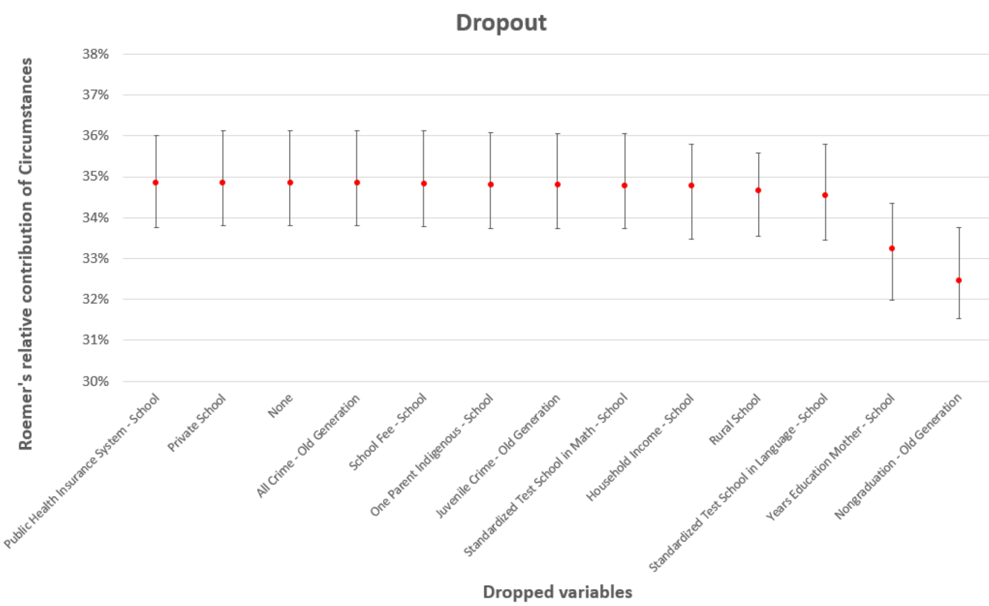
Figure 12: Effect of dropping one variable on Barry's relative contribution of agency



Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}^j_A, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

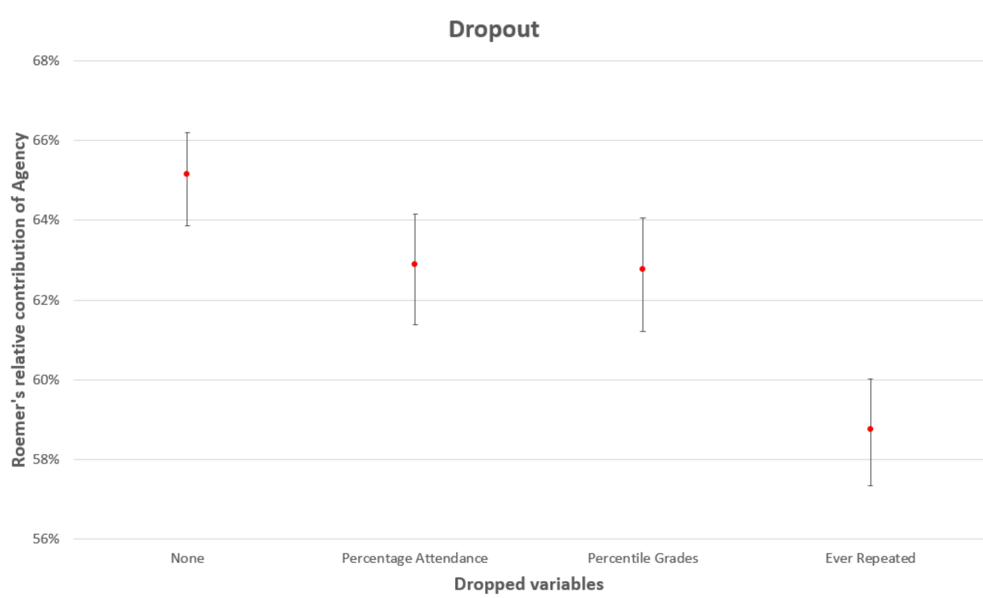
I The impact of variables on *Dropout*

Figure 13: Effect of dropping one variable on Roemer's relative contribution of circumstances



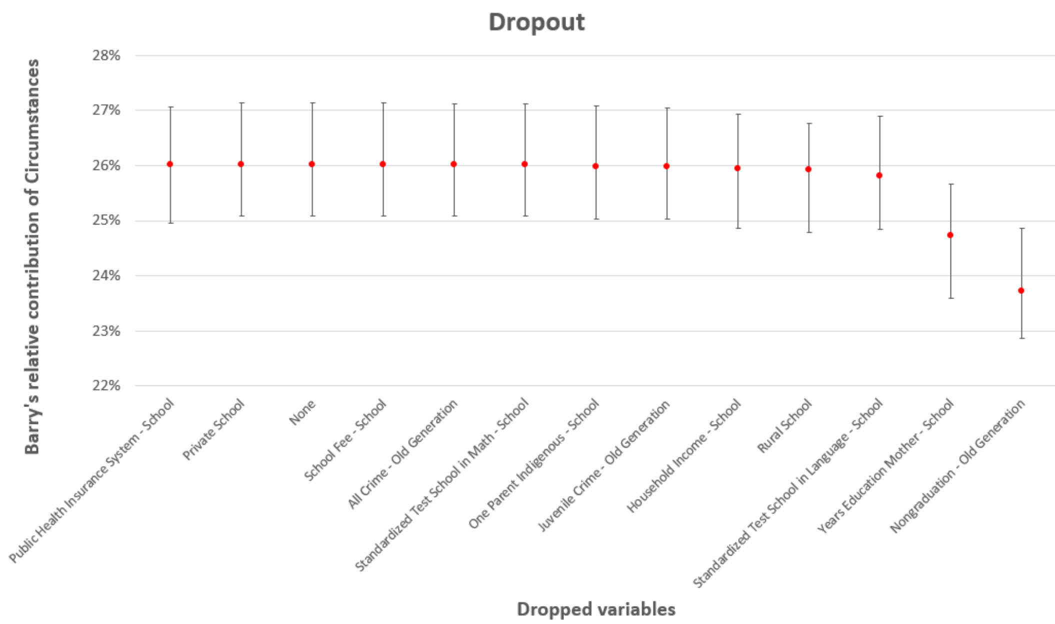
Notes: This table reports the effects of dropping one variable at a time on $\text{cov}\left(\hat{O}^j_C, \hat{O}^j\right) / \text{cov}\left(\hat{O}^j, \hat{O}^j\right)$

Figure 14: Effect of dropping one variable on Roemer's relative contribution of agency



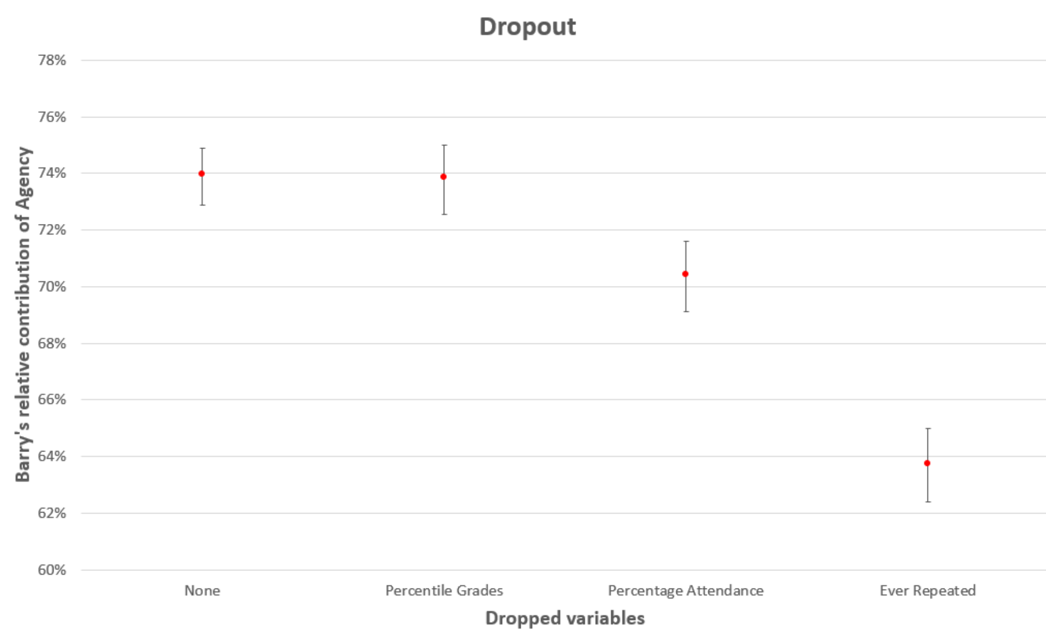
Notes: This table reports the effects of dropping one variable at a time on $\text{cov}\left(\hat{O}^j_A, \hat{O}^j\right) / \text{cov}\left(\hat{O}^j, \hat{O}^j\right)$

Figure 15: Effect of dropping one variable on Barry's relative contribution of circumstances



Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}_C^j, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

Figure 16: Effect of dropping one variable on Barry's relative contribution of agency



Notes: This table reports the effects of dropping one variable at a time on cov $\left(\hat{O}_A^j, \hat{O}^j\right)$ / cov $\left(\hat{O}^j, \hat{O}^j\right)$

J Proof that dropping one cicumstance variable does not necessarily imply that the relative contribution of circumstances has to diminish

To establish this proposition, we will consider an illustrative example where the outcome variable y is linearly determined according to the following equation:

$$y = \beta c_1 + \gamma c_2 + \alpha a_1 + \mu \tag{9}$$

where:

$$c_1 = \delta c_2 + \theta a_1 + \epsilon \tag{10}$$

y can be rewritten as:

$$y^* = (\beta\delta + \gamma)c_2 + (\alpha + \beta\theta)a_1 + \beta\epsilon + \mu \tag{11}$$

Let us consider the following assumptions: a_1, c_2, and μ are independent variables that follow a normal distribution with a mean of 0 and a standard deviation of 1. The variable ϵ follows a normal distribution with a mean of 0 and a standard deviation of 0.1.

Assuming a sufficiently large sample size, such that the estimated ordinary least squares (OLS) coefficients represent the true values, the variance of $\hat{y}$ and its decomposition can be expressed as follows:

$$var(\hat{y}) = E[(\beta c_1 + \gamma c_2 + \alpha a_1)(\beta c_1 + \gamma c_2 + \alpha a_1)] = \alpha^2 + 2\alpha\beta\theta + \beta^2(\delta^2 + \theta^2 + 0.1^2) + 2\beta\gamma\delta + \gamma^2 \tag{12}$$

$$cov(\hat{y}, \hat{y_C}) = E[(\beta c_1 + \gamma c_2 + \alpha a_1)(\beta c_1 + \gamma c_2)] = \alpha\beta\theta + \beta^2(\delta^2 + \theta^2 + 0.1^2) + 2\beta\gamma\delta + \gamma^2 \quad (13)$$

$$cov(\hat{y}, \hat{y_A}) = E[(\beta c_1 + \gamma c_2 + \alpha a_1)(\alpha a_1)] = \alpha^2 + \alpha\beta\theta \quad (14)$$

To investigate the impact of omitting c_1 as a regressor, it is necessary to analyze the revised decomposition of variances using Equation 11:

$$var(\hat{y}^*) = E[((\beta\delta + \gamma)c_2 + (\alpha + \beta\theta)a_1)((\beta\delta + \gamma)c_2 + (\alpha + \beta\theta)a_1)] = (\alpha + \beta\theta)^2 + (\beta\delta + \gamma)^2 \quad (15)$$

$$cov(\hat{y}^*, \hat{y_C}^*) = E[((\beta\delta + \gamma)c_2 + (\alpha + \beta\theta)a_1)((\beta\delta + \gamma)c_2)] = (\beta\delta + \gamma)^2 \quad (16)$$

$$cov(\hat{y}^*, \hat{y_A}^*) = E[((\beta\delta + \gamma)c_2 + (\alpha + \beta\theta)a_1)((\alpha + \beta\theta)a_1)] = (\alpha + \beta\theta)^2 \quad (17)$$

Table 24 provides a summary of the relative contribution of each factor in both the original model and the model with the omission of c_1. It presents a comparative analysis of the contributions to the overall variance under these different scenarios.

Table 24: Decomposition of inequality

	Relative contribution of circumstances	Relative contribution of agency
y	$\frac{\alpha\beta\theta+\beta^2(\delta^2+\theta^2+0.1^2)+2\beta\gamma\delta+\gamma^2}{\alpha^2+2\alpha\beta\theta+\beta^2(\delta^2+\theta^2+0.1^2)+2\beta\gamma\delta+\gamma^2}$	$\frac{\alpha^2+\alpha\beta\theta}{\alpha^2+2\alpha\beta\theta+\beta^2(\delta^2+\theta^2+0.1^2)+2\beta\gamma\delta+\gamma^2}$
y*	$\frac{(\beta\delta+\gamma)^2}{(\alpha+\beta\theta)^2+(\beta\delta+\gamma)^2}$	$\frac{(\alpha+\beta\theta)^2}{(\alpha+\beta\theta)^2+(\beta\delta+\gamma)^2}$

Notes: This table reports in its first column the cov $(\hat{y}_C, \hat{y})$ / cov $(\hat{y}, \hat{y})$ and on its second column the cov $(\hat{y}_A, \hat{y})$ / cov $(\hat{y}, \hat{y})$. First row corresponds to Equation 9 and second row to 11.

Depending on the values of α, β, γ, and δ, it is possible for the inequality related to circumstances (relative contribution of circumstances) to be greater under Equation 11. For example, when $\alpha = 0.5$, $\beta = 0.2$, $\gamma = 0.8$, $\delta = 0.43$, and $\theta = -0.62$, the relative contribution of circumstances, when considering all circumstance variables, amounts to 0.8. However, when the variable c_1 is excluded, the relative contribution of circumstances increases to 0.85.

Exploring the Decline in Juvenile Delinquency Rates among Students in Chile: A Blinder-Oaxaca Decomposition Analysis*

Preliminary and incomplete. Please do not cite or circulate.

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Abstract

This paper examines a notable decline in juvenile delinquency rates among male students in Chile spanning the cohorts born in 1996 (5.43%) and 2001 (3.73%). The analysis employs the Blinder-Oaxaca decomposition technique, which dissects the crime disparity into two components: one attributable to variances in the average values of independent variables across cohorts, and the other linked to distinct effects of the independent variable. The independent variables encompass individual attributes, along with school and peer influences. The research findings suggest that modifications made to these variables are associated with a reduction in crime ranging from 18.9% to 35.1%, contingent upon the specific category under consideration.

Keywords: Blinder-Oaxaca decomposition, Crime.

JEL Classification: D63, K14, O15.

*We thank the Chilean Public Defender Office (PDO) and the Chilean Education Ministry (MINEDUC) for providing the data. All remaining errors are our own.

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1 Introduction

This article provides a focused examination of juvenile crime, acknowledging its significance in terms of social and economic costs. Empirical evidence demonstrates a pronounced increase in criminal activity during the late teenage years, followed by a gradual decline. For instance, according to (Levitt et al., 2001), the likelihood of an eighteen-year-old being arrested for a property crime is approximately five times higher than that of a thirty-five-year-old, while the ratio for violent crime stands at two to one. Wilson and Petersilia (2010) further highlights that in 2005, juveniles aged 10-17 comprised 11% of the total US population, yet accounted for 16% of total violent felonies and 26% of total property felonies. These statistics suggest that, on average, crimes committed by juveniles tend to be less severe than those committed by adults.

In the context of Chile, Olavarria-Gambi (2007) estimates the economic cost of crime to be 2.06% of GDP. Jaitman et al. (2017), on the other hand, presents an alternative estimation from the Inter-American Development Bank, indicating that this percentage reaches 2.77%. If we assume juvenile crime constitutes 10-20% of this total, the social cost of teenage crime in Chile is estimated to range from 0.2% to 0.5% of GDP. It is important to note that the majority of these costs are not borne by juveniles themselves (e.g., through incarceration, foregone future earnings, or increased probability of death), but rather by society in the form of externalities (Levitt et al., 2001).

The empirical evidence demonstrates a substantial decline in crime rates in Chile over recent years. Notably, crimes of greater social connotation,[1] have witnessed a notable reduction of 20.4% between 2005 and 2022 per 100,000 inhabitants. It is worth mentioning that crime rates in 2020 and 2021 were lower than in 2022 due to government-imposed measures like mandatory social distancing in response to the COVID-19 pandemic. However, the magnitude of the crime decrease varies across categories. For instance, crimes such as theft or robbery in inhabited places experienced a substantial decline, while others like homicide or rape did not exhibit a similar reduction. This pattern is not unique to Chile, as studies by Boman and Gallupe (2020) in the United States and Andresen and Hodgkinson (2020) in Australia report similar outcomes.

[1] Crimes of greater social connotation refer to those crimes which affect life and property of people, thereby generating a public impact. Violent crimes include Robbery with Violence, Robbery with Intimidation, Surprise Robbery, Injuries, Homicide and Rape, and Property Crimes are subclassified in Motor Vehicle Theft, Theft of Vehicle Accessories, Robbery in an Inhabited Place, Robbery in an Uninhabited Place, Other Robberies with Force and Theft. (Chile Atiende. Retrieved February 4, 2023, from https://www.chileatiende.gob.cl/fichas/25162-estadisticas-de-delitos-de-mayor-connotacion-social-violencia-intrafamiliar-y-ley-de-drogas).

Regarding the proportion of crimes committed by juveniles, there has been a dramatic decrease since 2005. In that year, 19.5% of individuals prosecuted for criminal activities were under 18 years old, whereas in 2022, this percentage decreased to 9.5%. It is important to note that in 2020 and 2021, the percentage of cases involving juvenile perpetrators was only 6.8%, likely influenced by stay-at-home restrictions imposed to curb the spread of COVID-19. This is because juveniles tend to engage in criminal behavior in groups, as highlighted by McCord and Conway (2002) and Snyder (2008)). The decline in overall crime and the decreasing share of juvenile offenders contribute to a substantial reduction of 65.4% in crimes of greater social connotation involving juvenile prosecution, declining from 25,190 crimes in 2005 to 8,707 crimes in 2022. For detailed crime statistics per type of offense per 100,000 inhabitants, please refer to Appendix A, while Appendix B provides a breakdown of total crimes per year differentiating between individuals under 18 and the overall figures.[2]

Despite the absolute figures, violence emerged as the foremost concern in Chile in 2022, surpassing issues such as poverty, social inequality, COVID-19, inflation, unemployment, and financial/political corruption. A notable 48% of the Chilean population expressed worry regarding this matter, significantly exceeding the global average of 26%. Furthermore, this level of apprehension placed Chile as one of the countries with the highest levels of concern, trailing only behind Sweden (59%), Mexico (54%), Peru (52%), and South Africa (51%).[3]

To investigate the observed decline in juvenile delinquency as mentioned above, we employ Chilean administrative data obtained from the Ministry of Education, specifically focusing on all Chilean students born in 1996 or 2001. By merging this dataset with administrative records from the Public Defender's Office (*Defensoría Penal Pública*, PDO from now on), we can identify individuals who were prosecuted up to the age of 17. Our analysis reveals that 1.57% of girls born in 1996 experienced prosecution (0.67% for violent crimes and 1.06% for non-violent crimes), while the corresponding percentages for girls born in 2001 are 1.53% (0.70% for violent offenses and 1.05% for non-violent offenses). Conversely, males exhibited a significant reduction in criminal activity: 5.43% of males born in 1996 were prosecuted (3.13% for violent crimes and 3.51% for non-violent crimes), whereas this percentage decreased to 3.73% for those born in 2001 (2.32% for violent acts

[2]Both tables were obtained from the Center for Studies and Analysis of Crime (*Centro de Estudios y Análisis del Delito*) on March 1, 2023.

[3]Ipsos. Retrieved February 4, 2023, from https://www.ipsos.com/sites/default/files/ct/news/documents/2022-02/What-worries-the-world-February-2022.pdf).

and 2.34% for non-violent acts).

Employing the Oaxaca methodology, which allows us to decompose the mean difference in an outcome variable into the part explained by differences in mean values of independent variables and an unexplained component, we find that differences in explanatory factors account for 24.4% of the reduction in male juvenile crime. When focusing solely on violent offenses, this percentage increases to 35.1%, while for non-violent acts, it stands at 18.9%. It is important to note that applying this methodology to female students would not be meaningful due to the negligible differences in crime rates between those born in 1996 and 2001 across all three categories. The decrease in male juvenile crime can be attributed to factors such as improved performance of peers in standardized tests and higher educational levels of their mothers.

The present study pertains to the extensive body of literature examining the determinants of criminal engagement. While our aim is not to provide an exhaustive survey of this literature (for a comprehensive overview, refer to Siegel and Welsh (2014) and Wilson and Petersilia (2010)), we concentrate on identifying research that is particularly relevant given the available data. Broadly, crime prediction encompasses four categories of factors: biological, social, criminal justice, and economic factors.

Among the biological factors, gender unquestionably stands out as one of the most influential determinants, with males historically exhibiting higher levels of violence than females (Steffensmeier and Streifel (1991); Wilson and Herrnstein (1985)). Additionally, the age-crime curve, which depicts an increase in crime during teenage years followed by a decline, is widely acknowledged (Farrington (1986) and Sweeten et al. (2013)). Intelligence, influenced partly by heredity, emerges as an excellent predictor of crime both within and across countries ((Wilson and Herrnstein, 1985), 1985; (Rushton and Templer, 2009)).

Social factors exert a significant influence on crime through various channels (Hirschi (1969); Sampson (1985)). Numerous studies examine the quality of parenting as a protective factor against crime (Daag (1991); Burt et al. (2006); Sampson and Laub (1995); Palmer and Gough (2007); McCord (1991)). Female-headed households emerge as one of the strongest predictors of city crime rates (Glaeser et al., 1996). Interventions such as the Perry Preschool program in Ypsilanti, Michigan, and the Child-Parent Center in Chicago, which begin early in life and involve parental engagement, have demonstrated remarkable effectiveness in reducing crime (Greenwood et al., 2018). The Perry Preschool program, for instance, resulted in a return of over 17 USD to society for every dollar spent, encompassing savings in crime, education, welfare, and increased tax revenue (Belfield et al., 2006), while the Child-Parent Center program in Chicago yielded returns of 7 USD (Reynolds et al., 2003).

Peers play a pivotal role in shaping crime, particularly among juveniles who are more likely to engage in criminal activities in groups (Greenwood and Turner, 2011). Neighborhood peer effects have been reported regarding drug and alcohol use, church attendance, school dropout rates, employment status, and involvement in criminal activities (Case and Katz, 1991). Trust among neighbors has been highlighted as a mechanism for preventing crime and violence in Chilean neighborhoods (Olavarria-Gambi and Allende-González, 2014). Studies suggest that peer influence outweighs parental nurturance in explaining long-term behavior (Harris, 2011), deviant peers can counteract the influence of good parenting (Bowman et al., 2007), and positive peers can help high-risk individuals from delinquency (Barnes and Morris, 2012).

The economic model of crime, proposed by Becker (1968), posits that while most individuals are restrained by moral values, potential criminals rationally weigh the costs and benefits of engaging in criminal activities, considering factors such as the probability of apprehension, conviction, punishment, and the current set of opportunities. In the realm of criminal justice, evidence suggests that increased levels of policing (Levitt (2002); Marvell and Moody (1996), Durlauf and Nagin (2011)) and imprisonment (Spelman (1993); Marvell and Moody (1994)) contribute to a reduction in crime levels. Furthermore, there is some evidence to suggest that juveniles respond to these incentives in a manner comparable to adults Levitt (1998), as evidenced by significant behavioral changes that coincide with the transition from the juvenile to the adult justice systems.

Economic factors are expected to exert influence on crime rates due to the inherent monetary motivations associated with criminal activities. Freeman (1991) argues that there exists a substitution effect at the margin between criminal and noncriminal pursuits. Freeman (1996) investigates the surge in imprisonment rates in the United States, particularly among the black population, between the mid-1970s and mid-1990s, revealing a disproportionate likelihood of incarceration for high-school dropouts. Grogger (1998) asserts that declining real wages may have played a significant role in the rise of youth crime in the United States during the 1970s and 1980s. Additionally, wage differentials between racial groups contribute substantially to variations in criminal rates. Lochner (1999) and Lochner (2004) present models that shed light on why older, more intelligent, and more educated workers tend to engage in fewer property crimes compared to others. Lochner and

Moretti (2004) finds compelling evidence that schooling significantly reduces the probability of incarceration and arrest. Jacob and Lefgren (2003) report a decrease in juvenile property crime on days when school is in session, while violent crime exhibits an opposite trend. Numerous studies explore the impact of education on crime, including (Machin et al. (2011), Clay et al. (2012), Anderson (2014), Hjalmarsson (2008), and Cook and Kang (2016). Lochner (2010) argues for the effectiveness of school programs emphasizing social and emotional development in reducing crime. Fu et al. (2020) develop a dynamic model to analyze the choices of schooling and crime among teenagers, employing Chilean data for calibration.

Regarding the benefits derived from criminal activities, limited research exists on this aspect. (Levitt and Venkatesh, 2000) analyzes the financial operations of a drug-selling street gang and concludes that average earnings within the gang surpass those of legitimate market alternatives; however, when accounting for risks such as death and imprisonment, the overall remuneration falls below minimum wages. The highly skewed nature of compensation within gangs suggests that the prospect of future wealth or the pursuit of risky situations may serve as additional motivations for gang participation (Gruber, 2000).

Examining data at the country level, Soares (2004) finds that reductions in inequality, as well as increases in economic growth and education, are associated with decreases in crime rates. Similarly, Soares and Naritomi (2010) summarizes that the relatively high crime rates in Latin America can be well explained by three factors: high inequality, low incarceration rates, and limited police forces.

Our research is situated within the literature employing the Oaxaca decomposition method to elucidate differences in means. The seminal works by Blinder (1973) and Oaxaca (1973) employed this methodology to explain disparities in wages attributed to race and gender. Subsequently, numerous studies have utilized this framework to examine wage discrimination. We recommend consulting Weichselbaumer and Winter-Ebmer (2005) for a comprehensive meta-analysis on the subject of the gender wage gap. For the study of racial wage gaps, notable references include Mora (2008) and Kim (2010), while DeLeire (2001) focus on wage discrimination against individuals with disabilities. However, the versatility of the Oaxaca decomposition extends beyond wage differentials, finding application in various contexts. Krieg and Storer (2006) investigates whether performance differences between districts that achieved adequate yearly progress in standardized tests and those that did not can be attributed to factors beyond the control of school administrators. Etezady et al. (2021) examines the generational gap in transportation-related attitudes. Kelishadi et al. (2018)

explores differences in childhood obesity between children from high and low socioeconomic status, while Sharaf and Rashad (2016) decomposes rural-urban disparities in child nutrition. Emamian et al. (2011) concludes that differences in health-care access largely account for the visual impairment gap between economic groups.

The Oaxaca methodology has also found application in criminal studies. Frederick and Jozefowicz (2018) reveals that the rural-urban difference in crime rates primarily stems from observable characteristics such as unemployment, poverty, race, age, clearance rates, and the number of police officers. Another common line of research investigates the gender gap in criminal activity. Campaniello and Gavrilova (2018) seeks to explain the gender participation gap and argue that the differential responsiveness of males to changes in illegal earnings explains 56% of the disparity in crime rates. Sorensen et al. (2013) finds that women receive more lenient sentences, while black men face harsher punishments, even after controlling for factors such as offense severity and prior criminal history. Beatton et al. (2018) decomposes the female-male difference in crime and report that endowments account for 60% of the observed disparity. Additionally, they document gender convergence in crime rates between 1995 and 2013 in Australia, primarily driven by a substantial decline in crime among men, coupled with a lack of downward trend for women.

Our study contributes to the literature on juvenile crime in two significant ways. Firstly, to the best of our knowledge, this paper is the first to examine the notable reduction in juvenile crime that has occurred in Chile within a span of only five years between two generations. Secondly, we enhance the existing literature by utilizing a comprehensive dataset derived from administrative records, enabling us to identify key variables that should be prioritized by educational authorities in combating juvenile crime.

The structure of the paper is as follows: Section 2 provides an overview of the judiciary and educational landscape in Chile. Section 3 outlines the Oaxaca methodology employed in our analysis. Section 4 describes the data utilized in our study. Section 5 presents the empirical results, and Section 6 concludes the paper.

2 Background

2.1 The Criminal System in Chile

In developing nations such as Chile, crime rates tend to be higher in comparison to developed countries. According to World Prison Brief, as of October 2021, the prison population rate per 100,000 of the national population stood at 376 in the Americas (212 in Chile, 243 in Argentina, 381 in Brazil, 193 in Colombia, 169 in Mexico, 259 in Peru, 383 in Uruguay, 629 in the USA, and 113 in Venezuela), while in Europe, the rate reached 175.[4] Among the 45,338 individuals incarcerated in Chilean prisons as of December 2022, 40,537 (92.6%) were male, with only 3,350 (7.4%) being female, and minors constituted a mere 0.1% of the total population.[5]

However, relying solely on prison population rates may not always provide an accurate representation of crime levels, as these rates are contingent upon active prosecution. This is evident in countries known for their high levels of violence, such as Venezuela, Mexico, Brazil, or Colombia, which do not exhibit particularly high prison population rates. Alternatively, homicide rates can serve as a preferred measure of crime, as homicides are difficult to conceal. In this regard, Chile stands apart from its neighboring countries. While South America recorded a homicide rate of 21.0 per 100,000 in 2018, Chile's rate stood at a mere 4.4 per 100,000 during the same year (in comparison, Argentina had 5.3, Brazil 27.4, Colombia 25.3, Mexico 29.1, Peru 7.9, Uruguay 12.1, the USA 5.0, and Venezuela 36.7).[6] In other categories of crime, such as offenses against persons, sexual assaults, or property crimes, Chile is generally perceived as a relatively safe country within South America. However, making direct comparisons is challenging due to potential variations in reporting rates across countries.

[4] World Prison Population List, thirteenth edition, Institute for Crime $ Justice Policy Research, World Prison Brief (Retrieved February 4, 2023, from https://www.prisonstudies.org/sites/default/files/resources/downloads/world_prison_population_list_13th_edition.pdf)

[5] World Prison Brief: Chile. Retrieved February 4, 2023, from https://www.prisonstudies.org/country/chile.

[6] United Nations Office on Drugs and Crime. Retrieved February 4, 2023, from https://dataunodc.un.org/content/data/homicide/homicide-rate.

2.2 The Juvenile Criminal System in Chile

A law reform aimed at restructuring the juvenile criminal system in Chile was implemented through Act No 20084 in 2005 and became effective in 2007. The primary objective of this legislation was to align the Chilean legal framework with international human rights standards, as outlined in the United Nations Convention on the Rights of the Child. Key principles encompassed in this reform included the exceptional and measured application of criminal law and the utilization of confinement as a last resort (Langer and Lillo (2014)). The reform brought about three significant changes compared to the previous system. Firstly, it reduced the age of criminal liability from 16 to 14. Secondly, it eliminated the ambiguity in the previous system, where minors could be classified as either adults or juveniles based on judicial discretion. Lastly, for convicted juvenile defendants, the new law reduced the severity of punishment by one level relative to the corresponding sentence for adults (Couso and Duce, 2013).

The introduction of the new juvenile criminal system took place within the context of a comprehensive criminal justice reform initiated in 2000 and completed in 2005. This far-reaching reform replaced the longstanding inquisitorial model with an oral, public, and adversarial approach. Alongside this reform, several new institutions were established, including the PDO, the Public Prosecutor's Office, the Guarantee Court, and the Oral Criminal Trial Courts. The PDO offers free legal representation to nearly all individuals convicted of a crime and gathers comprehensive information on defendants utilizing their services, including minors and adults, which encompasses detailed data regarding the specific criminal offenses involved.

Under the new juvenile system, the juvenile penal process progresses through distinct stages. Initially, the juvenile is apprehended, either due to being apprehended by the police while committing or being in close proximity to the crime, or as a result of an investigation conducted by the Public Prosecutor that culminates in an accusation. This stage concludes with an arraignment hearing held in the Guarantee Court, typically lasting approximately 15 minutes. During this hearing, the arraignment judge must choose among three possible outcomes: commencing penal proceedings, opting for an alternative resolution (which may involve compensation agreements and the conditional suspension of proceedings), or dismissing the case. The majority of cases are resolved in the Guarantee Court, either through an alternative resolution or through the dismissal of proceedings. Generally, penal proceedings are reserved for serious crimes.

2.3 The Chilean Education System

In the Chilean educational context, primary education is structured into eight grades, catering to children between the ages of 6 and 14. Similarly, secondary education spans four grades and serves teenagers aged 15 to 18. Legislative provisions outlined in Law 19.876 establish primary and secondary schooling as obligatory for all citizens of Chile. However, it should be noted that not all students successfully complete their secondary education, thus highlighting a disparity in educational attainment. Furthermore, the progression from one grade to the next is not assured, as the Ministry of Education has devised guidelines pertaining to grade retention. Under these guidelines, students risk being retained if their academic performance, as measured by grade point average (GPA) or attendance records, falls below predetermined thresholds. Nevertheless, compliance with these regulations is not consistently observed, and educational institutions retain a certain level of discretion in their implementation practices (Díaz et al., 2021).

During most of our sample period spanning from 2002 to 2020, school admissions in Chile were decentralized, with individual schools responsible for the process.[7] Some schools not only considered primary school GPAs but also took into account students' family backgrounds as part of their selective admission procedure. The combination of selective admissions and differential fees contributed to the segregation of students from varying socioeconomic statuses (SES) across different schools. This has resulted in a significant level of segregation among both low-SES and high-SES students in Chile (Valenzuela et al., 2014).

In 1988, a system of national standardized tests known as SIMCE (Education Quality Measurement System or *Sistema de Medición de la Calidad de la Educación*) was introduced to assess student learning and school performance. All students in the corresponding grade levels are required to participate in these tests. For this study, we will focus on the Language and Mathematics SIMCE exams taken by fourth-grade students each year. The government utilizes SIMCE results to allocate resources and provide information to the public regarding school quality through the dissemination of school-level results. Given the stakes involved, educational institutions have incentives to discourage their underperforming students from taking the test, which may introduce an upward bias in the test results (Hofflinger and von Hippel, 2020).

[7] The Scholar Admission System or *Sistema de Admisión Escolar* (SAE) was introduced in 2016 but achieved nationwide implementation only in 2019. This system prohibits selection by educational establishments (Irarrázaval, 2021).

3 Oaxaca Methodology

Our analysis will employ the Oaxaca methodology as outlined by Jann et al. (2008). We recommend referring to Jann's article for a detailed understanding of the methodology. For the sake of convenience, we provide the essential equations used in that paper in Appendix C). In this section, we summarize the key information for readers already familiar with the methodology.

The Kitagawa-Blinder-Oaxaca decomposition, hereafter referred to as the Oaxaca decomposition, is a statistical technique that allows us to explain the difference in means of a dependent variable by decomposing the gap into two components. The first component is due to differences in the mean values of the independent variables, and the second component arises from differences in the effects of the independent variables.[8] The seminal references for this method are Kitagawa (1955), Blinder (1973), and Oaxaca (1973).[9]

There are several ways to decompose differences in means. Assuming the coefficients from the 1996 cohort are correct, we obtain Equation 6 (Model 1). Assuming the coefficients from the 2001 cohort are correct, we obtain Equation 11 (Model 2). However, it is unclear which coefficients should be used, which suggests the need to find a nondiscriminatory coefficient by using a sample that includes individuals from both cohorts. This leads us to Equation 12, where Neumark (1988) advocates for using coefficients from a pooled regression (Model 3) to remain agnostic about the discriminated cohort. Fortin (2006) and Jann et al. (2008) also suggest a pooled regression, but with the inclusion of a group indicator variable to address omitted variable bias (Model 4).[10] As we are utilizing probit models, the Oaxaca decomposition necessitates the use of Equations 18, 19, 20, and 21.

[8]It is important to note that this portion of the gap is often interpreted as discrimination, and the Oaxaca decomposition has been widely used to analyze wage gaps based on gender or race. In our context, it can be interpreted as the unexplained part of the gap between means.

[9]Specifically, in Stata, the Oaxaca decomposition is implemented using the command
oaxaca JuvenileCrime regressors , probit by (gen_1996),
where *Juvenile Crime* is the binary dependent variable, *Regressors* is the list of regressors, and *gen_1996* is a binary variable that takes the value 1 if the student is born in 1996, and 0 if student is born in 2001.

[10]If an independent variable is correlated with the discrimination factor, then the explained part of the composition may get overstated. For more on this point, we refer the reader to Section 2. Methods and formulas of Jann et al. (2008).

4 Data

Our dataset is constructed by merging administrative data from the Ministry of Education and the PDO. Our analysis focuses on two cohorts: individuals born in 1996 and those born in 2001. The Ministry of Education dataset comprises administrative records spanning from 2002 to 2020. These records include information on school attendance, grade level, educational achievement (such as grade promotion and average scores), student attendance rates, and basic demographic details such as birth date and gender. We identify a total of 479,716 students in our sample, with 244,717 born in 1996 and 234,999 born in 2001.

We combine this panel dataset with information regarding students' performance on the national standardized test, known as SIMCE, which is administered annually to all 4th-grade students. As part of the test procedure, parents of participating students are required to complete a survey, allowing us to gather detailed information on the socio-economic background of the children. Our baseline scenario involves selecting specific variables. In cases where a student did not take the standardized test, but at least one peer in their class did and their parent completed the survey, missing data can be minimized. Consequently, the primary reason for missing data is the non-participation of entire classes in the standardized test or the failure of some classes to respond to the parent survey. After excluding students with missing data, our final sample consists of 425,461 students, comprising 227,335 children from the 1996 cohort (115,496 males and 111,839 females) and 225,126 from the 2001 cohort (113,759 males and 111,367 females).

To complete our analysis, we connect our sample with the PDO's records of penal cases prosecuted between 2003 and 2018. It is important to note that our data does not include information on the verdicts of these cases. Therefore, when we refer to "crime," we specifically mean being criminally charged. Additionally, we have information on the type of offense, allowing us to distinguish between violent and non-violent crimes.

Throughout this paper, we will refer to this sample as the "baseline sample." Our analysis primarily focuses on male individuals, as the Oaxaca decomposition requires changes in crime rates, and female individuals exhibit similar crime rates across both generations. We will track these two cohorts until they reach 17 years of age.[11] Our ultimate objective is to understand the extent to

[11] We consider cases prosecuted up until December 2013 for the 1996 cohort and cases up until December 2018 for the 2001 cohort.

which the reduction in juvenile crime can be attributed to observable student characteristics versus unobserved factors. In the following subsections, we provide a broad overview of the variables considered. For a more precise definition of each variable, please refer to Appendix E.

4.1 Outcomes

We create a binary variable, denoted as *Juvenile Crime*, which takes the value of 1 if a student received criminal charges by 2013 for those born in 1996 and by 2018 for those born in 2001, and 0 otherwise. Our study primarily focuses on this variable, as it exhibits a decline from 5.43% among male students born in 1996 to 3.73% among those born in 2001. In comparison, female students demonstrate lower crime rates, with 1.57% for the 1996 cohort and 1.53% for the 2001 cohort.

Additionally, we construct two alternative measures of crime: *Violent Crime* and *Non-violent Crime*, based on broader offense categories. The category of violent offenses encompasses murder, attempted murder or manslaughter, assault, kidnapping, sexual offenses, robbery, criminal possession of a weapon, as well as arson or road traffic offenses resulting in injuries. Non-violent crimes include all other offenses, such as theft, vandalism, road traffic offenses without injuries, drug crimes, white-collar crimes, cybercrimes, and more. Similar to the *Juvenile Crime* variable, these measures are also binary indicators that take the value of 1 if a student received criminal charges related to the specific category up to 2013 for those born in 1996 and up to 2018 for those born in 2001, and 0 otherwise.

4.2 Explanatory variables

The explanatory variables in our analysis can be categorized into individual performance, school characteristics, geographic location, and peer effect factors. Given the high level of educational segregation in Chile (Valenzuela et al., 2014), it is reasonable to anticipate a correlation between individual characteristics and peer characteristics. Individual performance variables include whether students took both standardized tests (Mathematics and Language) in 4th grade and whether they repeated at least one of the first four years of school.[12]

School characteristics encompass class size, school size, the presence of full-day schooling, and

[12] It is worth noting that while these accomplishments are considered as causal factors, some scholars argue that they should be viewed as consequences of circumstances (Hufe et al. (2017), for example).

the school's public, subsidized, or private status. Geographic characteristics indicate the school's location in the northern, central, southern regions of Chile, or within the Santiago metropolitan area, as well as whether the school is situated in a rural area. Lastly, students are grouped based on the school and year they first attended 4th grade, allowing us to obtain average grades in standardized tests, the percentage of peers who repeated at least one of their first four years of schooling, average years of schooling for both fathers and mothers,[13] including their squared versions, and average household income (reported in the parents' survey). For a comprehensive description of each employed variable, we direct the reader to Appendix E.

4.3 Descriptive Statistics

Table 1 provides descriptive statistics on gender-specific rates of juvenile prosecutions, categorized by generation and type of crime. The offenses are divided into two broad types: violent and non-violent crimes. The overall average prosecution rate for both generations is 3.09%. However, substantial gender disparities exist, with 4.59% of males being prosecuted compared to only 1.55% of females. Consequently, the gender gap stands at 3.04%, indicating that female prosecutions are 66.20% of the male baseline. Furthermore, males account for 75.24% of all individuals prosecuted. When focusing on violent crimes, the male offending rate is 2.73%, while only 0.68% of females face prosecution. Thus, males constitute 80.41% of the prosecuted individuals. In the category of non-violent crimes, 2.93% of males are prosecuted compared to 1.06% of females, resulting in a male share of 73.99%, which is lower than that observed for violent offenses.

When examining intergenerational disparities, it is evident that males born in 2001 exhibit lower offending rates for both violent and non-violent crimes compared to their 1996 counterparts. The likelihood of male prosecutions experiences a substantial decrease of 31.3% (from 5.43% to 3.73%) across all crime categories within a mere five-year period, with violent crime rates declining by 25.8% and non-violent crime rates declining by 33.4%. In contrast, females do not undergo significant alterations in their offending rates; rather, they observe a marginal increase in their likelihood of being prosecuted for violent crimes, rising from 0.67% to 0.70%. As a result, there was a decrease in both the absolute and relative gaps between males and females in the 2001 cohort

[13] Years of schooling are obtained from parents survey. Existing literature, such as Haveman and Wolfe (1995), suggests that maternal schooling tends to exert a more substantial influence on a child's educational attainment compared to that of the father.

compared to the 1996 cohort. Furthermore, the proportion of crimes committed by males in the 2001 generation was lower than that observed in the 1996 generation for both violent and non-violent offenses.

In summary, male delinquency shows a decline while female delinquency rates remain relatively stable. This pattern of gender convergence in crime is not exclusive to Chile. Similar results are reported by Estrada et al. (2016) in Sweden for crimes committed between 1980 and 2010, Beatton et al. (2018) in Australia between 2001 and 2016, and Campaniello and Gavrilova (2018) for several developed countries (Germany, Greece, Italy, Japan, Norway, and the UK) between 1980 and 2006. Beatton et al. (2018) argues that while Becker (1968) economic model of crime may explain the decline in male crime, the stable female offending rates contradict the progress observed in the female labor market. Campaniello and Gavrilova (2018) offer a possible explanation, suggesting that instead of focusing solely on opportunity costs, the focus should shift to criminal earnings. According to their analysis, gender equality has also influenced criminal opportunities. In their sample, relative to property crimes, women earn 13% less than men but face a 9% lower probability of arrest, resulting in similar returns to crime for females and males.

Table 1: Male and female offending rates per generation and offense type

Generation	Broad offense types	Offending rates			Gender gap		Male share
		All	Males	Females	Male - Female gap	Male - Female % gap	
Both	Juvenile Crime	3.09%	4.59%	1.55%	3.04%	66.20%	75.24%
	Violent	1.72%	2.73%	0.68%	2.05%	74.98%	80.41%
	Non-violent	2.00%	2.93%	1.06%	1.87%	63.89%	73.99%
1996	Juvenile Crime	3.54%	5.43%	1.57%	3.86%	71.04%	78.10%
	Violent	1.92%	3.13%	0.67%	2.46%	78.68%	82.89%
	Non-violent	2.30%	3.51%	1.06%	2.45%	69.79%	77.37%
2001	Juvenile Crime	2.64%	3.73%	1.53%	2.20%	59.03%	71.37%
	Violent	1.52%	2.32%	0.70%	1.62%	69.94%	77.25%
	Non-violent	1.70%	2.34%	1.05%	1.28%	54.90%	69.39%
2001 % reduction	Juvenile Crime	25.25%	31.32%	2.83%	42.94%	16.91%	8.62%
	Violent	20.84%	25.81%	-4.60%	34.06%	11.11%	6.80%
	Non-violent	26.08%	33.36%	0.51%	47.58%	21.34%	10.31%

Note: This table provides an overview of prosecution rates, classified by offense types, gender, and generation. Additionally, it presents the absolute and relative disparities between male and female offending rates. The final column displays the percentage of male individuals involved in each offense.
Source: Center for Studies and Analysis of Crime

We proceed to conduct a comprehensive analysis of descriptive statistics based on generational cohorts. The descriptive statistics for the 1996 cohort are presented in Table 2, while the corresponding statistics for the 2001 cohort are provided in Table 3. Both tables exclusively focus on male students, and analogous tables for female students can be found in Appendix F and G, respectively. The trends observed for male students hold true for their female counterparts as well, except for the decrease in crime rates.

A comparative examination of the tables pertaining to male individuals reaffirms our previous discussions, highlighting notable differences between the older and younger cohorts. The 1996 cohort exhibits a significantly higher overall crime rate of 5.43% compared to the 3.73% rate observed in the 2001 cohort, encompassing both violent and non-violent offenses. Analyzing the explanatory variables, it becomes apparent that, on the whole, the 2001 cohort demonstrates more favorable statistics than their 1996 counterparts. Specifically, students from the 2001 cohort display improved performance in standardized tests, albeit with a higher repetition rate compared to the 1996 cohort.

Furthermore, the size of classes and schools in the 2001 cohort is relatively smaller, potentially influenced by a decline in the number of newborns in recent years. In 1996, there were 272,163 births recorded, while the number decreased to 248,651 in 2001.[14] Conversely, the number of schools remained relatively consistent, with 7,016 establishments catering to at least one male students in the 4th grade among those born in 1996, compared to 7,030 schools serving at least one male student in the 4th grade for individuals born in 2001.

Both generational cohorts primarily attend public or subsidized schools, accounting for approximately 93% of student enrollment.[15] Insights from the SIMCE parents survey reveal that parents from the 2001 cohort possess a superior educational background, with fathers averaging an additional 0.62 years of schooling and mothers averaging an additional 0.51 years compared to their 1996 counterparts. Finally, male students born in 2001 hail from more affluent households, exhibiting an average wealth level approximately 15.6% higher than those born in 1996.

Tables 4 and 5 present the mean values of *Juvenile crime*, *Violent Crime*, and *Non-violent Crime* for males born in 1996 and 2001, respectively. The corresponding tables for females can be found in Appendices H and I. It is observed that juveniles with lower grades on standardized tests, or those who do not take the tests, are more likely to engage in misbehavior compared to high achievers. Additionally, students who repeat the school year are at a higher risk of committing delinquent

[14] Instituto Nacional de Estadísticas de Chile. Anuario de estadísticas Vitales 2018. Retrieved February 4, 2023, from https://sochog.cl/wp-content/uploads/2021/09/anuario-de-estadisticas-vitales-2018-1_compressed-2.pdf.

[15] Public schools are under the administration of municipalities and receive full funding from the central government. Subsidized schools, on the other hand, are privately owned and managed, and their financing comes from a combination of a fixed per-student subsidy provided by the central government and fees charged to the students. In contrast, private schools are privately owned, managed, and financed, without any government funding. It is worth noting that private schools generally have higher costs compared to subsidized schools.

Table 2: Summary statistics for 1996 cohort (male students)

Variable	Obs	Mean	Std. Dev.	Min	Max
Test Score in Language	109,376	252.24	54.51	102.73	382.50
Test Score in Math	109,331	251.19	56.28	74.27	369.46
Dummy for Taking Test Scores at 4th Grade	115,496	93.76%	0.242	0	1
Repeat	115,496	11.18%	0.315	0	1
Size Class	115,496	32.13	9.74	1	83
Size Class - Standardized	115,496	0.035	1.011	-3.196	5.315
Size School	115,496	72.24	56.74	1	522
Size School - Standardized	115,496	0.057	1.096	-1.319	8.742
Full-Day Schooling	115,496	16.62%	0.372	0	1
Private School	115,496	6.42%	0.245	0	1
Subsidized School	115,496	44.80%	0.497	0	1
Public School	115,496	48.77%	0.500	0	1
North	115,496	13.36%	0.340	0	1
Centre	115,496	33.95%	0.474	0	1
South	115,496	14.33%	0.350	0	1
Santiago	115,496	38.35%	0.486	0	1
Rural School	115,496	9.10%	0.288	0	1
Years Education Father	98,949	11.05	3.96	0	22
Years Education Father Squared	98,949	137.84	82.41	0	484
Years Education Mother	100,912	11.14	3.54	0	22
Years Education Mother Squared	100,912	136.54	75.23	0	484
Household Income	100,623	323,417	383,273	38,609	1,800,000
Test Score in Language - Peers	115,496	254.50	25.89	127.19	358.72
Test Score in Language - Peers - Standardized	115,496	-0.290	1.011	-5.262	3.780
Test Score in Math - Peers	115,496	248.31	29.38	100.54	356.92
Test Score in Math - Peers - Standardized	115,496	-0.156	1.009	-5.230	3.573
Repeat - Peers	115,496	6.85%	0.089	0	1
Years Education Father - Peers	115,496	10.96	2.52	0	19
Years Education Father Squared - Peers	115,496	136.10	56.51	0	361
Years Education Mother - Peers	115,496	11.03	2.35	0	19
Years Education Mother Squared - Peers	115,496	134.64	51.76	0	361
Household Income - Peers	115,496	322,111	324,717	40,297	1,772,213
Juvenile Crime	115,496	5.43%	0.227	0	1
Violent Crime	115,496	3.13%	0.174	0	1
Non-violent Crime	115,496	3.51%	0.184	0	1

Note: This table presents the descriptive statistics of male students born in 1996, derived from the baseline sample. Detailed definitions of the variables can be found in Appendix E.

Table 3: Summary statistics for 2001 cohort (male students)

Variable	Obs	Mean	Std. Dev.	Min	Max
Test Score in Language	103,521	263.30	51.51	104.16	377.25
Test Score in Math	103,411	259.80	52.45	103.16	387.17
Dummy for Taking Test Scores at 4th Grade	113,759	89.62%	0.305	0	1
Repeat	113,759	14.28%	0.350	0	1
Size Class	113,759	30.99	9.60	1	55
Size Class - Standardized	113,759	-0.084	0.997	-3.196	2.409
Size School	113,759	65.16	46.84	1	336
Size School - Standardized	113,759	-0.080	0.904	-1.319	5.150
Full-Day Schooling	113,759	21.51%	0.411	0	1
Private School	113,759	7.46%	0.263	0	1
Subsidized School	113,759	51.70%	0.500	0	1
Public School	113,759	40.83%	0.492	0	1
North	113,759	13.27%	0.339	0	1
Centre	113,759	33.08%	0.471	0	1
South	113,759	14.90%	0.356	0	1
Santiago	113,759	38.75%	0.487	0	1
Rural School	113,759	8.11%	0.273	0	1
Years Education Father	92,241	11.67	3.66	0	22
Years Education Father Squared	92,241	149.57	82.32	0	484
Years Education Mother	95,158	11.65	3.46	0	22
Years Education Mother Squared	95,158	147.80	76.44	0	484
Household Income	94,903	374,022	430,371	38,609	1,851,805
Test Score in Language - Peers	113,759	267.37	23.74	139.47	358.65
Test Score in Language - Peers - Standardized	113,759	0.212	0.927	-4.782	3.777
Test Score in Math - Peers	113,759	256.77	28.71	125.66	365.96
Test Score in Math - Peers - Standardized	113,759	0.134	0.986	-4.368	3.884
Repeat - Peers	113,759	12.71%	0.119	0	1
Years Education Father - Peers	113,759	11.56	2.43	0	19
Years Education Father Squared - Peers	113,759	147.42	57.48	0	364.54
Years Education Mother - Peers	113,759	11.54	2.28	0	18.16
Years Education Mother Squared - Peers	113,759	145.57	52.52	0	333.90
Household Income - Peers	113,759	369,628	359,163	38,609	1,843,789
Juvenile Crime	113,759	3.73%	0.190	0	1
Violent Crime	113,759	2.32%	0.151	0	1
Non-violent Crime	113,759	2.34%	0.151	0	1

Note: This table presents the descriptive statistics of male students born in 2001, derived from the baseline sample. Detailed definitions of the variables can be found in Appendix E.

acts, with rates of 11.56% in 1996 and 8.40% in 2001. Furthermore, attending full-day schooling is associated with a slightly higher likelihood of committing crime, which may be attributed to its prevalence in public schools. In contrast, private schools exhibit better statistics. For instance, among those born in 1996 (respectively, 2001), individuals attending private schools have a juvenile crime prosecution rate of only 1.12% (respectively, 0.54%), compared to 4.34% (respectively, 2.82%) for subsidized schools and 7.01% (respectively, 5.47%) for public schools. Geographically, the central region (excluding the Santiago area) has lower delinquency rates compared to the rest of the country. Moreover, students attending rural schools exhibit significantly lower crime rates than those attending non-rural schools, with rates of 3.74% in rural schools versus 5.60% in non-rural schools in 1996, and 2.95% in rural schools versus 3.80% in non-rural schools in 2001. Finally, it is observed that parents with a higher level of education and household income tend to have children who engage in less misbehavior, which aligns with existing research highlighting the negative relationship between education and criminality (Lochner and Moretti, 2004).

In summary, the male population of the 2001 generation exhibited a significant reduction in *Juvenile Crime* by 31.3% compared to the 1996 generation, along with reductions of 25.8% in *Violent Crime* and 33.4% in *Non-violent Crime*. This substantial decline within a five-year period can be partially attributed to the improved socioeconomic profile of parents in the newer generation. Moreover, the presence of higher-achieving students in the 2001 cohort suggests a stronger overall peer effect.

Table 6 presents the marginal effects obtained from probit models using different specifications: Model 1 for the 1996 generation, Model 2 for the 2001 generation, Model 3 for the pooled sample, and Model 4, which includes a dummy variable indicating whether an individual was born in 1996 or not.[16] The marginal effects for the two alternative measures of crime, namely violent and non-violent crime, are reported in Appendix J for male individuals. For female marginal effects, please refer to Appendices K and L. The marginal effects in Model 4, provide valuable insights. Males who took both standardized tests have a lower likelihood of engaging in criminal behavior, with a marginal effect of -1.24 percentage points (pp). Notably, students who repeat a school year during their first four years of education are at a higher risk of delinquency, as indicated by the larger marginal effect of 2.88 pp. Full-day schooling has a minor deterrent effect on crime. While private schools do not outperform public schools, subsidized schools show better outcomes, with

[16]On Stata the command used in order to obtain marginal effects is:
probit outcome regressors; margins, dydx(*)

Table 4: Means per category for 1996 cohort (male students)

Classification	Obs	Juvenile Crime	Violent Crime	Non-violent Crime
High Test Score in Language	47,003	2.78%	1.48%	1.80%
Low Test Score in Language	62,373	7.14%	4.19%	4.60%
Chi square test		1,020 (0.000)	670 (0.000)	640 (0.000)
High Test Score in Math	54,084	3.10%	1.67%	2.00%
Low Test Score in Math	55,247	7.42%	4.36%	4.79%
Chi square test		1,020 (0.000)	676 (0.000)	644 (0.000)
Dummy for Taking Test Scores at 4th Grade=1	108,294	5.23%	3.00%	3.37%
Dummy for Taking Test Scores at 4th Grade=0	7,202	8.47%	5.10%	5.55%
Chi square test		138 (0.000)	98.1 (0.000)	95.1 (0.000)
Repeat	12,912	11.56%	6.74%	7.67%
Non Repeat	102,584	4.66%	2.67%	2.98%
Chi square test		1,060 (0.000)	625 (0.000)	743 (0.000)
Big Class	58,782	5.26%	3.03%	3.35%
Small Class	56,714	5.61%	3.23%	3.67%
Chi square test		6.97 (0.008)	4.09 (0.043)	9.000 (0.003)
Big School	60,040	5.17%	2.99%	3.33%
Small School	55,456	5.73%	3.28%	3.70%
Chi square test		17.5 (0.000)	7.73 (0.005)	11.3 (0.001)
Full-Day Schooling	19,197	6.14%	3.65%	3.79%
Non Full-Day Schooling	96,299	5.29%	3.02%	3.45%
Chi square test		22.4 (0.000)	20.4 (0.000)	5.32 (0.021)
Private School	7,419	1.12%	0.59%	0.63%
Subsidized School	51,745	4.34%	2.40%	2.81%
Public School	56,332	7.01%	4.13%	4.52%
Chi square test		662 (0.000)	436 (0.000)	426 (0.000)
North	15,433	5.59%	3.20%	3.73%
Centre	39,212	5.03%	2.96%	3.13%
South	16,556	5.67%	2.91%	4.06%
Santiago	44,295	5.65%	3.34%	3.56%
Chi square test		19.4 (0.000)	13.1 (0.004)	34.3 (0.000)
Rural School	10,506	3.74%	2.30%	1.95%
Non Rural School	104,990	5.60%	3.21%	3.66%
Chi square test		64.5 (0.000)	25.9 (0.000)	82.7 (0.000)
High Years Education Father	37,629	2.79%	1.46%	1.78%
Low Years Education Father	61,320	6.41%	3.70%	4.14%
Chi square test		640 (0.000)	421 (0.000)	416 (0.000)
High Years Education Mother	38,025	2.68%	1.43%	1.66%
Low Years Education Mother	62,887	6.48%	3.74%	4.23%
Chi square test		715 (0.000)	452 (0.000)	496 (0.000)
High Household Income	46,663	3.12%	1.67%	2.00%
Low Household Income	53,960	6.77%	3.93%	4.38%
Chi square test		692 (0.000)	457 (0.000)	449 (0.000)

Note: This table presents the category means for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime*. Additionally, it includes the results of the Pearson Chi-square test, providing information on the statistical significance of the differences in frequencies across each category (the associated p-value is reported in parentheses). The analysis is based on a sample of male students born in 1996, which was extracted from our baseline dataset. For variable definitions, please refer to Appendix E.

Table 5: Means per category for 2001 cohort (male students)

Classification	Obs	Juvenile Crime	Violent Crime	Non-violent Crime
High Test Score in Language	52,366	2.06%	1.24%	1.24%
Low Test Score in Language	51,155	4.96%	3.09%	3.15%
Chi square test		649 (0.000)	420 (0.000)	439 (0.000)
High Test Score in Math	56,092	2.02%	1.23%	1.22%
Low Test Score in Math	47,319	5.20%	3.22%	3.33%
Chi square test		772 (0.000)	487 (0.000)	536 (0.000)
Dummy for Taking Test Scores at 4th Grade=1	101,947	3.43%	2.11%	2.15%
Dummy for Taking Test Scores at 4th Grade=0	11,812	6.36%	4.13%	3.98%
Chi square test		253 (0.000)	191 (0.000)	156 (0.000)
Repeat	16,246	8.40%	5.35%	5.52%
Non Repeat	97,513	2.95%	1.82%	1.81%
Chi square test		1,150 (0.000)	767 (0.000)	838 (0.000)
Big Class	51,707	3.23%	2.04%	1.96%
Small Class	62,052	4.15%	2.55%	2.65%
Chi square test		67.2 (0.000)	32.0 (0.000)	58.2 (0.000)
Big School	50,809	2.95%	1.86%	1.80%
Small School	62,950	4.37%	2.70%	2.77%
Chi square test		157 (0.000)	87.5 (0.000)	116 (0.000)
Full-Day Schooling	24,471	4.66%	2.78%	3.06%
Non Full-Day Schooling	89,288	3.48%	2.20%	2.14%
Chi square test		75.1 (0.000)	28.9 (0.000)	70.7 (0.000)
Private School	8,492	0.54%	0.28%	0.27%
Subsidized School	58,819	2.82%	1.69%	1.75%
Public School	46,448	5.47%	3.49%	3.46%
Chi square test		770 (0.000)	538 (0.000)	507 (0.000)
North	15,096	3.90%	2.56%	2.43%
Centre	37,632	3.28%	1.88%	2.09%
South	16,945	3.97%	2.21%	2.65%
Santiago	44,086	3.97%	2.65%	2.40%
Chi square test		32.7 (0.000)	57.8 (0.000)	18.7 (0.000)
Rural School	9,224	2.95%	1.68%	1.72%
Non Rural School	104,535	3.80%	2.38%	2.39%
Chi square test		17.2 (0.000)	18.2 (0.000)	16.6 (0.000)
High Years Education Father	38,916	1.50%	0.91%	0.87%
Low Years Education Father	53,325	4.54%	2.79%	2.88%
Chi square test		659 (0.000)	409 (0.000)	457 (0.000)
High Years Education Mother	41,173	1.59%	0.97%	0.89%
Low Years Education Mother	53,985	4.59%	2.81%	2.94%
Chi square test		660 (0.000)	401 (0.000)	490 (0.000)
High Household Income	46,405	1.98%	1.24%	1.17%
Low Household Income	48,498	4.60%	2.80%	2.93%
Chi square test		506 (0.000)	291 (0.000)	363 (0.000)

Note: This table presents the category means for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime*. Additionally, it includes the results of the Pearson Chi-square test, providing information on the statistical significance of the differences in frequencies across each category (the associated p-value is reported in parentheses). The analysis is based on a sample of male students born in 2001, which was extracted from our baseline dataset. For variable definitions, please refer to Appendix E.

an average marginal effect of -0.662 pp. The preference for subsidized schools may be associated with higher parental engagement in children's education compared to public schools (Hanushek et al., 2007). Living in the metropolitan area is negatively associated with crime, as indicated by the negative coefficients for the northern, central, southern and rural regions. Finally, in Model 4, students with strong language skills, non-repeaters, and highly educated mothers contribute to a lower likelihood of their classmates engaging in criminal activities.

Table 6: Marginal effects in probit models for *Juvenile Crime* (male students)

Variables	Juvenile Crime			
	(1)	(2)	(3)	(4)
Dummy for Taking Test Scores at 4th Grade	-0.0122***	-0.0116***	-0.0114***	-0.0124***
	(0.00)	(0.00)	(0.00)	(0.00)
Repeat	0.0375***	0.0228***	0.0297***	0.0288***
	(0.00)	(0.00)	(0.00)	(0.00)
Size Class - Standardized	0.00232***	0.0141	0.00188***	0.00156***
	(0.01)	(0.15)	(0.00)	(0.01)
Size School - Standardized	-0.00229***	-0.0124	-0.00129**	-0.00176***
	(0.00)	(0.27)	(0.02)	(0.00)
Full-Day Schooling	-0.00383**	-0.00255*	-0.00423***	-0.00302**
	(0.05)	(0.08)	(0.00)	(0.01)
Private School	-0.00130	0.00266	0.00454	0.00261
	(0.87)	(0.68)	(0.37)	(0.61)
Subsidized School	-0.00510***	-0.00745***	-0.00650***	-0.00662***
	(0.00)	(0.00)	(0.00)	(0.00)
North	-0.00468**	-0.00446**	-0.00444***	-0.00480***
	(0.03)	(0.01)	(0.00)	(0.00)
Centre	-0.0120***	-0.0131***	-0.0121***	-0.0129***
	(0.00)	(0.00)	(0.00)	(0.00)
South	-0.00595***	-0.00528***	-0.00480***	-0.00604***
	(0.01)	(0.00)	(0.00)	(0.00)
Rural School	-0.0430***	-0.0275***	-0.0352***	-0.0356***
	(0.00)	(0.00)	(0.00)	(0.00)
Test Score in Language - Peers - Standardized	-0.0121***	-0.0452***	-0.0111***	-0.00703***
	(0.00)	(0.01)	(0.00)	(0.00)
Test Score in Math - Peers - Standardized	0.000977	-0.0554***	-0.000535	-0.00226**
	(0.60)	(0.00)	(0.61)	(0.03)
Repeat - Peers	0.00191	0.0446***	0.00479	0.0317***
	(0.81)	(0.00)	(0.27)	(0.00)
Years Education Father - Peers	0.00355	0.00384	-1.89e-06	0.00485***
	(0.19)	(0.12)	(1.00)	(0.01)
Years Education Father Squared- Peers	-0.000134	-0.000286**	-0.0000229	-0.000265***
	(0.39)	(0.03)	(0.81)	(0.01)
Years Education Mother - Peers	0.000831	-0.00127	-4.56e-06	-0.000211
	(0.79)	(0.66)	(1.00)	(0.92)
Years Education Mother Squared - Peers	-0.000470***	-0.0000739	-0.000303***	-0.000268**
	(0.01)	(0.62)	(0.01)	(0.02)
Household Income - Peers	1-68e-09	-1.18e-08*	-1.12e-08*	-6.81e-09
	(0.87)	(0.07)	(0.05)	(0.24)
Generation 1996				0.0140***
				(0.00)
Observations	115,496	113,759	229,255	229,255
Pseudo R-squared	5.42%	7.41%	6.40%	6.61%
Log likelihood	-23,061	-16,784	-39,969	-39,881

Note: This table presents the marginal effects and corresponding p-values (in parentheses) of the regression coefficients for each of the four probit models employed in the Oaxaca decompositions for *Juvenile Crime*. The sample employed in the analysis consists of male students extracted from our baseline sample. Detailed definitions of the variables can be found in Appendix E. Significance levels are indicated using asterisks, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% levels, respectively.

5 Results

As outlined in Section 3, our preferred model for analysis is Model 4. This model is advantageous because it avoids assumptions regarding the non-discriminated generation and prevents residual generation differences from affecting the slope parameters of the pooled model. Consequently, all Oaxaca decompositions are based on this model.

To provide further clarity, our probit model is specified as follows:

$$P(JC = 1|X) = \theta(\alpha + \sum_{j=1}^{J} \beta_j X_j + \gamma Generation\_1996) \tag{1}$$

This specification incorporates a dependent variable, such as *Juvenile Crime*, along with a comprehensive set of regressors encompassing individual performance, school characteristics, geographic location, socioeconomic background, and peer effect factors (for detailed information on these variables, see Subsection 4.2 and Appendix E). Additionally, a dummy variable for generation is included.

Once the unknown parameters in Equation 1 are estimated, we proceed with decomposing the differences in our three crime measures as presented in Table 7. The table displays the decomposition of differences under probit models in the third column (see Equations 20 and 21), and the Q/D ratio in the fourth column. As a robustness test, the fifth column employs Average Marginal Effects (AME) for the weightings (Equation 19). Finally, the last column reports the percentage of the explained part if a linear probability model (LPM) were utilized (Equation 12).

For *Juvenile Crime*, we observe a generation difference of 1.70 percentage points (pp), with -0.42 pp being explained by changes in the regressors. This implies that approximately 24.4% of the difference is accounted for by the model. Notably, this percentage remains quite similar even when considering alternative specifications, such as using AME or LPM. Turning to *Violent Crime*, the total difference amounts to 0.81 pp, with 0.28 pp explained by regressor changes. Thus, 35.1% of the difference is explained. On the other hand, for *Non-violent Crime*, the explained portion amounts to 0.22 pp, while the total difference is 1.17 pp. Consequently, only 18.9% of the difference is justified by the explored variables in this study.

In summary, approximately one-quarter of the variations in total crime can be explained by differences in regressors. However, while a substantial portion of the differences in violent crimes between generations can be accounted for, the decrease in non-violent crimes is not adequately justified by the variables examined in this study.

Table 7: Difference in means decomposition for Juvenile Crime in male students

Broad offense types	Variable	β^*	Quantity/Differences		
			β^*	AME	LPM
Juvenile Crime	Juvenile Crime mean (1996)	5.43%			
	Juvenile Crime mean (2001)	3.73%			
	Difference	-1.70%			
	Quantity	-0.42%	24.4%	24.4%	25.5%
	Unexplained	-1.29%	75.6%	75.6%	74.5%
Violent Crime	Juvenile Crime mean (1996)	3.13%			
	Juvenile Crime mean (2001)	2.32%			
	Difference	-0.81%			
	Quantity	-0.28%	35.1%	35.1%	34.1%
	Unexplained	-0.52%	64.9%	64.9%	65.9%
Non-violent Crime	Juvenile Crime mean (1996)	3.51%			
	Juvenile Crime mean (2001)	2.34%			
	Difference	-1.17%			
	Quantity	-0.22%	18.9%	18.6%	18.1%
	Unexplained	-0.95%	81.1%	81.4%	81.9%

Note: This table presents the decomposition of differences in means using Model 4 for male students. The third column showcases the decomposition of disparities under probit models, as described by Equations 20 and 21. The fourth column represents Q/D. To further assess the robustness of the findings, the fifth column applies the Average Marginal Effects (AME) as weightings, as outlined in Equation 19). Finally, the last column displays Q/D had a Linear Probability Model (LPM) been employed, as specified by Equation 12. The analysis is based on a sample size of 229,255 male individuals, with 115,496 born in 1996 and 113,759 born in 2001, which constitutes our baseline sample.

In Table 8, we provide the decomposition of Q for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime* by individual variables. This decomposition is based on Equations 19 and 21, and in order to obtain one for the sum of relative weights, we use the proper rescaling. Due to the high correlation among variables, we observe instances where the signs of the contributions deviate from the expected direction. For example, the variable *Repeat - Peers* exhibits a negative percentage contribution to total, violent, and non-violent crime, primarily because the younger generation displays higher rates of repetition. To facilitate comprehension, we group the variables into categories, as presented in Table 9 (refer to Table 10 to see which variables are included in each group). From this grouping, we draw the conclusion that the two most significant factors explaining the decline in overall criminal activity, as well as violent and non-violent offenses, between generations are *Performance - Peers* (52.4%) and *Education Mother - Peers* (68.4%).

Notably, *Performance - Peers* plays a particularly prominent role in understanding the higher Q/D ratio observed for violent crimes. The negative contribution of *Individual Performance* is a consequence of the higher likelihood of repetition and not taking both tests among students in the 2001 generation compared to those in the 1996 generation (see Tables 2 and 3). Moreover, the probit regression coefficients for *Dummy for Taking Test Scores at 4th Grade* and *Repeat* (see Appendix J) indicate that students who take both tests and do not repeat demonstrate lower levels of criminal activity.

To test the robustness of our findings, we present Table 11, which displays the results of the Oaxaca decomposition based on Model 4 (Equations 20 and 21) with one set of variables excluded at a time. The exclusion of a variable group is expected to decrease the percentage of the difference attributable to endowments, and our results generally align with this expectation. Overall, we find that our conclusions remain robust to specification changes.

Table 8: Decomposition of Q by variable (male students)

Variable	Juvenile Crime		Violent Crime		Non-violent Crime	
	Gap explained	%	Gap explained	%	Gap explained	%
Dummy for Taking Test Scores at 4th Grade	0.048%	-11.6%	0.032%	-11.4%	0.029%	-13.10%
Repeat	0.083%	-20.1%	0.048%	-16.7%	0.055%	-24.66%
Size Class - Standardized	-0.017%	4.1%	-0.014%	5.0%	-0.009%	3.91%
Size School - Standardized	0.022%	-5.4%	0.012%	-4.3%	0.016%	-7.11%
Full-Day Schooling	-0.014%	3.3%	-0.007%	2.4%	-0.011%	4.94%
Private School	0.003%	-0.6%	0.001%	-0.4%	0.004%	-1.90%
Subsidized School	-0.043%	10.3%	-0.033%	11.5%	-0.024%	10.84%
North	0.000%	-0.1%	0.000%	-0.1%	0.000%	-0.06%
Centre	0.011%	-2.5%	0.008%	-2.6%	0.006%	-2.83%
South	-0.003%	0.8%	-0.004%	1.4%	0.000%	0.10%
Rural School	0.033%	-7.9%	0.018%	-6.4%	0.026%	-11.62%
Test Score in Language - Peers - Standardized	-0.331%	79.5%	-0.254%	89.6%	-0.178%	80.33%
Test Score in Math - Peers - Standardized	-0.061%	14.8%	-0.018%	6.4%	-0.050%	22.52%
Repeat - Peers	0.174%	-41.9%	0.116%	-40.8%	0.133%	-60.02%
Years Education Father - Peers	0.273%	-65.7%	0.197%	-69.5%	0.247%	-111.68%
Years Education Father Squared- Peers	-0.280%	67.4%	-0.201%	70.8%	-0.223%	100.66%
Years Education Mother - Peers	-0.010%	2.4%	-0.005%	1.7%	-0.034%	15.29%
Years Education Mother Squared - Peers	-0.274%	65.9%	-0.163%	57.4%	-0.166%	75.00%
Household Income - Peers	-0.030%	7.3%	-0.017%	6.1%	-0.043%	19.38%
Total	-0.416%	100.0%	-0.284%	100.0%	-0.222%	100.0%

Note: This table presents the decomposition of the *quantity effect* in the third column of Table 7, for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime* by individual variables. The decomposition is conducted in both absolute and percentage terms.

Table 9: Decomposition of Q by group of variables (male students)

Variable	Juvenile Crime		Violent Crime		Non-violent Crime	
	Gap explained	%	Gap explained	%	Gap explained	%
Individual Performance	0.132%	-31.6%	0.080%	-28.1%	0.084%	-37.8%
Type School	-0.049%	11.7%	-0.040%	14.2%	-0.024%	10.7%
Area	0.041%	-9.8%	0.022%	-7.8%	0.032%	-14.4%
Performance - Peers	-0.218%	52.4%	-0.157%	55.2%	-0.095%	42.8%
Education Father - Peers	-0.007%	1.7%	-0.004%	1.3%	0.024%	-11.0%
Education Mother - Peers	-0.284%	68.4%	-0.168%	59.1%	-0.200%	90.3%
Household Income - Peers	-0.030%	7.3%	-0.017%	6.1%	-0.043%	19.4%
Total	-0.416%	100.0%	-0.284%	100.0%	-0.222%	100.0%

Note: This table provides the decomposition of the *quantity effect*, as presented in the third column of Table 7, for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime* by groups of variables (refer to Table 10). The decomposition is conducted in both absolute and percentage terms.

Table 10: Variables

Specification	Variables
Baseline scenario	Dummy for Taking Test Scores at 4th Grade, Repeat, Size Class - Standardized, Size School - Standardized, Full-Day Schooling, Private School, Subsidized School, North, Centre, South, Rural School, Test Score in Language - Peers - Standardized, Test Score in Math - Peers - Standardized, Repeat - Peers, Years Education Father - Peers, Years Education Father Squared- Peers, Years Education Mother - Peers, Years Education Mother Squared- Peers, Household Income - Peers
Individual performance	Dummy for Taking Test Scores at 4th Grade, Repeat
Type school	Size Class - Standardized, Size School - Standardized, Full-Day Schooling, Private School, Subsidized School
Area	North, Centre, South, Rural School
Performance - Peers	Test Score in Language - Peers - Standardized, Test Score in Math - Peers - Standardized, Repeat - Peers
Education Father - Peers	Years Education Father - Peers, Years Education Father Squared - Peers
Education Mother - Peers	Years Education Mother - Peers, Years Education Mother Squared - Peers
Household Income - Peers	Household Income - Peers

Note: This table presents the variables used in the baseline scenario and categorizes them into groups.

Table 11: Oaxaca decomposition excluding one group a time (male students)

Model	Explained/Difference		
	Juvenile Crime	Violent Crime	Non-violent Crime
(4)	24.4%	35.1%	18.9%
(4) w/o Individual Performance	19.9%	30.0%	14.5%
(4) w/o Type School	23.7%	33.9%	18.4%
(4) w/o Area	30.0%	44.7%	23.8%
(4) w/o Performance - Peers	21.0%	29.0%	19.6%
(4) w/o Education Father - Peers	27.3%	39.6%	22.9%
(4) w/o Education Mother - Peers	22.3%	32.4%	16.8%
(4) w/o Household Income - Peers	24.0%	34.6%	18.0%

Note: This table summarizes the Oaxaca decomposition using Model (4) and probit models by excluding one group of variables from the regression analysis at a time.

6 Conclusion

This economic journal article examines the substantial decrease in juvenile delinquency rates among male individuals in Chile, specifically analyzing cohorts born in 1996 and 2001. The study investigates the impact of various factors on overall crime rates, including violent and non-violent offenses. Results show a significant reduction in male juvenile delinquency rates from 5.43% to 3.73%. The decline is observed in both violent offenses (from 3.13% to 2.32%) and non-violent offenses (from 3.51% to 2.34%). In contrast, female crime rates exhibit minimal change, with an overall decrease from 1.57% to 1.53%. However, female violent crime rates experienced a slight increase from 0.67% to 0.70%, while non-violent crime rates decreased from 1.06% to 1.05%. As a result, this study focuses exclusively on male students to investigate the underlying factors contributing to this notable decline in male juvenile delinquency rates.

Empirical evidence suggests that male individuals who exhibit strong performance on standardized tests are associated with a lower likelihood of engaging in antisocial behavior. Similarly, individuals who do not experience grade repetition demonstrate a reduced inclination towards participating in unlawful activities. Furthermore, attending subsidized schools, particularly private ones, appears to be correlated with a decreased propensity for engaging in illegal conduct among young males. Moreover, males from households with higher income levels tend to exhibit lower rates of delinquency, as do those whose parents possess higher levels of education.

An examination of marginal effects within probit models focusing on various categories of crime, including *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime*, yields consistent findings. Notably, male individuals who experience grade repetition exhibit a significantly higher inclination towards engaging in criminal activities, *ceteris paribus*, as evidenced by an average marginal effect of 2.88 pp. The implementation of full-day schooling demonstrates a modestly successful measure in curbing delinquency, with a marginal effect of -0.302 pp. Moreover, subsidized schools exhibit a slight advantage over public schools in terms of mitigating student misbehavior, as indicated by a marginal effect of -0.662 pp. Residing in the Santiago area has a detrimental impact on juvenile crime rates. Additionally, male individuals who have peers with higher levels of parental education and greater household incomes display a lower likelihood of committing crimes. Conversely, having peers who have experienced grade retention can have a negative influence on students' propensity to engage in criminal activities.

Our primary finding comprises the Oaxaca decomposition, which utilizes probit models to disentangle the disparities in *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime* among cohorts into two distinct components: the explained part, attributed to differences in endowments, and the unexplained part. We deliberate on the suitability of various models but ultimately focus on employing a pooled model with group indicators. This choice is driven by the absence of a specific rationale for designating one generation as the non-discriminated reference group and to mitigate the potential bias stemming from omitted variables. The cohort born in 2001 exhibits superior individual, educational, and peer metrics compared to those born in 1996. In our baseline model, improvements in these endowments account for 24.4% of the observed decrease in deviant behavior. Regarding violent acts, the explained percentage of the reduction reaches 35.1%, significantly higher than the 18.9% for non-violent acts. Similar results are obtained when employing a linear probabilistic model. Analyzing the determinants of the decline in crime between cohorts, we identify peer effects, particularly the educational attainment of mothers and the academic performance of peers, as the most influential factors.

Future research should investigate various factors that may explain the decline in crime. For example, the enactment of Law No. 20,802[17] on January 9, 2015, which amends Law No. 19,718 establishing the Public Defender's Office (PDO), aimed to ensure the availability of at least 50 defenders specializing in the criminal defense of adolescents. According to a PDO article,[18] by 2016,

[17] *Diario Oficial de la República*. Retrieved February 4, 2023, from https://www.diariooficial.interior.gob.cl/media/2015/01/09/do-20150109.pdf.

[18] *Cámara de Diputadas y Diputados*. Retrieved February 4, 2023, from

these 50 specialized public defenders were already handling approximately 75% of all juvenile criminal cases. Coinciding with the introduction of public defenders with a focus on juveniles, there was a sharp decrease of 9.0% in juvenile cases in 2015 and 10.1% in 2016 (see Appendix B). It is plausible to suggest that these 50 defenders had an impact on the number of juveniles facing criminal charges and potentially influenced the recidivism rates among problematic juveniles.

The National Service for Minors (*Servicio Nacional de Menores*, SENAME from now on), the Chilean state agency responsible for protecting the rights of minors and adolescents in the judicial system, as well as regulating and supervising adoptions, caters to approximately 200,000 minors annually.[19] Recent years have seen increased scrutiny of the agency,[20] following incidents such as the 2016 death of Lissete Vega.[21] Consequently, the administrations of Piñera (2010-2014) and Bachelet (2014-2018) substantially augmented SENAME's budget, which witnessed an 85% increase from 114,562 million CLP in 2013[22] to 212,423 million CLP in 2018,[23], or 58% in real terms.[24] This significant budgetary expansion may have benefited at-risk children, including those under the care of SENAME,[25] by facilitating the implementation of programs such as the *Programa 24 horas*.[26] While our database lacks information regarding children's involvement with SENAME, it would be valuable to explore how its various programs may have influenced delinquency rates.

Additional factors that could potentially account for the disparity in delinquency rates between generational cohorts may encompass variations in the intensity of law enforcement efforts towards juvenile offenders in 2018 compared to 2013. Furthermore, it raises the question of whether judges exhibited comparable stringency towards individuals born in 2001 as they did towards those born in 1996, or if policy alterations resulted in a greater prevalence of warnings issued to most offenders.

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https://www.camara.cl/verDoc.aspx?prmID=95083&prmTIPO=DOCUMENTOCOMISION.

[19]SENAME. Retrieved February 4, 2023, FROM https://www.sename.cl/web/wp-content/uploads/2021/05/Resumen-de-Cifras-Cuenta-Publica-2020.pdf.

[20]CIPER. Retrieved February 4, 2023, from https://www.ciperchile.cl/2019/07/02/el-brutal-informe-de-la-pdi-sobre-abusos-en-el-sename-que-permanecio-oculto-desde-diciembre/.

[21]Soychile. Retrieved February 4, 2023, from https://www.soychile.cl/Santiago/Sociedad/2016/04/12/386548/Nina-de-12-anos-murio-en-centro-del-Sename-en-Santiago.aspx.

[22]DIPRES. Retrieved February 4, 2023, from https://www.dipres.gob.cl/597/articles-95499_doc_pdf.pdf.

[23]DIPRES. Retrieved February 4, 2023, from https://www.dipres.gob.cl/597/articles-168509_doc_pdf.pdf.

[24]To reach this number, we use annual inflation from Central Bank of Chile, retrieved February 4, 2023, from https://si3.bcentral.cl/Siete/ES/Siete/Cuadro/CAP_ESTADIST_MACRO/MN_EST_MACRO_IV/IPC_DICIEMBRE/IPC_DICIEMBRE.

[25]La Tercera. Retrieved February 4, 2023, from https://www.latercera.com/nacional/noticia/auditoria-arroja-42-los-ninos-del-sename-consume-alcohol-drogas/178303/.

[26]SENAME. Retrieved February 4, 2023, from https://www.sename.cl/web/index.php/el-programa-24-horas/.

Finally, the examination conducted in Appendix B unveils a discernible downward trend in juvenile crime rates throughout the years 2020 and 2021, potentially attributable to the well-documented propensity for young individuals to engage in criminal behaviors within social collectives (Snyder, 2008). This observed decline, relative to the preceding periods, sparks intrigue as to the future trajectory of crime rates. It prompts an exploration into whether the subsequent years will witness a reversion to pre-pandemic levels, a phenomenon that has exhibited partial resurgence during 2022, or if the observed reduction in delinquency signifies a sustained and enduring pattern over an extended time horizon.

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Appendices

A Crime statistics

Table 12: Crime statistics in Chile

Type of Crime	Year																	
	2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Homicide	3.51	3.59	3.48	3.34	3.52	2.85	3.15	2.77	2.73	3.03	2.93	2.72	3.46	3.49	3.62	4.57	3.53	4.71
Theft	959.43	940.27	1016.45	1051.96	1132.05	1095.77	1206.27	1095.51	1069.07	1080.58	1024.24	948.52	929.29	918.34	885.08	496.18	411.51	595.76
Minor injuries	469.99	487.35	519.30	559.91	559.67	540.73	573.40	492.56	435.91	389.71	356.05	330.27	317.84	316.54	324.19	238.11	229.46	290.55
Serious injuries	143.76	128.41	131.54	139.40	141.08	130.44	133.09	113.58	103.50	98.11	88.84	83.93	79.37	81.14	89.04	79.29	73.31	87.71
Other theft with force	80.73	104.17	52.91	42.50	44.01	51.31	38.41	28.69	32.84	35.66	33.77	32.70	37.79	36.56	38.67	27.64	29.03	43.00
Robbery with violence or intimidation	336.69	345.63	399.34	371.33	364.98	311.88	355.99	310.10	329.24	368.94	374.39	361.68	378.27	393.51	412.65	340.43	242.95	396.24
Robbery of objects or from vehicle	247.10	214.58	266.50	275.91	326.09	335.49	366.11	336.53	349.92	360.00	362.63	339.00	327.01	294.27	286.69	200.84	182.84	259.43
Motor vehicle theft	74.82	83.42	116.75	128.29	165.06	180.39	201.35	189.26	177.27	184.75	177.78	163.90	160.69	129.52	121.29	105.18	120.31	168.14
Robbery in an inhabited place	422.10	397.97	418.81	412.97	443.84	403.51	433.29	412.82	402.67	398.20	376.85	343.18	334.56	311.85	282.67	177.20	151.32	218.77
Robbery in an uninhabited place	214.89	235.08	231.27	241.19	271.37	266.90	286.23	267.41	269.52	288.08	284.81	272.89	264.49	245.71	268.43	191.20	145.60	227.69
Surprise robbery	123.42	133.03	166.49	165.47	179.43	166.71	177.11	158.06	199.17	228.90	218.08	200.43	189.88	182.60	169.90	106.01	90.50	145.88
Rape	16.71	17.54	17.81	20.06	20.16	18.40	20.81	18.77	18.11	16.06	15.32	15.48	16.12	18.71	21.53	19.55	22.10	24.58
Crimes of greater social connotation	3,093.15	3,091.05	3,340.63	3,412.33	3,651.26	3,504.39	3,795.19	3,426.09	3,389.94	3,452.01	3,315.69	3,094.70	3,038.76	2,932.24	2,903.77	1,986.21	1,702.46	2,462.45

Note: This table presents the annual crime rates per 100,000 inhabitants for different categories of crimes. The category ”Crimes of Greater Social Connotation” represents the aggregate of all aforementioned crime types.
Source: Center for Studies and Analysis of Crime

B Juvenile crime statistics

Table 13: Juvenile crime statistics in Chile

Type of Crime		2005	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	2021	2022
Homicide	U 18	47	43	42	34	69	49	50	51	34	34	28	26	30	23	18	19	11	17
	Total	420	376	343	402	455	376	417	469	379	361	302	307	333	295	299	299	215	250
Theft	U 18	13,277	13,586	17,386	15,824	16,677	14,926	16,302	13,419	12,471	12,128	11,143	9,931	8,691	7,876	6,217	2,254	1,463	1,990
	Total	71,975	72,444	85,639	88,040	97,211	91,457	101,315	88,302	83,601	85,108	81,477	77,273	76,849	79,158	73,999	40,633	25,380	36,424
Minor injuries	U 18	1,768	1,896	2,092	2,974	3,659	4,067	4,907	4,540	4,205	3,533	3,208	3,214	2,955	2,863	2,869	1,063	1,090	3,437
	Total	19,690	22,962	23,504	29,798	34,969	38,653	43,945	41,177	36,904	32,552	30,893	29,918	29,563	29,607	30,098	22,211	22,648	26,479
Serious injuries	U 18	675	631	624	926	1,060	1,052	1,055	919	813	776	651	591	505	436	424	262	251	517
	Total	7,813	7,035	6,860	8,774	9,915	9,946	10,154	9,268	8,275	7,605	6,932	6,407	6,341	6,476	6,584	5,856	5,642	6,041
Other thefts with force	U 18	655	1,368	683	622	639	517	447	316	300	268	231	210	186	129	84	38	50	57
	Total	2,115	4,531	2,428	2,282	2,341	2,258	1,765	1,417	1,163	1,160	1,069	1,088	1,068	1,036	1,039	984	990	1,905
Robbery with violence or intimidation	U 18	3,129	3,356	4,343	4,089	4,089	2,957	3,205	3,096	3,181	3,147	3,032	2,734	2,297	2,197	1,988	1,338	992	1,749
	Total	9,271	9,669	11,941	11,950	12,768	9,997	10,743	10,511	10,504	10,573	10,404	9,825	9,874	9,656	9,037	6,890	4,598	7,401
Robbery of objects in or from vehicle	U 18	640	558	698	636	813	652	631	680	682	673	609	550	394	291	201	93	50	48
	Total	1,944	1,657	2,035	2,131	2,630	2,337	2,242	2,642	2,776	2,732	2,651	2,761	2,593	2,277	2,083	1,313	1,040	1,398
Motor vehicle theft	U 18	311	246	510	483	785	902	968	1,254	1,156	1,047	816	591	364	231	121	51	63	112
	Total	1,111	827	1,497	1,479	2,301	2,625	2,757	3,616	2,944	2,512	2,024	1,624	1,135	800	506	363	387	507
Robbery in an inhabited place	U 18	1,821	1,838	1,644	1,554	1,606	1,391	1,359	1,653	1,667	1,575	1,431	1,193	875	775	547	250	166	193
	Total	5,353	5,364	5,117	5,290	5,737	5,408	5,547	6,198	6,211	6,134	6,069	5,716	5,755	5,550	4,757	3,125	2,148	3,062
Robbery in an uninhabited place	U 18	1,452	1,645	1,543	1,503	1,631	1,504	1,651	1,463	1,368	1,397	1,354	1,100	916	755	1,289	382	252	241
	Total	4,964	5,545	5,550	5,894	6,833	6,446	6,920	6,937	6,788	7,581	7,779	7,186	7,421	7,212	13,599	6,484	3,599	5,368
Surprise robbery	U 18	1,335	1,600	2,035	1,941	1,810	1,352	1,129	1,097	1,348	1,404	1,134	1,099	963	849	623	407	227	242
	Total	3,743	4,115	4,940	4,926	5,055	3,999	3,701	3,557	4,059	4,431	3,942	4,088	4,266	4,318	3,574	2,499	1,586	1,925
Rape	U 18	80	82	82	101	148	112	149	177	132	95	91	88	88	83	109	93	99	104
	Total	506	679	706	941	1,169	1,053	1,201	1,135	1,119	887	878	873	827	950	1,078	1,126	1,221	1,243
Crimes of greater social connotation	U 18	25,190	26,849	31,682	30,687	32,986	29,481	31,853	28,665	27,357	26,077	23,728	21,327	18,264	16,508	14,490	6,250	4,714	8,707
	Total	128,905	135,204	150,560	161,907	181,384	174,555	190,707	175,229	164,723	161,636	154,420	147,066	146,025	147,335	146,653	91,783	69,454	92,003
Crimes of greater social connotation	% U 18	19.5%	19.9%	21.0%	19.0%	18.2%	16.9%	16.7%	16.4%	16.6%	16.1%	15.4%	14.5%	12.5%	11.2%	9.9%	6.8%	6.8%	9.5%
	% G YoY	-	6.6%	18.0%	-3.1%	7.5%	-10.6%	8.0%	-10.0%	-4.6%	-4.7%	-9.0%	-10.1%	-14.4%	-9.6%	-12.2%	-56.9%	-24.6%	84.7%

Note: This table presents the annual count of criminal cases in Chile when someone is prosecuted disaggregated by type of crime, with a distinction made between total cases and cases involving individuals under the age of 18. The category "Crimes of Greater Social Connotation" represents the cumulative count of all aforementioned crime types. The last two rows provide the percentage of Crimes of Greater Social Connotation committed by juveniles in relation to the total cases, as well as the year-over-year increase in crimes involving juveniles. **Source:** *Center for Studies and Analysis of Crime*

C Oaxaca methodology in detail

This study introduces a Stata command, referred to as *oaxaca*, which has been utilized to conduct the Oaxaca decomposition and derive our findings. In our research framework, our aim is to decompose the disparities in the average values of the dependent variable, such as *Juvenile Crime*, between two distinct groups: individuals born in 1996 and those born in 2001. The key inquiry revolves around quantifying the extent to which the mean difference in the outcome variable,

$$D = E(JC_{2001}) - E(JC_{1996}) \tag{2}$$

where $E(JC_g)$ denotes the expected value of *Juvenile Crime* for generation *g*, is accounted for by group differences in the predictors.

For instructional purposes, let us assume from this point onward that our prediction is based on the linear model, as follows:[27]

$$JC_g = X_g^{'}\beta_g + \epsilon_g, \qquad E(\epsilon_g) = 0 \qquad g \in (1996, 2001) \tag{3}$$

where X ia vector containing our explanatory variables (see Subsection 4.2) and a constant, β contains the slope parameters and the intercept, and ϵ is the error. D may be expressed as the difference in the linear prediction evaluated at the group-specific means of the regressors:

$$D = E(JC_{2001}) - E(JC_{1996}) = E(X_{2001})^{'}\beta_{2001} - E(X_{1996})^{'}\beta_{1996} \tag{4}$$

given the fact that

$$E(JC_g) = E(X_g^{'}\beta_g + \epsilon_g) = E(X_g^{'}\beta_g) + E(\epsilon_g) = E(X_g)^{'}\beta_g \tag{5}$$

as $E(\beta_g) = \beta_g$ and $E(\epsilon_g) = 0$ by assumption. To assess the impact of disparities in predictor variables on the overall difference in outcome means, Equation (4) can be rearranged in various

[27] An extension to probit or logit models will we explained later on

ways. For instance, Winsborough and Dickinson (1971), Jones and Kelley (1984), and Daymont and Andrisani (1984) suggest the following one:

$$D = (E(X_{2001}) - E(X_{1996}))'\beta_{1996} + E(X_{1996})'(\beta_{2001} - \beta_{1996}) + (E(X_{2001}) - E(X_{1996}))'(\beta_{2001} - \beta_{1996}) \tag{6}$$

This is a *threefold* decomposition, meaning that D is divided into three components:

$$D = E + C + I \tag{7}$$

The first component,

$$E = (E(X_{2001}) - E(X_{1996}))'\beta_{1996} \tag{8}$$

is called the *endowment effect* and measures the part of the outcome differential which is caused by differences in the predictors between generations. The second component,

$$C = E(X_{1996})'(\beta_{2001} - \beta_{1996}) \tag{9}$$

is called the *coefficients effect* and measures the part of the outcome differential which is caused by differences in the coefficients (slope parameters and intercepts). The third component,

$$I = (E(X_{2001}) - E(X_{1996}))'(\beta_{2001} - \beta_{1996}) \tag{10}$$

is called the *interaction effect* and accounts for the fact that differences in predictor and coefficients exist simultaneously between the two generations.

Equation 6 is formulated from the perspective of individuals born in 1996. E represents the expected change in *Juvenile Crime* between the 2001 generation and the 1996 generation, assuming that the 2001 had the same coefficients as the 1996 generation. On the other hand, C quantifies the expected change in *Juvenile Crime* between the 2001 generation and the 1996 generation, assuming that the generation 1996 had the coefficients of the 2001 generation. Alternatively, the differential can be expressed from the viewpoint of the 2001 generation:

$$D = (E(X_{2001}) - E(X_{1996}))^{'}\beta_{2001} + E(X_{2001})^{'}(\beta_{2001} - \beta_{1996}) - (E(X_{2001}) - E(X_{1996}))^{'}(\beta_{2001} - \beta_{1996}) \tag{11}$$

Now E represents the portion of the differences in *Juvenile Crime* between the 2001 and 1996 generations that can be explained by disparities in predictor levels, assuming the coefficients of the 2001 generation as being the true coefficients. On the other hand, C quantifies the disparity in mean outcomes between the 2001 and 1996 generations, which the 2001 generation would experience if it had the coefficients of the 1996 generation.

At this stage, it is not evident whether Equation 6 or Equation 11 should be preferred. In various contexts, arguments have been put forth in favor of one equation over the other. For instance, if we substitute ”2001” with ”women” and ”1996” with ”men,” it would be logical to employ Equation 6. In this case, we would implicitly assume that wage discrimination is directed towards females and that there is no positive discrimination towards males. C would provide an answer to the question of whether women should have higher salaries than men, given the differences in predictors and assuming that the coefficients for men are ”fair.” Alternatively, it is also possible to assume that there is positive discrimination towards men but no discrimination towards women, in which case Equation 11 should be employed. This situation, known as the ”index number problem,” was identified by Oaxaca (1973).

An alternative decomposition has been proposed in the existing literature, which advocates for finding a nondiscriminatory coefficient vector. Equation 4 can be rearranged as follows:

$$D = (E(X_{2001}) - E(X_{1996}))^{'}\beta^{*} + (E(X_{2001})^{'}(\beta_{2001} - \beta^{*}) + E(X_{1996})^{'}(\beta^{*} - \beta_{1996})) \tag{12}$$

This is a *twofold* decomposition,

$$D = Q + U \tag{13}$$

where the first component,

$$Q = (E(X_{2001}) - E(X_{1996}))^{'}\beta^{*} \tag{14}$$

represents the part of the outcome differential that may be attributed to differences between generations in predictor means (*quantity effect*), and the second component,

$$U = E(X_{2001})^{'}(\beta_{2001} - \beta^{*}) + E(X_{1996})^{'}(\beta^{*} - \beta_{1996}) \tag{15}$$

is the unexplained part. Although this component is usually attributed to discrimination, it is important to acknowledge that it may also encompass disparities in unobservable factors across groups.

The estimation of the components of the threefold decomposition, as presented in Equation 6 (respectively, Equation 11), involves a straightforward procedure. In order to obtain $\hat{\beta}_{2001}$ (respectively, $\hat{\beta}_{1996}$), we utilize the entire population of individuals belonging to the 2001 generation (respectively, the 1996 generation), and employ Ordinary Least Squares methodology. Additionally, we calculate the group mean $\hat{X}_{2001}$ (respectively, $\hat{X}_{1996}$).

Determining the nondiscriminatory coefficient β^{*} from Equation 12 in a rigorous manner has received considerable attention in the literature. Various suggestions have been put forth to address this question. Firstly, it is worth noting that if $\beta^{*} = \beta_{2001}$ or $\beta^{*} = \beta_{1996}$, then it can be shown straightforwardly that Q from Equation 12 is equivalent to E from Equation 6 or 11.

Reimers (1983) proposes an alternative approach by using the average coefficients over both groups, which can be expressed as:

$$\beta^{*} = 0.5\beta_{2001} + 0.5\beta_{1996} \tag{16}$$

On the other hand, Cotton (1988) suggests weighting the coefficients by group sizes:

$$\beta^{*} = \frac{n_{2001}}{n_{2001} + n_{1996}}\hat{\beta}_{2001} + \frac{n_{1996}}{n_{2001} + n_{1996}}\hat{\beta}_{1996} \tag{17}$$

Based on theoretical considerations, Neumark (1988) suggests using coefficients obtained from a pooled regression that includes both generations. However, Fortin (2006) and Jann et al. (2008) argue that Neumark's approach may result in transferring some of the unexplained component in the outcome differential into the explained portion (See Appendix D for an illustrative example).

Therefore, they propose incorporating a group indicator as an additional predictor in the pooled model.[28]

Finally, given that our dependent variable, *Juvenile Crime*, is binary in nature, we employ probit models for our analysis. In order to conduct the nonlinear decomposition of the binary variable, Stata applies the weighting method outlined by by Yun (2004). Specifically, we refer to Section 2.1.2. Example B (Probit decomposition) of the aforementioned paper for guidance.

Finally, as we are dealing with a binary outcome variable, *Juvenile Crime*, we will be using probit models. In order to make the nonlinear decomposition of the binary variable, Stata uses the weighting method described by Yun (2004) (in particular, see Section 2.1.2. Example B. Probit decomposition).

To assist the reader, we highlight the key equations from that paper that are relevant to our specific study. Within probit models, the difference in outcomes can be explained by two components: the explained part and the unexplained part.

$$D = \overline{JC}_{2001} - \overline{JC}_{1996} = \overline{\Phi(X_{2001}\beta_{2001})} - \overline{\Phi(X_{1996}\beta_{1996})} = \sum_{i=1}^{i=K} W^i_{\Delta x}[\overline{\Phi(X_{2001}\beta^*)} - \overline{\Phi(X_{1996}\beta^*)}] + U \tag{18}$$

To appropriately account for the contribution of each variable in the explained part of the difference, we employ the following weighting scheme:

[28]The *oaxaca* command in Stata generates the Oaxaca decomposition. The decomposition type is selected as an option:

threefold computes the three-fold decomposition from the viewpoint of Group 2 (in Stata indicates which generation is Group 2. If we group by a variable called *G1996* which is 1 for those born in 1996 and 0 for those born in 2001, then Group 2 is generation 1996 and Stata will use Equation 6

threefold[(reverse)] computes the three-fold decomposition from the viewpoint of Group 1, employing Equation 11

omega computes the two-fold decomposition (Equation 12) using the coefficients from a pooled model over both group as the reference coefficients. Notably, this option does not include a dummy variable for generation as a control variable in the pooled model.

pooled computes the two-fold decomposition (Equation 12) using the coefficients from a pooled model over both groups as the reference coefficients. In this case, the dummy variable *G1996* is included in the pooled model as a control variable.

$$W^i_{\Delta x} = \frac{(\bar{X}^i_{2001} - \bar{X}^i_{1996})\beta^{i*}}{(\bar{X}_{2001} - \bar{X}_{1996})\beta^*} \tag{19}$$

However, for Model 4, a slight correction is necessary as β^* incorporates the dummy variable indicating membership to a specific generation. Thus, Equation 18 can be rewritten as:

$$D = \sum_{i=1}^{i=K-1} W^i_{\Delta x}[\overline{\Phi(X_{2001}\beta^*)} - \overline{\Phi(X_{1996}\beta^*)}] + W^K_{\Delta x}[\overline{\Phi(X_{2001}\beta^*)} - \overline{\Phi(X_{1996}\beta^*)}] + U \tag{20}$$

The explained part of the model (referred to as the *quantity effect*) is then given by:

$$Q = \sum_{i=1}^{i=K-1} W^i_{\Delta x}[\overline{\Phi(X_{2001}\beta^*)} - \overline{\Phi(X_{1996}\beta^*)}] \tag{21}$$

This *quantity effect* can be expressed as a percentage of the total difference Q/D.

Furthermore, it should be noted that if we desire $\sum_{i=1}^{i=K-1} W^i_{\Delta x}$ to sum up to one, we need to rescale $W^i_{\Delta x}$ by multiplying it by $\frac{(\bar{X}^i_{2001} - \bar{X}^i_{1996})\beta^*}{\sum_{i=1}^{i=K-1}(\bar{X}_{2001} - \bar{X}_{1996})\beta^{i*}}$.

D Proof that neglecting a group indicator in the pooled model may lead to overstating the explained part of the outcome differential.

Consider a simplified model of *Juvenile Crime* (JC) with respect to a *Test Score* (TS), incorporating generation-specific intercepts α_{2001} and α_{1996}. The model can be represented as follows:

$$JC = \begin{cases} \alpha_{1996} + \gamma TS + \epsilon, & \text{if generation 1996} \\ \alpha_{2001} + \gamma TS + \epsilon, & \text{if generation 2001} \end{cases} \tag{22}$$

Let us denote α_{1996} as α and α_{2001} as $\alpha + \delta$, where δ represents the discrimination parameter.[29] Rearranging Equation 22, we obtain:

$$JC = \alpha + \gamma TS + \delta \textbf{\textit{G2001}} + \epsilon, \tag{23}$$

where *G2001* is an indicator that takes the value of 1 for students born in 2001 and 0 otherwise.

Assuming $\gamma < 0$ (indicating a negative relationship between TS and JC) and $\delta < 0$ (suggesting that the generation born in 2001 exhibits lower crime levels even after controlling for TS).

If we utilize γ^* from a pooled model without incorporating a generation indicator dummy variable:

$$JC = \alpha^* + \gamma^* TS + \epsilon^*, \tag{24}$$

in Equation 14, and we follow the theory of omitted variables (see Gujarati (2003), pp. 510-513), then:

[29] Alternatively, this parameter could account for the effects of unobserved variables.

$$Q = [E(TS_{2001}) - E(TS_{1996})]\gamma^* = [E(TS_{2001}) - E(TS_{1996})]\left(\gamma + \delta \frac{Cov(TS, \textbf{\textit{G2001}})}{Var(TS)}\right) \quad (25)$$

In the scenario where individuals born in 2001 demonstrate higher standardized test scores ($\gamma < 0$), and there exists a positive covariance between the test scores (TS) and the indicator variable for the 2001 generation (*G2001*), while $\delta < 0$, the explained part of the decomposition becomes overstated. Specifically, a fraction of the explained variation in juvenile crime across generations can be attributed to the generation itself. This outcome is undesirable, highlighting the critical significance of incorporating a generation indicator within the pooled model.

E Variables' definition

E.1 Outcome variables

- **Juvenile Crime**: This binary variable takes the value of 1 if a student has been criminally charged up until December 2013 for those born in 1996 and up until December 2018 for those born in 2001. Otherwise, it takes the value of 0.
- **Violent Crime**: This binary variable takes the value of 1 if a student has been criminally charged up until December 2013 for those born in 1996 and up until December 2018 for those born in 2001, specifically for a violent offense such as murder, attempted murder or manslaughter, assault, kidnapping, sexual offenses, robbery, criminal possession of a weapon, and incidents of arson or road traffic resulting in injuries. It takes the value of 0 otherwise.
- **Non-violent Crime**: This binary variable takes the value of 1 if a student has been criminally charged up until December 2013 for those born in 1996 and up until December 2018 for those born in 2001, for a non-violent offense such as theft, vandalism, incidents of arson or road traffic without injuries, drug crimes, white-collar crimes, or cybercrimes. Otherwise, it takes the value of 0.

E.2 Individual variables

- **Female**: This binary variable takes the value of 1 if a student is female and 0 if the student is male.
- **Dummy for Taking Test Scores at 4th Grade**: This binary variable takes the value of 1 if a student has taken both the standardized test score (*Sistema de Medición de Calidad de la Educación*, SIMCE) in language and the standardized test score in math during the 4th grade of Elementary School, and 0 otherwise.
- **Test Score in Language**: This variable represents the grade obtained by a student in the lecture exam on the national standardized test (SIMCE) conducted during the 4th grade of Elementary School. It is classified as *High* if the score is above 266.80, which is the median

score when both female and male students from the 1996 and 2001 generations are included in the sample, and *Low* otherwise.

- **Test Score in Math**: This variable represents the grade obtained by a student in the mathematics exam on the national standardized test (SIMCE) conducted during the 4th grade of Elementary School. It is classified as *High* if the score is above 255.55, which is the median score when both female and male students from the 1996 and 2001 generations are included in the sample, and *Low* otherwise.
- **Repeat**: This binary variable takes the value of 0 if a student successfully completed the first 4 grades of primary school in 4 academic years, and 1 otherwise.
- **Years Education Father**: This variable represents the number of years of formal education completed by the father. It is classified as ”High” if the father’s education level is greater than or equal to 13 years, and ”Low” otherwise.
- **Years Education Father Squared**: This variable represents the squared value of the *Years Education Father* variable.
- **Years Education Mother**: This variable represents the number of years of formal education completed by the mother. It is classified as ”High” if the mother’s education level is greater than or equal to 13 years, and ”Low” otherwise.
- **Years Education Mother Squared**: This variable represents the squared value of the *Years Education Mother* variable.
- **Household Income**: This variable refers to the total income of the household during the first year the student took the SIMCE, expressed in 2005 Chilean pesos (CLP). It is considered ”High” if the income is greater than 201,486 CLP (approximately 360 USD) per month (the median when considering both female and male students from the 1996 and 2001 cohorts), and ”Low” otherwise. The conversion rate of 560 CLP per USD in 2005 was obtained from the Central Bank of Chile.

E.3 School Variables

- **Size Class**: This variable represents the size of the class in which the student took the 4th grade for the first time. It is classified as *High* if the size is 34 or greater, as the median score of *Size Class* for both female and male students from the 1996 and 2001 cohorts in the sample is 33. Conversely, it is classified as *Low* for class sizes of 33 or below.
- **Size Class - Standardized**: This variable is the standardized version of *Size Class* when considering a sample of both female and male students from the 1996 and 2001 generations. The mean value of *Size Class* is 31.79, and the standard deviation is 9.63.
- **Size School**: This variable represents the number of 4th graders in the school where the student took the 4th grade for the first time. It is classified as *High* if the size is 63 or greater, as the median score of *Size School* when considering both female and male students from the 1996 and 2001 cohorts in the sample is 62. Conversely, it is classified as *Low* for school sizes of 62 or below.
- **Size School - Standardized**: This variable represents the standardized version of the school size variable when both female and male students from the 1996 and 2001 generations are included in the sample. The mean of *Size School*, is 69.31, with a standard deviation of 51.78.
- **Full-Day Schooling**: This binary variable takes the value of 1 if full-day schooling was implemented in the first grade when the student entered school, and 0 otherwise.
- **Private School**: This binary variable takes the value of 1 if the student attended a private school when they took the fourth grade for the first time, and 0 otherwise.
- **Subsidized School**: This binary variable takes the value of 1 if the student attended a subsidized school when they took the fourth grade for the first time, and 0 otherwise.
- **Public School**: This binary variable takes the value of 1 if the student attended a public school when they took the fourth grade for the first time, and 0 otherwise.
- **North**: This binary variable is assigned the value of 1 if a student attended a school located in the northern regions of Chile (specifically regions 1, 2, 3, 4, or 15) during the academic year 2006 or the first available year up to 2009 for those born in 1996, and 2011 or the first available year up to 2014 for those born in 2001. Otherwise, the variable takes a value of 0.

- **Centre**: This binary variable is assigned the value of 1 if a student attended a school located in the central regions of Chile (specifically regions 5, 6, 7, or 8) during the academic year 2006 or the first available year up to 2009 for those born in 1996, and 2011 or the first available year up to 2014 for those born in 2001. Otherwise, the variable takes a value of 0.

- **South**: This binary variable is assigned the value of 1 if a student attended a school located in the southern regions of Chile (specifically regions 9, 10, 11, 12, 14, or 16) during the academic year 2006 or the first available year up to 2009 for those born in 1996, and 2011 or the first available year up to 2014 for those born in 2001. Otherwise, the variable takes a value of 0.

- **Santiago**: This binary variable is assigned the value of 1 if a student attended a school located in the Metropolitan region of Santiago during the academic year 2006 or the first available year up to 2009 for those born in 1996, and 2011 or the first available year up to 2014 for those born in 2001. Otherwise, the variable takes a value of 0.

- **Rural School**: This binary variable is assigned the value of 1 if a student attended a rural school during the academic year 2006 or the first available year up to 2009 for those born in 1996, and 2011 or the first available year up to 2014 for those born in 2001. Otherwise, the variable takes a value of 0.

E.4 Peer Variables

- **Test Score in Language - Peers**: This variable refers to the average grade achieved by students who were enrolled in the same school and completed their fourth-grade education during the same academic year, when they participated in the language section of the SIMCE.

- **Test Score in Language - Peers - Standardized**: This variable refers to the standardized version of the *Test Score in Language - Peers*. This version is derived by considering both male and female students from the 1996 and 2001 generations as the sample. The mean of *Test Score in Language - Peers* is 261.93, with a standard deviation of 25.60.

- **Test Score in Math - Peers**: This variable refers to the average grade achieved by students who were enrolled in the same school and completed their fourth-grade education during the same academic year, when they participated in the mathematical section of the SIMCE.

- **Test Score in Math - Peers - Standardized**: This variable refers to the standardized version of the *Test Score in Math - Peers*. This version is derived by considering both male and female students from the 1996 and 2001 generations as the sample. The mean of *Test Score in Math - Peers* is 252.86, with a standard deviation of 29.12.

- **Repeat - Peers**: This variable refers to the average value of *Repeat* among students who attended the same school and completed their fourth-grade education during the same academic year.

- **Years Education Father - Peers**: This variable refers to the average value of *Years Education Father* among students who attended the same school and completed their fourth-grade education during the same academic year.

- **Years Education Father Squared - Peers**: This variable refers to the average value of *Years Education Father Squared* among students who attended the same school and completed their fourth-grade education during the same academic year.

- **Years Education Mother - Peers**: This variable refers to the average value of *Years Education Mother* among students who attended the same school and completed their fourth-grade education during the same academic year.

- **Years Education Mother Squared - Peers**: This variable refers to the average value of *Years Education Mother Squared* among students who attended the same school and completed their fourth-grade education during the same academic year.

- **Household Income - Peers**: This variable refers to the average value of *Household Income* among students who attended the same school and completed their fourth-grade education during the same academic year.

F Summary statistics for 1996 cohort (female students)

Table 14: Summary statistics for 1996 cohort (female students)

Variable	Obs	Mean	Std. Dev.	Min	Max
Test Score in Language	106,852	259.76	51.13	105.91	381.82
Test Score in Math	106,966	247.24	54.15	76.62	369.55
Dummy for Taking Test Scores at 4th Grade	111,839	94.81%	0.222	0	1
Repeat	111,839	8.14%	0.273	0	1
Size Class	111,839	32.55	9.65	1	83
Size Class - Standardized	111,839	0.078	1.001	-3.196	5.315
Size School	111,839	73.04	55.84	1	522
Size School - Standardized	111,839	0.072	1.078	-1.319	8.742
Full-Day Schooling	111,839	16.65%	0.373	0	1
Private School	111,839	6.34%	0.244	0	1
Subsidized School	111,839	45.29%	0.498	0	1
Public School	111,839	48.37%	0.500	0	1
North	111,839	13.23%	0.339	0	1
Centre	111,839	34.13%	0.474	0	1
South	111,839	14.41%	0.351	0	1
Santiago	111,839	38.23%	0.486	0	1
Rural School	111,839	8.79%	0.283	0	1
Years Education Father	97,828	11.02	3.98	0	22
Years Education Father Squared	97,828	137.28	82.90	0	484
Years Education Mother	99,848	11.07	3.59	0	22
Years Education Mother Squared	99,848	135.43	76.01	0	484
Household Income	99,282	323,335	387,344	40,297	1,800,000
Test Score in Language - Peers	111,839	256.24	25.74	135.23	361.75
Test Score in Language - Peers - Standardized	111,839	-0.222	1.005	-4.949	3.898
Test Score in Math - Peers	111,839	249.00	28.83	114.01	387.17
Test Score in Math - Peers - Standardized	111,839	-0.133	0.990	-4.768	4.612
Repeat - Peers	111,839	6.29%	0.084	0	1
Years Education Father - Peers	111,839	11.00	2.51	0	19.5
Years Education Father Squared - Peers	111,839	136.93	56.41	0	386.5
Years Education Mother - Peers	111,839	11.07	2.34	0	19
Years Education Mother Squared - Peers	111,839	135.60	51.65	0	361
Household Income - Peers	111,839	324,603	326,615	38,609	1,781,747
Juvenile Crime	111,839	1.57%	0.124	0	1
Violent Crime	111,839	0.67%	0.081	0	1
Non-violent Crime	111,839	1.06%	0.102	0	1

Note: This table presents the descriptive statistics of female students born in 1996, derived from the baseline sample. E. Detailed definitions of the variables can be found in Appendix E

G Summary statistics for 2001 cohort (female students)

Table 15: Summary statistics for 2001 cohort (female students)

Variable	Obs	Mean	Std. Dev.	Min	Max
Test Score in Language	103,151	274.66	47.98	105.32	377.25
Test Score in Math	103,180	255.35	50.43	87.87	387.17
Dummy for Taking Test Scores at 4th Grade	111,367	91.54%	0.278	0	1
Repeat	111,367	9.95%	0.299	0	1
Size Class	111,367	31.51	9.47	1	55
Size Class - Standardized	111,367	-0.029	0.983	-3.196	2.409
Size School	111,367	66.75	46.22	1	336
Size School - Standardized	111,367	-0.049	0.893	-1.319	5.150
Full-Day Schooling	111,367	20.88%	0.406	0	1
Private School	111,367	7.30%	0.260	0	1
Subsidized School	111,367	52.20%	0.500	0	1
Public School	111,367	40.50%	0.491	0	1
North	111,367	13.13%	0.338	0	1
Centre	111,367	33.21%	0.471	0	1
South	111,367	14.77%	0.355	0	1
Santiago	111,367	38.89%	0.488	0	1
Rural School	111,367	7.72%	0.267	0	1
Years Education Father	93,160	11.66	3.66	0	22
Years Education Father Squared	93,160	149.36	82.80	0	484
Years Education Mother	96,272	11.62	3.47	0	22
Years Education Mother Squared	96,272	147.12	77.09	0	484
Household Income	96,020	370,214	431,318	38,609	1,851,805
Test Score in Language - Peers	111,367	269.80	23.35	140.54	357.41
Test Score in Language - Peers - Standardized	111,367	0.307	0.912	-4.741	3.729
Test Score in Math - Peers	111,367	257.48	28.29	127.44	365.96
Test Score in Math - Peers - Standardized	111,367	0.159	0.971	-4.307	3.884
Repeat - Peers	111,367	11.81%	0.113	0	1
Years Education Father - Peers	111,367	11.62	2.41	0	18.92
Years Education Father Squared - Peers	111,367	148.47	57.18	0	363.33
Years Education Mother - Peers	111,367	11.59	2.27	0	18.16
Years Education Mother Squared - Peers	111,367	146.61	52.26	0	333.90
Household Income - Peers	111,367	372,662	359,848	38,609	1,851,805
Juvenile Crime	111,367	1.53%	0.123	0	1
Violent Crime	111,367	0.70%	0.083	0	1
Non-violent Crime	111,367	1.05%	0.102	0	1

Note: This table presents the descriptive statistics of female students born in 2001, derived from the baseline sample. Detailed definitions of the variables can be found in Appendix E

H Means per category for 1996 cohort (female students)

Table 16: Means per category for 1996 cohort (female students)

Classification	Obs	Juvenile Crime	Violent Crime	Non-violent Crime
High Test Score in Language	50,551	0.84%	0.33%	0.58%
Low Test Score in Language	56,301	2.13%	0.92%	1.42%
Chi square test		297 (0.000)	148 (0.000)	185 (0.000)
High Test Score in Math	48,996	0.83%	0.34%	0.57%
Low Test Score in Math	57,970	2.13%	0.91%	1.42%
Chi square test		297 (0.000)	134 (0.000)	192 (0.000)
Dummy for Taking Test Scores at 4th Grade=1	106,031	1.52%	0.64%	1.02%
Dummy for Taking Test Scores at 4th Grade=0	5,808	2.60%	1.21%	1.74%
Chi square test		41.6 (0.000)	26.8 (0.000)	27.0 (0.000)
Repeat	9,105	4.05%	1.76%	2.75%
Non Repeat	102,734	1.35%	0.57%	0.91%
Chi square test		393 (0.000)	178 (0.000)	269 (0.000)
Big Class	59,006	1.57%	0.67%	1.06%
Small Class	52,833	1.57%	0.67%	1.06%
Chi square test		0.0008 (0.978)	0.0019 (0.965)	0.0050 (0.944)
Big School	59,873	1.49%	0.61%	1.02%
Small School	51,966	1.67%	0.74%	1.10%
Chi square test		5.62 (0.018)	6.79 (0.009)	1.72 (0.190)
Full-Day Schooling	18,625	1.60%	0.69%	1.09%
Non Full-Day Schooling	93,214	1.57%	0.66%	1.05%
Chi square test		0.0999 (0.752)	0.221 (0.638)	0.197 (0.657)
Private School	7,088	0.28%	0.08%	0.21%
Subsidized School	50,652	1.21%	0.46%	0.86%
Public School	54,099	2.08%	0.94%	1.36%
Chi square test		209 (0.000)	130 (0.000)	114 (0.000)
North	14,791	1.77%	0.78%	1.23%
Centre	38,176	1.45%	0.73%	0.85%
South	16,121	1.46%	0.63%	1.01%
Santiago	42,751	1.66%	0.59%	1.21%
Chi square test		10.8 (0.013)	9.59 (0.022)	29.5 (0.000)
Rural School	9,827	0.86%	0.53%	0.36%
Non Rural School	102,012	1.64%	0.68%	1.13%
Chi square test		34.9 (0.000)	3.09 (0.079)	50.8 (0.000)
High Years Education Father	36,743	0.76%	0.28%	0.53%
Low Years Education Father	61,085	1.86%	0.80%	1.24%
Chi square test		194 (0.000)	105 (0.000)	120.8 (0.000)
High Years Education Mother	37,148	0.73%	0.29%	0.48%
Low Years Education Mother	62,700	1.89%	0.81%	1.26%
Chi square test		216 (0.000)	101 (0.000)	149 (0.000)
High Household Income	45,274	0.88%	0.34%	0.59%
Low Household Income	54,008	1.92%	0.83%	1.28%
Chi square test		184 (0.000)	96.7 (0.000)	123 (0.000)

Note: This table presents the category means for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime*. Additionally, it includes the results of the Pearson Chi-square test, providing information on the statistical significance of the differences in frequencies across each category (the associated p-value is reported in parentheses). The analysis is based on a sample of female students born in 1996, which was extracted from our baseline dataset. For variable definitions, please see Appendix E.

I Means per category for 2001 cohort (female students)

Table 17: Means per category for 2001 cohort (female students)

Classification	Obs	Juvenile Crime	Violent Crime	Non-violent Crime
High Test Score in Language	61,497	0.90%	0.39%	0.62%
Low Test Score in Language	41,654	2.28%	1.04%	1.57%
Chi square test		333 (0.000)	159 (0.000)	225 (0.000)
High Test Score in Math	52,287	0.82%	0.34%	0.59%
Low Test Score in Math	50,893	2.07%	0.95%	1.42%
Chi square test		282 (0.000)	148 (0.000)	180 (0.000)
Dummy for Taking Test Scores at 4th Grade=1	101,950	1.43%	0.64%	0.99%
Dummy for Taking Test Scores at 4th Grade=0	9,417	2.57%	1.28%	1.73%
Chi square test		74.0 (0.000)	51.2 (0.000)	45.2 (0.000)
Repeat	11,077	3.74%	1.72%	2.65%
Non Repeat	100,290	1.29%	0.58%	0.88%
Chi square test		398 (0.000)	187 (0.000)	302 (0.000)
Big Class	53,041	1.36%	0.58%	0.97%
Small Class	58,326	1.69%	0.81%	1.13%
Chi square test		20.3 (0.000)	20.7 (0.000)	7.35 (0.007)
Big School	52,636	1.25%	0.55%	0.88%
Small School	58,731	1.78%	0.83%	1.21%
Chi square test		52.3 (0.000)	33.5 (0.000)	30.4 (0.000)
Full-Day Schooling	23,251	1.78%	0.94%	1.09%
Non Full-Day Schooling	88,116	1.46%	0.63%	1.04%
Chi square test		12.3 (0.000)	24.4 (0.000)	0.412 (0.521)
Private School	8,131	0.31%	0.12%	0.20%
Subsidized School	58,137	1.19%	0.51%	0.86%
Public School	45,099	2.19%	1.05%	1.46%
Chi square test		256 (0.000)	150 (0.000)	151 (0.000)
North	14,622	1.50%	0.75%	0.94%
Centre	36,988	1.26%	0.62%	0.81%
South	16,445	1.35%	0.66%	0.83%
Santiago	43,312	1.84%	0.76%	1.38%
Chi square test		49.6 (0.000)	6.64 (0.084)	75.2 (0.000)
Rural School	8,592	0.99%	0.52%	0.57%
Non Rural School	102,775	1.57%	0.71%	1.09%
Chi square test		18.0 (0.000)	4.07 (0.044)	20.9 (0.000)
High Years Education Father	39,157	0.77%	0.34%	0.50%
Low Years Education Father	54,003	1.82%	0.81%	1.27%
Chi square test		184 (0.000)	81.3 (0.000)	144 (0.000)
High Years Education Mother	41,336	0.67%	0.30%	0.45%
Low Years Education Mother	54,936	1.93%	0.85%	1.35%
Chi square test		271 (0.000)	115 (0.000)	203 (0.000)
High Household Income	46,774	0.85%	0.39%	0.56%
Low Household Income	49,246	1.91%	0.84%	1.33%
Chi square test		196 (0.000)	80.5 (0.000)	148 (0.000)

Note: This table presents the category means for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime*. Additionally, it includes the results of the Pearson Chi-square test, providing information on the statistical significance of the differences in frequencies across each category (the associated p-value is reported in parentheses). The analysis is based on a sample of female students born in 2001, which was extracted from our baseline dataset. For variable definitions, please see Appendix E.

J Marginal effects in probit models for *All Crime*, *Violent Crime*, and *Non-violent Crime* (male students)

Table 18: Marginal effects in probit models for *All Crime*, *Violent Crime*, and *Non-violent Crime* (male students)

	All Crime	Violent Crime	Non-violent Crime
Variables	(4)	(4)	(4)
Dummy for Taking Test Scores at 4th Grade	-0.0124***	-0.00859***	-0.00760***
	(0.00)	(0.00)	(0.00)
Repeat	0.0288***	0.0169***	0.0191***
	(0.00)	(0.00)	(0.00)
Size Class	0.000162***	0.000136***	0.0000827*
	(0.01)	(0.00)	(0.09)
Size School	-0.0000339***	-0.0000191**	-0.0000242***
	(0.00)	(0.03)	(0.01)
Full-Day Schooling	-0.00302**	-0.00156*	-0.00243**
	(0.01)	(0.09)	(0.01)
Private School	0.00261	0.00118	0.00439
	(0.61)	(0.78)	(0.31)
Subsidized School	-0.00662***	-0.00521***	-0.00378***
	(0.00)	(0.00)	(0.00)
North	-0.00480***	-0.00366***	-0.00152
	(0.00)	(0.00)	(0.17)
Centre	-0.0129***	-0.00951***	-0.00784***
	(0.00)	(0.00)	(0.00)
South	-0.00604***	-0.00771***	-0.000418
	(0.00)	(0.00)	(0.71)
Rural School	-0.0356***	-0.0203***	-0.0283***
	(0.00)	(0.00)	(0.00)
Test Score in Language - Peers	-0.000275***	-0.000218***	-0.000150***
	(0.00)	(0.00)	(0.00)
Test Score in Math - Peers	-0.0000776**	-0.0000236	-0.0000641**
	(0.03)	(0.41)	(0.03)
Repeat - Peers	0.0317***	0.0217***	0.0246***
	(0.00)	(0.00)	(0.00)
Years Education Father - Peers	0.00485***	0.00361**	0.00446***
	(0.01)	(0.01)	(0.00)
Years Education Father Squared- Peers	-0.000265***	-0.000196**	-0.000214***
	(0.01)	(0.01)	(0.01)
Years Education Mother - Peers	-0.000211	-0.000103	-0.000716
	(0.92)	(0.95)	(0.67)
Years Education Mother Squared - Peers	-0.000268**	-0.000164*	-0.000165*
	(0.02)	(0.07)	(0.08)
Household Income - Peers	-6.81e-09	-4.02e-09	-9.80e-09**
	(0.24)	(0.38)	(0.04)
Generation 1996	0.0140***	0.00599***	0.0105***
	(0.00)	(0.00)	(0.00)
Observations	229,255	229,255	229,255
Pseudo R-squared	6.61%	6.34%	6.55%
Log likelihood	-39,881	-26,869	-28,321

Note: This table presents the marginal effects and corresponding p-values (in parentheses) of the regression coefficients for probit models utilized in the Oaxaca decompositions for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime* under Model 4. The sample used in the analysis comprises male students extracted from our baseline sample. For the definition of variables, please refer to Appendix E. The significance levels are denoted by ***, **, and *, indicating statistical significance at 1%, 5%, and 10% levels, respectively.

K Marginal effects in probit models for *Juvenile Crime* (female students)

Table 19: Marginal effects in probit models for *Juvenile Crime* (female students)

Variables	**Juvenile Crime**			
	(1)	(2)	(3)	(4)
Dummy for Taking Test Scores at 4th Grade	-0.00350**	-0.00402***	-0.00380***	-0.00378***
	(0.01)	(0.00)	(0.00)	(0.00)
Repeat	0.0131***	0.00983***	0.0110***	0.0110***
	(0.00)	(0.00)	(0.00)	(0.00)
Size Class	0.0000837	0.0000443	0.0000627*	0.0000634*
	(0.11)	(0.40)	(0.09)	(0.09)
Size School	-0.0000232**	-0.0000118	-0.0000186***	-0.0000185***
	(0.01)	(0.28)	(0.01)	(0.01)
Full-Day Schooling	-0.00217**	-0.00147	-0.00178**	-0.00180**
	(0.05)	(0.13)	(0.02)	(0.01)
Private School	0.00218	0.00520	0.00408	0.00412
	(0.66)	(0.22)	(0.20)	(0.20)
Subsidized School	-0.00300***	-0.00242***	-0.00285***	-0.00284***
	(0.00)	(0.01)	(0.00)	(0.00)
North	-0.000157	-0.00440***	-0.00236***	-0.00235***
	(0.89)	(0.00)	(0.00)	(0.00)
Centre	-0.00380***	-0.00771***	-0.00590***	-0.00588***
	(0.00)	(0.00)	(0.00)	(0.00)
South	-0.00328***	-0.00642***	-0.00510***	-0.00507***
	(0.01)	(0.00)	(0.00)	(0.00)
Rural School	-0.0146***	-0.0128***	-0.0139***	-0.0139***
	(0.00)	(0.00)	(0.00)	(0.00)
Test Score in Language - Peers	-0.000166***	-0.000035	-0.0000740***	-0.0000775***
	(0.00)	(0.27)	(0.00)	(0.00)
Test Score in Math - Peers	0.0000295	-0.000104***	-0.0000577***	-0.0000562**
	(0.43)	(0.00)	(0.01)	(0.01)
Repeat - Peers	0.00753	0.0211***	0.0175***	0.0170***
	(0.11)	(0.00)	(0.00)	(0.00)
Years Education Father - Peers	0.00388**	0.000726	0.00294***	0.00284**
	(0.02)	(0.67)	(0.01)	(0.01)
Years Education Father Squared- Peers	-0.000178*	-0.0000470	-0.000141**	-0.000136**
	(0.06)	(0.60)	(0.02)	(0.03)
Years Education Mother - Peers	-0.000458	0.000571	0.000201	0.000202
	(0.81)	(0.77)	(0.88)	(0.88)
Years Education Mother Squared - Peers	-0.0000665	-0.000110	-0.0000975***	-0.0000980
	(0.53)	(0.29)	(0.18)	(0.18)
Household Income - Peers	-5.68e-09	-5.15e-09	-5.06e-09	-5.17e-09
	(0.37)	(0.25)	(0.16)	(0.16)
Generation 1996				-0.000280
				(0.66)
Observations	111,839	111,367	223,206	223,206
Pseudo R-squared	4.72%	6.21%	5.34%	5.35%
Log likelihood	-8,626	-8,262	-16,908	-16,908

Note: This table presents the marginal effects and corresponding p-values (in parentheses) of the regression coefficients for each of the four probit models employed in the Oaxaca decompositions for *Juvenile Crime*. The sample employed in the analysis consists of female students extracted from our baseline sample. Detailed definitions of the variables can be found in Appendix E. Significance levels are indicated using asterisks, with ***, **, and * denoting statistical significance at the 1%, 5%, and 10% levels, respectively.

L Marginal effects in probit models for *All Crime*, *Violent Crime*, and *Non-violent Crime* (female students)

Table 20: Marginal effects in probit models for *All Crime*, *Violent Crime*, and *Non-violent Crime* (female students)

	Juvenile Crime	Violent Crime	Non-violent Crime
Variables	(4)	(4)	(4)
Dummy for Taking Test Scores at 4th Grade	-0.00378***	-0.00236***	-0.00230***
	(0.00)	(0.00)	(0.00)
Repeat	0.0110***	0.00482***	0.00748***
	(0.00)	(0.00)	(0.00)
Size Class	0.0000634*	0.0000332	0.0000479
	(0.09)	(0.18)	(0.12)
Size School	-0.0000185***	-9.28e-06*	-0.0000126**
	(0.01)	(0.06)	(0.03)
Full-Day Schooling	-0.00180**	-0.000446	-0.00155**
	(0.01)	(0.35)	(0.01)
Private School	0.00412	0.000423	0.00595**
	(0.20)	(0.85)	(0.03)
Subsidized School	-0.00284***	-0.00204***	-0.00103**
	(0.00)	(0.00)	(0.04)
North	-0.00235***	0.000117	-0.00254***
	(0.00)	(0.83)	(0.00)
Centre	-0.00588***	-0.00119***	-0.00567***
	(0.00)	(0.01)	(0.00)
South	-0.00507***	-0.00146**	-0.00438***
	(0.00)	(0.01)	(0.00)
Rural School	-0.0139***	-0.00498***	-0.0122***
	(0.00)	(0.00)	(0.00)
Test Score in Language - Peers	-0.0000775***	-0.0000160	-0.0000649***
	(0.00)	(0.329)	(0.00)
Test Score in Math - Peers	-0.0000562**	-0.0000382***	-0.0000331*
	(0.01)	(0.01)	(0.07)
Repeat - Peers	0.0170***	0.00692***	0.0137***
	(0.00)	(0.00)	(0.00)
Years Education Father - Peers	0.00284**	0.00110	0.00233**
	(0.01)	(0.14)	(0.02)
Years Education Father Squared- Peers	-0.000136**	-0.0000627	-0.000100*
	(0.03)	(0.13)	(0.06)
Years Education Mother - Peers	0.000202	0.000115	-0.0000510
	(0.88)	(0.90)	(0.96)
Years Education Mother Squared - Peers	-0.0000980	-0.0000315	-0.0000713
	(0.18)	(0.51)	(0.24)
Household Income - Peers	-5.17e-09	-2.61e-09	-5.53e-09*
	(0.16)	(0.29)	(0.08)
Generation 1996	-0.000280	-0.000549	-0.000364
	(0.66)	(0.20)	(0.49)
Observations	223,206	223,206	223,206
Pseudo R-squared	5.35%	4.57%	5.76%
Log likelihood	-16,908	-8,698	-12,326

Note: This table presents the marginal effects and corresponding p-values (in parentheses) of the regression coefficients for probit models utilized in the Oaxaca decompositions for *Juvenile Crime*, *Violent Crime*, and *Non-violent Crime* under Model 4. The sample used in the analysis comprises male students selected from our baseline sample. For the definition of variables, please refer to Appendix E. The significance levels are denoted by ***, **, and *, indicating statistical significance at 1%, 5%, and 10% levels, respectively.

Testing the Effect of Option Introduction on Market Efficiency Using the Overlapping Serial Test*

Preliminary and incomplete. Please do not cite or circulate.

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Abstract

This article investigates the market efficiency of shares trading on the New York Stock Exchange (NYSE) and Nasdaq, focusing on the introduction of options between 1999 and 2011. The Overlapping Serial Test, a Random Number Generator test, is employed to assess the randomness of market movements before and after the option introduction. The findings reveal that the sequences of market movements exhibit non-random behavior during both pre- and post-option periods. Notably, Nasdaq stocks demonstrate a significantly higher degree of randomness after the introduction of options compared to the pre-option period. Furthermore, the study explores the uniformity of these results across various dimensions, including market capitalization, beta, and volatility. Specifically, small-cap, low volatility, and mid and low beta stocks traded on Nasdaq exhibit an increased level of randomness subsequent to the option initiation.

Keywords: market efficiency, random number generator test, market cap, beta, volatility.

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1 Introduction

The exponential growth of the options market since its inception in 1973 has raised questions regarding the impact of option listings on the price efficiency of the underlying assets. With the options market reaching a substantial size, surpassing $100 trillion in open interest by the second quarter of 2021, and the outstanding notional amount of over-the-counter derivatives nearing $600 trillion,[1] it becomes important to examine the informational effects of new option listings. According to Grossman and Stiglitz (1980), the informativeness of the price system is contingent upon the incentives to acquire information when information acquisition carries a cost. Consequently, it is necessary, from a modeling perspective, to endogenize information acquisition in order to comprehend the informational effects associated with the introduction of a new option listing. Several theoretical studies have pursued this line of inquiry by employing various models of noisy rational expectations (Cao (1999), Massa (2002), and Huang (2015)) to examine the impact of introducing a new derivative listing. While the effects of derivative introductions are contingent upon market informational structure, trading opportunities, and information acquisition costs, an empirical analysis is necessary to evaluate the net impact of these factors on the informational efficiency of the underlying asset. Consequently, this study utilizes the Overlapping Serial Test (OST) to empirically test the price efficiency of the underlying asset surrounding the introduction of an option.

This paper offers several contributions to the existing literature. Firstly, it investigates the impact of introducing an option on the efficiency of the underlying stock market using a novel testing strategy in this context. By employing this innovative approach, we aim to provide insights into the informational effects of option introductions that may not be captured by traditional tests of informational efficiency. As highlighted by Doyle and Chen (2013), the chosen testing strategy, the Overlapping Serial Test (OST), has the unique ability to identify departures from efficiency that differ from those detected by conventional approaches, making its results complementary and non-redundant.

Secondly, we incorporate various factors into our analysis that have been previously identified in the literature as crucial for understanding the potential informational effects associated with the introduction of options. By conditioning our analysis on these identified factors, we seek to enhance

[1] https://www.bis.org

our understanding of the complex dynamics between option introductions and the informational efficiency of the underlying asset.

The findings of our research have significant implications for both investors in general and specifically for those engaged in short-term trading. This study provides valuable insights into an abnormal return trading strategy within the given context. Furthermore, policymakers who aim to establish an efficient framework for financial markets can also derive benefits from the outcomes of our investigation.

The structure of this paper is as follows. Section 2 provides a comprehensive overview of the options market and the relevant academic literature pertaining to these contracts. In Section 3, we outline the methodology employed in this study, along with a review of Random Number Generators (RNGs) in tests relating to the Efficient Market Hypothesis. The results and analysis are presented in Section 4. Finally, Section 5 presents the concluding remarks.

2 Background Theory

This sections briefly describes the options market and academic literature relative to options. The existing literature on the use of RNGs tests to assess market efficiency is subsequently reviewed.

2.1 Options Market

Contracts resembling options have been utilized since ancient Greece, with Thales of Miletus employing them in the 6th century BC to speculate on olive harvests (Zarkos et al., 2007). However, the contemporary stock options market originated on April 26, 1973, when the Chicago Board Options Exchange initiated the trading of call options linked to a limited selection of 16 underlying stocks. Since then, the exchange-traded option market has experienced exponential growth, transforming into a vast industry. In the United States alone, options are traded on 16 diverse exchanges, encompassing a wide range of underlying assets such as equities, bonds, interest rates, futures, indexes, commodities, and currencies. As of December 2021, the notional amount outstanding in exchange-traded options reached a staggering \$45.96 trillion, while the over-the-counter options market amounted to \$52.31 trillion (including \$3.31 trillion in equity-linked contracts).[2] Evidently, this pervasive and escalating trend signifies that this financial instrument fulfills a structural economic demand. For instance, the introduction of options, subject to specific conditions (Detemple and Selden, 1991), can alter the range of potential payoffs.

2.2 Related Literature

Numerous aspects pertaining to the introduction of options have been extensively examined in the academic literature. This includes empirical analyses that investigate the impact of options listings on key underlying variables such as price, volatility, volume, and liquidity. For instance, Conrad (1989) delves into the price effects stemming from options introduction during the period of 1974-1980. Their findings suggest the possibility of earning excess returns of approximately three percent within a market model framework. However, subsequent studies, such as Detemple and Jorion (1990), focusing on the time window of 1982-1986, reveal that cumulative abnormal returns

[2] https://www.bis.org/

are not statistically different from zero. This finding aligns with the observation that the cumulative proportion of the market's value covered by options typically increases over time, indicative of growing market completeness.

Furthermore, Danielsen and Sorescu (2001) contribute to this body of literature by uncovering a negative association between option introduction and abnormal returns during the period from July 1981 to December 1995. This unexpected effect can be attributed to the mitigated short sale constraints that accompany option listing, which facilitate the entry of pessimistic short sellers into the market. In addition, assets characterized by significant investor disagreement are more likely to experience higher levels of overpricing in the absence of short sellers, leading to a more pronounced shift towards negative abnormal returns. Additionally, Danielsen and Sorescu (2001) highlights the potential impact of the introduction of index options in 1982 on the observed change in expected returns.

The impact of option listings on volatility does not exhibit a consistent pattern. Skinner (1989) discovers a decrease of approximately 10-20% in the volatility of returns on common stocks following the listing of exchange-traded call options. This finding challenges the widely held belief in the popular press that option introduction leads to increased price volatility, which could occur if trading volume shifts from the underlying stock to the corresponding option. Detemple and Jorion (1990) examine the effect of option listings on variance in the returns of 322 companies listed on either NYSE or AMEX between April 1973 and December 1986. They find that the volatility of underlying stocks declines by approximately 7% after the introduction of options when considering a time window of 60 days before and after the initiation of options.

However, recent research indicates that this decline in variance following option introduction may no longer be observed. Rahman (2001) investigates the introduction of futures and futures options on the 30 stocks comprising the Dow Jones Industrial Average and concludes that no structural changes in conditional volatility of component stocks were identified. Wen (2020) suggests that option introduction does not play a significant role in explaining crash risk and realized volatility of the underlying stock. These recent studies cast doubt on the persistence of the decrease in variance observed after option introduction and highlight the need for further examination of the evolving dynamics of volatility in response to option listings.

Ma and Rao (1988) present an alternative explanation for the potential decrease in variance following the introduction of options. They argue that the non-random listing of options by exchanges may lead to the selection of assets that have recently exhibited increased variance. Consequently, the observed decline in variance could be partly attributed to mean reversion. Furthermore, they demonstrate the asymmetric impact of option trading on underlying stocks, distinguishing between volatile stocks, primarily traded by uninformed investors, and less volatile stocks, mainly attracting informed traders. The introduction of options tends to reduce the variance of volatile stocks due to hedging behavior that mitigates noise, while stable stocks become more volatile as a result of increased speculation in the options market. Jubinski and Tomljanovich (2007) analyze a sample of 1,576 companies between 1973 and 1996 and find that smaller companies tend to experience a reduction in variance in their returns after option listing, while the variance in returns of larger companies remains unchanged.

Mayhew and Mihov (2004), employing control sample methodology to address the endogeneity of option listing, find no evidence supporting the notion that volatility declines after the introduction of options. They also investigate the factors influencing the selection of stocks for option listing. During the early years from 1973 to 1977, market capitalization and trading volume played key roles in determining which stocks were listed as options. This can be understood within the context of the nascent industry, as regulators perceived option trading as potentially risky. Consequently, exchanges had a strong incentive to list options on larger firms to build reputational capital. Between 1977 and 1980, the Securities and Exchange Commission (SEC) imposed a moratorium on option listings to conduct a comprehensive review of the structure and regulatory practices of all option exchanges. Between 1980 and 1996, the stocks selected for option listing tended to exhibit high volatility.

Evidence regarding option introductions in countries other than the United States is limited. Linden et al. (2010) discuss the effects of option introductions on the price and risk of underlying assets in the Nordic markets (Denmark, Finland, Norway, and Sweden). Analyzing data from 58 introductions during the period of 1985-1997, they find a persistent increase in stock returns shortly after the announcement date, rather than on the date of introduction. Volatility is found to decrease steadily during the ten-month period following the introduction of stock options.

In terms of the liquidity of the underlying stock, Kumar et al. (1998) suggest that option introductions tend to reduce bid-ask spreads, while also increasing quoted depth, trading volume, trading frequency, and transaction size. According to these authors, derivatives trading enhances market efficiency by augmenting the availability of public information. Jong et al. (2006) utilize an economic experiment to provide evidence that the introduction of an option improves the market quality of the underlying asset. However, Danielsen et al. (2007) conclude that options do not consistently improve bid-ask spreads, indicating that the reduction in the bid-ask spread is a crucial factor in the decision to list options.

In summary, the evidence suggests that options markets have an informational role, but their impact is contingent upon the underlying characteristics of the assets and the specific trading period.

From a theoretical perspective, Cao (1999) investigate the impact of option introduction using a noisy rational expectation model that incorporates endogenous information acquisition. Their model considers two types of investors: informed investors who can enhance the precision of their information and uninformed investors who are unable to purchase information. In this framework, the presence of informed investors leads to the acquisition of more precise information, thereby increasing the overall informational efficiency of the system when an option is introduced.

On a related note, Massa (2002) extend the analysis of the interaction between options and their underlying assets by introducing a fully dynamic framework that incorporates the initial level of information asymmetry. They consider two scenarios representing different information structures: one in which uninformed investors acquire information to gain an informational advantage, resulting in low initial informational asymmetry, and another in which information is acquired primarily for hedging purposes, leading to high initial asymmetry. In the first scenario, the introduction of an option initially reduces information efficiency but significantly improves it in the long run. In the second scenario, there are opposing effects: more information is collected, but less trading occurs. The net effect depends on the proportion of informed investors, and if it is sufficiently large, market efficiency increases.

Furthermore, Huang (2015) examine the effect of an option market within a rational expectations framework that considers asymmetric information. In this model, information acquisition is driven by either profit-seeking or hedging motives. The author argues that the impact of option listing on efficiency depends on the costs associated with information acquisition. When information acquisition costs are low, a larger number of informed investors participate, resulting in a higher supply of options and lower option prices. In this case, the dominance of the hedging motive reduces price informativeness. Conversely, when information costs are high, informed investors find it more attractive to utilize options, leading to increased informational efficiency in the system.

In summary, these theoretical studies highlight the effects of option markets on information acquisition and market efficiency, emphasizing factors such as the type of investors, initial information asymmetry, and the costs associated with acquiring information.

2.3 Use of RNGs Tests to Assess Market Efficiency

The Efficient-Market Hypothesis (EMH) posits that asset prices incorporate and reflect the totality of available information. It categorizes market efficiency into three distinct forms based on the extent of the information set considered: Weak, Semi-Strong, and Strong (Fama, 1970). Weak form efficiency asserts that prices incorporate market information such as prices, volume, and open interest. Semi-Strong efficiency broadens the information set to encompass all publicly available information, such as announcements of acquisitions, dividend payouts, and changes in accounting policy. Strong form efficiency contends that prices reflect both public and private information. In this study, our focus revolves around semi-strong efficiency, specifically utilizing price data and the introduction date of an option as our information set.

Numerous researchers have proposed a range of tests to challenge the weak form of the Efficient-Market Hypothesis (EMH). These tests include autoregression analysis, the Box-Pierce test, Dickey Fuller test, the KPSS test, rescaled range (R/S) test, runs tests, Variance Ratio tests, and others (refer to Fama (1965), Campbell et al. (1998), Buguk and Brorsen (2003), Giraitis et al. (2003), Kim and Shamsuddin (2008), Tabak and Lima (2009), and Islam and Khaled (2005)). While these tests share a common objective of identifying patterns in returns, typically focusing on short-term effects, several researchers have also examined long-term effects spanning months or even years (see Lo (1991) and Campbell et al. (1998)).

Doyle and Chen (2013) has proposed that if the Efficient-Market Hypothesis (EMH) holds true, the directional movements of returns should be unpredictable. By coding market direction as 0 for positive returns and 1 for positive returns, an efficient market would exhibit a random sequence of 0s and 1s. Simplifying returns into binary form offers the advantage of bypassing the complexities of heteroscedasticity and positive kurtosis, which are common characteristics observed in financial data (Morgan, 1976).

Associating markets with hypothetical random numbers proves to be highly advantageous as it facilitates the evaluation of market efficiency through the assessment of binary sequence randomness. RNGs are commonly evaluated using a battery of tests, often bundled into publicly accessible software suites. Prominent examples include TestU01 (L'Ecuyer and Simard, 2007), Diehard (Marsaglia, 1996), and the NIST Statistical Test Suite for Random and Pseudorandom Number Generators (Rukhin et al., 2001). One particular test that features in all three RNG-testing suites is the Overlapping Serial Test proposed by Good (1953). Xu and Tsang (2007) conducted a comprehensive study involving 57 RNGs, demonstrating that the OST is equally or even more powerful than the Gorilla test, which (Marsaglia and Tsang, 2002) suggests is is among the three most challenging tests for an RNG to pass. In comparison to runs tests, which are similar in nature, the OST holds the advantage of examining all possible patterns for a given length. This distinction will be further elaborated upon in Section 3. It is important to acknowledge that the OST is not the only option, as highlighted by L'Ecuyer et al. (2002), as various test types are designed to identify specific deficiencies within a system. The effectiveness of the test battery is enhanced through its diversification. However, due to practical constraints, our study focuses exclusively on the OST. Additionally, this test has been previously employed in testing market efficiency by Doyle and Chen (2013) and Noakes and Rajaratnam (2016).

3 Data and Methodology

This section is bifurcated into two distinct parts. The first part encompasses a comprehensive review of the data utilized and the sample period under consideration. The second part delineates the complete methodology employed in the study.

3.1 Data

We conducted our study by identifying options introduced between December 29, 1999, and November 9, 2011, for shares listed on either the NYSE/AMEX or the Nasdaq. Option data was obtained from OptionMetrics[3]. In cases where multiple options were introduced for the same share, only the first option introduced was considered.

To augment our analysis, we retrieved daily closing prices, volatilities deciles, market capitaliza-

[3]https://optionmetrics.com/

tion deciles, and beta deciles from the Center for Research in Security Prices (CRSP)[4].

For each test, we decided to utilize 500 distinct chains. Considering chains with five elements, this necessitated a requirement of 504 trading days prior to the option introduction and 504 trading days following it. This selection of different chains aligns with the rule of thumb proposed by Marsaglia and Tsang (2002), as explained in Sub-subsection 3.2.2. Shares that did not fulfill the criterion of having 504 trading days both before and after the option introduction (with the day of option introduction included in the post-introduction segment) were excluded from the sample. Finally, we also discarded stocks with a significant proportion of negative prices, missing prices, or days without volume, as well as stocks with incomplete data. Ultimately, 1,326 shares satisfied all conditions.[5]

We conducted an empirical analysis to investigate whether the returns of the 1,326 shares examined exhibit a random pattern before and after the introduction of their first option. Additionally, we explored the possibility of heterogeneity in the sense that observable characteristics of the shares are correlated with their randomness. To test these hypotheses, we classified the shares based on their market capitalization, betas, and standard deviation,[6] metrics that as shown in Subsection 2.2

[4]https://www.crsp.org/

[5]Initially, a total of 5,366 stocks were identified with the initiation of option trading during the specified analysis period. Subsequently, after filtering, we narrowed down the dataset to 1,815 stocks that had 504 trading days both before and after the introduction of options. Further refining the selection, we considered stocks with specific criteria: having less than one percent of days with negative prices, missing prices, or days with volume equal to 0. This led to 1,462 stocks meeting these conditions. However, for the final sample, we excluded 136 stocks due to a lack of information regarding their market capitalization decile, beta decile, or standard deviation decile. In conclusion, our final dataset comprised 1,326 stocks that satisfied all the aforementioned conditions.

[6]The specific metrics employed were as follows:

CapN: denotes the decile ranking of a stock's capitalization at the end of the previous calendar year. To calculate CapN for a stock (e.g., stock A) in a specific year (e.g., 2002), we first determine the capitalization for all stocks in the year 2001 using data from December 31, 2001. Subsequently, CRSP assigns decile rankings to all capitalizations in 2001, providing each stock with a rank ranging from 1 (lowest decile/low capitalization) to 10 (highest decile/high capitalization). The decile rankings for 2001 are stored in the database under the variable "CapN" for the year 2002, indicating the stock's capitalization decile rank at the end of the previous year.

SdevN: represents the decile ranking of a stock's returns standard deviation at the end of the previous calendar year. To calculate SdevN for a stock (e.g., stock A) in a specific year (e.g., 2002), we first compute the standard deviation of returns for all stocks in the year 2001, using daily data from January 1, 2001, to December 31, 2001. Subsequently, CRSP assigns decile rankings to all standard deviations in 2001, providing each stock with a rank ranging from 1 (lowest decile/high standard deviation) to 10 (highest decile/low standard deviation). The decile rankings for 2001 are stored in the database under the variable "SdevN" for the year 2002, indicating the stock's standard deviation decile rank at the end of the previous year.

BetaN: represents the decile ranking of a stock's beta at the end of the previous calendar year. To calculate BetaN for a stock (e.g., stock A) in a specific year (e.g., 2002), we first calculate the betas for all stocks in the year 2001, using daily data from January 1, 2001, to December 31, 2001. Subsequently, CRSP assigns decile rankings to all betas in 2001, providing each stock with a rank ranging from 1 (lowest decile/high beta) to 10 (highest decile/low beta). The decile rankings for 2001 are stored in the database under the variable "BetaN" for the year 2002, indicating the stock's are commonly used in the literature. Table 1 presents the classification of stocks based on these attributes.

3.2 Methodology

The methodology utilized in this study incorporates specific adjustments and tests from previous research. To account for thin trading, we apply the adjustment introduced by Mlambo et al. (2003). The Overlapping Serial Test, which assesses patterns in data, is closely followed as outlined in Doyle and Chen (2013) and Noakes and Rajaratnam (2016).

3.2.1 Thin Trading Adjustments

In this study, a thin trading adjustment technique is employed whenever the volume of trading is observed to be zero, the price is negative, or the price is missing. The thin trading adjustment approach described by Mlambo et al. (2003) and replicated by Noakes and Rajaratnam (2016) is utilized. This adjustment involves applying a weighting factor to the trade-to-trade return based on the length of the interval:

$$\tilde{R}_t = \frac{1}{K_t}[ln(P_t) - ln(P_{t-K_t})] \tag{1}$$

where:

$\tilde{R}_t$ is the trade-to-trade return adjusted for the interval effect.

P_t is the closing share price on day t.

P_{t-K_t} is the closing share price on day t–K_t.

K_t is the length of time (in days) between the trade in day t and the previous day when a trade was executed.

beta decile rank at the end of the previous year.

For NYSE/AMEX Beta the Market is INDNO = 1000053 – A trade-only value-weighted index of the market.

For NASDAQ Beta it is the Value-Weighted Market index – INDNO = 1000060

THe NYSE/AMEX beta calculated the beta using trade-only returns, while NASDAQ include returns calculated using bid-ask averages.

Furthermore, the days where the volume of trading was 0 are removed from the sample.

3.2.2 Overlapping Serial Test

This section follows closely Good and Gover (1967) and Doyle and Chen (2013).

Step 1: Coding the returns in binary format

The first step involves coding the return series into a sequence of 0's and 1's based on the following rule:

If $\tilde{R}_t > m$ then $B_t = 1$

If $\tilde{R}_t \leq m$ then $B_t = 0$

where m is the median of logarithmic returns.

Step 2: Calculating the expected count for each pattern

Consider a series of N consecutive adjusted returns coded as 0 or 1. Let λ denote the window length. The number of positions that a rolling window of length λ can occupy is given by $N - \lambda + 1$. Moreover, there are $p = 2^\lambda$ possible permutations with repetitions. For instance, if $\lambda = 3$, there are $p = 2^3$ possible permutations: 000, 001, 010, 011, 100, 101, 110, and 111. Given N and λ, the expected count for each permutation is computed as:

$C = \frac{(N-\lambda+1)}{p}$

To ensure that the distribution of statistics aligns with the chi-square distribution, Marsaglia (2005) suggests that $C \geq 10$.

Step 3: Calculating the psi-square statistics and performing the overlapping serial test

Using the expected count C and the actual count C_i for each permutation, the psi-square statistic for a given length λ is defined as:

$$\psi_\lambda^2 = \sum_{i=1}^{p} \frac{(C_i - C)^2}{C} \tag{2}$$

In spite of typographical similarities, ψ_λ^2 does not asymptotically distribute as a chi-square because the windows overlap, therefore violating the assumption of independence between patterns.

We define the first difference as follows:

$$\nabla\psi_\lambda^2 = \psi_\lambda^2 - \psi_{\lambda-1}^2 \qquad\qquad (\lambda = 1, 2, 3, \dots) \tag{3}$$

with $df_\lambda^1 = 2^{(\lambda-1)}$ degrees of freedom and where ψ_0^2 and ψ_{-1}^2 are defined as 0. Notably, as we have chosen to define 1's and 0's using the median, by construction, $\psi_1^2 = 0$.

Furthermore, we introduce the second difference:

$$\nabla^2\psi_\lambda^2 = \nabla\psi_\lambda^2 - \nabla\psi_{\lambda-1}^2 = \nabla\psi_\lambda^2 - 2\nabla\psi_{\lambda-1}^2 + \nabla\psi_{\lambda-2}^2 \qquad\qquad (\lambda = 1, 2, 3, \dots) \tag{4}$$

with $df_\lambda^2 = 2^{(\lambda-2)}$ degrees of freedom and where ψ_0^2 and ψ_{-1}^2 are defined as 0.

While the first differences are asymptotically chi-square, they are not asymptotically independent. Therefore, in accordance with the recommendation made by Good and Gover (1967), we will employ the second differences, which are both asymptotically chi-square and asymptotically independent.

4 Results

4.1 Analysis of Logarithmic Returns Before and After Option Introduction

Shares were analyzed using a window length of 504 prices before the introduction of the option and 504 prices after the introduction. This choice of window length ensures the availability of 500 different return windows with a length of 4. The selection of 504 prices aligns with the guideline proposed by Marsaglia (2005), which recommends that the expected occurrences for each permutation should exceed 10. A total of 1,326 shares were included in the analysis.

To evaluate the performance of shares after the introduction of options, we establish four distinct portfolios: *Shares Before Option*, *S&P500 Before Option*, *Shares After Option*, and *S&P500 After Option*.

The *Shares Before Option* portfolio involves purchasing $\frac{1}{1{,}326}$ of a USD worth of each share on day -501, which corresponds to 501 trading days prior to the option's introduction. Subsequently, the shares are sold on day -1, the previous day when the option was introduced. Similarly, the *Shares After Option* portfolio purchases $\frac{1}{1{,}326}$ of a USD worth of each share on day -1, which is the day before the option's introduction, and sells them on day 499.

The *S&P500 Before Option* portfolio follows a comparable approach, buying $\frac{1}{1{,}326}$ of a USD worth of the S&P500 index on day -501 and selling it on day -1. This ensures a consistent buy and hold period for each $\frac{1}{1{,}326}$ of a USD in relation to the corresponding share. Similarly, the *S&P500 after option* portfolio purchases $\frac{1}{1{,}326}$ of a USD worth of the S&P500 index on day -1 and sells it on day 499.[7]

It is noteworthy that the buy-and-hold periods for the portfolios typically extend over approximately two years. Furthermore, within each portfolio, daily rebalancing is employed to ensure that no specific asset disproportionately influences the outcomes.

Figure 1 presents several notable observations. Firstly, the returns of shares prior to the option's introduction exhibit a remarkably high performance. This finding aligns with the findings of Mayhew and Mihov (2004), who asserted that stocks with greater trading volume and market capitalization are more likely to be chosen for option listing. Interestingly, the extraordinary returns appear to cease approximately five trading days before the option is officially listed.

In Figure 2, we present the same portfolios excluding the *Shares Before Option* portfolio. Notably, the returns of the S&P500 prior to the option's introduction surpass those observed after the introduction. This outcome is consistent with expectations, as periods of favorable performance in the stock market tend to facilitate the selection of more stocks for option listing, given the relevance of market capitalization. The relative performance of *Shares After Option* outperforms *S&P500 After Option* but it is important to note that their respective confidence intervals overlap, indicating that we cannot assert statistical significance in their differences.

Table 2 reports the means, standard errors, and confidence intervals for the means of the logarithmic returns of the aforementioned portfolios, along with their final valuations. By observing the non-intersecting 95% confidence intervals, we confirm our previous speculation that certain returns are statistically superior to others.

[7]When a stock applies the thin trading adjustment proposed by Mlambo et al. (2003), its relative S&P return is similarly subjected to this adjustment.

4.2 OST Results

Table 3 presents the compiled findings of the $\bigtriangledown^2\psi^2_\lambda$ statistics, which differentiate returns before and after the introduction of an option, across various window lengths. The table provides the count and percentage of shares that reject the null hypothesis of randomness at a significance level of 5%. Additionally, the figures in parentheses denote the probability of observing k or more shares rejecting the null hypothesis of randomness out of the total number of shares, assuming a true rejection probability of 5%.

To calculate this probability, we employ a binomial distribution where the number of successes (shares rejecting the null hypothesis) follows a binomial distribution with n representing the total number of shares and a success probability of 5%. For instance, if stock returns are genuinely random, we would anticipate approximately 66 or 67 shares to reject the null hypothesis out of a total of 1,326 shares. The likelihood of observing 83 shares (as seen in N=3, Before) or more, where the null hypothesis of randomness is rejected, amounts to 0.2492.

Based on the findings presented in Table 3, it is observed that prior to the introduction of an option, for a time window length of 2, out of the total 1,326 shares examined, 246 shares reject the null hypothesis of randomness. The probability of achieving 246 successes out of 1,326 trials (18.55%), assuming a true rejection probability of 5%, is practically zero. Consequently, we reject the null hypothesis of randomness. Similarly, when considering the stocks after the introduction of an option, the probability of obtaining 220 or more shares out of 1,326 shares (16.59%) is exceedingly low, leading us to conclude that the sequence of 0's and 1's following the introduction of an option cannot be deemed random.

For a time window length of 3 prior to the option, we reject the null hypothesis of randomness in 90 shares. The probability of achieving 90 or more successes among 1,326 trials is minimal (0.003). Conversely, after the introduction of an option, the number of nonrandom stocks decreases to 78 (probability of having 78 or more is 0.082) When considering a window length of 4, the sequence of 0's and 1's representing returns before and after does not conform to randomness, as the probability of having 78 or more non-random shares is 0.082. However, for a window length of 5, both the results before and after seem to be completely random.

The statistical analysis conducted involved employing a chi-square test of independence to explore the relationship between the number of nonrandom shares before and after the introduction of an option across various window lengths. Specifically, for a window length of 2, the chi-square statistic yielded a value of 2.2603, with 1 degree of freedom and a corresponding p-value of 0.1327 (resulting in insignificance at a significance level of $\alpha = 0.05$). This implies that there is no significant statistical evidence to support the notion that the probability of a share's stream of 0's and 1's being nonrandom before the option introduction differs from the probability after the introduction of an option (the observed difference between 18.55% and 16.59% can be attributed to sample variance).

Similar conclusions were reached for window lengths of 3, 4, and 5, respectively, indicating that the introduction of an option does not lead to an increase or decrease in randomness. These findings align with recent research, such as the works of Detemple and Jorion (1990), Rahman (2001), and Wen (2020), which suggest that the impact of derivatives introduction tends to diminish over time.

Table 4 examines the prevalence of specific chains when considering a window length of two days. The occurrences of chains 00, 01, 10, and 11 were aggregated before and after the introduction of an option, resulting in a total of 663,000 occurrences (500 * 1,326). The second difference psi-square statistic was then constructed using these occurrences, which follows a chi-square distribution with 1 degree of freedom. Notably, both before and after the introduction of an option, chains 01 and 10 occur more frequently than chains 00 and 11. These differences in frequencies are statistically significant at a 1% level of significance.

This finding is further supported by analyzing a subset of shares with a window length of two days. Out of the 246 shares considered nonrandom before the option introduction, the majority (182) exhibited a higher sum of chains 01 and 10 compared to the sum of chains 00 and 11. Similarly, among the 220 non-random shares after the introduction of the option, 147 showed a higher count of chains 01 and 10 relative to the sum of chains 00 and 11.

Subsequent tables will differentiate between shares traded on the NYSE and NASDAQ. These two prominent stock exchanges differ significantly in terms of market type (NYSE being an auction market and NASDAQ a dealer's market (Huang and Stoll, 1996)), establishment year (1792 versus 1971), market capitalization (as of December 2021, NYSE's market cap reached 27.69 USD trillion while NASDAQ's was 24.56 USD trillion),[8] volatility (NASDAQ stocks tend to be more volatile than NYSE stocks (Jiang et al., 2011)), listing fees (NYSE being more expensive), and quoted

[8]https://www.statista.com/statistics/270126/largest-stock-exchange-operators-by-market-capitalization-of-listed-companies/?msclkid=1062cf70a85e11ec8be4bae79f83e140

spreads (NASDAQ exhibiting larger quoted and effective spreads compared to NYSE (Huang and Stoll (1996) and Chung et al. (2001)), among other factors. Additionally, Lin et al. (1998) argue that Nasdaq market-making firms incur higher costs related to information search and security analysis compared to NYSE market makers. These distinctions between the two stock exchanges may lead to different effects resulting from the introduction of an option.

In Table 5, we distinguish between shares traded in the NYSE (NYSE, AMEX, or NYSE MKT) and shares traded in Nasdaq, both before and after the introduction of an option. We observe that in case of chaing of two or three elements, shares are not considered random, except for NYSE shares after the option introduction. However, for longer chains, shares are considered essentially random.

The chi-square test of independence yields significant results. We find no evidence that the introduction of an option has any impact on the number of random shares in the NYSE. However, for Nasdaq shares, the test indicates that the introduction of an option affects the randomness of underlying assets, specifically for chains of two elements. The percentage of non-random shares in this category decreases from 18.38% to 14.25% after the introduction of the derivative, and this difference is statistically significant according to the chi-square test. These results align with the view presented by Lin et al. (1998) regarding higher information acquisition costs for Nasdaq stocks and the predictions made by Massa (2002) and Huang (2015) that such markets would benefit from the presence of derivatives.

In the following paragraphs, we investigate whether stock characteristics influence randomness and changes in randomness after the introduction of an option. Stock size, a common classification criterion, is considered. Previous studies by Noakes and Rajaratnam (2016) indicate that small stocks exhibit a higher degree of non-randomness, which is not surprising given their distinct characteristics compared to large capitalization stocks. For instance, small companies suffer the size effect, or small firm effect, which is the observation that small-cap tend to have higher return rates even when accounting for their greater volatility. This size effect may arise from higher information acquisition costs for small companies, as suggested by Merton et al. (1987) and Ho and Michaely (1988). Empirical evidence provided by Atiase (1985) supports the hypothesis of differential information based on firm size, indicating that private predisclosure information increases with firm size, thereby leading to greater stock price revaluation for small firms after the release of public earnings reports. Additionally, Han and Wild (2000) demonstrate the occurrence of price revaluations in response to earnings reports for similar firms (referred to as earnings information transfer). They find that the magnitude of these revaluations is negatively correlated with both the size of the disclosing firm and the size of the non-disclosing firm. Moreover, thin trading and illiquidity[9] could contribute to increased non-randomness in small stocks, as noted by Noakes and Rajaratnam (2016).

We employed the year-end capitalization portfolio assignment method, based on the previous year's data, to classify stocks into small, mid, and large caps. This classification was determined by the introduction of options trading for a particular stock, obtained from CRSP. Specifically, stocks in the bottom four deciles were classified as small-cap, stocks in the 5th, 6th, and 7th deciles were classified as mid-cap, and stocks in the top three deciles were classified as large-cap.[10]

The findings presented in Table 6 suggest that prior to the introduction of the derivative for a chain of two elements, a notable portion of shares demonstrate non-random behavior. Specifically, 19.13% of small cap shares, 18.15% of mid cap shares, and 18.85% of large cap shares can be classified as non-random. Conducting a chi-square test of independence shows that there is no significant association between market cap and randomness at this chain length ($X^2(2) = 0.136, p = 0.9340$). It is noteworthy that the percentage of non-random small-cap stocks, mid-cap stocks, and large-cap shares are lower than the percentages found in the Johannesburg Stock Exchange study conducted by Noakes and Rajaratnam (2016), which reported 51.61% of small-cap, 45.45% of mid-cap, and 25.00% of large-cap stocks as non-random.

In Tables 7 and 8, we differentiate between NYSE and Nasdaq shares. For NYSE shares, there is no significant change in their degree of randomness across small, mid, or large caps after the derivative listing. However, upon examining Nasdaq shares, we observe small stocks exhibit a reduction in the percentage of non-random shares. The reduction for small-cap Nasdaq shares is from 24.10% to 12.05%. This reduction is statistically significant at the 10% level, as indicated by the Chi-square test of independence with a p-value of 4.4%.

From our study, we conclude that small-cap stocks trading on Nasdaq, which are suggested to have higher information costs by Lin et al. (1998), Merton et al. (1987), and Ho and Michaely (1988), benefit from the introduction of options. This is evident in their increased level of randomness, as predicted by the theoretical models of Massa (2002) and Huang (2015).

[9] Liquidity is an elusive concept which may be captured by several metrics. We refer the reader to Amihud (2002) for a discussion on this topic.

[10] Small Cap: CapN = 1, 2, 3, or 4 Mid Cap: CapN = 5, 6, or 7 Large Cap: CapN = 8, 9, or 10. The market cap portfolio assignment includes a mixture of NYSE/AMEX and Nasdaq shares.

Another measure under investigation is volatility, which has long been suggested as a potential indicator of information incorporation.[11] Previous studies by French and Roll (1986), Barclay et al. (1990), and Ross (1989) have indicated that higher volatility during exchange trading hours compared to non-trading hours suggests the influence of private information on stock prices. Ross (1989) further establishes a direct relationship between price volatility and the flow of information in an arbitrage-free market. Recent research by Eleswarapu et al. (2004) examines the impact of Regulation Fair Disclosure on volatility surrounding earnings announcements and finds a marginal decrease, possibly due to firms adopting alternative methods of public disclosure.

However, other authors such as Shiller (1981), LeRoy and Porter (1981), and West (1988) present evidence suggesting that stock returns exhibit more volatility than would be expected from the random arrival of new information in efficient markets. They argue that rapid information incorporation should result in lower volatility, as changes in firm value would be smaller when dividends are discounted earlier.

To explore the influence of volatility on the probability of non-randomness, we analyze Tables 9, 10, and 11. We categorize shares into low, mid, and high volatility groups based on their standard deviation portfolios from the previous year using CRSP data. Low volatility shares are in the bottom four deciles, mid volatility shares are in the 5th, 6th, and 7th deciles, and high volatility shares are in the top three deciles.[12] On Table 9

The findings presented in Table 9 suggest that prior to the introduction of the derivative for a chain of two elements, a notable proportion of shares exhibit non-random behavior. Specifically, 21.87% of low volatility shares, 17.30% of mid volatility shares, and 15.47% of high volatility shares can be categorized as non-random. A chi-square test of independence reveals a significant association between volatility and randomness for this chain length ($X^2(2) = 6.34, p = 0.0419$). These results align with the assertions made by Morck et al. (2000) regarding the relatively lower informativeness of high R-squared (which tend to be low volatility) shares.

[11] According to Kelly (2014), standard models typically explain only a small portion of the variation in daily (17%) and monthly (29%) returns. Consequently, volatility is expected to exhibit a close correlation with idiosyncratic volatility, which is measured as the residual standard error from an asset-pricing model. Another indicator associated with volatility and idiosyncratic volatility is the model's R-squared, which Morck et al. (2000) interprets as an inverse measure of price informativeness.

[12] Low Volatility: SdevN = 7, 8, 9, 10 Mid Volatility: SdevN = 4, 5, or 6 High Volatility: SdevN = 1, 2, or 3. It is important to note that there are separate standard deviation portfolio assignments for NYSE/AMEX and Nasdaq exchanges.

This table also reveals that there is a slight reduction in the percentage of non-random shares for low, mid, and high volatility groups for chains of two elements, but this change is not statistically significant. No clear pattern emerges for longer chains. Examining NYSE shares in Table 10, we find no significant changes in non-randomness after the introduction of an option. However, in Table 11, we observe that low volatility shares in Nasdaq substantially reduce their chances of being non-random for chains of two elements (from 22.51% to 16.40%), which is statistically significant (p-value = 0.054). In contrast, mid and high volatility shares do not show a statistically significant reduction in non-randomness. For chains of three or more elements, there are no statistical differences between the pre-period and the post-period in the probabilities of being non-random.

In summary, our findings suggest that low volatility shares in Nasdaq, which were less random than mid and high volatility shares before the introduction of the option, experience an increase in randomness after the derivative is introduced. This supports Ross (1989) argument and the idea that stocks with low price informativeness may enhance this characteristic following the introduction of options.[13]

We may focus now on the relationship between the Capital Asset Pricing Model's (CAPM) beta stock randomness. Lambert et al. (2007) and Riedl and Serafeim (2011) suggest that higher-quality accounting information should result in lower β. Additionally, the relationship between volatility and beta is expected to be correlated.[14]

In Tables 12, 13, and 14, we employ the year-end beta portfolio assignment obtained from CRSP for NYSE or Nasdaq. The classification of shares is based on deciles, with shares in the bottom four deciles categorized as low beta, shares in the 5th, 6th, and 7th deciles classified as mid beta, and shares in the top three deciles designated as high beta.[15]

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[13]We observe that both small-cap and low volatility stocks demonstrate an increase in their price informativeness after the introduction of the option, despite the negative relationship between market capitalization and volatility documented by Banz (1981) and Chen et al. (2005) (see Table 15).

[14]According to the Capital Asset Pricing Model (CAPM), the estimated β can be calculated as $\hat{\beta} = \frac{\sigma_i \rho_{im}}{\sigma_m}$, where σ_i represents the standard deviation of stock i, ρ_{im} denotes the correlation between stock i and the market, and σ_m represents the standard deviation of the market. Consequently, if two stocks exhibit the same correlation with the overall market, the one with higher volatility should have a higher beta. This relationship is supported by the findings presented in Table 17, which demonstrate that high (low) volatility shares tend to have high (low) β values.

Furthermore, Table 16 explores the association between market capitalization and beta. The results of this analysis validate prior research conducted by Fama and French (1992), which indicates that small firms tend to have higher betas compared to large firms, on average.

[15]Low Beta: BetaN = 7, 8, 9, 10 Mid Beta: BetaN = 4, 5, or 6 High Beta: BetaN = 1, 2, or 3. There are separate standard deviation portfolio assignments for NYSE/AMEX and Nasdaq.

The findings presented in Table 12 suggest that prior to the introduction of the derivative for a chain of two elements, a notable proportion of shares exhibit non-random behavior. Specifically, 23.35% of low beta shares, 19.37% of mid beta shares, and 14.07% of high beta shares can be categorized as non-random. A chi-square test of independence reveals a significant association between beta and randomness for this chain length ($X^2(2) = 11.39, p = 0.004$). These results align with the idea that low beta shares are less price informative.

For all shares, there is not a statistically significant change in the proportion of non-random chances, with the exception of an increase in the chances of non-randomness (p-value = 0.021) only in the case of a chain of five elements and low beta. However, given the lack of a clear pattern for smaller chains, this result may not be highly meaningful. Analyzing NYSE shares in Table 13, the introduction of an option does not bring about a statistically significant change in the proportion of non-random shares for a chain of two elements. Conversely, for Nasdaq stocks and chains of two elements, the introduction of an option does not lead to a significant reduction in the percentage of non-random shares. However, for chains of 3 elements, the introduction of an option leads to a reduction in the percentage of non-random shares (from 25.60% to 17.39%, significant at a 10% level). For longer chains, there is no discernible pattern linking betas and randomness.

In conclusion, low beta shares in both NYSE and Nasdaq exhibit less randomness compared to mid and high beta shares. However, the reduction in randomness occurs only in mid-beta Nasdaq shares for chains of 2 elements. We postulate that Nasdaq low beta and mid betsa stocks may possess lower levels of information compared to Nasdaq high beta stocks, and the derivative instrument may slightly enhance their price informativeness.

5 Conclusion

This study employs the Overlapping Serial Test (OST) to analyze a sample of 1,326 shares traded in either NYSE or Nasdaq that experienced the introduction of an option for the first time between Decemeber 29, 1999, and November 09, 2011. The weak form of the Efficient Market Hypothesis (EMH) is tested using various window lengths, and it is found that the EMH can be rejected when observing window lengths of two days but cannot be rejected otherwise. For shares that are considered inefficient, as well as for the entire sample, the chains 01 and 10 are more frequent than the chains 00 and 11.

The introduction of an option in Nasdaq-traded shares is a statistically significant factor in reducing the probability of non-randomness, whereas it appears to be irrelevant in the case of NYSE. This finding aligns with previous research, such as the study by Lin et al. (1998), which suggests that Nasdaq stocks entail higher information search and security analysis costs. When examining different market capitalization categories among Nasdaq-listed stocks for chains of 2 elements, it is observed that only small-cap stocks experience a statistically significant reduction in the probability of being non-random (from 21.89% to 14.43%). Despite the negative correlation between market capitalization and volatility, it is also discovered that low-volatility stocks trading in Nasdaq benefit from the introduction of an option, as their proportion of non-randomness decreases from 22.51% to 16.40%. Furthermore, Nasdaq low β stocks exhibit a decrease in the likelihood of being non-random from 24.43% to 19.32%, and Nasdaq mid β stocks suffer a reduction in the probability of being non-random from 19.34% to 14.10%, after the initiation of option trading. These findings suggest that low-volatility, and mid and low β securities possess less informative prices prior to the introduction of options but may have experienced improved price informativeness afterward.

The conclusions of this study are consistent with the theoretical work of Massa (2002) and Huang (2015), which demonstrate that the introduction of an options market, particularly for securities characterized by high information acquisition costs (such as small, low-volatility, and mid and low β stocks in the Nasdaq market), should enhance the price informativeness of the underlying assets.

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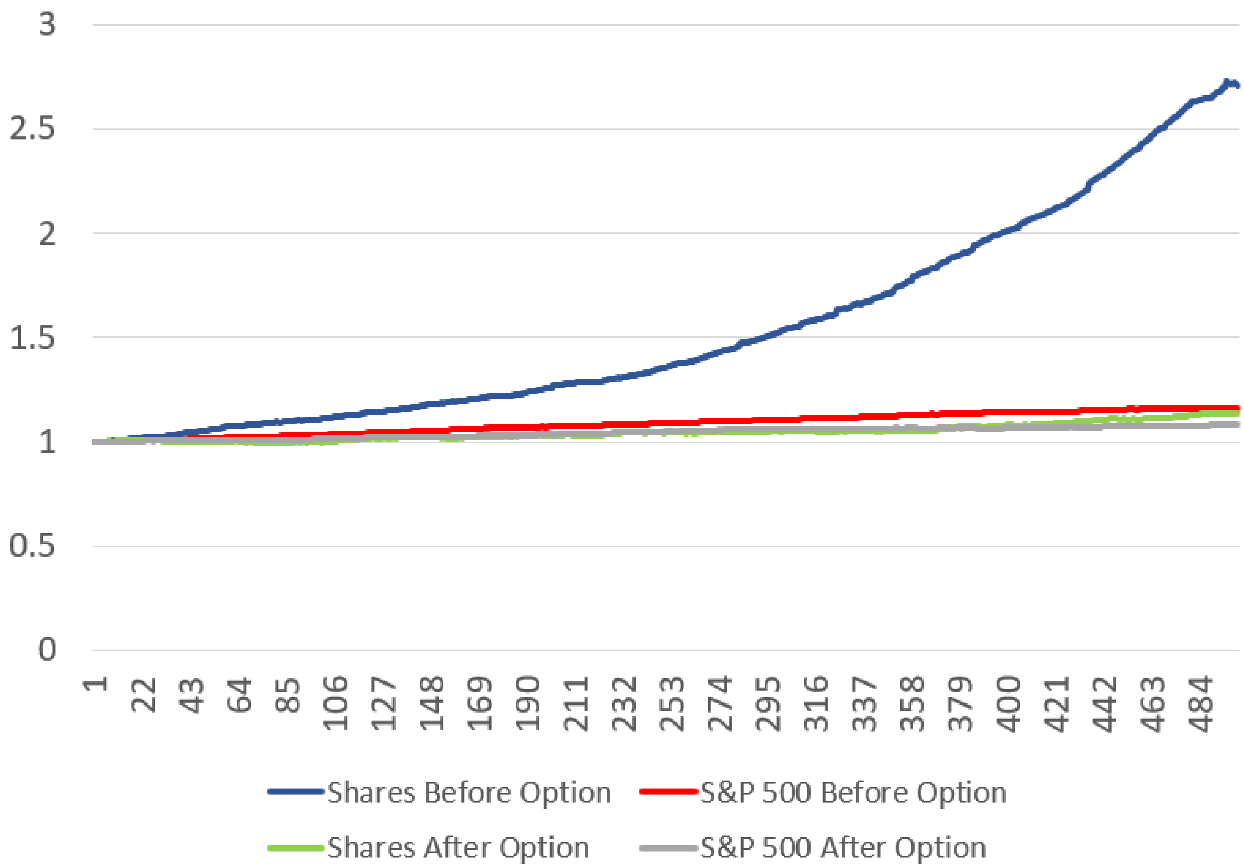
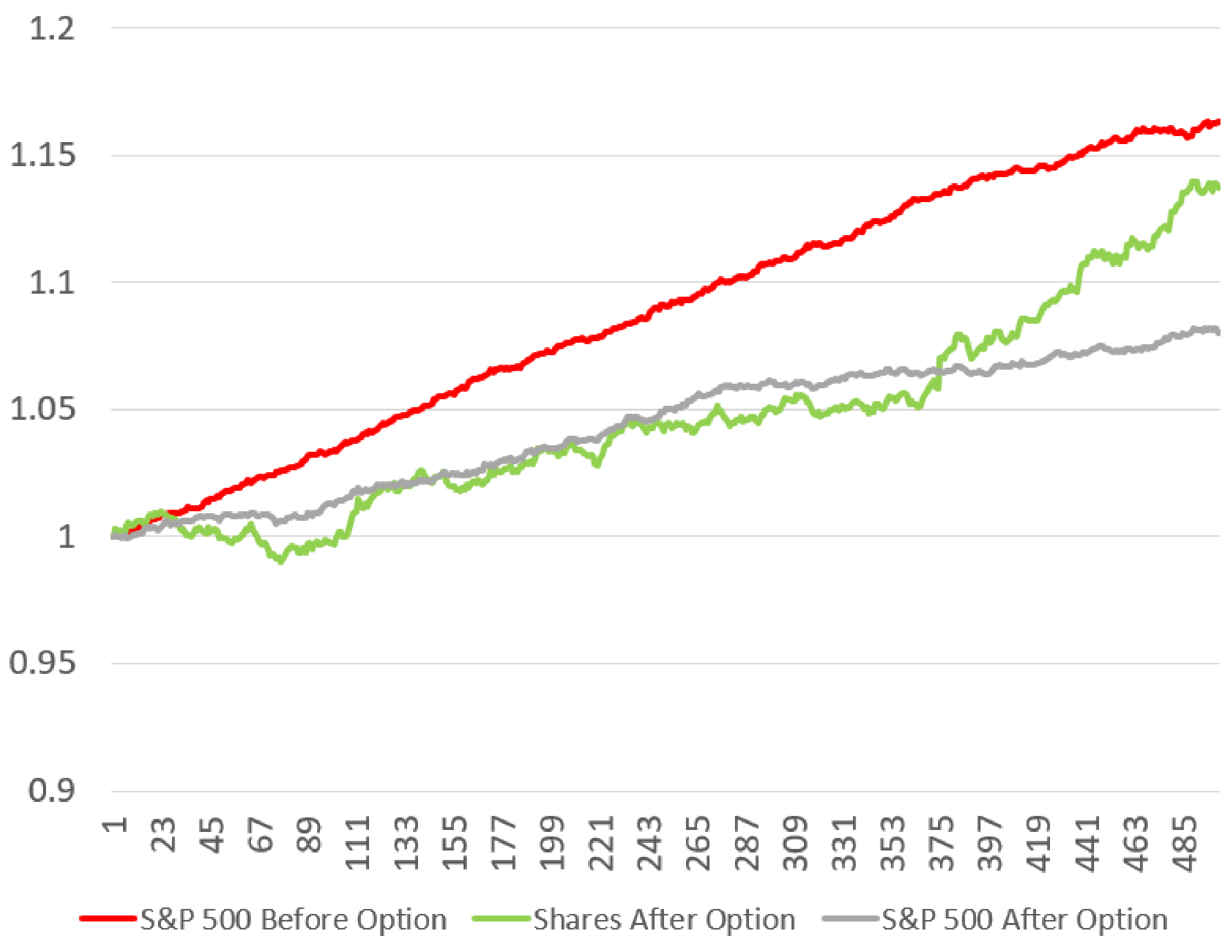
Figures

Figure 1: Portfolio valuation



Notes: This figure presents the performance of four distinct portfolios over a two-year duration, namely *Shares before option*, *SP500 before option*, *Shares after option*, and *SP500 after option*.

Figure 2: Portfolio valuation (detail)



Notes: This figure presents the performance of three distinct portfolios over a two-year duration, namely *Shares before option*, *Shares after option*, and *SP500 after option*.

Tables

Table 1: Classification according to size, volatility and beta characteristics

Characteristic	Classification	Metric	Values
Market Cap	NYSE, small cap	capn	1, 2, 3, 4
	NYSE, mid cap	capn	5, 6, 7
	NYSE, large cap	capn	8, 9, 10
Market Cap	Nasdaq, small cap	capn	1, 2, 3, 4
	Nasdaq, mid cap	capn	5, 6, 7
	Nasdaq, large cap	capn	8, 9, 10
Volatility	NYSE, low volatility	sdevn	7, 8, 9, 10
	NYSE, mid volatility	sdevn	4, 5, 6
	NYSE, high volatility	sdevn	1, 2, 3
Volatility	Nasdaq, low volatility	sdevn	7, 8, 9, 10
	Nasdaq, mid volatility	sdevn	4, 5, 6
	Nasdaq, high volatility	sdevn	1, 2, 3
Beta	NYSE, low beta	betan	7, 8, 9, 10
	NYSE, mid beta	betan	4, 5, 6
	NYSE, high beta	betan	1, 2, 3
Beta	Nasdaq, low beta	betan	7, 8, 9, 10
	Nasdaq, mid beta	betan	4, 5, 6
	Nasdaq, high beta	betan	1, 2, 3

Note: The table displays the classification of shares based on various metrics, including *capn*, *sdevn*, and *betan*. The first column specifies the characteristics (size, volatility, or beta) being examined. The second column represents the classification category. The third column identifies the specific metric obtained from CRSP used for classification. The last column presents the metric values associated with each classification category.

Table 2: Portfolio characteristics

Portfolio	Observations	Mean	Std. err.	[95% conf. interval]		Final Portfolio Value
Shares Before Option	500	0.1993%	0.2030%	0.1814%	0.2171%	2.708
S&P500 Before Option	500	0.0302%	0.0530%	0.0256%	0.0349%	1.163
Shares After Option	500	0.0257%	0.1533%	0.0122%	0.0392%	1.137
S&P500 After Option	500	0.0155%	0.0622%	0.0100%	0.0209%	1.080

Note: This table examines various characteristics of the four portfolios under investigation. The first column specifies the portfolio being analyzed. The second to sixth columns present the number of observations, mean, standard error, and confidence intervals for the mean of the logarithmic returns of each portfolio. The last column provides the valuation of each portfolio at the end of the holding period.

Table 3: Results from the OST before and after the introduction on an option

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before	1,326	246*** (0.000)	90*** (0.003)	78* (0.082)	66 (0.532)	18.55%	6.79%	5.88%	4.98%
After	1,326	220*** (0.000)	78* (0.082)	78* (0.082)	70 (0.338)	16.59%	5.88%	5.88%	5.28%
Chi-square		2.2603 (0.1327)	0.9151 (0.3388)	0.0000 (1.0000)	0.1240 (0.7247)				

Note: A total of 1,326 shares that had an option trading for the first time between December 29, 1999, and November 9, 2011 were included in the analysis. The $\bigtriangledown^2\psi_\lambda^2$ statistic was constructed using 500 consecutive overlapping windows before and after the introduction of the option, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the shares that are statistically significant at the 5% level, along with the percentage of shares that are significant. The values in parentheses indicate the probability of having k or more significant shares at the 5% level, given the total number of shares, assuming a true probability of a significant share of 5%. In the last two rows, a chi-square test of independence is conducted, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 4: Aggregation of results for a 2 day's window length

Period	Number of chains	Chain				Percentage				$\bigtriangledown^2\psi_2^2$	p-value
		00	01	10	11	00 (%)	01 (%)	10 (%)	11 (%)		
Before	663,000	162,730	168,738	168,735	162,797	24.54%	25.45%	25.45%	24.55%	215.26	(0.0000)
After	663,000	163,755	167,814	167,840	163,591	24.70%	25.31%	25.32%	24.67%	104.19	(0.0000)

Note: We analyzed a total of 1,326 shares that had an option trading for the first time between December 29, 1999, and November 9, 2011. The occurrences (00, 01, 10, and 11) were aggregated before and after the introduction of an option, resulting in a total of 768,000 occurrences (500 occurrences per share). The $\bigtriangledown^2\psi_2^2$ statistic was then calculated using these occurrences, following a chi-square distribution with degrees of freedom (df) equal to 1. The p-value is shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5: Results for the OST before and after the introduction of an option for NYSE and Nasdaq shares

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, NYSE	575	108*** (0.000)	39** (0.036)	35 (0.136)	25 (0.789)	18.78%	6.78%	6.09%	4.35%
After, NYSE	575	113*** (0.000)	30 (0.432)	28 (0.584)	27 (0.658)	19.65%	5.22%	4.87%	4.70%
Chi-square		0.140 (0.708)	1.249 (0.264)	0.823 (0.364)	0.081 (0.777)				
Before, Nasdaq	751	138*** (0.000)	51** (0.019)	43 (0.201)	41 (0.304)	18.38%	6.79%	5.73%	5.46%
After, Nasdaq	751	107*** (0.000)	48* (0.051)	50** (0.026)	43 (0.201)	14.25%	6.39%	6.66%	5.73%
Chi-square		4.687** (0.030)	0.097 (0.755)	0.562 (0.454)	0.050 (0.822)				

Note: We analyzed a total of 1,326 shares that had an option trading for the first time between December 29, 1999, and November 9, 2011. We differentiated between shares trading in NYSE and shares trading in NASDAQ for the period before and after the introduction of an option. The $\bigtriangledown^2\psi_\lambda^2$ statistic was computed using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows present the results of a chi-square test for independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 6: Results for the OST before and after the introduction of an option for small, mid, and large market cap shares

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, small cap	183	35*** (0.000)	10 (0.433)	12 (0.207)	11 (0.309)	19.13%	5.46%	6.56%	6.01%
After, small cap	183	25*** (0.000)	14* (0.076)	12 (0.207)	7 (0.814)	13.66%	7.65%	6.56%	3.83%
Chi-square		1.993 (0.158)	0.713 (0.398)	0.000 (1.000)	0.935 (0.334)				
Before, mid cap	639	116*** (0.000)	43** (0.032)	41* (0.065)	32 (0.522)	18.15%	6.73%	6.42%	5.01%
After, mid cap	639	107*** (0.000)	39 (0.120)	32 (0.522)	32 (0.522)	16.74%	6.10%	5.01%	5.01%
Chi-square		0.440 (0.507)	0.208 (0.648)	1.177 (0.278)	0.000 (1.000)				
Before, large cap	504	95*** (0.000)	37** (0.014)	25 (0.545)	23 (0.702)	18.85%	7.34%	4.96%	4.56%
After, large cap	504	88*** (0.000)	25 (0.545)	34** (0.049)	31 (0.140)	17.46%	4.96%	6.75%	6.15%
Chi-square		0.327 (0.567)	2.475 (0.116)	1.458 (0.227)	1.252 (0.263)				

Note: We conducted an analysis on a total of 1,326 shares that had an option trading for the first time between December 29, 1999, and November 9, 2011. We differentiated between small cap, mid cap, and large cap shares for the period before and after the introduction of an option. The $\bigtriangledown^2\psi^2_\lambda$ statistic was calculated using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows display the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 7: Results for the OST before and after the introduction of an option for small, mid, and large market cap shares trading in NYSE

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, small cap, NYSE	100	15*** (0.000)	4 (0.742)	8 (0.128)	7 (0.234)	15.00%	4.00%	8.00%	7.00%
After, small cap, NYSE	100	15*** (0.000)	4 (0.742)	7 (0.234)	1 (0.994)	15.00%	4.00%	7.00%	1.00%
Chi-square		0.000 (1.000)	0.000 (1.000)	0.072 (0.788)	4.687** (0.030)				
Before, mid cap, NYSE	315	67*** (0.000)	21 (0.113)	20 (0.166)	10 (0.955)	21.27%	6.67%	6.35%	3.17%
After, mid cap, NYSE	315	65*** (0.000)	17 (0.409)	10 (0.955)	17 (0.409)	20.63%	5.40%	3.17%	5.40%
Chi-square		0.038 (0.845)	0.448 (0.503)	3.500 (0.061)	1.896 (0.169)				
Before, large cap, NYSE	160	26 (0.000)	14 (0.031)	7 (0.693)	8 (0.550)	16.25%	8.75%	4.38%	5.00%
After, large cap, NYSE	160	33 (0.000)	9 (0.407)	11 (0.179)	9 (0.407)	20.63%	5.63%	6.88%	5.63%
Chi-square		1.018 (0.313)	1.171 (0.279)	0.942 (0.332)	0.062 (0.803)				

Note: We conducted an analysis on a total of 575 shares trading in NYSE that had an option trading for the first time between December 29, 1999, and November 9, 2011. We differentiated between small cap, mid cap, and large cap shares for the period before and after the introduction of an option. The $\bigtriangledown^2\psi^2_\lambda$ statistic was calculated using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows display the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 8: Results for the OST before and after the introduction of an option for small, mid, and large market cap shares trading in Nasdaq

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, small cap, Nasdaq	83	20*** (0.000)	6 (0.236)	4 (0.601)	4 (0.601)	24.10%	7.23%	4.82%	4.82%
After, small cap, Nasdaq	83	10*** (0.009)	10*** (0.009)	5 (0.401)	6 (0.236)	12.05%	12.05%	6.02%	7.23%
Chi-square		4.069** (0.044)	1.107 (0.293)	0.118 (0.732)	0.426 (0.514)				
Before, mid cap, Nasdaq	324	49*** (0.000)	22* (0.093)	21 (0.137)	22* (0.093)	15.12%	6.79%	6.48%	6.79%
After, mid cap, Nasdaq	324	42*** (0.000)	22* (0.093)	22* (0.093)	15 (0.656)	12.96%	6.79%	6.79%	4.63%
Chi-square		0.626 (0.429)	0.000 (1.000)	0.025 (0.875)	1.405 (0.236)				
Before, large cap, Nasdaq	344	69*** (0.000)	23* (0.099)	18 (0.455)	15 (0.741)	20.06%	6.69%	5.23%	4.36%
After, large cap, Nasdaq	344	55*** (0.000)	16 (0.651)	24* (0.065)	22 (0.145)	15.99%	4.65%	6.98%	6.40%
Chi-square		1.928 (0.165)	1.332 (0.248)	0.913 (0.339)	1.400 (0.237)				

Note: We conducted an analysis on a total of 751 shares trading in Nasdaq that had an option trading for the first time between December 29, 1999, and November 9, 2011. We differentiated between small cap, mid cap, and large cap shares for the period before and after the introduction of an option. The $\bigtriangledown^2\psi^2_\lambda$ statistic was calculated using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows display the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 9: Results for the OST before and after the introduction of an option for low, mid, and high volatility shares

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, low volatility	503	110*** (0.000)	31 (0.138)	28 (0.307)	18 (0.947)	21.87%	6.16%	5.57%	3.58%
After, low volatility	503	97*** (0.000)	24 (0.622)	36** (0.022)	27 (0.380)	19.28%	4.77%	7.16%	5.37%
Chi-square		1.028 (0.311)	0.942 (0.332)	1.068 (0.301)	1.884 (0.170)				
Before, mid volatility	474	82*** (0.000)	32* (0.055)	31* (0.080)	33** (0.037)	17.30%	6.75%	6.54%	6.96%
After, mid volatility	474	73*** (0.000)	25 (0.421)	20 (0.810)	25 (0.421)	15.40%	5.27%	4.22%	5.27%
Chi-square		0.625 (0.429)	0.915 (0.339)	2.507 (0.113)	1.175 (0.278)				
Before, high volatility	349	54*** (0.000)	27** (0.018)	19 (0.385)	15 (0.760)	15.47%	7.74%	5.44%	4.30%
After, high volatility	349	50*** (0.000)	29*** (0.006)	22 (0.159)	18 (0.480)	14.33%	8.31%	6.30%	5.16%
Chi-square		0.181 (0.671)	0.078 (0.780)	0.233 (0.629)	0.286 (0.593)				

Note: We analyzed a total of 1,326 shares that had an option trading for the first time between December 29, 1999, and November 9, 2011. We differentiated between small, mid, and high volatility shares for the period before and after the introduction of an option. The $\bigtriangledown^2\psi^2_\lambda$ statistic was calculated using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows display the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 10: Results for the OST before and after the introduction of an option for small, mid, and high volatility shares trading in NYSE

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, low volatility, NYSE	192	40*** (0.000)	7 (0.849)	7 (0.849)	7 (0.849)	20.83%	3.65%	3.65%	3.65%
After, low volatility, NYSE	192	46*** (0.000)	10 (0.493)	11 (0.366)	12 (0.255)	23.96%	5.21%	5.73%	6.25%
Chi-square		0.539 (0.463)	0.554 (0.457)	0.933 (0.334)	1.384 (0.239)				
Before, mid volatility, NYSE	203	35*** (0.000)	17** (0.027)	17** (0.027)	14 (0.141)	17.24%	8.37%	8.37%	6.90%
After, mid volatility, NYSE	203	38*** (0.000)	11 (0.436)	7 (0.885)	10 (0.564)	18.72%	5.42%	3.45%	4.93%
Chi-square		0.150 (0.698)	1.381 (0.240)	4.428** (0.035)	0.709 (0.400)				
Before, high volatility, NYSE	180	33*** (0.000)	15** (0.037)	11 (0.291)	4 (0.981)	18.33%	8.33%	6.11%	2.22%
After, high volatility, NYSE	180	29*** (0.000)	9 (0.548)	10 (0.413)	5 (0.949)	16.11%	5.00%	5.56%	2.78%
Chi-square		0.312 (0.577)	1.607 (0.205)	0.051 (0.822)	0.114 (0.736)				

Note: We analyzed a total of 575 shares trading in NYSE that had an option trading for the first time between December 29, 1999, and November 9, 2011. We differentiated between small, mid, and high volatility shares for the period before and after the introduction of an option. The $\bigtriangledown^2\psi_\lambda^2$ statistic was calculated using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows display the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 11: Results for the OST before and after the introduction of an option for small, mid, and high volatility shares trading in Nasdaq

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, low volatility, Nasdaq	311	70 (0.000)	24 (0.024)	21 (0.102)	11 (0.912)	22.51%	7.72%	6.75%	3.54%
After, low volatility, Nasdaq	311	51 (0.000)	14 (0.693)	25** (0.014)	15 (0.593)	16.40%	4.50%	8.04%	4.82%
Chi-square		3.704* (0.054)	2.803* (0.094)	0.376 (0.540)	0.642 (0.423)				
Before, mid volatility, Nasdaq	271	47*** (0.000)	15 (0.380)	14 (0.489)	19 (0.089)	17.34%	5.54%	5.17%	7.01%
After, mid volatility, Nasdaq	271	35*** (0.000)	14 (0.489)	13 (0.600)	15 (0.380)	12.92%	5.17%	4.80%	5.54%
Chi-square		2.069 (0.150)	0.036 (0.849)	0.039 (0.843)	0.502 (0.479)				
Before, high volatility, Nasdaq	169	21*** (0.000)	12 (0.142)	8 (0.613)	11 (0.227)	12.43%	7.10%	4.73%	6.51%
After, high volatility, Nasdaq	169	21*** (0.000)	20*** (0.000)	12 (0.142)	13* (0.083)	12.43%	11.83%	7.10%	7.69%
Chi-square		0.000 (1.000)	2.209 (0.137)	0.850 (0.356)	0.179 (0.672)				

Note: A total of 751 shares trading in Nasdaq, which had an option trading for the first time between December 29, 1999, and November 9, 2011, were analyzed. We categorized the shares into small, mid, and high volatility groups based on their characteristics before and after the introduction of an option. The $\bigtriangledown^2\psi^2_\lambda$ statistic was computed using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows display the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 12: Results for the OST before and after the introduction of an option for small, mid, and high beta shares

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, low beta	334	78*** (0.000)	22 (0.117)	21 (0.169)	8 (0.994)	23.35%	6.59%	6.29%	2.40%
After, low beta	334	71*** (0.000)	17 (0.505)	16 (0.605)	20 (0.235)	21.26%	5.09%	4.79%	5.99%
Chi-square		0.423 (0.515)	0.681 (0.409)	0.715 (0.398)	5.368** (0.021)				
Before, mid beta	537	104*** (0.000)	31 (0.231)	34* (0.097)	28 (0.437)	19.37%	5.77%	6.33%	5.21%
After, mid beta	537	84*** (0.000)	32 (0.177)	42*** (0.003)	28 (0.437)	15.64.%	5.96%	7.82%	5.21%
Chi-square		2.579 (0.108)	0.017 (0.897)	0.906 (0.341)	0.000 (1.000)				
Before, high beta	455	64*** (0.000)	37*** (0.003)	23 (0.509)	30* (0.078)	14.07%	8.13%	5.05%	6.59%
After, high beta	455	65*** (0.000)	29 (0.111)	20 (0.753)	22 (0.595)	14.29%	6.37%	4.40%	4.84%
Chi-square		0.009 (0.924)	1.045 (0.307)	0.220 (0.639)	1.305 (0.253)				

Note: The analysis included a total of 1,326 shares that had an option trading for the first time between December 29, 1999, and November 9, 2011. We categorized the shares into small, mid, and high beta groups based on their characteristics before and after the introduction of an option. The $\bigtriangledown^2\psi^2_\lambda$ statistic was computed using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We present the significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows display the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 13: Results for the OST before and after the introduction of an option for small, mid, and high beta shares trading in NYSE

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, low beta, NYSE	158	35*** (0.000)	7 (0.680)	10 (0.267)	2 (0.997)	22.15%	4.43%	6.33%	1.27%
After, low beta, NYSE	158	37*** (0.000)	6 (0.806)	6 (0.806)	10 (0.267)	23.42%	3.80%	3.80%	6.33%
Chi-square		0.072 (0.789)	0.080 (0.777)	1.053 (0.305)	5.544** (0.019)				
Before, mid beta, NYSE	232	45*** (0.000)	15 (0.187)	16 (0.123)	12 (0.494)	19.40%	6.47%	6.90%	5.17%
After, mid beta, NYSE	232	41*** (0.000)	14 (0.274)	15 (0.187)	11 (0.614)	17.67%	6.03%	6.47%	4.74%
Chi-square		0.228 (0.633)	0.037 (0.848)	0.035 (0.853)	0.046 (0.831)				
Before, high beta, NYSE	185	28*** (0.000)	17** (0.012)	9 (0.581)	11 (0.321)	15.14%	9.19%	4.86%	5.95%
After, high beta, NYSE	185	35*** (0.000)	10 (0.447)	7 (0.822)	6 (0.905)	18.92%	5.41%	3.78%	3.24%
Chi-square		0.937 (0.333)	1.958 (0.162)	0.261 (0.609)	1.541 (0.214)				

Note: The analysis focused on 575 shares traded in NYSE that had an option trading for the first time between December 29, 1999, and November 9, 2011. We categorized the shares into small, mid, and high beta groups based on their characteristics before and after the introduction of an option. The $\bigtriangledown^2\psi_\lambda^2$ statistic was computed using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. The significant shares and the percentage of significant shares at a 5% level of significance are reported. In parentheses, we provide the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. The last two rows present the results of a chi-square test of independence, with the p-value shown in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 14: Results for the OST before and after the introduction of an option for small, mid, and high beta shares trading in Nasdaq

Period	N	Significant shares				Significant shares percentage			
		2	3	4	5	2 (%)	3 (%)	4 (%)	5 (%)
Before, low beta, Nasdaq	176	43*** (0.000)	15** (0.032)	11 (0.267)	6 (0.878)	24.43%	8.52%	6.25%	3.41%
After, low beta, Nasdaq	176	34*** (0.000)	11 (0.267)	10 (0.386)	10 (0.386)	19.32%	6.25%	5.68%	5.68%
Chi-square		1.347 (0.246)	0.664 (0.415)	0.051 (0.822)	1.048 (0.306)				
Before, mid beta, Nasdaq	305	59*** (0.000)	16 (0.458)	18 (0.268)	16 (0.458)	19.34%	5.25%	5.90%	5.25%
After, mid beta, Nasdaq	305	43*** (0.000)	18 (0.268)	27*** (0.004)	17 (0.358)	14.10%	5.90%	8.85%	5.57%
Chi-square		3.014 (0.083)	0.125 (0.724)	1.943 (0.163)	0.032 (0.858)				
Before, high beta, Nasdaq	270	36*** (0.000)	20* (0.053)	14 (0.483)	19* (0.086)	13.33%	7.41%	5.19%	7.04%
After, high beta, Nasdaq	270	30*** (0.000)	19* (0.086)	13 (0.595)	16 (0.278)	11.11%	7.04%	4.81%	5.93%
Chi-square		0.621 (0.431)	0.028 (0.868)	0.039 (0.843)	0.275 (0.600)				

Note: The analysis included 751 shares traded in Nasdaq that had an option trading for the first time between December 29, 1999, and November 9, 2011. We categorized the shares into small, mid, and high beta groups based on their characteristics before and after the introduction of an option. The $\bigtriangledown^2\psi^2_\lambda$ statistic was computed using 500 consecutive overlapping windows, following a chi-square distribution with degrees of freedom (df) equal to $2^{(\lambda-2)}$. We provide the results for significant shares and the percentage of significant shares at a 5% level of significance. In parentheses, we indicate the probability of having k or more significant shares at a 5% level among the total number of shares, assuming the true probability of a significant share is 0.05. Additionally, we conducted a chi-square test of independence in the last two rows, with the p-value presented in parentheses. Significance codes: *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 15: Contingency table (Market Cap and Volatility)

Market Cap	Volatility		
	Low Volatility	Mid Volatility	High Volatility
Small Cap	26	44	113
Mid Cap	164	279	196
Large Cap	313	151	40

Note: The presented table represents a contingency table encompassing all stocks, with the categorical variables being market capitalization and volatility.

Table 16: Contingency table (Market Cap and Beta)

Market Cap	Beta		
	Low Beta	Mid Beta	High Beta
Small Cap	54	60	69
Mid Cap	149	247	243
Large Cap	131	230	143

Note: The presented table represents a contingency table encompassing all stocks, with the categorical variables being market capitalization and beta.

Table 17: Contingency table (Volatility and Beta)

Volatility	Beta		
	Low Beta	Mid Beta	High Beta
Low Volatility	207	242	54
Mid Volatility	73	196	205
High Volatility	54	99	196

Note: The presented table represents a contingency table encompassing all stocks, with the categorical variables being volatility and beta.