The Relationship Between Crime and Socio-Demographic Factors in Italy

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The Relationship Between Crime and Socio-Demographic Factors in Italy

Crime continues to exert substantial social and economic pressure on Italian society, negatively affecting economic performance, diminishing living standards, and undermining citizens' quality of life.

While organised crime and corruption, widely studied in the literature, substantially reduce regional GDP (Pinotti (2015) estimates 16–20% reductions in southern Italy alone), the broader socio-economic implications of other crime categories, such as property crimes, violent offences, and economic crimes, are also considerable. Indeed, Detotto and Vannini (2010) estimate the overall societal cost of crime at €38 billion in 2006, representing roughly 2.6% of Italy's GDP. Beyond economic losses, whether through reduced GDP or direct costs, persistent crime also significantly lowers satisfaction with life through the experiences of victimisation and fear of crime (Hanslmaier, 2013).

While considerable research has linked socio-economic and demographic factors to crime rates, a notable deficiency persists regarding structured, comparative analyses across different crime categories and multiple factors. Existing studies often focus on isolated explanatory variables (Buonanno & Leonida, 2005) or single dimensions of crime. Buonanno (2006) and Speziale (2014) highlight how unemployment significantly correlates with increased crime rates, especially in Italy's southern provinces.

Nevertheless, such literature tends to examine crime broadly, without a systematic comparison. Recognising these gaps, my thesis explicitly addresses the following research question: “Is there a relation between various demographic and socio-economic factors, and different types of crime in Italy?” Using a province-based fixed-effects panel dataset of 100 provinces over 14 years, complemented by a specific dummy to capture the unique shock of the 2020 COVID-19 pandemic, I provide a structured and comprehensive analysis. This methodological approach not only captures geographical heterogeneity effectively, but also isolates the Pandemic's temporal shock.

By precisely quantifying how multiple factors (such as unemployment, wages, immigration, education, and population density) affect different crime rates (such as property, violent and white-collar crimes), the presented findings can directly inform policy interventions, giving the analysis both economic and policy relevance.

This specification aims to aid policymakers in solving a common optimisation problem (Højbjerg, 2013): given the expected effects and costs of different policy strategies, which renders the largest decrease in the specific crime category (subsequently reducing social costs and increasing life quality)?

1. Theoretical Framework

The link between crime and social-economic conditions is a surprisingly recent idea. In the late-nineteenth century the Italian anthropologist Cesare Lombroso proposed an anatomical difference between the "natural born criminal" and "the honest man". For Lombroso, the indicative signs of deviance were not wages, schools, or neighbourhoods, but phenotypical stigmata: a smaller cranial volume, asymmetrical facial bones, pronounced brow-ridges or a powerful jaw. Crime proceeded unavoidably from inherited degeneration (Lombroso, 1897). This biological determinism opened the door to the early twentieth century eugenic policies, which aspired to reduce offenses not by altering incentives or opportunities, but by isolating (or sterilising) those identified as born criminals.

Modern research rejects that essentialism. Empirical evidence shows that criminal behaviour is much better explained by neighbourhood context, socioeconomic opportunity, and peer dynamics rather than race (Sampson et al., 2005), and it responds systematically to prices, wages, policing, and social opportunities (Gould et al., 2002; Levitt, 1997; Lochner & Moretti, 2004; Sampson et al., 2005). The decisive intellectual turn came with Gary Becker's (1968) economic model of crime, which considers it a rational, calculated choice. This framework shifted policy discussion from skull dimensions to opportunity costs, posing the basis for the contemporary analysis used in this thesis.

1.1 General Model of Crime

The theoretical foundation for analysing crime from an economic perspective was introduced for the first time by Becker (1968) (Buonanno, 2003). According to Becker's economic model, the decision to commit a crime is fundamentally rational, based on comparing expected benefits (monetary or psychological rewards from criminal activities) to expected costs (severity and likelihood of punishment).

Becker formalized this as an individual optimization problem, where potential criminals weigh the utility derived from illegal activities against the utility from legal alternatives, explicitly accounting for risks and punishments.

Ehrlich (1973) expanded upon Becker's initial framework, emphasizing how income levels, wage inequality, and economic opportunities within legitimate markets influence these decisions. Individuals facing poorer legitimate opportunities, or experiencing substantial income gaps, show increased incentives to commit crimes, especially those motivated by economic gain.

Sjoquist (1973) and Block and Heineke (1975) further refined the model, introducing the concept of opportunity cost related explicitly to time allocation. Criminal activities compete directly with legal work or education opportunities, implying that the benefits from criminal activities must exceed both the direct risks (probability of apprehension and punishment) and the indirect costs (foregone legal earnings and time spent incarcerated). These models are the foundation of my approach, guiding the selection of explanatory variables considered throughout this thesis.

1.2 Demographic Structure

Age is a critical determinant of crime, extensively confirmed by empirical evidence (Buonanno, 2003; Freeman, 1991 and 1996; Grogger, 1998). Young adults, particularly males aged between 15 and 24, are statistically more likely to engage in criminal activities due to lower opportunity costs, fewer familial responsibilities, and higher impulsivity or risk tolerance (Freeman, 1996). This demographic segment demonstrates significantly higher crime rates, particularly for property and violent crimes, often driven by socioeconomic exclusion, lower legitimate employment prospects, and peer influences (Grogger, 1998).

The theoretical implication, following Becker's framework, is straightforward: younger individuals typically face lower legitimate wages and fewer work opportunities, resulting in a comparatively lower cost of participating in illegal activities. Older age groups, by contrast, typically have higher wages, stable employment, and greater personal responsibilities, increasing their implicit cost of crime, and consequently reducing crime rates among these populations (Freeman, 1996; Buonanno, 2003).

To implement the effect of demographic structure, a variable expressing the mean age of the population is included in the model.

1.3 Education and Schooling Performance

Education is widely recognised as a fundamental factor affecting criminal behaviour. Economic theories posit that education raises legitimate earning potential, thus increasing the opportunity cost of crime (Lochner & Moretti, 2001).

Furthermore, education may have a “civilizing effect,” indirectly reducing antisocial behaviours through socialization, moral education, and inculcating civic values. This creates a “civic externality” that increases the deterrence of crime caused by education (Usher, 1997). Yet, the effects of education on crime can be nuanced: increased education levels could, paradoxically, enhance the potential to commit certain sophisticated crimes, such as white-collar offenses. Ehrlich (1975) noted that individuals with higher education might engage in fewer violent or property crimes but could become more proficient in crimes requiring intellectual capital, complicating the estimation of the overall effect of education.

To proxy for schooling performance, I measure the portion of students repeating a school year.

1.4 Youth Unemployment and General Unemployment

Unemployment is extensively studied within crime economics, though its relationship with crime remains complex. Classical economic reasoning postulates unemployment as increasing crime through reduced legitimate income opportunities, thus lowering the opportunity cost of criminal activities (Becker, 1968; Ehrlich, 1973).

The supposed effect would be more pronounced in younger populations due to their lower initial labour market attachment, increased risk of exclusion, and higher marginal benefits from immediate economic rewards (Grogger, 1998).

However, empirical research shows this link to be statistically loose, as is the misconception viewing most criminals as unemployed. As shown by Merlo and Rupert (2001) only 21% of the people engaging in criminal activities are unemployed, and most of the research regarding labour and crime resulted inconclusive (Gould et al., 2002). The connection between employment and crime is more nuanced, and decomposing the effect of the labour market onto crime is essential for its analysis (Buonanno, 2003).

To disentangle the specific impact of youth unemployment, I follow a gap approach, using difference between youth unemployment rates and overall unemployment rates. This method, detailed in Chapter 3, directly addresses the empirical issue of collinearity and allows a clearer interpretation of unemployment’s impact on youth crime.

1.5 Income, Salaries, and Economic Opportunities

Income, measured as average salaries or wages, is directly linked to crime through Becker’s opportunity-cost framework (Becker, 1968). Higher legitimate incomes reduce the relative attractiveness of illegal activities by increasing their opportunity costs. Empirical studies consistently support this theoretical prediction: lower real wages correlate robustly with higher property crime rates, particularly among disadvantaged youth (Grogger, 1998; Freeman, 1994).

Income inequality further complicates this relationship. Economic disparities create both incentives and motivations for crime through mechanisms of “relative deprivation”: the perception that individuals’ access to desired resources, such as money or social status, is lower than that of their peers. (Ehrlich, 1973; *APA Dictionary of Psychology*, 2007). Individuals with lower incomes find themselves close to individuals with “goods worth taking”, increasing the perceived returns of economically motivated criminal activity (Kelly, 2000; Buonanno, 2003).

In the model I propose, average salary of employees is used to represent the varying level of income and economic opportunities.

1.6 Immigration, Residence Permits, and Social Inclusion

Immigration and crime have an interesting and often politically charged relationship. Economic literature offers mixed insights, highlighting that immigration could either increase or reduce crime depending on broader socioeconomic contexts (Bianchi et al., 2012). On one hand, recent immigrants may face significant labour market exclusion and social marginalization, factors associated with increased crime rates through reduced opportunity costs and social alienation. On the other hand, immigrants may commit fewer crimes due to heightened deterrent effects (risk of deportation or stricter surveillance) or selective migration of individuals with lower criminal propensities.

To navigate this theoretical ambiguity, I include residence permits as a measure of legal immigration presence. A higher number of residence permits may reflect better integration and increased legitimate employment opportunities, theoretically reducing criminal participation. Conversely, higher residence permits could reflect greater overall immigration, potentially increasing crime if integration policies fail to provide adequate economic and social inclusion (Pinotti, 2017).

1.7 Synthesis and Empirical Implications

The theoretical literature clearly indicates that crime is influenced by rational economic decision-making processes grounded in opportunity cost and expected utility.

Table 1 shows the a-priori hypothesised relationships between factors and different crime types, based on the literature presented above.

Table 1

Hypothesized relationships between factors and outcomes.

Factor	Total Crime	Property Crime	White Collar Crime	Violent Crime
Age	?	−	+	−
Education	−	−	+	−
Unemployment	?	?	?	?
Income	−	−	+	−
Immigration	?	+	0	0

Note. “+” indicates a positive effect; “−” indicates a negative effect; “0” indicates no effect; “?” indicates unknown effect.

2 Methodology

In this thesis, I empirically analyse how various socio-economic and demographic factors, mean provincial age, schooling performance (proxied by the share of repeating students), the youth unemployment gap, average salary levels, and immigration (measured by residence permits), influence four types of crime: total crime, property crime, violent crime, and white-collar crime. The analysis covers a balanced panel of 100 Italian provinces (97 after outlier removal) across 14 years (2009–2022). The chosen econometric approach is a one-way fixed-effects model at the province level, complemented by specific dummies capturing the 2020-2021 COVID-19 pandemic shock.

2.1 Dataset Assembly

All variables were sourced consistently from the Italian National Institute of Statistics (ISTAT), ensuring uniform geographic definitions, temporal coherence, and population metrics. Data cleaning involved merging province-year data from multiple ISTAT datasets based on NUTS2021 codes. For consistency, the dataset was formed through an "inner merge", a function that takes various databases as inputs, and outputs one containing only the intersection of their indices (in my case, only province-year couples present in all databases were kept). This obviously resulted in the loss of some territorial data. Provinces instituted or eliminated in the 2009-2022 time-period were discarded, namely:

- The Sardinian Provinces (ex. L.R. 4 Feb 2016):
  - Carbonia-Iglesias (2005-2016),
  - Medio-Campidano (2005-2016),
  - Ogliastra (2005-2016),
  - Olbia-Tempio (2005-2016),
  - Sud Sardegna (2016-2024).
- The Monza and Brianza Province (ex. L. n. 183, 2009),
- The Val d'Aosta Region (it does not contain any provinces, and because of data inconsistencies),
- The Autonomous Provinces of Trento and Bolzano (because of data inconsistencies),
- The Province of Fermo (became operative in 2009 ex. L. n. 147, 2004),
- The Province of Barletta-Andria-Trani (became operative in 2009 ex. L. n. 148, 2004).

2.1.1 Dependent Variables. The data pertaining to the regressands was obtained in the form of crime rates per individual crimes. These were then aggregated into the following categories:

- Property Crime
- White Collar Crime
- Violent Crime
- Total Crime

The specific crimes pertaining to the classifications are available on demand, together with the code used to clean and consolidate the crime categories.

Table 2

Dependent variables, their origin databases and cleaning R scripts.

Crime Category	Database Name	Relevant Cleaning Script
Violent Crimes	ISTAT - Crime rate - provinces (IT1,73_67_DF_DCCV_DELITTIPS_9,1.0)	*categorise_crimes.R*
Property Crimes	ISTAT - Crime rate - provinces (IT1,73_67_DF_DCCV_DELITTIPS_9,1.0)	*categorise_crimes.R*
White Collar Crimes	ISTAT - Crime rate - provinces (IT1,73_67_DF_DCCV_DELITTIPS_9,1.0)	*categorise_crimes.R*
Total Crime	ISTAT - Crime rate - provinces (IT1,73_67_DF_DCCV_DELITTIPS_9,1.0)	*categorise_crimes.R*

Note. Table 2 shows the origin database for the dependant variables.

2.1.2 Independent Variables. To construct the regressors, various variables were used. The following table shows the origin datasets, all provided by ISTAT.

The variables are the following:

- meanAge: Mean population age on the 1st of January,
- UNEM1524_pct: Unemployment rate of inhabitants aged 15 to 24,
- UNEM1574_pct: Unemployment rate of inhabitants aged 15 to 74,
- RESPERWORLD: Permits of stay to all citizens on the 1st of January,
- POP_count: Inhabitant population on the 1st of January,
- SALARY_eur: Average annual salary of employees in Euros,
- repeatingStudents: Upper secondary students repeating a school year, expressed in percentage values.

Table 3

Independent variables, their origin databases and cleaning R scripts.

Independent Variable	Database Name	Relevant Cleaning Script
meanAge	ISTAT - Demographic indicators (IT1,22_293_DF_DCIS_INDDEMOG1_1,1.0)	*final_model.Rmd*
UNEM1524_pct	ISTAT - Provincial data (IT1,151_1193_DF_DCCV_TAXDISOCCU1_UNT2020_7,1.0)	*full_db_creator.R*
UNEM1574_pct	ISTAT - Provincial data (IT1,151_1193_DF_DCCV_TAXDISOCCU1_UNT2020_7,1.0)	*full_db_creator.R*
RESPERWORLD	ISTAT - Province and citizenship (IT1,29_348_DF_DCIS_PERMSOGG1_5,1.0)	*relative_variables.R*
POP_count	ISTAT - Italy, regions, provinces (IT1,164_164_DF_DCIS_RICPOPRES2011_1,1.0)	*full_db_creator.R*
SALARY_eur	ISTAT - Economic well-being (IT1,DF_BES_TERRIT_4,1.0)	*full_db_creator.R*
repeatingStudents	ISTAT - Upper secondary school - repeaters per school year level (IT1,52_1044_DF_DCIS_SCUOLE_15,1.0)	*final_model.Rmd*

Note. Table 3 shows the origin database for the independent variables.

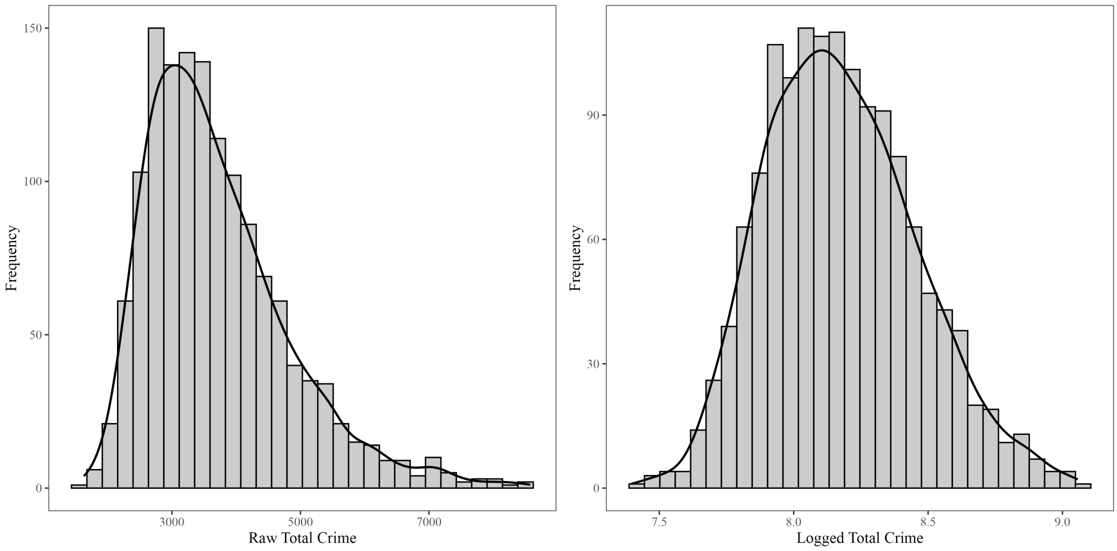
2.2 Variable Creation and Transformation

In this section, I present the rationale behind the construction and transformations applied to each variable, motivated by theoretical considerations, statistical properties, and empirical regularities observed in previous research.

2.2.1 Outcome Variables. Crime rates were initially expressed per 100,000 inhabitants. Due to pronounced right-skewness and heavy tails, I applied a logarithmic transformation. This normalizes distributions, reduces the weight of extreme values, and simplifies the interpretation of regression coefficients as elasticities (Kelly, 2000; Gould et al., 2002). Moreover, as shown by Ehrlich (1996), logarithmic specifications help reduce the effect of the notorious underreporting errors commonly associated with aggregate crime data.

Figure 1

Histogram of Raw Total Crime (left) and Logged Total Crime (right)



Note. Fig. 1(a), on the left, shows the initial, pre-log transform distribution of total crime; Fig 1(b), on the right, shows the same distribution after a logarithmic transformation.

Further histograms involving other key independent variables pre and post transformation will be available in Appendix A for comprehensive reference.

2.2.2 Core Independent Variables:

- Youth Unemployment Gap (unemploymentGap):

To isolate the specific effect of youth unemployment, I calculated the unemployment gap as the difference between youth unemployment (ages 15-24) and overall unemployment (ages 15-74). The difference between the two rates expresses how much higher youth unemployment is than general unemployment. This approach reduces multicollinearity and enhances interpretability (Grogger, 1998).

- Average Salary (log_salary):

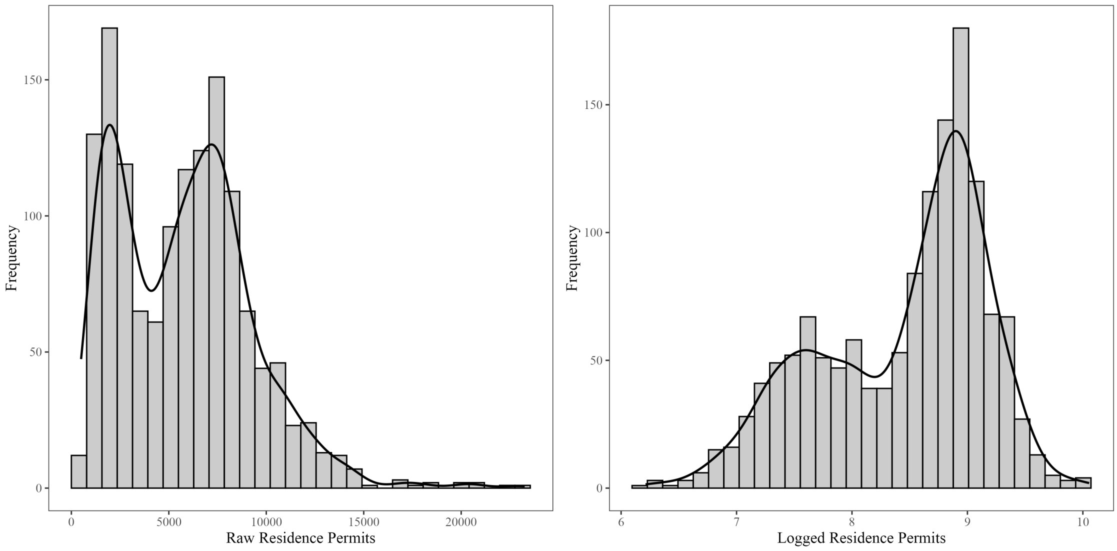
  Provincial average salaries were highly skewed, suggesting a log transformation. The resulting logged salaries allow interpretations of percentage changes in salaries, clearly linking to the theoretical notion of economic opportunity costs, where an increase in salaries should result in crimes being potentially more costly for the perpetrator (Becker, 1968; Freeman, 1996).

- Immigration Levels (log_residencePermits):

  Residence permits were strongly skewed, motivating the application of a logarithmic transformation. This improves normality and allows coefficient interpretation as elasticities, useful for discussing policy impacts related to immigration (Bianchi et al., 2012; Pinotti, 2017).

Figure 2

Histogram of Raw Residence Permits (left) and Logged Residence Permits (right)



Note. Fig. 2(a), on the left, shows the initial, pre-log transform distribution of residence permits; Fig 2(b), on the right, shows the same distribution after a logarithmic transformation.

Further histograms involving other key dependent variables pre and post transformation will be available in Appendix A for comprehensive reference.

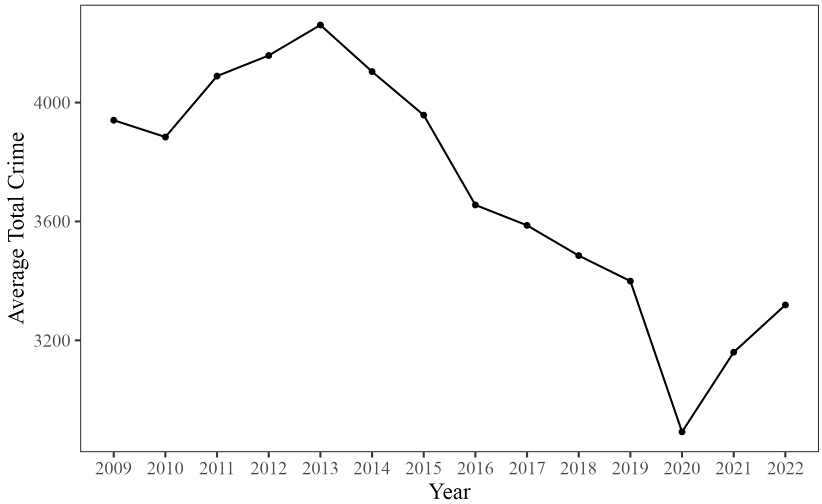
2.2.3 Control Variables:

- Pandemic Shock (year_2020, year_2021):

Binary dummies for the years 2020 and 2021 were included explicitly to capture the COVID-19 pandemic's temporal impact on crime rates. Unlike typical time effects, these represent a unique and exogenous shock affecting all provinces similarly. The choice of including two different dummy variables resides in the dissimilarity between those two crucial years. While 2020 was a year of total closure in Italy, 2021 was closer to a transitory period for the country.

Figure 3

Time Series Plot of Average Total Crime 2009-2022



Note. Fig. 3 shows the evolution of average crime during the period taken into consideration. Note the anormal shock in the year 2020 and 2021.

Further time series plots showing the evolution of other crime aggregates (property, white-collar and violent) will be available in Appendix A.

2.2.4 Considered but Not Included Variables. Several initially considered variables were ultimately excluded due to severe multicollinearity, redundancy, or theoretical irrelevance. When the model was selected as described in Section 2.4, all variables including province specific characteristics (population density, size, geographical position) were removed, as their effects would be absorbed by the intercept. Other variables, such as general unemployment, were removed after diagnostic checks showed severe collinearity and redundancy.

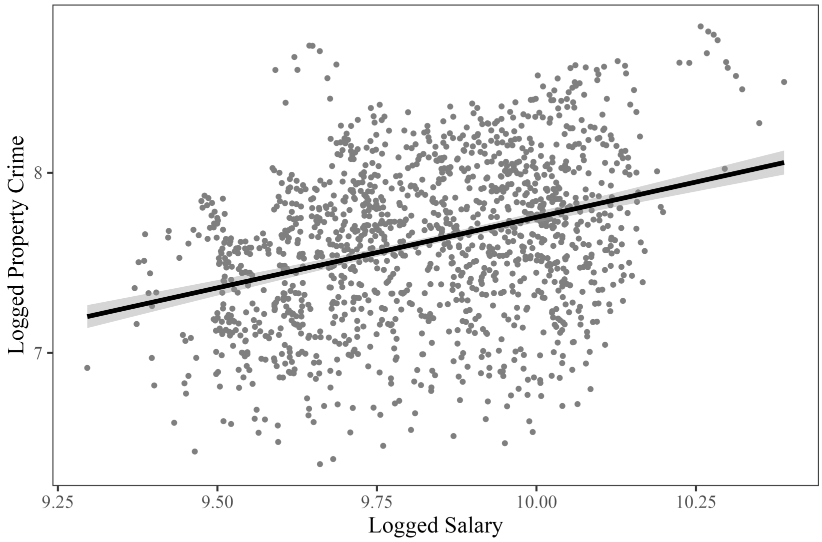
2.3 Exploratory Data Analysis

Before proceeding with econometric analysis, I conducted a comprehensive exploratory data analysis. A visual inspection of distributions (see Appendix A1-A4) suggested pronounced skewness and the presence of extreme values in many variables. As seen in the previous section, logging salary, crime rates, and residence permits dramatically improved the distribution properties, stabilizing variance and reducing skewness, consistent with standard practices in econometric literature.

2.3.1 Bivariate Relationships. I also assessed the initial relationships between dependent and independent variables visually, to detect clear patterns and potential non-linearities. For conciseness only Fig. 4 was kept here, showing the relationship between average salary and property crime, but almost all the remaining couples showed the same characteristic. Further scatterplots involving other key independent variables (such as youth unemployment gap or logged residence permits) against different crime categories will be available in Appendix A for comprehensive reference.

Figure 4

Scatter Plot of Logged Average Salary against Logged Property Crime



Note. Fig. 4 shows a scatterplot between Logged Property Crime and Logged Salary. A least squares regression line was included to aid the visualization of the relationship. The grey area around the line represents the 95% confidence interval.

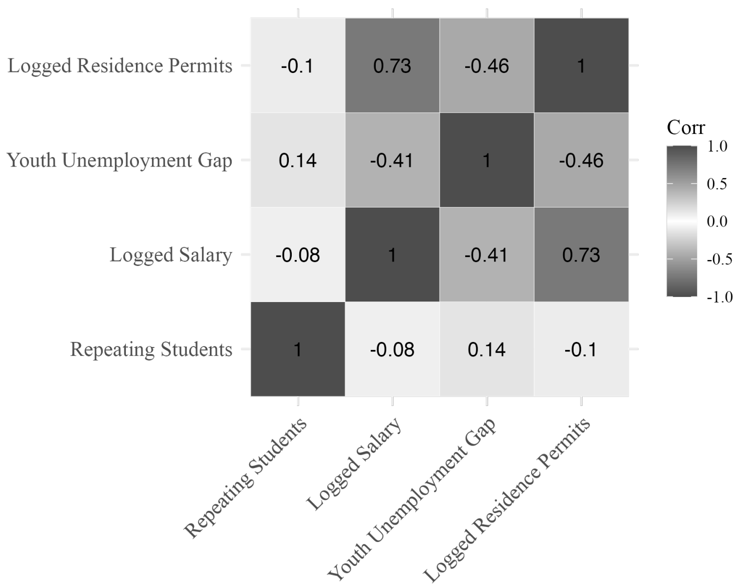
As exemplified by Fig. 4, the assumption of linearity is plausible enough for now. To ensure the robustness of this assumption, all the regressors' scatterplots were analysed. F-tests comparing models with non-linear specifications and base models were performed, AIC and BIC values were compared. The result was the adoption of a non-linear relation for $meanAge$ only (more on that in Section 2.5).

2.3.2 Initial Collinearity Assessment. For an initial assessment, I generated correlation heatmaps. While not sufficient to establish the presence of higher order multicollinearity, these serve well the Exploratory Data Analysis. In Results Discussion, once the final model has been established, more thorough evaluations will take place to ensure statistical requirements are (at least to some degree) respected.

As shown by Fig. 5, the only couple of regressors with considerable corelation is the pair “Logged Residence Permits – Logged Salary”. Their correlation is significantly different from zero, as the 95% confidence interval is [0.705, 0.754]. While this level does not automatically invalidate regression results, it may affect the stability and interpretability of individual coefficient estimates.

Figure 5

Independent Variables Correlation Heatmap



Note. Fig. 5 shows a correlation heatmap between the independent variables. The colour scale is limited to two colours as the magnitude, rather than the direction, of correlation is the statistic under examination. The correlation coefficient displayed is the Pearson Correlation Coefficient.

The overall results from the Exploratory Data Analysis start shedding some light into the possible relationships between the variables. The quality of the data was deemed sufficient to start designing the regression model, although further tests will need to take place to ensure full theoretical confirmation.

2.4 Model Selection

Having shown that criminal behaviour is moulded less by phrenology than by income, age, and education, the next task is to draw a map of those forces. What follows is that map. It is purposely lean, no map tries to reproduce every blade of grass, but if it aids in locating the salary, labour structure, and education background that steer would-be offenders' choices, the omissions are an acceptable toll for clarity. In that sense, the model is judged not by how faithfully it traces every boundary of reality, but by whether it shows the roads along which policy can travel.

2.4.1 Pooled OLS. The initial set of regressions (one per each crime category), including all the variables specified earlier, is then:

$$\log\left(CR_{it}^{(k)}\right) \;=\; \alpha^{(k)} \;+\; \boldsymbol{\beta}^{(k)}\boldsymbol{X}_{it} \;+\; \varepsilon_{it}^{(k)}, \quad k = 1, \dots, 4 \tag{1}$$

where:

$$\boldsymbol{\beta}^{(k)} = \left(\beta_1^{(k)},\, \beta_2^{(k)},\, \beta_3^{(k)},\, \beta_4^{(k)},\, \beta_5^{(k)},\, \delta_{2020}^{(k)},\, \delta_{2021}^{(k)}\right), \tag{1.1}$$

$$\boldsymbol{X}_{it} = \begin{pmatrix} \text{meanAge}_{it}, \\ \text{repeatingStudents}_{it}, \\ log(\text{salary}_{it}), \\ \text{unemploymentGap}_{it}, \\ log(\text{residencePermits}_{it}), \\ D_{2020}, \\ D_{2021} \end{pmatrix}, \tag{1.2}$$

and:

$$CR_{it}^{(1)} = \log(\text{totalCrime}_{it})\,, \qquad (1a)$$

$$CR_{it}^{(2)} = \log(\text{propertyCrime}_{it})\,, \qquad (1b)$$

$$CR_{it}^{(3)} = \log(\text{whiteCollarCrime}_{it})\,, \qquad (1c)$$

$$CR_{it}^{(4)} = \log(\text{violentCrime}_{it})\,. \qquad (1d)$$

Table 4 shows coefficients and R^2s for the four regressions. These initial values are considered to get a rough estimate of the effects' direction.

Table 4

Comprehensive Summary of Pooled OLS Models

	Total Crime	Property Crime	White Collar Crime	Violent Crime
(Intercept)	0.706	-0.751	-7.265***	2.497***
meanAge	-0.019***	-0.050***	0.088***	0.010***
repeatingStudents	0.025***	0.039***	-0.009+	0.014***
log_salary	0.082+	0.286***	0.199**	-0.427***
unemploymentGap	0.006***	0.009***	0.003**	0.003***
log_residencePermits	0.205***	0.323***	-0.019	0.034**
year_2020	-0.216***	-0.446***	0.429***	-0.122***
year_2021	0.017	-0.137**	0.519***	0.014
Num.Obs.	1400	1400	1400	1400
R2	0.318	0.448	0.432	0.177
R2 Adj.	0.315	0.445	0.429	0.173
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Note. Table 4 shows the results of a Pooled OLS regression. Variables are descripted in Section 2.2. The model was generated using R's *plm* function, with model = "pooling".

Most of the variables are statistically significant in all models, and the results seem compatible with the hypothesis expressed in Table 1.

While expressing useful insights, a pooled OLS model implicitly assumes that all provinces share the same underlying tendency to experience crime, accounting for the observed explanatory variables (*note that the reason why there are four* $\alpha^{(k)}$ *in equation* (1)*, is that I construct four regressions, but each regression has a single intercept*). I believe that assumption to be unrealistic.

2.4.2 Fixed Effects. Research shows that crime rates across provinces are shaped not only by current economic and demographic conditions, but also by intrinsic historical, cultural, and geographical differences that tend to be stable over time. Buonanno et al. (2015) demonstrate that the current presence of mafia organizations in Sicily is strongly linked to geological and historical factors, such as the location of sulphur mines and the quality of local institutions in the 19th century. Putnam's (1993) work documents regional variations in social capital across Italy, and Buonanno et al. (2009) find that higher levels of civic norms are associated with significant reductions in property crime.

Because these characteristics are often constant over time and may correlate with key explanatory variables, ignoring them risks biased estimates. A fixed-effects model allows each province to have its own baseline level of crime that does not change over the period studied. This approach effectively controls for all unchanging local characteristics, whether we can observe them or not, and focuses the analysis on how changes within each province relate to changes in crime rates. In such way, the fixed-effects model offers a more accurate and policy-relevant picture of the factors driving crime across Italy's diverse provinces.

I nonetheless verify this empirically with R's *pFtest* function. The pFtest is an F-test that contrasts the pooled OLS and fixed-effects estimators by asking whether the unit-specific intercepts are jointly equal to zero. Under the null hypothesis of no individual effects, pooled OLS is sufficient; rejection of the null indicates that unobserved province-level factors systematically influence crime rates, validating the fixed-effects model on mathematical grounds as well as on substantive grounds suggested by the literature.

Indeed, all the tests' results show $\text{p-value} < 2.2{\times}10^{-16}$, indicating significant effects are present in all models. The script running these tests is available on demand for consultation.

The new set of regressions, now encompassing an intercept per each province, acting equivalently to a dummy variable, is then:

$$\log\left(CR_{it}^{(k)}\right) \;=\; {\alpha_i}^{(k)} \;+\; \boldsymbol{\beta}^{(k)}\boldsymbol{X}_{it} \;+\; \varepsilon_{it}^{(k)}, \quad k = 1, \dots, 4 \tag{2}$$

Where $\boldsymbol{X}$ and $\boldsymbol{\beta}$ are defined as in (1.1) and (1.2), and $CR_{it}^{(k)}$ is defined as in (1a) to (1d). Note the only difference between (1) and (2) being that α is allowed to vary on i, resulting in a different intercept per each of the 100 provinces examined. Table 5 shows coefficients and R^2s for the four regressions under the fixed effects specification.

Table 5

Comprehensive Summary of Fixed Effects Models

	Total Crime	Property Crime	White Collar Crime	Violent Crime
meanAge	-0.063***	-0.152***	0.268***	-0.007
repeatingStudents	-0.005*	-0.009**	-0.017***	0.002
log_salary	-0.451***	-0.505***	2.323***	-0.600***
unemploymentGap	0.002***	0.004***	0.002***	0.001+
log_residencePermits	0.135***	0.225***	-0.224***	-0.001
year_2020	-0.206***	-0.384***	0.294***	-0.120***
year_2021	-0.088***	-0.260***	0.142***	-0.037*
Num.Obs.	1400	1400	1400	1400
R2	0.652	0.843	0.845	0.212
R2 Adj.	0.623	0.830	0.833	0.147
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Note. Table 5 shows the results of the fixed effects regression. Variables are descripted in Section 2.2. The model was generated using R's *plm* function, with model = "within", effect = "individual".

The results, as expected, are notably better. All coefficients of determination are significantly higher (*note that R's fixed effect function does not include the variability explained by the territorial dummies in the calculation for R^2s, so this increase stems from the regressors only*). The "Violent Crime" model gives an interesting insight: compared to the pooled OLS regression, fixed effects rendered most of the regressors statistically insignificant. This is most probably related to the variability explained by the territorial dummies, but a more in-depth analysis will be performed in the Results Discussion section.

2.4.3 Other Models. Other solutions were considered but discarded for various reasons. The choice between fixed effects (FE), random effects (RE), and two-way fixed effects must be based both on theoretical and empirical considerations. While pooled OLS ignores unobserved heterogeneity, RE assumes province-specific effects are uncorrelated with regressors, an unsustainable assumption given Italy's regional disparity in history, geography, and institutions (Putnam, 1993; Buonanno et al., 2015). To verify, Hausman tests were run per each model (script available on demand), showing $\text{p-value} < 2.2{\times}10^{-16}$, for all models except Violent Crime.

Indeed, for Violent Crime, I could not reject the null that the RE estimator is consistent, revealing that RE is the preferred specification for this category. In Results Discussion I will discuss the implications of this outcome in more detail, which could stem from the fact that province-specific factors influencing violent offences (e.g., policing culture, mafia presence, social cohesion) are only weakly correlated with the observable covariates in the model. Because for this crime rate the RE assumption of zero correlation seems plausible, and because Violent Crime rates display relatively little within-province variation, the RE estimator outperforms FE in this single case. For every other model, the tests confirmed systematic differences between FE and RE estimates, rejecting RE in favour of FE.

Two-way FE, which adds year fixed effects to province FE, initially appeared fitting. Joint F-tests confirmed the year dummies' statistical significance, suggesting time-specific shocks (e.g., national policy changes) influence crime. However, this specification absorbed excessive variance: all adjusted R^2 values turned negative (remember R's *plm* function excludes the variance explained by the fixed effects dummies when calculating R^2 values), indicating probable overfitting. Table 6 shows coefficients and R^2s for the two-way FE model.

Table 6

Comprehensive Summary of Two-Way Fixed Effects Models

	Total Crime	Property Crime	White Collar Crime	Violent Crime
meanAge	0.027***	-0.010	0.024	-0.015
repeatingStudents	0.006*	-0.000	-0.007	0.009**
log_salary	-0.115	-0.054	0.641***	-0.540***
unemploymentGap	0.000	0.000	0.001+	0.000
log_residencePermits	0.104***	0.127***	-0.217***	0.013
Num.Obs.	1400	1400	1400	1400
R2	0.074	0.032	0.055	0.033
R2 Adj.	-0.010	-0.057	-0.032	-0.055
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Note. Table 6 shows the results of the two-way fixed effects regression. Variables are descripted in Section 2.2. The 2020 and 2021 dummies are missing, as the year FE dummies already cover their roles. The model was generated using R's *plm* function, with model = "within", effect = "twoways", index = "Territory, Year".

Crucially, variables with slow-moving trends (e.g., education attainment, wage growth) lost significance, a known issue when time dummies dominate models with slow regressor changes (Beck & Katz, 2001; Plümper et al., 2005).

This corresponds with criminological evidence: socio-economic factors like unemployment or inequality affect crime through cumulative, multiyear channels (Buonanno, 2003; Gould et al., 2002). For example, wage increases may reduce property crime only after sustained labour market improvements, not annual fluctuations. Two-way FE restricts analysis to within-year variation, obscuring these types of effects. By contrast, one-way FE preserves cross-temporal variation, letting regressors explain crime trends over the full 2009–2022 period.

While omitting year dummies risks ignoring unobserved time shocks, including 2020 and 2021 pandemic dummies addresses the largest shock, mitigating omitted variable bias. The final approach is a balance of theoretical coherence with empirical pragmatism, ensuring policy-relevant estimates of socioeconomic determinants.

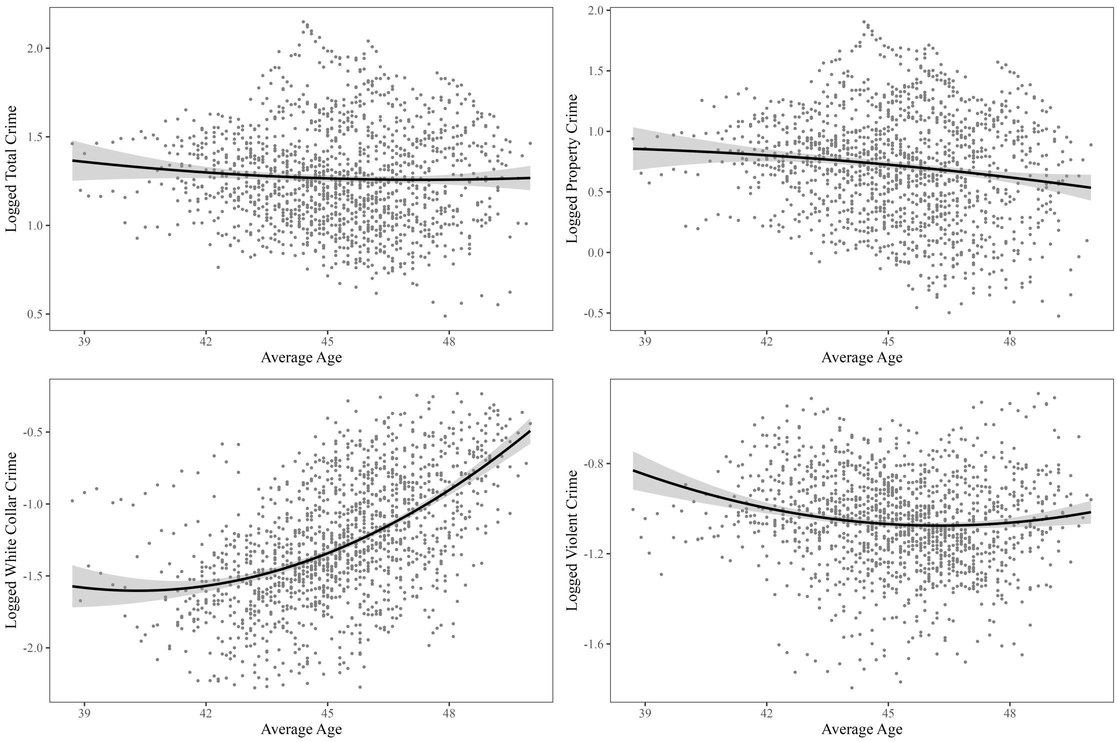
2.5 Non-Linear Variables

The specification incorporates a quadratic term for *meanAge* because both criminological theory and the preliminary exploratory analysis indicate that the association between a province average age and its crime incidence is intrinsically non-linear. Classic literature describes an "age-crime curve", showing participation in most conventional offences rises during adolescence, peaks in early adulthood, and declines as individuals acquire stable employment, family responsibilities, and stronger social controls, while the opportunity structure for white-collar offences tends to rise later, as access to organisational resources becomes available (Hirschi & Gottfredson, 1983).

Figure 6 confirms these expectations, showing a slightly concave relationship for Property Crime and a convex pattern for White-Collar crime.

Figure 6

Quadratic Scatterplots Between Logged Crime Rates and Average Age



Note. Fig. 6 shows scatterplots between Logged Total Crime (top-left), Logged Property Crime (top-right), Logged White Collar Crime (bottom-left), Logged Violent Crime (bottom-right) and Logged Salary. A quadratic least squares regression line was included to aid the visualization of the relationship. The grey area around the line represents the 95% confidence interval.

A linear model would therefore misrepresent marginal effects at younger and older age ranges. Including the squared age term gives the additional flexibility necessary to capture these curvatures while avoiding saturating the model excessively.

2.6 Outlier Removal

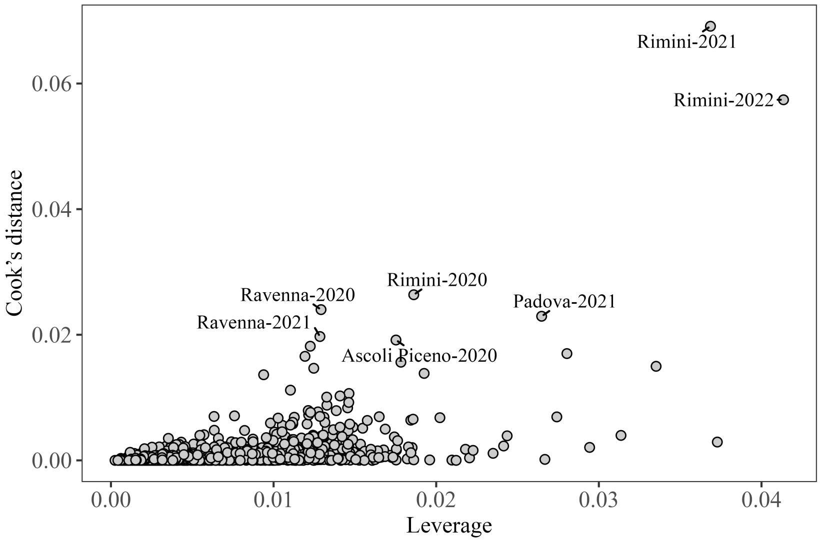
Before turning to the final estimation, it is important to ensure that the fitted relationships are not dominated by a small number of highly influential province-year datapoints. To this end, I build on the earlier specification checks with a classical influence diagnostic: a scatterplot of Cook's distance against leverage for every observation.

Cook's distance summarises how much the full set of estimated coefficients would change if a single data point were to be omitted, while leverage captures how abnormal the observation is in the context of the regressors. Plotting the two measures together, quickly highlights cases that are both extreme in regressor values and are powerful in determining the regression fit. Observations surpassing the conventional threshold for Cook's distance ($\frac{4}{n} = \frac{4}{1400} \approx 0.0025$) indicate cases whose removal would notably change the estimated coefficients (Belsley et al., 1980).

The Cook's distance-leverage plots (Figures 7, A12–A14) reveal a handful of highly influential province-year observations. For conciseness only Fig. 7, showing the aforementioned analysis for Total Crime, was kept here, while the rest are available in appendix A.

Figure 7

Scatterplot of Cook's Distance and Leverage for Logged Total Crime



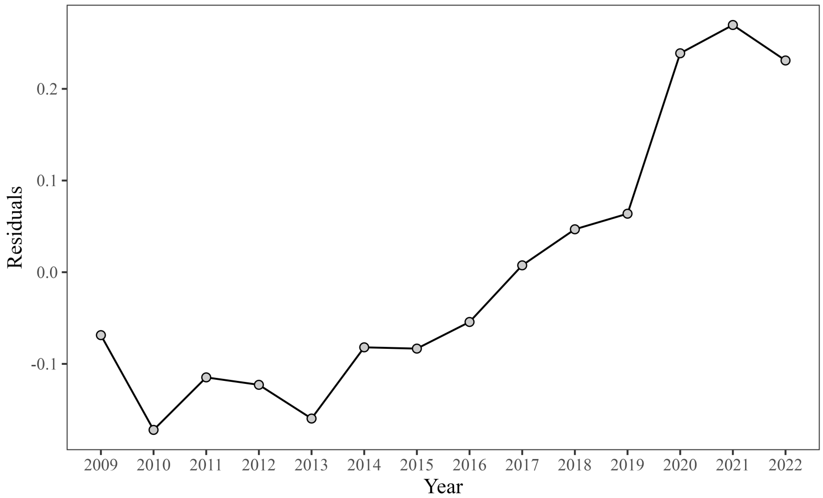
Note. Fig. 7 shows the scatterplot between Cook's distance and Leverage for, Logged Total. The seven province-year couples showing the highest Cook's distanced are labelled.

Throughout Fig 7, and Figs. A12-14, Rimini (years 2021–2022), Ascoli Piceno (years 2009, 2020–2022), and Padova (year 2021) exhibit Cook's distance values above 0.03, more than ten times the conventional threshold. These influential points, as argued by Wooldridge (2010), should be examined and justified carefully, as their presence may wrongly dominate the overall fit of the regressions.

Residual time plots for these provinces (Figures 8 for Rimini shown here, A14, A15 for the other potential outliers in Appendix A) support the identification of these anomalies, indicating clear breaks around the COVID-19 pandemic.

Figure 8

Time Plot of Rimini's Residuals, 2009-2022



Note. Fig. 8 shows the evolution of the model residuals for the province of Rimini, in the time-period 2009-2022.

Each province shows a significant divergence between observed and predicted crime rates during the 2020–2022 period, reflecting the influence of factors not captured by the current model.

Rimini is a prominent Italian tourist destination with a strongly concentrated summer tourism period. It regularly experiences intense seasonal fluctuations in population and associated crime levels, as extensively documented in tourism studies and national crime statistics. Following the easing of COVID-19 restrictions, Rimini saw a sharp increase in offences linked to a dramatic rebound in tourism inflows. Local authorities attributed increased crime rates in 2021-2022 to the resurgence of mass tourism (Il Sole 24 Ore, 2024). Residual analysis confirms that the model systematically under-predicted crime rates for Rimini in these years, thus justifying its exclusion to prevent this unique fluctuation from influencing the estimates.

Ascoli Piceno shows a different type of anomaly, characterized by a high incidence of financial and economic crimes rather than street-level offences. This province experienced an unusually high number of financial irregularities (with a peak of 450 suspicious-transaction reports in 2022 alone) probably related to criminal infiltration into local economic activities during the post-earthquake reconstruction period (Banca d'Italia, 2022). The residual plot illustrates that the regressors fail to capture these dynamics, particularly from 2020 onwards. To avoid biasing the model, it is excluded.

Padova shows yet another scenario, which might be linked to a noticeable increase in irregularities and indictments during the initial rollout of the National Recovery and Resilience Plan (PNRR). Local reports indicate numerous fraud cases and irregular contracts linked specifically to PNRR-funded projects (Il Sole 24 Ore, 2024; ANSA, 2025). The sudden positive residual spike in 2021 matches these events, indicating that the reason the model significantly underestimated actual crime levels for this year could be due to these shocks.

Removing these provinces is thus justified both by statistical diagnostics and by reasoning stemming from a thorough review of regional contexts and literature. Methodological guidelines confirm that handling these influential observations appropriately improves the robustness and reliability of econometric results (Aguinis et al., 2013).

2.7 Final Model

The culmination of data preparation, variable transformation, and diagnostic testing yields a *one-way province fixed-effects panel model* as the optimal framework for analysing the relationship between socio-demographic factors and crime rates across Italian provinces.

The equations describing the four models, one per each crime type, are as follows:

$$log(totalCrime_{it}) = \alpha_i^{(1)} + {\beta_1}^{(1)} meanAge_{it} + {\beta_2}^{(1)} meanAge_{it}^2 + \ \beta_3^{(1)} repeatingStudents_{it} + \beta_4^{(1)} log(salary_{it}) + \beta_5^{(1)} unemploymentGap_{it} + \beta_6^{(1)} log(residencePermits_{it}) + \delta_1^{(1)} D_{2020} + \delta_2^{(1)} D_{2021} + {\varepsilon_{it}}^{(1)} \tag{3}$$

$$log(propertyCrime_{it}) = \alpha_i^{(2)} + {\beta_1}^{(2)} meanAge_{it} + {\beta_2}^{(2)} meanAge_{it}^2 + \ \beta_3^{(2)} repeatingStudents_{it} + \beta_4^{(2)} log(salary_{it}) + \beta_5^{(2)} unemploymentGap_{it} + \beta_6^{(2)} log(residencePermits_{it}) + \delta_1^{(2)} D_{2020} + \delta_2^{(2)} D_{2021} + {\varepsilon_{it}}^{(2)} \tag{4}$$

$$log(whiteCollarCrime_{it}) = \alpha_i^{(3)} + {\beta_1}^{(3)} meanAge_{it} + {\beta_2}^{(3)} meanAge_{it}^2 + \ \beta_3^{(3)} repeatingStudents_{it} + \beta_4^{(3)} log(salary_{it}) + \beta_5^{(3)} unemploymentGap_{it} + \beta_6^{(3)} log(residencePermits_{it}) + \delta_1^{(3)} D_{2020} + \delta_2^{(3)} D_{2021} + {\varepsilon_{it}}^{(3)} \tag{5}$$

$$
\begin{aligned}
&log(violentCrime_{it}) = \\
&\qquad \alpha_i^{(4)} + {\beta_1}^{(4)} meanAge_{it} + {\beta_2}^{(4)} meanAge_{it}^2 + \ \beta_3^{(4)} repeatingStudents_{it} \\
&\qquad + \beta_4^4 log(salary_{it}) + \beta_5^{(4)} unemploymentGap_{it} \\
&\qquad + \beta_6^{(4)} log(residencePermits_{it}) + \delta_1^{(4)} D_{2020} + \delta_2^{(4)} D_{2021} + {\varepsilon_{it}}^{(4)}
\end{aligned} \tag{6}
$$

Here, $\alpha_i^{(k)}$ represent province-specific fixed effects for all 97 remaining provinces, representing unobserved heterogeneity stable over time. The dependent variables are the natural logarithm of crime rates (total, property, violent, or white-collar) in province i at year t. The quadratic term for $meanAge$ represents the non-linear age-crime relationship theorised in criminological literature, as detailed Section 2.3. Pandemic dummies for 2020 and 2021 explicitly address COVID-19 shocks.

2.8 Methodology Summary

Transformations applied to variables mitigated skewness and increased interpretability. Coefficients for logged variables now represent elasticities, easing policy discussions (e.g., a 1% salary increase corresponds to a $\beta_4^{(k)}$ % change in crime rate k).

The one-way fixed-effects specification was prioritised over alternative models for both theoretical and empirical reasons. First, it controls for unobserved province-level heterogeneity (as historical, geographical, and cultural factors) that remain constant over time. This choice is consistent with findings of Section 2.4, where two-way fixed effects (incorporating year dummies) led to overfitting. Year dummies absorbed excessive variance, making slow-moving variables like education and income statistically insignificant. Random effects were rejected following a Hausman test, which confirmed systematic differences between fixed- and random-effects estimates.

In the following section, I will present and discuss the estimates for all four crime categories, followed by robustness assessments.

3 Results Discussion

Overall, the panel regressions show reasonable explanatory power. Property and white-collar crime models have notably higher adjusted R^2 values compared to total and violent crime models. The fixed-effects violent crime model presents the lowest explanatory capability, a remainder that violent crime may be influenced significantly by factors outside the model's scope, consistent with the work of Buonanno et al. (2015). Table 7 shows a summary of the final model. The analysis demonstrates marked heterogeneity in how different factors affect various crime categories, providing important insights for both criminological theory and policy design.

Table 7

Comprehensive Summary of Final Models

	Total Crime	Property Crime	White Collar Crime	Violent Crime
I(meanAge)	0.399***	0.787***	-0.684***	0.323***
I(meanAge^2)	-0.005***	-0.011***	0.011***	-0.004***
repeatingStudents	-0.005*	-0.010***	-0.016***	0.001
log_salary	-0.247**	-0.085	1.888***	-0.448***
unemploymentGap	0.002***	0.003***	0.003***	0.000
year_2020	-0.181***	-0.336***	0.248***	-0.104***
year_2021	-0.079***	-0.242***	0.120***	-0.031+
log_residencePermits	0.117***	0.199***	-0.216***	-0.010
Num.Obs.	1358	1358	1358	1358
R2	0.664	0.860	0.853	0.223
R2 Adj.	0.636	0.848	0.841	0.159
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Note. Table 7 shows the results of the final regression. Variables are descripted in Section 2.2. A Fixed Effect model was chosen for all crime rates, as the assumptions behind it resonated best with the criminological theory considered. This had the pleasant consequence of delivering the highest R^2.

3.1 Results Analysis

For interpretation purposes, it is important to remember that some of the coefficients expressed in Table 7 represent elasticities while others show semi-elasticities. Specifically, logged regressors coefficients' (Salary and Residence Permits) express the percentage change in the relevant crime rate associated with a 1 % increase in the regressor. This is an elasticity, so the value at hand is *already* the percentage value and must not be multiplied by a factor of 100. The rest of coefficients show the change in the logged relevant crime rate associated with a 1 point increase in the variables at hand (whose unit of measure change depending on the variable, of course). The values in exam must then be multiplied by 100 to show the relevant percentage change. Particular attention should be displayed when interpreting semi-elasticities with regressors expressed in percentage points. For instance, the value of -0.010, tying repeating students to property crime, must be seen as "a 1 percentage point increase in the repeating students rate is associated with a 1% decrease in property crime"; not to be confused with "a 1% increase in the repeating students rate is associated with a 0.01% decrease in property crime".

3.1.1 Crime and Demographic Structure. The quadratic age specifications confirm the presence of age-crime curves across all crime categories, though with different structures. To find the points of inflection on the curves, first-order conditions (FOC) were applied.

For conventional crimes, the results follow established criminological theory. Property crime peaks at approximately 36 years, while total and violent crime reach their maximum around 40 years. This follows Becker's (1968) economic theory of crime, where younger populations engage more in crime due to lower opportunity costs, and with Hirschi and Gottfredson's (1983) classic age-crime curve, though the peak ages are somewhat higher than typically observed in individual-level studies (which would make sense, given the extremely different social and demographic situation between 1980's United States and 2010s Italy).

The most interesting result happens with white-collar crime, where the age relationship is inverted: the negative linear coefficient (-0.684) with a positive quadratic term (0.011) shows that white-collar crime rates decline with age until approximately 31 years. As the population ages beyond this point, white-collar crime rises significantly, consistent with Ehrlich's (1975) theory, suggesting greater opportunities for sophisticated financial offenses among older demographics.

3.1.2 Crime and Human Capital. The proxy for education quality, measured inversely by the rate of repeating students, showed unexpected relationships. Surprisingly, lower educational quality (higher rate of repeating students) correlated with lower total and property crime rates. One interpretation, following Lochner and Moretti (2004), is that extended structured school environments (due to repeating school years) might temporarily reduce opportunities for youth criminal involvement.

Contrarily, better educational quality significantly corresponded to higher white-collar crime rates, supporting Ehrlich's (1975) hypothesis that higher education provides greater opportunities for sophisticated crimes. The model estimated that a 1 percentage point decrease in the repeating student rate would associate to a 1.6% increase in white collar crimes. No significant relationship between education and violent crime materialised, a finding that supports that violent offenses might be more closely associated with immediate socio-cultural factors rather than educational attainment.

I must express an important methodological disclaimer for these findings: the contrast found with preceding literature might be more indicative of the quality of the proxy variable chosen, than of the actual effect of education. The percentage of repeating students might act as a confounding variable. By analysing the increase of repeating students, I don't consider the number of students exiting the schooling system. Under this view, the regressor might actually represent a direct proxy (opposed to an inverse one) for education levels, where a student repeating the year could be an expression of a high education level, as the student might have chosen to keep investing time and resources into her learning, rather than giving up education. For this reason, the coefficients relative to this regressor should be handled with care.

3.1.3 Crime and Income Effect. The salary effects reveal the most dramatic diversity between crime types, demonstrating strong support for different opportunity cost mechanisms. Property crime shows minimal sensitivity to wages (-0.085, not significant), while violent crime shows negative elasticity (-0.448). Most remarkably, white-collar crime exhibits a strong positive elasticity (1.888). It might seem that the relationship between income and white-collar crime contradicts traditional opportunity cost theories, but it does follow empirical findings from advanced economies. Higher-income areas tend to attract more complex financial institutions, greater concentrations of wealth, and expanded opportunities for sophisticated crime (Weisburd & Waring, 2001). The magnitude of this effect (a 1% increase in average salary corresponds to nearly a 2% increase in white-collar crime) suggests that economic development may accidentally create new criminal opportunities. The negative effect on violent crime (-0.448) behaves as expected from strain theory and relative deprivation arguments, consistent with Gould et al.'s (2002) findings that improved labour market conditions reduce interpersonal violence. While for total crime, the negative coefficient (-0.247) shows the averaging effect across crime types.

It appears from these results that, were crime to be considered as a type of good, it would be unwise to categorise it directly as inferior good. Indeed, the subdivision of crime into more specific categories shows that some conducts, such as white collar crimes, show a behaviour more closely related to a luxury good, while others act closer to inferior ones. Total crime would simply act as the average of these effects, tipping towards a negative elasticity, given the higher presence of property crimes compared to white collar ones.

3.1.4 Crime and Youth Unemployment. The unemployment gap variable, measuring the difference between youth and overall unemployment, shows significant positive effects on total, property, and white-collar crime, but no effect on violent crime. The strongest impact occurs for white-collar and property crime, where a 1 percentage point increase in the gap would result in a 0.3% increase in the crime rate, suggesting that youth labour market exclusion particularly increases economically motivated offenses.

These findings support Speziale's (2014) analysis of unemployment and crime in Italian provinces. They may also reflect Italy's specific context, where family support systems and economic participation shield young adults from the consequences of unemployment (Caroleo & Pastore, 2003), lowering the opportunity cost of joblessness even more.

3.1.5 Immigration and Social Integration. Residence permits demonstrate contrasting effects across crime categories that show different aspects of the immigration-crime relationship. Before heading into the figures, it is important to specify that the variable refers only to legal immigration. The assumption that legal immigration can be used as a proxy for illegal immigration is non-trivial, yet it is not without precedent; Bianchi et al. (2012) have already navigated these *perilous* waters with some success.

The positive effects on total and property crime appear to support concerns about immigration and crime. Specifically, a 1% increase in residence permits is associated with a 0.2% increase in property crime, and with a 0.1% increase in total crime. The negative effect on white-collar crime (-0.22%), however, suggests a deeper relationship.

The association with property crime could reflect economic stress in immigrant communities facing labour market barriers, consistent with Bianchi et al.'s (2012) findings on immigrant integration challenges in Italy. While the negative relationship with white-collar crime likely indicates that immigrant populations have limited access to positions enabling sophisticated financial crimes, supporting institutional opportunity theories. There are no statistically significant effects of residence permits on violent crimes, consistent with Bianchi et al.'s (2012).

It seems that the hypothesised increased deterrence that immigrants might face, because of the harsher consequences of being caught, does not emerge (at least for crimes related to property).

3.1.6 Pandemic Effects and Temporal Shocks. The COVID-19 pandemic had a distinctive effect across all crime. The 2020 effects show substantial reductions in total (-18.1%), property (-33.6%), and violent crime (-10.4%), but a significant increase in white-collar crime (24.8%).

The decline in conventional crimes matches international evidence on pandemic crime patterns, reflecting reduced opportunity structures due to lockdowns and altered routine activities (Campedelli et al., 2021). The particularly large effect on property crime is most probably a consequence of the impact of mobility restrictions and distancing measures onto theft, burglary, and robbery.

The positive pandemic effect on white-collar crime (24.8% in 2020, 12% in 2021) represents perhaps the most policy-relevant finding. This increase likely shows expanded opportunities for cybercrime, fraud targeting pandemic response programs, and financial crimes exploiting uncertainty. The persistence into 2021, even if diminished, could be a consequence of a onetime opportunity persisting onto habitual activities.

3.2 Policy Implications

3.2.1 Economic Development Strategies. The different effects of income across crime types require particularly careful policy responses. While higher wages effectively reduce violent crime (elasticity = -0.448), the strong positive relationship with white-collar crime (elasticity = 1.888) points towards the fact that economic development must be accompanied by more attentive regulatory oversight. Policymakers cannot simply assume that prosperity reduces all forms of crime; indeed, rapid economic growth may require proportional investments in white-collar crime detection and prosecution.

For violent crime reduction, the results support policies that improve legitimate earning opportunities, particularly for young adults. A 10% increase in average provincial wages corresponds to approximately 4.5% reduction in violent crime rates, suggesting that labour market investments could incorporate significant public safety returns.

3.2.2 Youth-Focused Labour Interventions. The consistent positive coefficients of the unemployment gap across multiple crime types show youth joblessness as a particular policy priority. The results suggest that specifically targeting youth unemployment (rather general unemployment whose effects on crime are still disputed, as shown by Merlo and Rupert in 2001) would yield crime reduction benefits across total, property, and white-collar offenses. This result supports policies such as youth employment guarantees, apprenticeship programs, and targeted hiring incentives (or tax deductions) for young workers.

3.2.3 Educational Investment and Early Intervention. Given the methodological uncertainties expressed in the previous section, policy implications should be considered with significant reservations. If the classic interpretation holds, where higher educational levels would deter crime by increasing opportunity costs and creating a civilising effect, policies promoting structured educational environments and preventing early school departure might reduce conventional crimes, though potentially at the cost of increased white-collar. Were the interpretation proposed in the previous section to be correct, the results may reflect selection effects rather than causal educational impacts.

Without more direct measures of education levels, completion rates, or learning outcomes, definitive policy recommendations are premature.

Future research should employ more robust educational indicators, such as graduation rates, standardised test scores (INVALSI being an interesting candidate), or a school dropout rate, to clarify these relationships before designing targeted educational interventions for crime prevention. The findings of my thesis mainly call attention to the importance of careful variable selection in empirical crime research rather than providing clear guidance for educational policy.

3.2.4 Immigration and Integration Policy. The mixed effect of residence permits across crime types focuses once again attention on the importance of successful immigrant integration rather than immigration restriction per se. Whether the responsibility of this integration should fall on the host country or on the immigrants themselves is outside the scope of this research. Yet, considering the symbiotic relationship, in which newcomers gain higher living standards while the Italian economy fills shortages in its low-skill labour market (Ambrosini, 2011), a *Solomonic compromise* seems the most plausible outcome.

The positive effects on property crime suggest that economic integration, ensuring access to legitimate employment opportunities, should be prioritized to minimize crime-related social costs.

3.2.5 Pandemics and Crime Prevention. The distinctive pandemic effects on white-collar crime create important precedents for future crisis response. The 25% increase in white-collar crime during 2020 suggests that emergency economic programs must incorporate robust fraud prevention measures from their inception. Future pandemic or economic crisis responses should include cybercrime monitoring and strengthened financial oversight of emergency programs. While in emergency situations most of the resources are usually devoted towards resolution of the emergency itself, ignoring ramifications of the emergency might result unwise.

The sharp declines in conventional crimes during lockdowns also demonstrate the potential for targeted situational crime prevention. Understanding which mobility restrictions and social distancing measures most effectively reduced property and violent crime can inform future public safety strategies, even outside pandemic contexts.

3.2.6 Resource Allocation. The variation in model fit across crime types suggests that enforcement resources should be allocated accordingly. Property crime, with the highest explanatory power ($R^2 = 0.860$), seems most responsive to socio-economic conditions and may benefit from prevention-focused interventions. Violent crime, with the lowest explanatory power ($R^2 = 0.223$), could require different approaches.

The strong age-crime relationships across all categories support age-targeted interventions, but with different emphases. Conventional crime prevention should focus on young adults (peak ages 36-41 years), while for white-collar crime prevention, attention should be dedicated to mid-career professionals who have accumulated sufficient access to more sophisticated offenses.

4 Limitations

George Box's classic reminder that "all models are wrong, but some are useful" offers the right lens for approaching this chapter. The model developed here has proved informative for understanding part of Italy's crime functioning, yet, like any abstraction, its utility is bounded. The section that follows outlines the most notable limitations that should advise both the interpretation of the results and any policy inferences drawn from them.

4.1 Data Quality Issues

The most significant limitation concerns the measurement of crime itself. As for most research in this area, this thesis relies on official police reports (or "denunce") as a proxy for actual criminal activity. However, it is well known that not all crimes are reported to the authorities, and the extent of underreporting can vary dramatically across regions, crime types, and social groups (For example, ISTAT (*Reati Contro la Persona e la Proprietà: Vittime ed Eventi, 2019)* estimates that up to 98% of car thefts are reported, while for assaults the value drop to 21%). In southern provinces, the presence of organised crime can create a climate of fear and mistrust, discouraging victims from coming forward. The same ISTAT report estimates that in areas with a strong mafia presence, 40-50% of crimes against property and the individual go unreported.

The problem is not limited to organised crime. Illegal migrants might be unwilling to report crimes due to fears of deportation, or simply because of language and cultural barriers. Taverriti (2019) suggests that a majority of migrant victims in Italy never contact the authorities. These disparities mean that the same crime might be much more likely to appear in the official statistics in one province than another, regardless of the underlying reality.

Beyond the challenges of crime measurement, limitations related to the explanatory variables used in the analysis are present. Some variables, such as the share of repeating students as a proxy for educational quality, may not represent the intended concept. This measure does not account for students who leave the school system altogether, nor does it distinguish between different reasons for repeating a year. As discussed in the results section, this could introduce selection bias or even invert the expected relationship between education and crime. Similarly, the use of residence permits as a measure of immigration does not account for undocumented migrants, who may represent a significant share of the population in some provinces.

There are also broader data quality issues. The unemployment gap variable does not capture informal employment, which is particularly widespread in the South and in certain sectors salary data, while useful, may not fully reflect the true income distribution, especially in areas with high levels of tax evasion or undeclared work (ISTAT, *L'economia sommersa e il lavoro non regolare,* 2005).

Finally, there are practical challenges in translating these findings into policy. High-profile anti-mafia operations, for example, require important resources and coordination, and not all regions have the same ability to implement these policy measures. In some areas, local governments themselves may be compromised by organised crime, further limiting the potential impact of policy interventions.

In addition to the data limitations presented above, while the individual fixed-effects model mitigates time-invariant provincial heterogeneity, several potential sources of endogeneity must yet be addressed. First, reverse causality may bias relationships: for instance, high crime rates could deter economic investment, suppressing wages and employment opportunities (Buonanno, 2003), creating a negative feedback loop where crime both influences and is influenced by economic conditions. Second, omitted variable bias persists for time-varying factors unobserved in the data, such as shifts in policing strategies or informal social control mechanisms, which could correlate with both regressors and crime outcomes.

In future research Instrumental Variables (variables correlated with regressors but uncorrelated with the error term) should be implemented to solve these issues. For example, "natural experiments" could be exploited, such as sudden policy changes in minimum wages or school reforms, to better isolate exogenous variation.

4.2 Robustness Check

The robustness of the regression results was tested to ensure econometric reliability.

The Shapiro-Wilk test, performed to assess residual normality, produced results showing that residuals were approximately normal for total crime ($W = 0.997$, $p = 0.029$) and property crime ($W = 0.999$, $p = 0.371$). Contrarily, residuals for white-collar crime ($W = 0.995$, $p < 0.001$) and violent crime ($W = 0.995$, $p < 0.001$) significantly deviated from normality. This, while relevant, does not substantially invalidate the fixed-effects estimator, but suggest caution when interpreting significance tests for these models.

The Breusch-Pagan test, to detect heteroscedasticity, shown evidence of variance instability in total crime ($\chi^2 = 23.847$, $p < 0.001$), property crime ($\chi^2 = 14.602$, $p < 0.001$), and violent crime ($\chi^2 = 5.096$, $p = 0.024$). White-collar crime did not show evidence of heteroscedasticity ($\chi^2 = 0.154$, $p = 0.694$). Cluster-robust standard errors at the provincial level are used to assess this issue.

Serial correlation is tested using the Breusch-Godfrey test, showing evidence of autocorrelation across all models (total crime: $\chi^2 = 632.185$, property crime: $\chi^2 = 569.204$, white-collar crime: $\chi^2 = 503.253$, violent crime: $\chi^2 = 381.112$; all $p < 0.001$).

As shown by Table 8, models estimated using cluster-robust standard errors showed minimal changes in the significance of coefficients compared to the previous estimates, confirming the stability of the original findings. The previously discussed theoretical expectations and policy implications remain valid.

Table 8

Comprehensive Summary of Models Estimated with Cluster Robust SEs

	Total Crime	Property Crime	White Collar Crime	Violent Crime
I(meanAge)	0.399**	0.787***	-0.684*	0.323*
I(meanAge^2)	-0.005***	-0.011***	0.011**	-0.004**
repeatingStudents	-0.005+	-0.010**	-0.016**	0.001
log_salary	-0.247*	-0.085	1.888***	-0.448***
unemploymentGap	0.002***	0.003***	0.003***	0.000
year_2020	-0.181***	-0.336***	0.248***	-0.104***
year_2021	-0.079***	-0.242***	0.120**	-0.031
log_residencePermits	0.117*	0.199***	-0.216**	-0.010
Num.Obs.	1358	1358	1358	1358
R2	0.664	0.860	0.853	0.223
R2 Adj.	0.636	0.848	0.841	0.159
+ p < 0.1, * p < 0.05, ** p < 0.01, *** p < 0.001				

Note. Table 8 shows the results of the final regression estimated with cluster robust standard errors. Variables are descripted in Section 2.2.

Be that as it may, results should be interpreted with appropriate caution, particularly regarding statistical significance, which could be mildly overstated due to the residual dependencies. Future research should explore more sophisticated methods, such as dynamic panel estimators, to further enhance robustness and precision.

5 Conclusions

Through this thesis, I tried to show the relationship between a set of six socio-demographic factors (Age, Salary, Schooling, Youth Unemployment, Immigration and the COVID-19 Pandemic) and different crime categories (Property, White Collar and Violent crimes). The results obtained, while constrained by both idiosyncratic and technical limitations, showed interesting, and sometimes unexpected, implications.

First, the age-crime curve well documented in classic criminology literature is confirmed: Property and Violent crime show a concave relationship, peaking earlier for Property than for Violent Crimes. Oppositely, White Collar crime showed a convex pattern, increasing with age after the mid-thirties.

Second, I found salary to behave similarly to the opportunity-cost theories of crime for Violent and Property crimes, as in provinces where salary deviated positively, those crime rates increased likewise. A “greed-effect” appeared for White Collar crimes, as they rose in years where salary increased in respect to the mean.

Third, the results on schooling remain dubious, not because of statistical significance, rather as a consequence of research design. This illustrates that even when mathematical rigor is respected, reasonableness is still a key factor to take into consideration.

Fourth, youth unemployment acted as expected from existing literature: when juvenile joblessness increases, crimes related with economic gains rise accordingly, while no significant relation with Violent Crime was found.

Fifth, immigration showed difficult effects, not because of statistical complexity, but due to interpretability reasons. It is my view that research should let the data do the speaking, yet even the most expert scholar cannot entirely control the listening, for better and for worse. In provinces where residence permits increased, property crimes rose, and white collar crimes decreased. The depth of this research does not allow for causality to be discussed, but were it to be present, it would manifest the results of failed integration.

Finally, the results related to the Pandemic are probably the most notable, seeming to indicate that during times where crimes requiring physical presence decrease, financial and electronic frauds emerge as the natural substitute. During 2020, Property crimes decreased by almost 34%, while White Collar crimes increased by almost 25%. The ramifications of this finding show that even in times of emergencies, resources must be allocated to combat alternative criminal opportunities.

By quantifying elasticities between crimes and influenceable factors, this research enriches criminological literature, and might aid policymakers in estimating the effects of socio-demographic changes. Future research should expand the considered variables ensuring robustness, and contemplate the inclusion of more advanced statistical models.

"The only true voyage of discovery, the only fountain of Eternal Youth, would be not to visit strange lands but to possess other eyes, to behold the universe through the eyes of another, of a hundred others, to behold the hundred universes that each of them beholds, that each of them is."

Marcel Proust

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Appendix A

Figure A1

Histogram of Raw Property Crime (left) and Logged Property Crime (right)

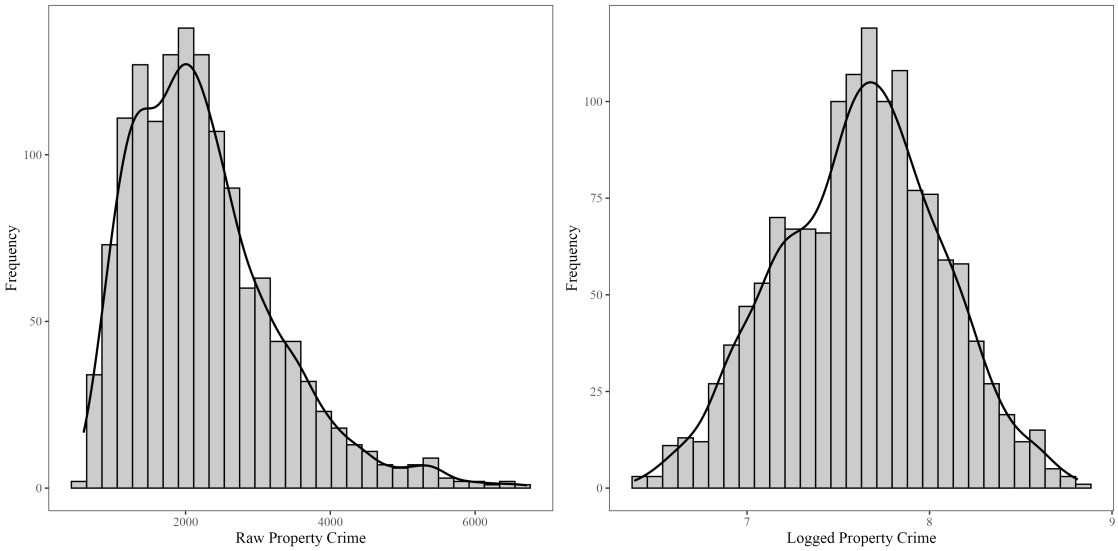

Figure A2

Histogram of Raw White Collar Crime (left) and Logged White Collar Crime (right)

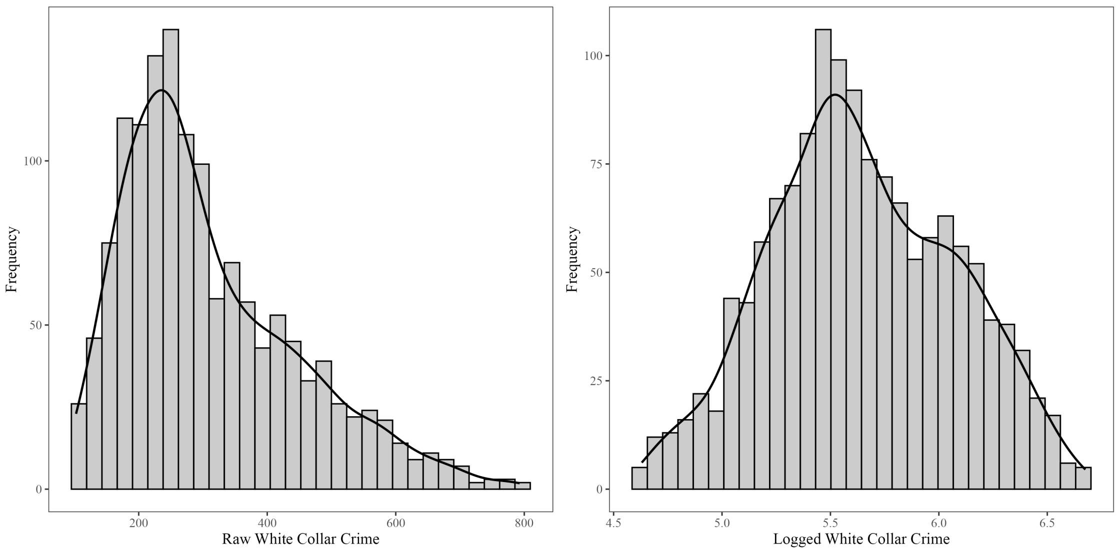

Figure A3

Histogram of Raw Violent Crime (left) and Logged Violent Crime (right)

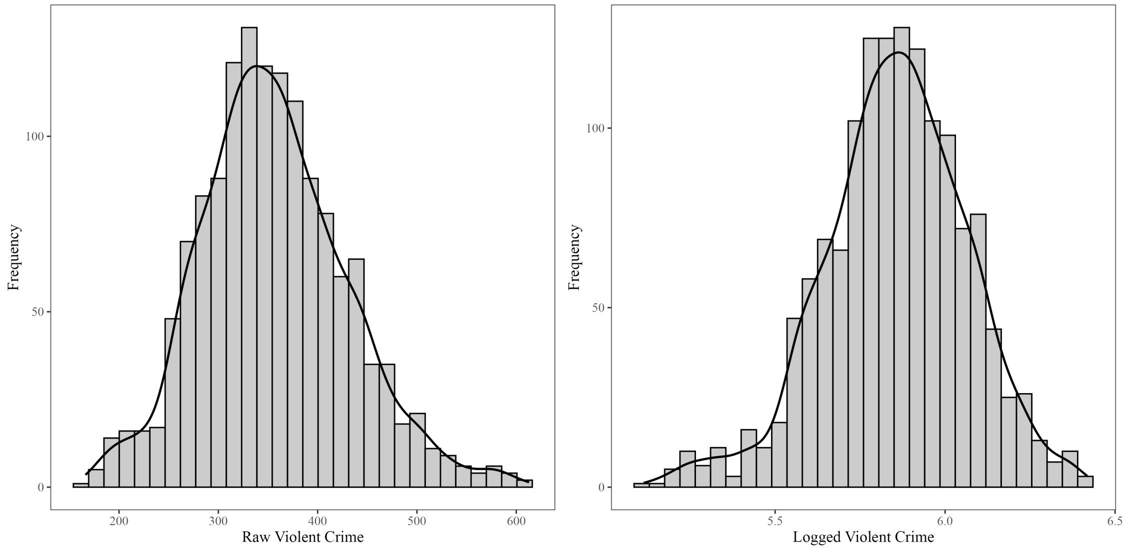

Figure A4

Histogram of Youth Unemployment Gap

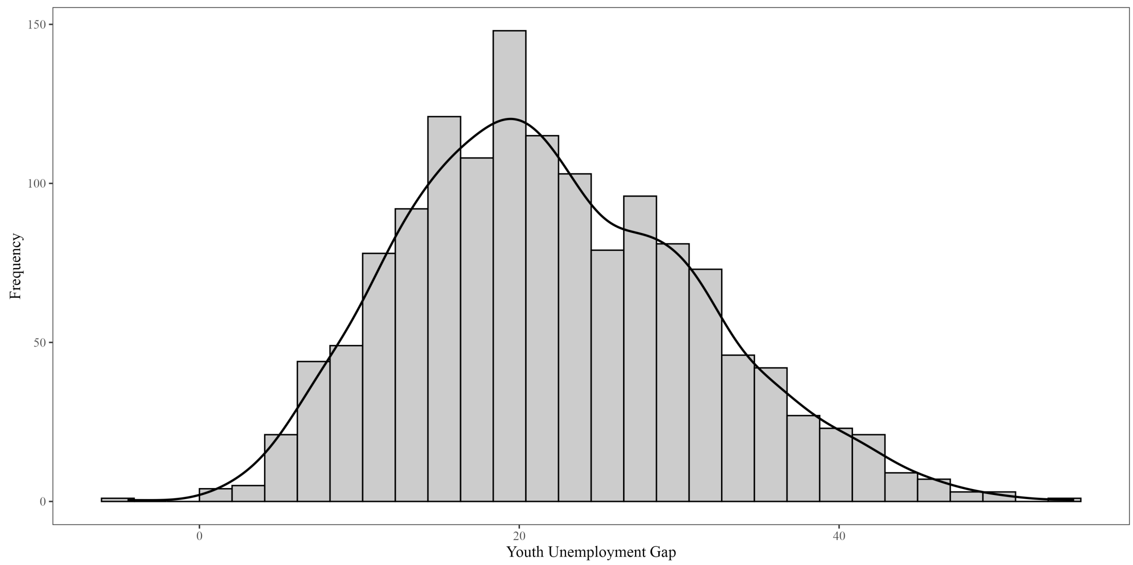

Figure A5

Time Series Plot of Average Property Crime 2009-2022

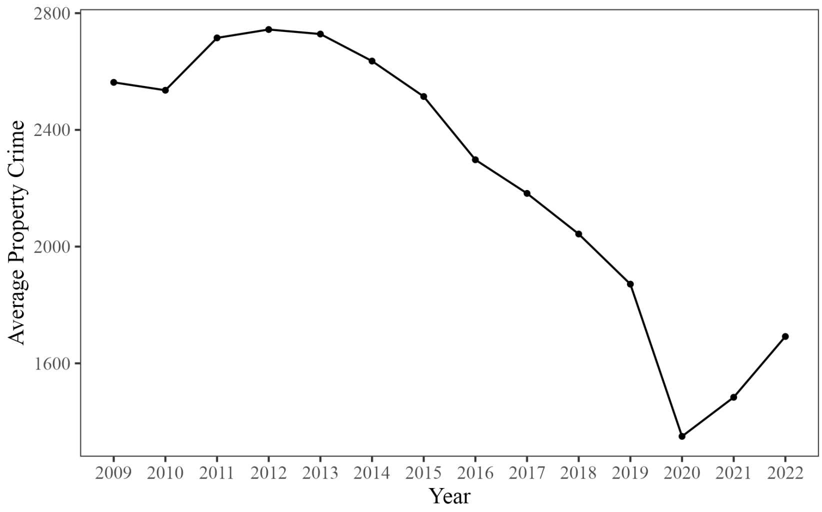

Figure A6

Time Series Plot of Average White Collar Crime 2009-2022

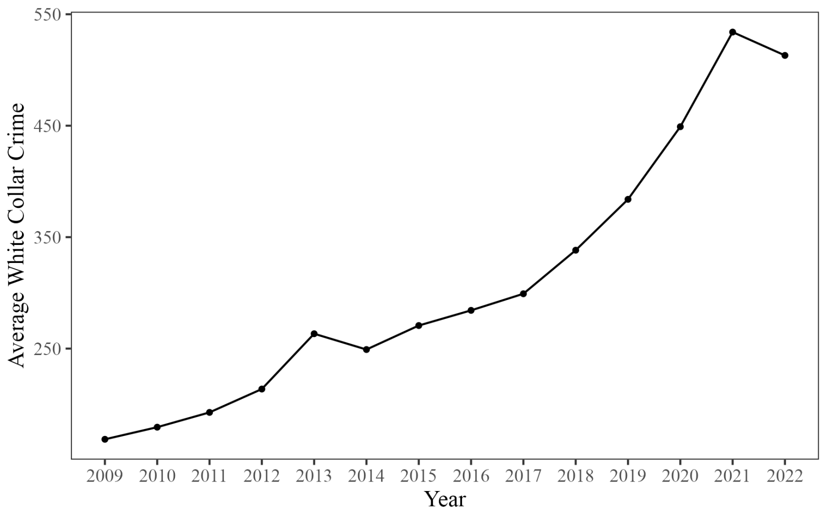

Figure A7

Time Series Plot of Average White Collar Crime 2009-2022

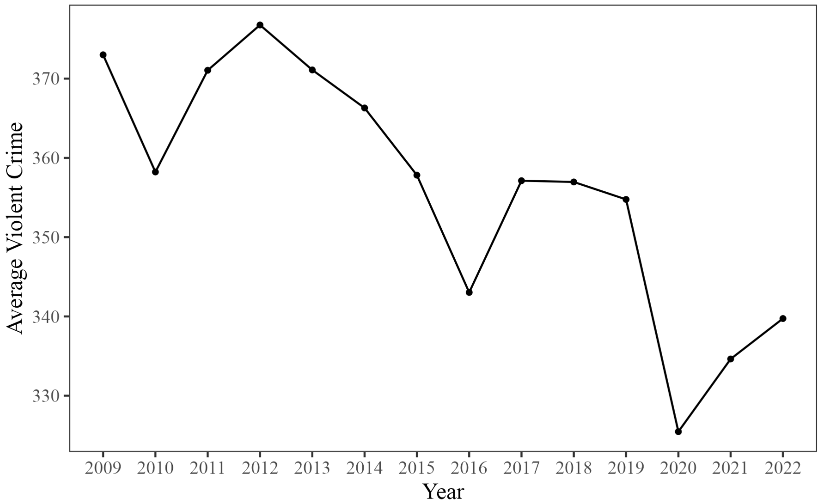

Figure A8

Scatterplots of Logged Salary Against all Crime Rates

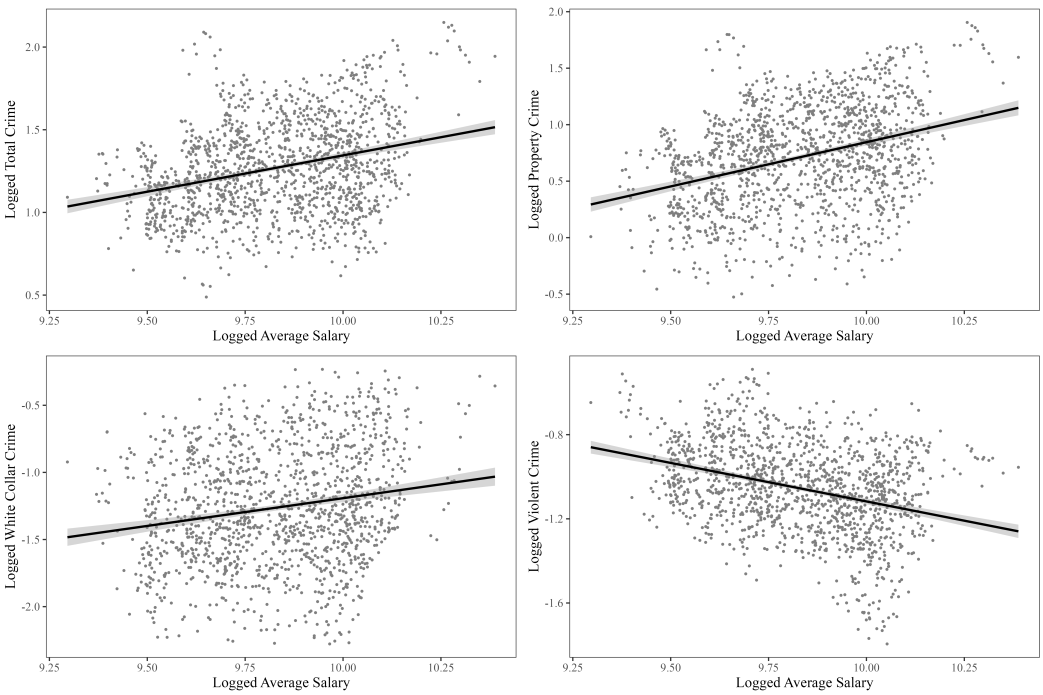

Figure A9

Scatterplots of Logged Salary Against all Crime Rates Figure

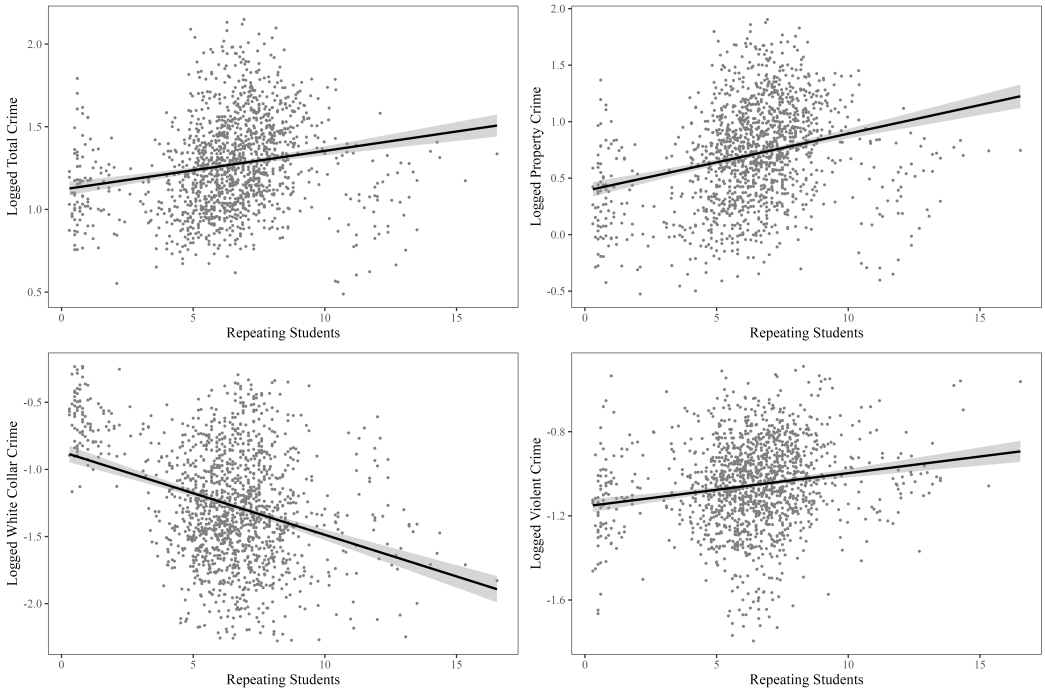

Figure A10

Scatterplots of Logged Salary Against all Crime Rates

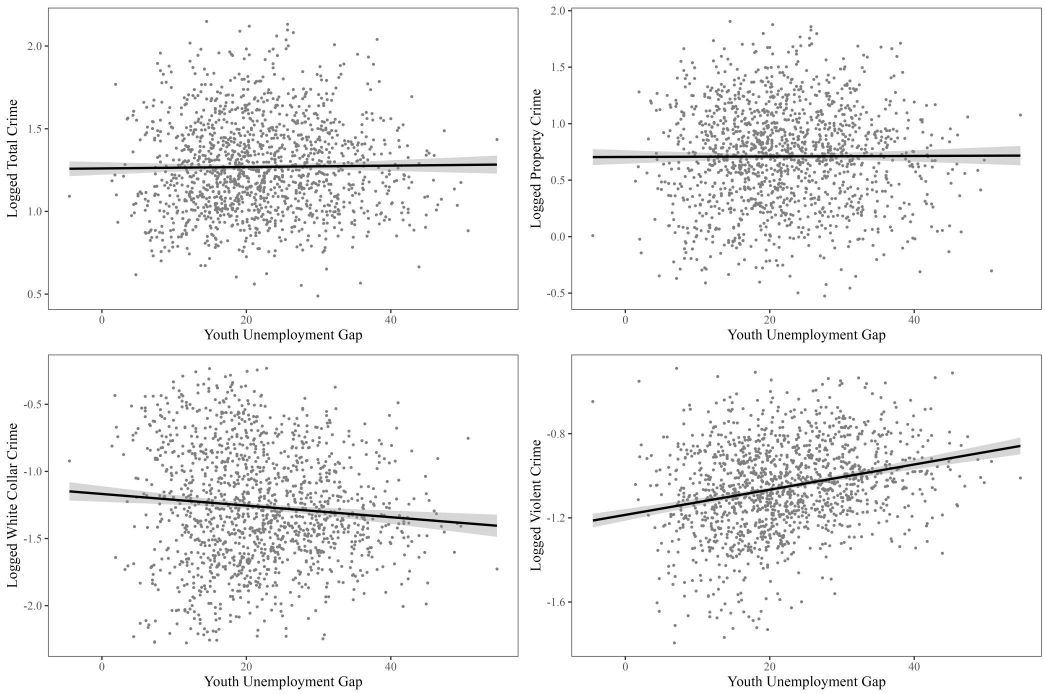

Figure A11

Scatterplots of Logged Salary Against all Crime Rates

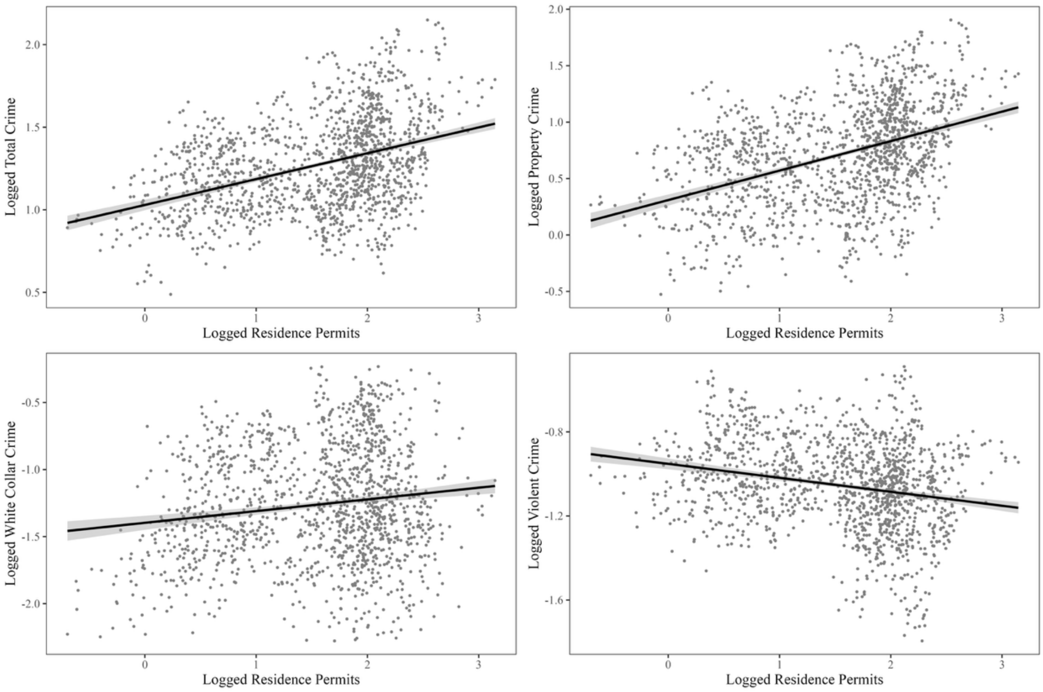

Figure A12

Scatterplot of Cook's Distance and Leverage for Logged Property Crime

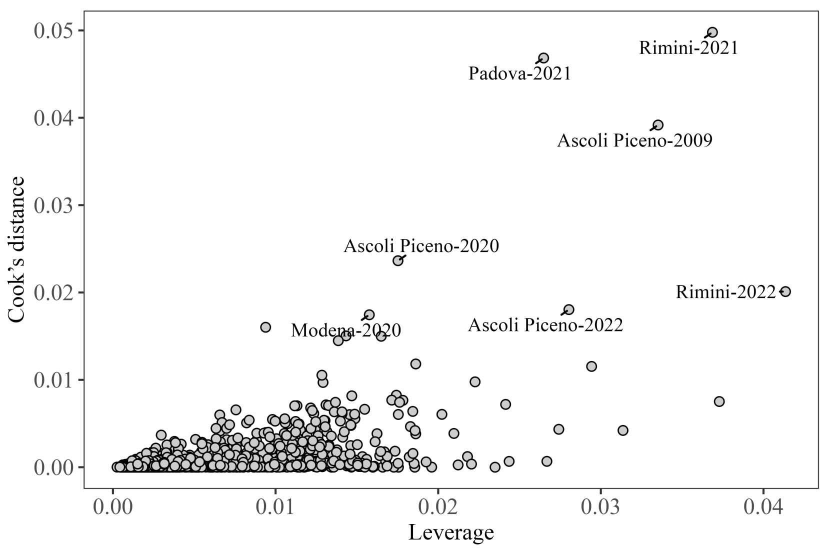

Figure A13

Scatterplot of Cook's Distance and Leverage for Logged White Collar Crime

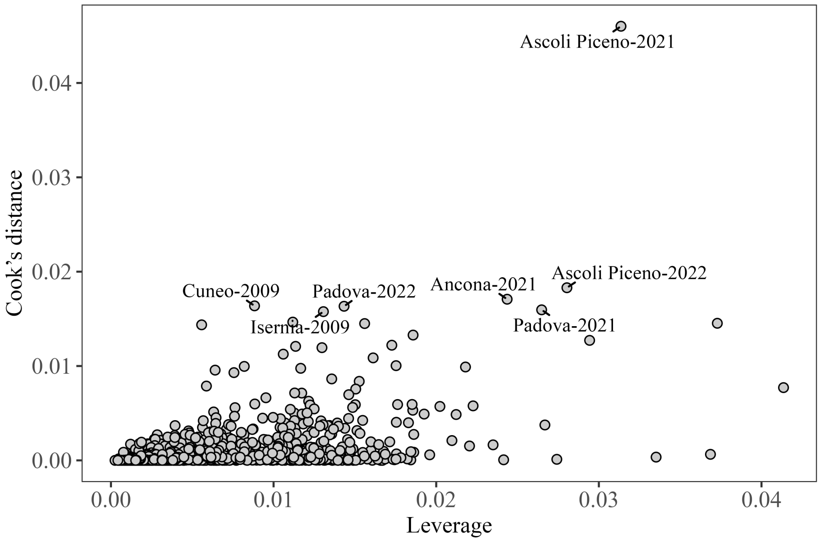

Figure A14

Scatterplot of Cook's Distance and Leverage for Logged Violent Crime

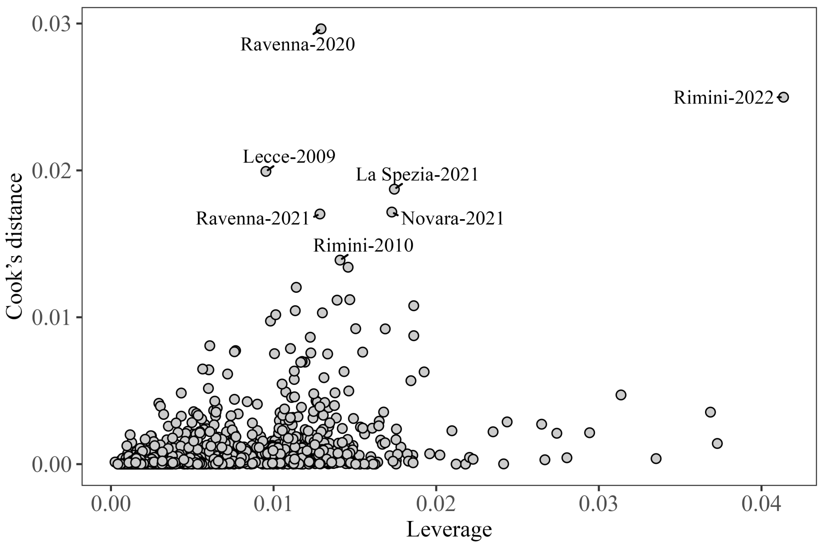

Figure A15

Time Plot of Ascoli Piceno's Residuals, 2009-2022

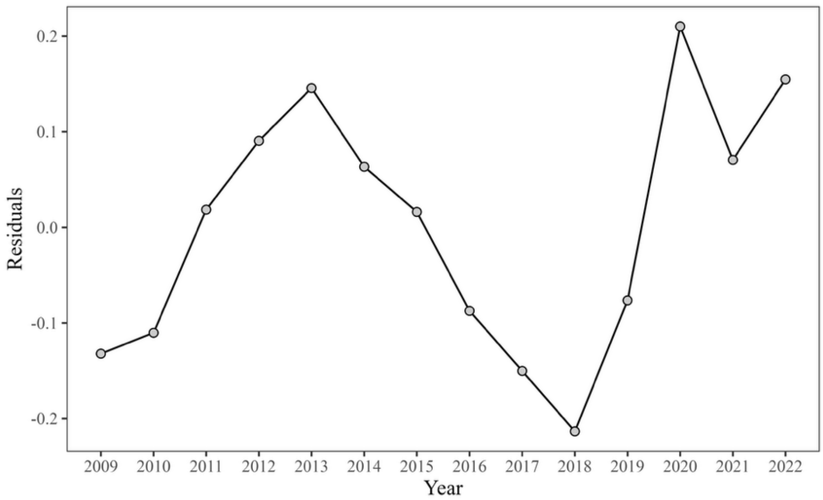

Figure A16

Time Plot of Ascoli Piceno's Residuals, 2009-2022