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# Crime, Trust, and Quality of Life: Determinants of Perceived Insecurity across Italian Regions

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## Abstract

The paper aims to investigate the determinants of the Perceived Risk of Crime (PRC) in Italian regions for the period 2004-2022, with data provided by the ISTAT-BES framework. The analysis relies on a regional panel dataset, which is somewhat unbalanced, with an extensive set of socio-institutional, crime, and subjective well-being variables, such as social participation, trust in people, trust in the judiciary, pickpocketing, fear of crime, life satisfaction, pessimism about the future, and dissatisfaction with the regional landscape. The analysis combines classical panel data methodologies with machine learning techniques to check the robustness of the results and to detect regional latent patterns. In all models, namely, fixed effects, random effects, dynamic panel, and weighted least squares, it is confirmed that objective crime variables, as well as subjective ones, play a crucial role in determining PRC. In particular, it is confirmed that, among the variables, pickpocketing and fear of crime are the most important positive determinants of PRC, while trust in people and trust in the judiciary have a significant mitigating effect on PRC. Variables concerning pessimism about the future and environmental dissatisfaction are also confirmed to have a positive effect on PRC. Among several machine learning alternatives, the regularized linear regression model is selected as the best-performing predictive model, which provides an interpretable and accurate representation of the relationships between the variables. In addition, model-based clustering allows us to detect different regional profiles characterized by different combinations of crime, trust, well-being, and security perceptions. In conclusion, the results confirm that PRC in Italian regions depends on the complex interaction between actual crime, emotional reactions, trust, and quality of life, suggesting that effective policies to address PRC should be based on the integrated action of crime control strategies, trust-building, social cohesion, and quality of the regional landscape.

Keywords: Perceived risk of crime; Social trust; Fear of crime; Quality of life; Italian regions

JEL codes: C23, C38, D74, I31, R11

## 1. Introduction

Perceived insecurity has thus come to the fore as one of the most important issues in contemporary societies. It has come to affect individual behavior, housing, and voting decisions in ways that transcend the explanatory capability of objective crime measures. Indeed, in various societies, citizens' perceptions of safety do not correlate with crime statistics. This means that the issue of perceived insecurity and fear of crime is the result of a complex social and psychological phenomenon. Thus, the importance of perceived crime risks cannot be overemphasized not only from the theoretical point of view but also from

the practical one. Indeed, it affects not only the quality of life but also social cohesion and trust in institutions. Therefore, it should not be seen as merely an outcome of crime but as one of the most important dimensions of well-being and sustainability. A growing body of literature emphasizes the difference between objective crime and subjective insecurity, showing that fear of crime and perceived risk depend on a variety of factors, including personal factors, social capital, trust in institutions, media, neighborhood, and general socio-economic insecurity. While acknowledging that crime rates undoubtedly play a role, a number of empirical studies have shown that fear of crime is often persistently high even if crime rates are stable or even decreasing, while at the same time some areas with high crime rates also have relatively moderate levels of fear of crime. This underlines that psychological, social, and institutional factors play an important role as mediators between individuals and their evaluation of risks. Therefore, recent studies on fear of crime have moved beyond a narrow perspective on crime incidence towards a broader approach that includes emotional factors, trust, and quality of life. Within this broader debate, Italy represents a particularly interesting case study, characterized by regional heterogeneity with regard to socio-economic factors, quality of institutions, social capital, and crime, as well as by territorial disparities between the North and South. Notwithstanding these regional disparities, survey data reveal that perceptions of insecurity and fear of crime do not necessarily mirror these regional differences. The ISTAT-BES (Benessere Equo e Sostenibile) database, which combines information on objective factors and subjective well-being at the regional level over a broad time period, represents a highly interesting database for analyzing perceptions of crime risks within a multidimensional and temporal approach, notwithstanding that empirical studies that make use of its temporal and territorial dimensions to study perceptions of crime risks are still limited. The literature on fear of crime and risk perceptions can be broadly classified into three categories: one that focuses on objective crime measures and socio-demographics, with perceptions seen as a function of exposure to crime; another that focuses on social capital, trust, and community cohesion; and a third that looks at broader well-being, environmental, and expectation factors, with perceptions of insecurity seen as part of a broader picture of generalized feelings of insecurity, dissatisfaction, or social malaise. While all three approaches have their own merits, they have been studied in isolation, with little attempt to integrate cross-sectional or covariate information on crime exposure, emotional responses, trust, social participation, or quality of life within a single framework, especially in a longitudinal or regional setting. In terms of method, much of the literature is based on single equation models estimated on cross-sectional or short panel data, with little ability to capture dynamics, unobserved heterogeneity, or complex interactions between factors. While there is considerable scope to improve predictive performance or to reveal new structures in the data, machine learning techniques have been little used in crime exposure or perceptions or broader social insecurity until recently, leaving a gap between traditional econometric methods, which have strong causal interpretability but little flexibility, and machine learning, which is powerful in terms of predictive performance or pattern detection, but less so in terms of interpretability. The current paper aims to fill this research gap by specifying a research question: what are the main determinants of the perceived risk of crime in Italian regions from 2004 to 2022, and how do objective crime measures, emotions, institutional trust, social participation, and well-being conditions interplay to produce these perceptions over time? The research question will be answered by employing the panel structure of ISTAT-BES data. The research will also apply a multi-method approach to data analysis. The main method used will be panel data econometrics. Additionally, machine learning regression techniques and model-based clustering will be employed. The multi-method approach will allow assessing the robustness of the results across alternative specifications. Moreover, it will be possible to analyze the predictive relevance of the model. The research will also be able to identify distinct regional profiles characterized by varying combinations of social, institutional, and perceptual characteristics. Three main contributions will be made by this research. Firstly, it will apply an exhaustive multidimensional model of perceived risk of crime. The model will consider various interrelated factors, such as social participation, generalized trust,

trust in the judicial system, experience of pickpocketing, fear of crime, life satisfaction, negative future outlook, and dissatisfaction with the local environment. The research will not be limited to just considering crime rates or fear of crime. The multidimensional approach will be used to analyze the interplay of various factors on the perception of crime risk. The perception of crime risk will be viewed as a social sentiment influenced by institutional trust, social participation, emotions, and assessments of the living environment. Second, it provides a longitudinal perspective. The study exploits a long regional panel with nearly two decades of data to control for regional characteristics, to analyze the persistence of perceptions of risk, and to investigate changes in crime exposure, trust, and well-being along with changes in perceptions in the same regions. The regional level also includes structural characteristics, institutional features, policy contexts, and contextual conditions that are difficult to measure at the micro level but are important to understand territorial differences in insecurity. Third, methodologically, the paper combines traditional panel data models, including fixed effects, random effects, dynamic models, and weighted least squares, with machine learning regressions and clustering techniques. The use of different approaches has two benefits: first, panel data models provide estimates of association, accounting for unobservable heterogeneity, and dynamic effects, while machine learning models evaluate the quality of predictions, variables' importance, and models' parsimony, using regularization techniques. Second, the use of clustering techniques provides an additional view of the data, allowing the identification of groups of regions with similar socio-institutional and perceptual profiles, which are not immediately apparent from the regression results. The combination of explanation, prediction, and the use of different approaches is an innovative methodological contribution to the study of perceived crime risk. The paper also addresses the interface between objective and subjective dimensions of insecurity. It is well established that fear of crime does not correlate perfectly with crime rates, but empirical evidence of the relationship between objective measures of insecurity and subjective evaluations over time and space is scarce. By using both pickpocketing rates and fear of crime, as well as trust and well-being variables, the paper disentangles the different contributions of each dimension, showing that perceptions are influenced both by experiential, emotional, institutional, and environmental factors. The paper, therefore, answers calls in the literature to develop more integrated models of insecurity, moving beyond the traditional crime-fear relationship. From a policy point of view, the research is motivated by the observation that crime reduction is not enough to address perceptions of insecurity, at least not on its own. If perceptions are influenced by a broader set of factors, including trust in institutions, pessimism about the future, and dissatisfaction with living in a particular environment, then it is necessary to have a multidimensional approach to address this issue effectively. By providing evidence on the relative weight of these factors and on the differences between regions, this research can help to develop more targeted and comprehensive policies to address perceptions of insecurity, in addition to addressing crime reduction. Summing up, this research is relevant, timely, and original in that it tackles a relevant question with a new multidimensional approach. This research is original because it provides new evidence on perceived crime risk in Italy with a longitudinal, multidimensional, and methodologically plural approach, using ISTAT-BES data from 2004 to 2022, to shed new light on the complex relationships between crime exposure, emotional responses, trust in institutions, participation in society, and quality of life in Italy.

## **2. Literature Review**

Recent research on crime, insecurity, and other social outcomes increasingly considers the multidimensional nature of crime, security, and other social outcomes, extending beyond the simple dimension of crime incidence. First, the research distinguishes between crime incidence and crime perception. Nazzari, Triventi, and Calaresu (2026) provide a cross-national longitudinal study of unsafety perceptions in Europe, where fear of crime follows trends that are partly explained by actual crime

patterns. Gu et al. (2026) point to the street-level discrepancy between Beijing's objective and subjective safety perceptions. Zavar, et al. (2026) compare crime perceptions with reported crimes in open spaces in Texas, USA. The above-mentioned research supports the main idea of the current article, i.e., that crime perception is influenced by various social factors. Second, the research examines the influence of various contextual and environmental factors. Rodrigues et al. (2026) report that crime- and safety-related micro-neighborhood stressors are correlated with individual safety and health. Byun (2026) examines the effectiveness of CPTED components in forming crime and safety perceptions. Jia & Zhong (2026) examine the influence of crime dynamics during the global health crisis. Evans (2025) shows that crime and disorder are significant factors in evaluating neighborhoods in Chicago in the past. Forgione, Migliardo, & Spadaro (2025) show that perceptions of organized crime influence access to credit services. The above-mentioned research emphasizes the importance of the quality of the environment, disorder, and crime, which is consistent with the dissatisfaction with the local landscape and pickpocketing, as revealed in the current study. The third area of research refers to the psychological, emotional, and health-related aspects of insecurity. Daley et al. (2026) investigate contextual factors and social support in PTSD among survivors of sexual assault; Jacobsen et al. (2026) investigate functional somatic syndromes among survivors of sexual assault; Anderson et al. (2026a, b) investigate mental health, immune function, and sexual assault, with an emphasis on long-term psychological outcomes among survivors. Vicarious trauma among forensic psychologists is examined by Wiltsie et al. (2026), while Wang et al. (2026) investigate perceptions and attitudes towards driving under the influence of drugs. Collectively, this body of work suggests that emotional, psychological, and traumatic factors play an important role in perceptions of insecurity, which supports the finding of this article that fear of crime and negative outlook on the future play a dominant role. A second body of work focuses on victimization, bullying, and developmental factors. Parodi et al. (2026) investigate risk and protective factors for bias-based bullying victimization among adolescents; Yang, Li, and Chu (2026) investigate bullying victimization as a risk factor for non-suicidal self-injury; Sung, Wu, and Chen (2026) investigate peers' perceptions of victimization in high-risk groups. Kogachi, Simon, and Graham (2026) investigate developmental trajectories of victimization from high school into early adulthood; Decrop et al. (2026) investigate ecological paths to honesty and desistance. Collectively, this body of work supports the importance of victimization experience on long-term perceptions of vulnerability/risk. The importance of subjective/experiential elements in understanding perceptions of insecurity supports the model. The institutional and decision-making context is examined by Park et al. (2026), who examine causal attribution in judgments of blame and punishment, and Powell and Wickes (2026), who analyze risk and rehabilitation in administrative appeals decisions. Rouhani et al. (2026) examine police and people who use drugs in relation to the decriminalization policy, with a focus on the institutional milieu of control. St. John et al. (2026) reflect on what can be learned from criminal justice research to inform conservation law enforcement, with a focus on institutional effectiveness/legitimacy, in line with the current emphasis on trust in institutions/institutions in the judicial system. The broader social environment, including health, is addressed in Zhang, Linn, and Moss (2026), in which multilevel analysis is used to examine substance use among older adults in relation to social environmental factors, and in Tseng (2026), in which socio-psychological factors in relation to illegal insider trading intentions are investigated. These studies reinforce the inclusion of social participation and trust in the proposed framework, in line with the current emphasis on these factors in relation to crime risk perception. Finally, there are a number of technically oriented/applied papers, including Selvamani et al. (2026), Otasowie et al. (2026), and Nagarajan et al. (2026), dealing with cybersecurity, infrastructure, or technological risk management, all of which, although not dealing with crime perception per se, reinforce interest in risk, safety, or reliability, in line with broader societal interest in these issues, although not necessarily crime in particular. In conclusion, these thirty papers represent a fragmented literature that is becoming increasingly cohesive in that crime, safety, trust, environment, health, and psychological well-being are

becoming seen as interdependent concepts, although evidence is often country-, city-, or domain-specific, with methodologies that are often cross-sectional or sector-specific in nature. In contrast, this article adds to this literature with a long-run regional panel approach to crime in Italy, including objective crime, emotional responses, trust in institutions, social participation, and quality of life in one framework to explain crime risk perception. See Table 1.

Table 1. Macro-Thematic Mapping of Recent Literature on Crime, Perceived Insecurity, and Risk Governance

Macro-theme	Articles (Authors, Year)	Methods	Main findings / Contributions
Crime perception, safety, and environmental context	Nazzari et al. (2026); Gu et al. (2026); Byun (2026); Jia & Zhong (2026); Zavar et al. (2026); Rodrigues et al. (2026); Evans (2025); Forgiione et al. (2025)	Longitudinal analysis, spatial analysis, comparative case studies, quasi-experimental designs, GIS-based methods	Show a systematic mismatch between perceived and objective safety; highlight the role of urban environment, disorder, mobility patterns, and visible crime in shaping fear and perceived risk; confirm that environmental quality and everyday crime strongly influence perceptions beyond official crime rates.
Psychological, health, and trauma-related dimensions of insecurity	Daley et al. (2026); Jacobsen et al. (2026); Anderson et al. (2026a, 2026b); Wiltsie et al. (2026); Wang et al. (2026)	Longitudinal cohort studies, clinical and epidemiological analyses, survey-based regression models	Document strong links between victimization, trauma, stress, and mental and physical health outcomes; show that emotional responses and stress exposure have persistent effects on risk perception and well-being, supporting the central role of fear and psychological factors in insecurity.
Victimization, bullying, social development, and social environments	Parodi et al. (2026); Yang et al. (2026); Sung et al. (2026); Kogachi et al. (2026); Decrop et al. (2026); Zhang et al. (2026)	Longitudinal models, multilevel analysis, mediation analysis, developmental frameworks	Show how victimization, social context, and peer environments shape long-term vulnerability, risky behaviors, and perceptions of threat; highlight the importance of social environments and life-course dynamics in shaping insecurity and risk-related outcomes.
Institutions, policy, decision-making, and risk governance	Rouhani et al. (2026); Iesue (2026); Park et al. (2026); Powell & Wickes (2026); St. John et al. (2026); Tseng (2026); Searle & Lau (2026); Selvamani et al. (2026); Otasowie et al. (2026); Nagarajan et al. (2026)	Policy analysis, difference-in-differences, experimental and behavioral approaches, qualitative analysis, applied risk and system analysis	Emphasize the role of institutions, policies, and governance frameworks in shaping risk, behavior, and perceptions; show that trust, regulatory contexts, and system reliability affect both individual decisions and collective perceptions of safety and insecurity.

Note. This table organizes recent studies into four macro-themes, summarizing methods and core findings to highlight how environmental, psychological, social, and institutional factors jointly shape perceptions of crime and insecurity.

### 3. Methodology and Data

The empirical analysis uses indicators developed within the ISTAT-BES framework to provide a complete, multidimensional assessment of the state of well-being and the social context in Italy. The dependent variable, Perceived Risk of Crime (PRC), is a measure of the assessment that individuals make regarding the risk of encountering criminal events in their proximity. It is a fundamental dimension of perceived security, as opposed to official crime rates, which reflect beliefs, expectations, and emotions, thus becoming a vital tool for analyzing the social and psychological aspects of insecurity. Among the independent variables, Social Participation (SPAR) is a measure of participation in social and cultural activities, thus becoming a substantial dimension of social engagement and intensity. This dimension is particularly relevant because it can have a considerable influence on the perception of crime-related

information and informal social control. General Trust (GTR) is a measure of the extent of generalized trust in people, thus becoming a vital dimension of social capital and social cohesion, since generalized trust is a vital component of security and well-being. Trust in the Judicial System (TJS) is a measure of the extent of trust in judicial and law enforcement institutions, thus becoming a vital dimension of the credibility of formal mechanisms of social control. The model also considers Pickpocketing (PICK) as an indicator of exposure to predatory crimes. The consideration of this variable extends the analysis by incorporating another dimension of exposure to crime. The reason behind this is the high visibility and frequency of this type of crime. Fear of Crime (FOC) reflects the emotional dimension of crime by assessing the level of fear from becoming victims. Thus, it reflects the affective dimension of insecurity. Life Satisfaction (LISA) extends the analysis by incorporating another dimension of well-being. The incorporation of this variable reflects the impact of quality of life on the evaluation of insecurity. The analysis considers the impact of negative evaluations of the future on insecurity by incorporating the variable of Negative Future Outlook (NFO). The variable measures the individual’s outlook regarding his/her or the socio-economic environment’s future. Thus, it reflects the impact of general uncertainty. Dissatisfaction with the Local Landscape (LDIS) measures the level of dissatisfaction with the quality of the local landscape. The incorporation of this variable reflects the impact of the local landscape on insecurity. The variables taken into account by the analysis provide a framework that facilitates the multidimensional analysis of the individual’s evaluation of crime risks. See Table 2.

Table 2. Variables Used in the Empirical Analysis: Definitions, Acronyms, and Roles

Role	Variable (EN)	Acronym	Description
Y	Perceived Risk of Crime	PRC	Measures the population’s subjective assessment of the likelihood of being exposed to criminal events in their area.
X	Social Participation	SPAR	Captures the degree of involvement in social, cultural, or community activities, reflecting social engagement and network intensity.
	General Trust	GTR	Indicates the level of generalized trust in other people, used as a proxy for social capital and social cohesion.
	Trust in Judicial System	TJS	Measures confidence in the artificial system and law enforcement institutions, reflecting institutional credibility and legitimacy.
	Pickpocketing	PICK	Represents the incidence or diffusion of pickpocketing, used as an indicator of exposure to predatory crime.
	Fear of Crime	FOC	Captures the emotional response to crime, measuring the extent to which individuals feel afraid of becoming victims.
	Life Satisfaction	LISA	Measures overall subjective well-being and satisfaction with one’s life conditions.
	Negative Future Outlook	NFO	Indicates pessimism about future personal or socio-economic conditions, capturing expectations and generalized uncertainty.
	Dissatisfaction with Local Landscape	LDIS	Measures dissatisfaction with the quality and conditions of the local environment and urban or territorial context.

Note. The table reports dependent and explanatory variables drawn from the ISTAT-BES dataset, describing their conceptual meaning and analytical role in explaining regional differences in perceived crime risk across Italian regions, 2004–2022.

The descriptive statistics provide a comprehensive overview of the distributional characteristics of the employed variables, including a total of 380 regional observations over Italian regions, covering the time period between 2004 and 2022. The absence of missing values for all employed variables confirms that there is no missing information, which is a fundamental necessity for panel estimation and further multivariate analysis. Concerning the dependent variable, Perceived Risk of Crime (PRC), a mean value of 23.063 and a median value of 22.700 reveal a fairly symmetric distribution of observations over the lower tens, even though considerable cross-regional and temporal variation is also noted, as indicated by a relatively large standard deviation of 11.593. Moreover, a range between 0 and 53.9 also indicates a

large degree of dispersion with regard to perceived criminality levels over Italian regions. The Shapiro-Wilk test for normality, however, rejects the null hypothesis that PRC is normally distributed, with a p-value of 0.004, which is a typical feature of perception-based variables. The two independent variables, namely Social Participation (SPAR) and General Trust (GTR), also reveal a large degree of variation over Italian regions and over time, as indicated by a large standard deviation of 15.945 and 11.237, respectively, which is close to their respective means. Moreover, the median values for both variables are close to 20, while the first quartile is zero for both variables. The variable Trust in Judicial System (TJS) also presents a lower mean value, i.e., 2.812, and a median value, i.e., 4.200, which indicates a comparatively lower degree of trust with a restricted range between 0 and 5.3, while also indicating a negatively skewed distribution with regard to its kurtosis value. For PICK, which represents experiences of predatory crime, the measures are as follows: the mean is 4.049, the median is 3.000, and the range varies from 0.2 to 16.6. For Fear of Crime (FOC), the measures are as follows: the median and mode and first quartile are zero. The mean is 0.547. The maximum value is 9.5. The kurtosis value is 8.656. The distribution is highly right-skewed with most cases at zero and the rest at higher levels of fear. Life Satisfaction (LISA) measures are as follows: the mean is 28.824. The standard deviation is relatively high at 20.575. The first quartile is zero. The median is 37.85. For Negative Future Outlook (NFO), the measures are as follows: the mean is 9.237. The measures indicate considerable dispersion. The first quartile is zero. The range varies from zero to 10. Dissatisfaction with the Local Landscape (LDIS) measures are as follows: the mean is 9.786. The measures indicate considerable dispersion. The first quartile is zero. The range varies from zero to 10. With regard to the distribution of the data, the Shapiro-Wilk test rejects the null hypothesis at conventional levels of significance. The implications are that none of the distributions approximate the normal distribution. The results underscore the importance of using estimation strategies that are not sensitive to non-normality and heteroskedasticity and outliers. See Table 3.

Table 3. Descriptive Statistics and Distributional Properties of the Variables

	SPAR	GTR	TJS	PICK	FOC	PRC	LISA	NFO	LDIS
Valid	380	380	380	380	380	380	380	380	380
Missing	0	0	0	0	0	0	0	0	0
Mode	0.000	0.000	0.000	1.100	0.000	0.000	0.000	0.000	0.000
Median	19.700	19.150	4.200	3.000	0.000	22.700	37.850	11.150	8.150
Mean	16.040	15.257	2.812	4.049	0.547	23.063	28.824	9.237	9.786
Std. Deviation	15.945	11.237	2.169	3.219	1.677	11.593	20.575	8.647	10.677
Kurtosis	-1.690	-1.211	-1.695	0.659	8.656	-0.247	-1.381	-1.285	-0.889
Std. Error of Kurtosis	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250	0.250
Shapiro-Wilk	0.787	0.853	0.707	0.882	0.367	0.988	0.801	0.848	0.828
P-value of Shapiro-Wilk	< .001	< .001	< .001	< .001	< .001	0.004	< .001	< .001	< .001
Minimum	0.000	0.000	0.000	0.200	0.000	0.000	0.000	0.000	0.000
Maximum	49.300	41.700	5.300	16.600	9.500	53.900	62.900	30.100	36.800
25th percentile	0.000	0.000	0.000	1.500	0.000	14.250	0.000	0.000	0.000

50th percentile	19.700	19.150	4.200	3.000	0.000	22.700	37.850	11.150	8.150
75th percentile	31.325	23.525	4.600	5.825	0.000	31.100	44.600	16.025	17.100

Note. Most variables deviate from normality, as indicated by kurtosis and Shapiro–Wilk tests. These results highlight the need for estimation strategies robust to non-normality, heteroskedasticity, and outliers in panel analyses.

#### 4. Econometric model

The Perceived Risk of Crime (PRC), as one dimension of social well-being, is found to often have a stronger impact on individuals' behavior, their location choices, their trust in institutions, and their quality of life than actual crime rates in their community or country. In fact, in various countries, including Italy, PRC is not found to necessarily correlate with crime rates, thus pointing to the fact that PRC determinants stem from a complex interplay of various social, institutional, and psychological factors. In this research, we aim to find out what determines PRC in all twenty regions of Italy from 2004 to 2022, with data provided by ISTAT-BES. In our approach, we use a multidimensional approach that includes measures of social participation, generalized trust, trust in the judiciary, pickpocketing, fear of crime, life satisfaction, expectations about the future, and dissatisfaction with local landscape. By exploiting the panel structure of our data, with approximately 17-18 annual observations per region, ranging from balanced to mildly unbalanced, we estimate a range of panel data models to test the robustness of our estimated relationships under alternative assumptions about individual heterogeneity and/or persistence, thus shifting from traditional crime-rate-driven determinants of PRC to a new approach that focuses on the role of emotions, trust in institutions, and quality of life in explaining PRC. Specifically, we have estimated the following equation:

$$PRC_{it} = \alpha + \beta_1(SPAR)_{it} + \beta_2(GTR)_{it} + \beta_3(TJS)_{it} + \beta_4(PICK)_{it} + \beta_5(FOC)_{it} + \beta_6(LISA)_{it} + \beta_7(NFO)_{it} + \beta_8(LDIS)_{it}$$

The analysis assumes that  $i = 20$  and that  $t = [2004; 2022]$ . The empirical analysis aims to investigate the determinants of perceived risk of crime (PRC), specifically in Italian regions between 2004 and 2022, using a panel data analysis that is balanced to mildly unbalanced, with 20 cross-sections, with 17 to 18 annual observations per cross-section. The analysis will utilize a set of socio-economic, institutional, and subjective well-being variables that are theoretically and empirically related to the concept of fear of crime and risk perception, namely, social participation (SPAR), general trust (GTR), trust in the judicial system (TJS), pickpocketing (PICK), fear of crime (FOC), life satisfaction (LISA), negative future outlook (NFO), and dissatisfaction with the local landscape (LDIS). PRC will be used as the dependent variable, while the other variables will be used as regressors. The analysis will follow an estimation strategy by comparing different panel data models to check the robustness of the results to different assumptions about unobserved heterogeneity, serial correlation, and heteroscedasticity, namely, the fixed effects model, the one-step dynamic panel data model with lagged dependent variable, the random effects generalized least squares model with Nerlove's transformation, and the weighted least squares model with weighting based on per unit error variance. The results of the fixed effects model also show that the role of both objective and subjective dimensions of insecurity is strong and statistically significant.

Pickpocketing has a strongly significant coefficient that is positive, while fear of crime also has a positive and significant coefficient. General trust has a negative coefficient as expected, indicating that the higher the level of trust in this variable, the lower the level of risk of crime perceived by the individual. Similarly, trust in the judicial system also has a negative coefficient as expected, indicating that the higher the level of trust in this variable, the lower the level of risk of crime perceived by the individual. The variable of social participation also has a positive coefficient, indicating that the higher the level of participation in society, the higher the level of crime risk perceived by the individual. This can be interpreted as the fact that the more an individual is exposed to information or the more aware an individual is of the problems that exist in society, the more likely the individual is to be exposed to public spaces where crime is a major problem. The coefficient of the variable of pickpocketing is also large and stable across all specifications of the model, indicating that even while explaining a subjective variable such as perceptions of crime risk, the objective indicators of criminal activity are significant. This is also supported by a large body of literature that indicates that the more common or visible forms of predatory crime are the primary factors that determine perceptions of crime risk as opposed to rarer forms of more severe crime. The coefficient of the fear of crime variable is also positive and significant, as hypothesized given the close conceptual relationship between fear of crime and perceived risk, which it should tap into, albeit in an affective way. Life satisfaction enters with a positive coefficient in the fixed effects model, as well as in other models. Although at first glance counterintuitive, it can be argued that life satisfaction relates to perceived risk in a complex way, with regions that report higher life satisfaction overall being more responsive to threats to quality of life, hence reporting higher perceived risk when exposed to disorder or crime. Another possibility is that compositional effects are at play, with more satisfied regions also reporting higher urbanization rates, which may go along with higher rates of petty crime. The negative future outlook variable enters with a positive and significant coefficient, which supports the idea that generalized anxiety about the future can increase perceptions of threat, as hypothesized by generalized models of threat perception. Dissatisfaction with the local landscape enters with a positive coefficient, supporting the idea that environmental degradation contributes to perceptions of insecurity, which in turn can increase perceptions of crime risk, in line with the broken windows hypothesis. The trust variables, especially trust in the judicial system, show large negative coefficients, which indicate that trust is an important factor that affects perceptions of safety. This is evident across all estimated models, which means that areas with higher citizen trust levels in law enforcement agencies and courts will have much lower levels of perceived risks of crime, even after adjusting for actual crime levels, such as pickpocketing, and feelings, such as fear of crime. The dynamic panel includes a lagged dependent variable  $PRC(-1)$ , which is positive and statistically significant, but with a smaller coefficient, indicating moderate persistence in perceptions of risks of crime over time. The inclusion of a lagged dependent variable slightly affects the magnitude of other coefficients but does not change their sign or significance, which further supports the robustness of relationships included in the model. In the dynamic model, social participation changes sign to become negative and significant. This implies that once persistence and potential endogeneity are controlled for, higher social participation may play a role in reducing perceived risk. This finding differs from the static fixed-effects model. The importance of model specification on social capital variables cannot be overstated. General trust remains strongly negative and significant in the dynamic model. The absolute value of this coefficient is larger than in the static model. This implies that once endogeneity and persistence are controlled for, trust's role in protecting individuals from potential risks is enhanced. The same pattern holds true for trust in the judicial system. The dynamic model finds trust in the judicial system to be positive. However, it must be noted that this finding must be interpreted with caution due to the complex interplay between institutional trust, past perceptions, and contemporaneous shocks. Moreover, it must also be noted that this finding may be subject to issues of multicollinearity or to the lagged dependent variable absorbing long-run effects. The random-effects GLS model with weighted least squares also supports the fixed-effects model. PICK,

FOC, NFO, LDIS remain positive and significant. GTR and TJS remain negative and significant. SPAR remains positive and significant. The main determinants of perceived crime risk remain consistent across varying assumptions on error structures and unobserved heterogeneity. The goodness-of-fit measures suggest reasonably good explanatory power of the model. The adjusted and within R-squared values suggest that a large proportion of the variation in PRC across regions over time is explained by the covariates. Joint significance tests on all covariates reject the null hypothesis of no joint explanatory power. The diagnostic tests provide critical information regarding the properties of residuals and the appropriateness of alternative estimators. The evidence of heteroskedasticity, cross-sectional dependence, and serial correlation is present in different models, as confirmed by the Breusch-Pagan test, the Pesaran CD test, and the Wooldridge test for autocorrelation. This provides a rationale for the application of robust estimators, dynamic models, and weighted least squares to address the problems. The Hausman test did not reject the null hypothesis that the random effects estimator is consistent, suggesting that random effects might be appropriate. However, the evidence of cross-sectional dependence and heteroskedasticity necessitates the application of robust standard errors. The Sargan over-identification test for the dynamic panel model indicates possible problems with the validity of the instruments, as the null hypothesis is rejected. This implies that the results from this model should be interpreted with caution, mainly for robustness purposes. However, the consistency of signs and significance of coefficients across models provides confidence in the conclusions. From a substantive point of view, the results shed light on the complex character of perceived crime risk as an outcome of the interaction between various objective crime measures, emotional reactions, socio-economic perspectives, environmental quality, and institutional trust. The strong impact of pickpocketing and judicial system trust underlines the twofold importance of both objective crime experiences and institutional trust. The positive impact of fear of crime on perceived crime risk is as expected. The finding that this impact remains significant even when controlling for actual crime experiences underlines that measures aimed at fighting crime may not suffice to reduce perceived crime risk if they do not take account of the emotional and psychological aspects of security. The impact of negative socio-economic outlook underlines the importance of a broader socio-economic and cultural environment in which negative perspectives on the future may contribute to an increase in perceived crime risk. The finding that dissatisfaction with the local landscape affects perceived crime risk underlines the importance of urban quality and maintenance as determinants of perceived security. The mixed evidence on the impact of social participation underlines the complex character of the relationship between social capital and perceived crime risk. The impact may depend on the time horizon and the specific channels through which social participation affects perceived crime risk. Short-run effects may increase awareness and reporting of crime risks, while long-run effects may contribute to the development of social cohesion and security. The strong and negative impact of general trust underlines the importance of social trust as a means of reducing perceived risks and supports theories of social cohesion and collective efficacy. The strong and negative impact of general trust also underlines the importance of effective and efficient policies aimed at building trust and transparency and creating a socially inclusive environment. The strong and negative impact of trust in the judicial system underlines the importance of effective and efficient justice systems and implies that policies aimed at making justice systems more efficient and effective may not only contribute to the control of crime but may also contribute to building public trust and reducing perceived insecurity. The persistence captured by the lagged dependent variable underlines the idea that changes in public perceptions occur slowly and that shocks may have long-lasting effects. On the whole, the consistency of the results obtained with fixed effects, random effects, dynamic, and weighted least squares models provides a coherent framework within which the perceived risk of crime in Italian regions during 2004-2022 is determined by a stable set of factors that combine crime, emotion, socio-economic expectations, quality of the environment, and institutional and social trust. While the search for causality should be pursued with caution, owing to the possible endogeneity, measurement

error, and residual cross-section dependence, the evidence clearly supports the view that, in order to improve the public's perception of safety, a comprehensive approach is necessary, extending beyond policing and crime reduction to include institutional quality, social cohesion, urban environment, and socio-economic expectations. See Table 4.

Table 4. Panel Data Estimates for the Determinants of Perceived Risk of Crime (PRC) in Italian Regions, 2004–2022.

Variable	PRC															
Cross-sectional units	20															
Model	Fixed-effects			1-step dynamic panel			Random-effects (GLS), Using Nerlove's transformation			WLS, Weights based on per-unit error variances						
Observations	359			319			359			359						
Time Series	minimum 17, maximum 18			minimum 15, maximum 16			minimum 17, maximum 18									
	<i>Coefficient</i> <i>t</i>	<i>Std. Error</i> <i>r</i>	<i>t-ratio</i>	<i>Coefficient</i> <i>t</i>	<i>Std. Error</i> <i>r</i>	<i>z</i>	<i>Coefficient</i> <i>t</i>	<i>Std. Error</i> <i>r</i>	<i>z</i>	<i>Coefficient</i> <i>t</i>	<i>Std. Error</i> <i>r</i>	<i>t-ratio</i>				
const	12.91***	1.43	9.02	0.20***	0.03	6.91	13.16***	2.00	6.55	11.6***	0.86	13.42				
SPAR	0.19***	0.04	4.29	-0.44***	0.08	-5.56	0.19***	0.04	4.30	0.18***	0.04	3.92				
GTR	-0.32**	0.16	-1.98	-3.34***	0.60	-5.55	-0.32**	0.15	-2.04	-0.52***	0.15	-3.41				
TJS	-2.89***	0.74	-3.89	1.08***	0.28	3.89	-2.95***	0.73	-4.04	-3.32***	0.74	-4.44				
PICK	1.95***	0.30	6.45	0.18**	0.08	2.11	1.90***	0.26	7.17	2.00***	0.14	13.80				
FOC	0.89***	0.22	3.96	0.13***	0.03	3.81	0.89***	0.22	3.97	0.83***	0.25	3.31				
LISA	0.20**	0.08	2.45	0.46***	0.09	4.96	0.20**	0.08	2.41	0.26***	0.08	3.11				
NFO	0.40***	0.11	3.65	0.17***	0.04	4.25	0.41***	0.10	3.86	0.49***	0.10	4.59				
LDIS	0.12*	0.07	1.79	0.20***	0.03	6.91	0.15***	0.07	2.17							
PRC(-1)				0.11**	0.05	2.10										
Statistics	Mean dependent var	23.20		Sum squared resid	8833.05		Mean dependent var	23.20		S.E. of regression	0.98					
	Sum squared resid	16360.03		S.E. of regression	3.72		Sum squared resid	31057.20		Adjusted R-squared	0.48					
	LSDV R-squared	0.66					Log-likelihood	-1310.01		P-value(F)	3.25e-48					
	LSDV F(27, 331)	24.54					Schwarz criterion	2672.98		Akaike criterion	1020.40					
	Log-likelihood	-1194.95					rho	0.06		Hannan-Quinn	1034.30					
	Schwarz criterion	2554.65					S.D. dependent var	11.71		Mean dependent var	23.20					
	rho	0.06					S.E. of regression	9.40		Sum squared resid	30271.81					
	S.D. dependent var	11.71					Akaike criterion	2638.03		S.D. dependent var	11.71					
	S.E. of regression	7.03					Hannan-Quinn	2651.93		S.E. of regression	9.30					
	Within R-squared	0.33					Durbin-Watson	1.32								
	P-value(F)	3.38e-63														
	Akaike criterion	2445.91														
	Hannan-Quinn	2489.15														
	Durbin-Watson	1.32														

Tests	<p>Joint test on named regressors - Test statistic: <math>F(8, 331) = 20.6507</math> with <math>p\text{-value} = P(F(8, 331) &gt; 20.6507) = 2.37817e-25</math></p>	<p>Number of instruments = 138 Test for AR(1) errors: <math>z = -3.81647 [0.0001]</math> Test for AR(2) errors: <math>z = -2.2043 [0.0275]</math> Sargan over-identification test: Chi-square(129) = 237.392 [0.0000] Wald (joint) test: Chi-square(9) = 363.84 [0.0000]</p>	<p>'Between' variance = 44.1447 'Within' variance = 45.5711 mean theta = 0.766787 Joint test on named regressors - Asymptotic test statistic: Chi-square(8) = 177.283 with <math>p\text{-value} = 3.82785e-34</math></p>	<p>Test for normality of residual - Null hypothesis: error is normally distributed Test statistic: Chi-square(2) = 28.2291 with <math>p\text{-value} = 7.41543e-07</math></p>
	<p>Test for differing group intercepts - Null hypothesis: The groups have a common intercept Test statistic: <math>F(19, 331) = 13.7271</math> with <math>p\text{-value} = P(F(19, 331) &gt; 13.7271) = 1.33672e-31</math></p>	<p>Test for normality of residual - Null hypothesis: error is normally distributed Test statistic: Chi-square(2) = 0.487275 with <math>p\text{-value} = 0.783772</math></p>	<p>Breusch-Pagan test - Null hypothesis: Variance of the unit-specific error = 0 Asymptotic test statistic: Chi-square(1) = 392.594 with <math>p\text{-value} = 2.2551e-87</math></p>	<p>Pesaran CD test for cross-sectional dependence - Null hypothesis: No cross-sectional dependence Asymptotic test statistic: <math>z = 37.8711</math> with <math>p\text{-value} = 0</math></p>
	<p>Distribution free Wald test for heteroskedasticity - Null hypothesis: the units have a common error variance Asymptotic test statistic: Chi-square(20) = 153.009 with <math>p\text{-value} = 1.66545e-22</math></p>	<p>Pesaran CD test for cross-sectional dependence - Null hypothesis: No cross-sectional dependence Asymptotic test statistic: <math>z = 26.5489</math> with <math>p\text{-value} = 2.64636e-155</math></p>	<p>Hausman test - Null hypothesis: GLS estimates are consistent Asymptotic test statistic: Chi-square(8) = 11.6655 with <math>p\text{-value} = 0.166765</math></p>	
	<p>Test for normality of residual - Null hypothesis: error is normally distributed Test statistic: Chi-square(2) = 76.0014 with <math>p\text{-value} = 3.13698e-17</math></p>		<p>Test for normality of residual - Null hypothesis: error is normally distributed Test statistic: Chi-square(2) = 20.085 with <math>p\text{-value} = 4.35107e-05</math></p>	
	<p>Wooldridge test for autocorrelation in panel data - Null hypothesis: No first-order autocorrelation (<math>\rho = -0.5</math>) Test statistic: <math>F(1, 19) = 179.582</math> with <math>p\text{-value} = P(F(1, 19) &gt; 179.582) = 3.92883e-11</math></p>		<p>Wooldridge test for autocorrelation in panel data - Null hypothesis: No first-order autocorrelation (<math>\rho = -0.5</math>) Test statistic: <math>F(1, 19) = 179.582</math> with <math>p\text{-value} = P(F(1, 19) &gt; 179.582) = 3.92883e-11</math></p>	
	<p>Pesaran CD test for cross-sectional dependence - Null hypothesis: No cross-sectional dependence Asymptotic test statistic: <math>z = 40.4783</math> with <math>p\text{-value} = 0</math></p>		<p>Pesaran CD test for cross-sectional dependence - Null hypothesis: No cross-sectional dependence Asymptotic test statistic: <math>z = 40.3811</math> with <math>p\text{-value} = 0</math></p>	

Note. The table reports coefficients and diagnostics from fixed-effects, dynamic panel, random-effects GLS, and WLS models. Robustness checks address heteroskedasticity, serial correlation, and cross-sectional dependence. Significance levels are denoted by asterisks.

## 5. Clustering

Based on the normalized validation indicators reported in Table X, the choice of the most appropriate clustering algorithm may be justified by means of a comparative evaluation of the achieved performance with regard to the compactness and separateness of the clusters. Although each of these indicators reflects a particular and partially overlapping aspect of clustering quality, the evaluation of the results as a whole reveals a very clear and consistent pattern. The first Model-Based solution consistently outperforms the

other solutions with regard to the majority of criteria conventionally maximized. Specifically, it obtains the highest normalized value with regard to Minimum Separation, Pearson’s gamma, the Dunn index, and the Calinski-Harabasz index. These criteria are very frequently applied in the literature as means of evaluating the balance between homogeneity and heterogeneity in clusters. The simultaneous maximization of these criteria strongly supports the quality of the obtained clusters. Furthermore, the same Model-Based solution also exhibits comparatively good performance with regard to Maximum Diameter. Most notably, it attains the lowest normalized score on Entropy, which is a positive attribute because a lower entropy score translates into a greater degree of homogeneity within clusters, with a clearer distinction between what observations belong to a particular group and what do not. The overall performance profile, with very high normalized scores on the principal separation and structure indices and a very low normalized score on entropy, suggests a strong clustering solution. The performance profiles of the other algorithms, on the other hand, appear less consistent. For instance, the Fuzzy C-Means algorithm performs poorly on a number of important indices, including Minimum Separation and the Dunn Index, while the K-Means and Random Forest algorithms, although performing well on some indices, fail to match the strong performance profile of the Model-Based approach across a range of indices. The hierarchical approach, as well as the second Model-Based approach, also appear unbalanced, with some indices being well satisfied but with a number of indices being less well satisfied. The overall impression that one draws from these results is that the first Model-Based approach offers a better clustering solution than the other approaches considered. See Table 5.

Table 5. Comparative Performance of Clustering Algorithms Based on Normalized Validation Indices

Indicator	Model Based	Fuzzy C-Means	Hierarchical	Model Based	K-Means	Random Forest
Maximum diameter	0.881	1.000	0.226	0.380	0.000	0.841
Minimum separation	1.000	0.000	0.289	0.172	0.254	0.274
Pearson’s $\gamma$	1.000	0.307	0.689	0.386	0.247	0.000
Dunn index	1.000	0.000	0.358	0.208	0.349	0.278
Entropy	0.000	0.433	0.629	0.719	1.000	0.814
Calinski-Harabasz index	1.000	0.128	0.000	0.383	0.868	0.273

Note. All indicators are normalized between zero and one for comparability. Higher values indicate better performance, except for entropy, where lower values are preferred. The table supports selecting the most suitable clustering method.

The clustering solution obtained from the model-based clustering methodology reveals eight clusters with considerable heterogeneity in terms of cluster size and quality. The initial five clusters are relatively small in size, with high homogeneity among their units. The units in these clusters vary from 20 to 22. On the other hand, clusters 6, 7, and 8 are relatively large in size, with 88, 112, and 78 units, respectively. Thus, it may be concluded that most of the units are forming part of clusters 6, 7, and 8. The heterogeneity metrics also support this argument. The heterogeneity metrics indicate that clusters 1 to 5 have extremely low heterogeneity metrics. On the other hand, clusters 6 and 7 have considerably higher heterogeneity metrics. The same phenomenon is observed in the within-cluster sum of squares. The clusters 1 to 5 have relatively low values in the within-cluster sum of squares. On the other hand, clusters 6 and 7 have considerably high values in the within-cluster sum of squares. The silhouette analysis also reveals considerable information regarding the quality of the clusters. The clusters 1, 2, 4, and 8 have relatively high silhouette values. The high silhouette value indicates good clustering quality. On the other hand,

cluster 6 has a relatively low silhouette value. The low silhouette value indicates poor clustering quality and greater chances of overlap between clusters. See Table 6.

Table 6. Cluster Composition and Quality Metrics from Model-Based Clustering.

Cluster	1	2	3	4	5	6	7	8
Size	20	22	20	20	20	88	112	78
Explained proportion within-cluster heterogeneity	0.044	0.038	0.083	0.033	0.038	0.350	0.285	0.129
Within sum of squares	40.837	34.923	76.507	30.864	35.158	322.227	262.617	118.628
Silhouette score	0.412	0.471	0.320	0.413	0.372	0.065	0.268	0.407

Note. The table reports cluster sizes and internal validity measures, including within-cluster heterogeneity, within sum of squares, and silhouette scores, to assess compactness and separation of the identified regional clusters.

The cluster profiles show significant variance in the nine standardized variables, with special emphasis given to Perceived Risk of Crime, which remains the central focus of the analysis. The eight clusters can be considered different socio-institutional and perceptual configurations, with differentiation based on variables of social participation, trust, crime exposure, subjective well-being, and dissatisfaction with the environment. Clusters 1 and 8 are strikingly similar, with strong negative values in PRC, as well as in most of the variables associated with PRC, including pickpocketing, fear of crime, trust in general, and trust in the judicial system. It is possible that these two clusters represent socio-institutional environments with low levels of perceived crime risk, as well as low levels of exposure to crime, but with low levels of trust and social participation, suggesting closed environments where insecurity is not an issue of concern. The interesting case of Cluster 2 is that, despite low levels of pickpocketing, fear of crime, and with relatively high levels of life satisfaction, PRC shows the highest positive value among all the configurations, suggesting an insecurity that is not directly associated with objective measures of crime but may relate to increased sensitivity to risk or some other form of uncertainty unrelated to objective levels of crime. Cluster 3 shows a clearer and more consistent pattern, with high levels of social participation, trust in institutions, crime-related variables, fear of crime, and, finally, a moderately positive PRC value. In this case, increased levels of perceived risk are clearly associated with increased levels of exposure and information, which are presumably linked to higher levels of social participation. Clusters 4 and 5 show low or near-zero levels of PRC, fear of crime, trust in the judicial system, but higher levels of pickpocketing, as well as moderate levels of dissatisfaction with the local landscape, in Cluster 5. The patterns of these two clusters point to scenarios where perceived risk is low despite other possible signs of environmental or social stress. The last of the clusters, Cluster 6, shows a clearly positive PRC value, accompanied by high levels of fear of crime, moderate levels of crime-related variables, and positive levels of trust in institutions, suggesting a scenario where perceived risk is confirmed by both affective and experiential dimensions of fear of crime. The last of the clusters, Cluster 7, shows negative PRC levels despite high levels of pickpocketing, fear of crime, and dissatisfaction with the future, suggesting the normalization of risk or, at least, its adaptive dimension. Overall, the above analysis of the different clusters shows that PRC is clearly the result of the complex interplay between objective crime, subjective emotions, trust, and quality of life dimensions, as opposed to being merely an objective measure of crime exposure. See Table 7.

Table 7. Standardized Cluster Profiles of Crime, Trust, Well-Being, and Environmental Indicators

Cluster	SPAR	GTR	TJS	PICK	FOC	PRC	LISA	NFO	LDIS
1	2.512	-1.358	-0.917	-1.401	-1.068	-0.138	0.036	-1.006	-1.296
2	-0.326	-1.358	-0.917	-1.401	-1.068	1.476	1.308	-1.006	-1.296
3	3.037	0.449	0.904	0.622	0.737	0.216	0.839	1.093	0.654
4	-0.326	0.613	-0.917	0.775	-1.068	-0.158	-0.137	-1.006	-1.296
5	-0.326	0.628	-0.917	0.906	-1.068	0.011	-0.183	-1.006	0.804
6	-0.326	0.674	0.677	0.517	0.937	0.732	0.442	0.459	0.773
7	-0.326	0.623	0.616	0.683	0.658	-0.619	-0.319	0.882	0.753
8	-0.326	-1.358	-0.917	-1.401	-1.068	-0.336	-0.551	-1.006	-1.296

Note. Values are standardized scores showing deviations from the overall mean. Positive values indicate above-average levels, while negative values indicate below-average levels, allowing comparison of cluster-specific profiles across all dimensions.

The profiles indicate that specific latent factors underlie the joint effects of the social, institutional, crime-related, and well-being variables. Particular emphasis is given to the Perceived Risk of Crime (PRC). The first and eighth components have markedly negative values for social participation, general trust, and trust in the judicial system. Additionally, these components have low levels of life satisfaction and pessimism. The PRC has close to zero or slightly negative values. The profiles represented by these two components may indicate that PRC does not strongly relate to negative conditions in society and the institutional system. The second component has high positive values for pickpocketing and a clearly positive PRC. The levels of trust and social participation are similarly low. The profile represented by this component may indicate that PRC strongly relates to experiences of crime, as represented by pickpocketing. The third component represents a markedly different profile. High positive values are found for social participation, trust in the judicial system and in general, fear of crime, and PRC. Higher levels of life satisfaction and less pessimistic attitudes are also found. The profile represented by this component may indicate that when more information is available and when people are more socially active, they experience more insecurity and perceive their surroundings as more risky. The Perceived Risk of Crime is then high. The fourth and fifth components have negative or close to zero PRC. They also have moderate levels of trust and high levels of life satisfaction. The profiles represented by these two components may indicate that well-being and trust in the institutional system are important. They may function as buffers against feelings of insecurity. The sixth component represents a coherent and well-rounded profile. High positive levels are found for trust in the judicial system and in general. Additionally, moderate levels of crime-related variables and pessimism about the future are found. The PRC has a positive value. The profile represented by this component may indicate that people have a comprehensive and experiential view of the Perceived Risk of Crime. The seventh component represents a profile with relatively high levels of trust and social participation. The PRC has negative values. The profile represented by this component may indicate that the institutional system and social participation function as buffers against feelings of insecurity. See Table 8.

Table 8. Standardized Component Scores for Crime, Trust, Well-Being, and Environmental Dimensions

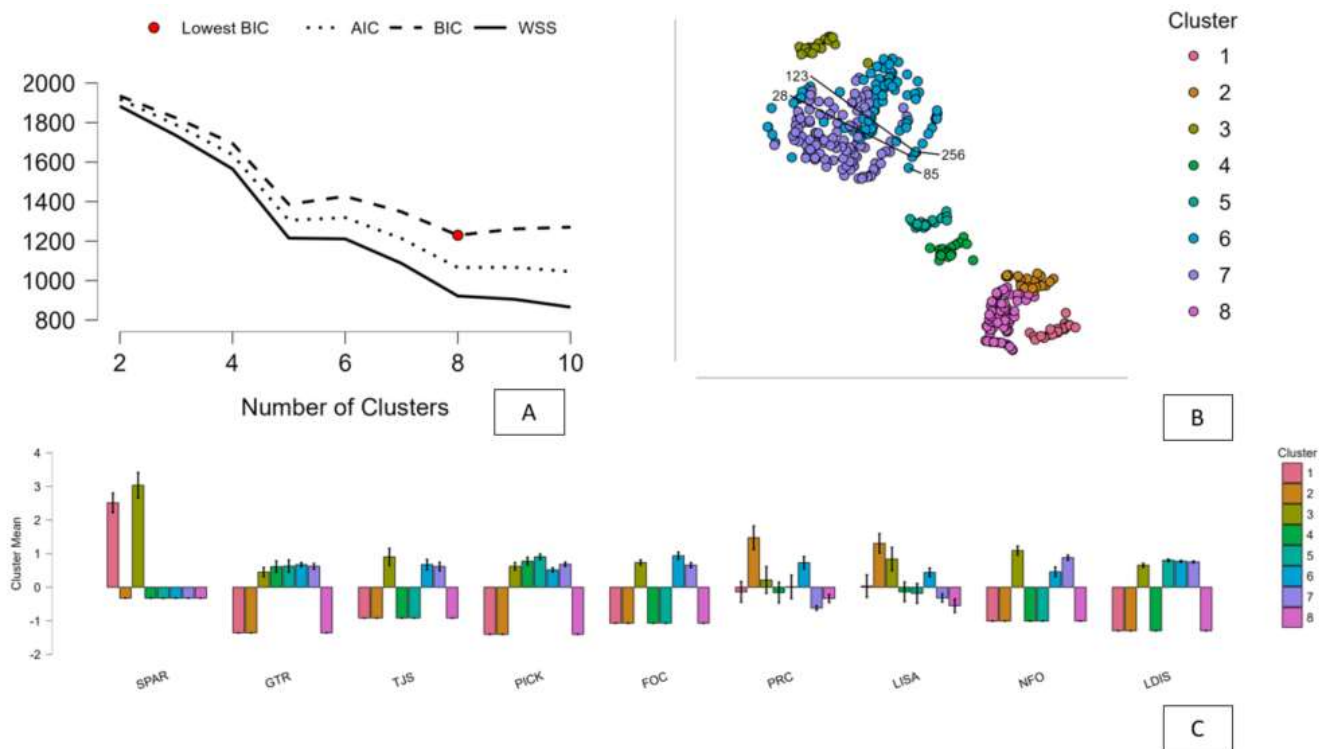
Component	SPAR	GTR	TJS	PICK	FOC	PRC	LISA	NFO	LDIS
1	-1.006	-1.358	-1.296	-0.143	2.464	0.020	-1.401	-1.068	-0.917

2	-1.006	-1.358	-1.296	1.311	-0.326	1.115	-1.401	-1.068	-0.917
3	1.093	0.449	0.654	0.216	3.037	0.839	0.622	0.737	0.904
4	-1.006	0.613	-1.296	-0.158	-0.326	-0.137	0.775	-1.068	-0.917
5	-1.006	0.628	0.804	0.011	-0.326	-0.183	0.906	-1.068	-0.917
6	0.459	0.676	0.774	0.718	-0.326	0.433	0.522	0.922	0.690
7	0.885	0.622	0.751	-0.619	-0.326	-0.318	0.681	0.668	0.605
8	-1.006	-1.358	-1.296	-0.312	-0.322	-0.518	-1.401	-1.068	-0.917

Note. The table reports standardized component scores summarizing multivariate patterns across variables. Positive values indicate above-average contributions, while negative values indicate below-average contributions, facilitating interpretation of latent structures underlying regional profiles.

The figure presents an informative picture of the process of selecting a model, along with a meaningful interpretation of the clustering solution that is provided by the model-based approach. In particular, panel A shows how the fit indices, namely AIC, BIC, and within clusters sum of squares, vary with an increasing number of clusters. All three indices show a declining pattern with an increasing number of clusters, a pattern that is in line with the expectation that fit increases with an increasing number of clusters in the solution. Of particular interest is the pattern of BIC, where there is a penalty for increasing complexity in the solution, with a minimum at eight clusters, as evidenced by the marker on that point on the plot. This is in line with choosing eight clusters as offering an optimal solution in terms of fit and parsimony. In panel B, there is a plot of the two-dimensional representation of the data, with colors representing the clusters that are determined by the model-based approach. From the figure, it is clear that there are a number of clusters that are well differentiated, with some of them forming tight clusters, while others are less differentiated. This is in line with the heterogeneity in terms of cluster size that is evidenced in the numerical outcomes. Finally, panel C shows a plot of standardized means of the nine variables that are used in the analysis, with each cluster determined by the model-based approach. From the figure, it is clear that there are significant differences between clusters in terms of social participation, trust, crime, perceived crime, life satisfaction, future expectations, and environmental dissatisfaction. Of particular interest is that, in terms of the solution for perceived risk of crime, there is considerable variation between clusters in terms of combinations of objective crime, emotional, and socio-institutional factors. In conclusion, it is quite clear that all three panels offer evidence that not only is there a statistically well-founded solution provided by the model-based approach, but there is also a solution that is clearly differentiated into a small number of clusters. See Figure 1.

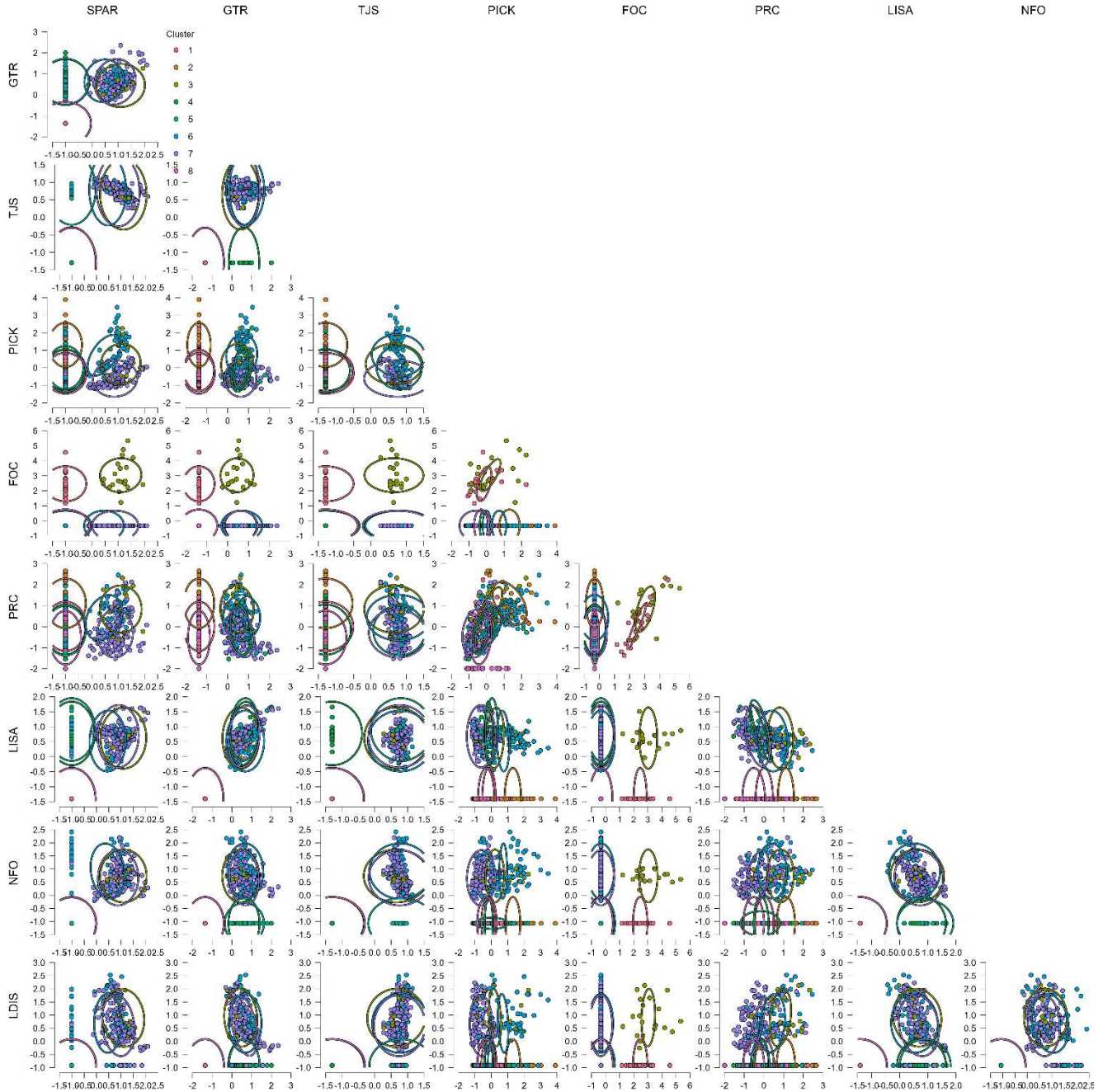
Figure 1. Model-Based Clustering Results: Model Selection, Cluster Allocation, and Profile Comparison



Note. Panel A shows information criteria and WSS for selecting the optimal number of clusters, Panel B displays cluster assignments, and Panel C reports standardized cluster means across crime, trust, well-being, and environmental indicators.

The figure displays the scatter plot matrix of the different variables under consideration. The observations are colored according to the clusters. The clusters' dispersion is represented by the use of 'ellipses.' The figure facilitates the evaluation of the level of separation among the clusters and the relationships between the different indicators. From different panels of the figure, it is clearly shown that some clusters overlap. However, some clusters are clearly distinguished from one another. The clusters are distinguished along the dimensions of 'fear of crime' (FOC), 'perceived risk of crime' (PRC), and 'trust' indicators. The 'ellipses' suggest that some clusters are more compact than the others. The figure clearly shows the relationships between 'PICK' and 'FOC' and 'PRC.' From different panels of the figure, it is clearly shown that these clusters are positively related. The clusters that are exposed to 'predatory crime' and 'fear of crime' are consistently at higher levels. Therefore, these variables are highly related. The variables 'PICK,' 'FOC,' and 'PRC' are highly related. The variables 'GTR,' 'TJS,' and 'LISA' relate to 'trust' and 'well-being.' The clusters are positioned at different ends of the axes. Therefore, these variables may have a mitigating impact on 'perceived risk of crime.' The figure clearly supports the validity of the clusters. The clusters are clearly positioned in different and partially overlapping regions of multidimensional space. The figure clearly shows that 'perceived risk of crime' emerges as an outcome of the interaction among 'objective crime indicators,' 'emotional responses,' and 'socio-institutional conditions.' See Figure 2.

Figure 2. Pairwise Scatterplots and Cluster Separation Across Crime, Trust, Well-Being, and Environmental Indicators



Note. The figure displays pairwise relationships among standardized variables with cluster assignments. Ellipses highlight cluster dispersion and overlap, illustrating multidimensional structure, correlations, and partial separation among regional profiles identified by model-based clustering.

## 6. Machine Learning Regressions

The comparison of all seven algorithms has been carried out on a set of normalized performance metrics. Here, lower values represent better performance for MSE, scaled MSE, RMSE, and MAE/MAD, while higher values represent better performance for R<sup>2</sup>. The performance metrics suggest that Neural Network has performed poorly on all accounts. The worst values are recorded by Neural Network on all error-based metrics, along with the lowest R<sup>2</sup>. Therefore, Neural Network can be discarded. Decision Tree and KNN also perform relatively poorly. The metrics suggest relatively higher error rates along with lower R<sup>2</sup> values. Therefore, Decision Tree and KNN are not suitable options. Boosting and SVM perform moderately well. Both algorithms record relatively lower error rates along with decent R<sup>2</sup> values. However, it seems that no single algorithm has a significant edge over others on any single parameter. Moreover, both are overtaken by at least one algorithm on all accounts. The Random Forest algorithm has recorded the highest R<sup>2</sup> values. Therefore, it has superior explanatory power compared to all other algorithms. However, error-based metrics also suggest relatively better performance. Nevertheless, it seems that Random Forest has marginally lower error rates compared to all algorithms. Therefore, it cannot be considered the best option. The Regularized Linear algorithm has recorded the lowest or near-lowest values on all error-based metrics. Therefore, it has superior predictive accuracy compared to all other algorithms. Moreover, it has recorded high values on all R<sup>2</sup> metrics. Therefore, it has superior explanatory power compared to all algorithms. The combined performance metrics suggest that Regularized Linear has an edge over all other algorithms. The algorithm has superior predictive accuracy as well as superior explanatory power. Therefore, it can be considered the most appropriate algorithm. See Table 9.

Table 9. Comparative Predictive Performance of Machine Learning and Regression Models for PRC.

Metric	Boosting	Decision Tree	KNN	Linear Regression	Neural Network	Random Forest	Regularized Linear	SVM
MSE	0.170	0.622	0.812	0.000	1.000	0.109	0.010	0.104
MSE (scaled)	0.124	0.863	0.435	0.114	1.000	0.000	0.208	0.409
RMSE	0.191	0.653	0.831	0.000	1.000	0.123	0.011	0.118
MAE / MAD	0.088	0.635	0.588	0.000	1.000	0.245	0.093	0.089
R <sup>2</sup>	0.839	0.096	0.480	0.851	0.000	1.000	0.735	0.508

Note. All performance metrics are normalized between zero and one for comparability. Lower values indicate better performance for error measures, while higher values indicate better performance for R<sup>2</sup>.

This being the case, the mean dropout loss values provide a clear ranking of the relative importance of the predictors in terms of their contribution to the model's predictive performance, with larger loss values reflecting a greater loss in predictive accuracy for the model upon removal of the corresponding variable. Within this context, it is clear that PICK has the greatest influence on the model, given that it has the highest loss value, reflecting a greater loss in predictive accuracy for the model upon removal of this variable compared to removal of the other variables. This finding, therefore, points to the fact that the variable used as a proxy for exposure to predatory crimes, i.e., pickpocketing, plays a key role in explaining the model's predictive power, thus supporting the argument for the relevance of objective

crime indicators in explaining observed insecurity phenomena. The second- and third-highest loss values reflect removal of the LDIS variable and FOC, respectively, thus suggesting that, alongside the variable for pickpocketing, dissatisfaction with the local environment and fear of crime play a key role in explaining the model's predictive power. This finding, therefore, supports the argument that environmental conditions play a key role in determining crime-related behaviors. The remaining variables, although related to lower loss values, also reflect their relative contribution to the model's predictive power. The intermediate levels of general trust and trust in the judicial system suggest that these dimensions play a less prominent role in the model's performance compared to direct crime experiences and security issues. The lowest dropout loss levels are related to negative future outlook, social participation, and life satisfaction. The low dropout loss levels for these dimensions suggest that general levels of well-being play a less prominent role. The hierarchy of mean dropout loss levels supports the idea that a specific hierarchy of the determinants' influence can be constructed, with the most influential being objective crime indicators/direct insecurity experiences, then environmental dissatisfaction/trust in institutions, and finally general levels of well-being/social dimensions being the least influential. All of the above evidence supports the idea that the phenomenon under investigation is driven mainly by specific crime-related determinants/direct insecurity experiences, with general socio-psychological dimensions playing a less prominent role. See Table 10.

Table 10. Variable Importance Based on Mean Dropout Loss in the Regularized Linear Model.

	PICK	LDIS	FOC	GTR	TJS	NFO	SPAR	LISA
Mean dropout loss	11.956	9.419	9.151	9.026	8.818	8.815	8.799	8.698

Note. Mean dropout loss measures the increase in prediction error when each variable is removed. Higher values indicate greater importance, showing that pickpocketing, environmental dissatisfaction, and fear of crime are the strongest predictors of perceived risk.

The output of a regularized linear regression model on the data set of Italian regions from 2004 to 2022 provides an unambiguous decomposition of Perceived Risk of Crime (PRC) into a base component common to all regions and the specific impact of each variable on it: Social Participation (SPAR), General Trust (GTR), Trust in the Judicial System (TJS), Pickpocketing (PICK), Fear of Crime (FOC), Life Satisfaction (LISA), Negative Future Outlook (NFO), and Dissatisfaction with Local Landscape (LDIS). The Base component always has a constant value of 22.633, which represents the average level of Perceived Risk of Crime in an average Italian region. The rest of the components show how variations in social, institutional, criminal, and well-being factors contribute to an increase or decrease in predicted Perceived Risk of Crime. The regions of Case 2 exhibit the highest Perceived Risk of Crime at 37.024. The main driver of this high Perceived Risk of Crime level is a significantly large positive component of PICK. Additionally, a high positive component of FOC also contributes to high Perceived Risk of Crime. This implies that regions with higher rates of predatory crimes and higher fear of crime tend to exhibit higher Perceived Risk of Crime. The positive components of SPAR, LISA, NFO, and LDIS also support

this assertion. The predicted PRC values in Cases 1 and 3 are above the baseline by a small margin. The values are 25.340 and 26.086, respectively. In both cases, the positive effect of PICK remains at the core. However, it is offset by negative values of well-being variables and environmental dissatisfaction. In Case 1, institutional trust variables provide positive offsetting values to negative values. Conversely, in Case 3, social participation and crime exposure provide positive offsetting values to institutional trust. In Cases 4 and 5, the predicted PRC values are well below the baseline. The values are 16.269 and 15.379, respectively. The negative effect of PICK is compounded by negative values of LISA, NFO, and LDIS. The predicted PRC values are significantly reduced. The above analysis again affirms the overwhelming effect of crime exposure and fear of crime on regional perceptions of insecurity in Italy during 2004-2022. The other variables play an important role in modulating the final predicted PRC values. See Table 11.

Table 11. Decomposition of Predicted PRC Values from the Regularized Linear Regression Model.

Case	Predicted	Base	SPAR	GTR	TJS	PICK	FOC	LISA	NFO	LDIS
1	25.340	22.633	-1.300	2.564	1.640	5.234	-0.628	-1.006	-1.359	-2.438
2	37.024	22.633	1.293	-0.745	-0.795	8.970	2.799	0.510	0.915	1.445
3	26.086	22.633	1.200	-1.843	-1.085	3.278	-0.628	0.650	0.486	1.396
4	16.269	22.633	-1.300	2.564	1.640	-3.837	-0.628	-1.006	-1.359	-2.438
5	15.379	22.633	-1.300	2.564	1.640	-4.726	-0.628	-1.006	-1.359	-2.438

Note. The table reports predicted PRC values decomposed into the baseline and variable-specific contributions, illustrating how each covariate increases or decreases the final prediction for selected regional cases over the study period.

The regularized linear regression analysis provides insights on what affects the Perceived Risk of Crime (PRC) across Italian regions over time, i.e., between 2004 and 2022. The intercept for this model is 22.271, indicating that PRC is still present even if all independent variables are at their means. Among these, PICK and FOC have the highest positive coefficients, at 5.726 and 2.210, respectively. The significance of PICK and FOC as determinants of PRC indicates that being exposed to street crimes, especially pickpocketing, and fear of crime play a significant role in PRC, thereby substantiating the argument that both objective and subjective factors affecting crime are important factors for PRC. The positive sign for Social Participation (SPAR) indicates that PRC is positively related to social participation levels. This could also be true for Negative Future Outlook (NFO), as indicated by its positive coefficient. Similarly, a positive relationship between PRC and Life Satisfaction (LISA) also exists, as indicated by its positive coefficient. The positive coefficient for Dissatisfaction with the Local Landscape (LDIS) indicates that PRC is positively related to dissatisfaction with the local landscape. On the contrary, a higher value for General Trust (GTR) at -1.841 and Trust in the Judicial System (TJS) at -1.258 indicates a lower PRC. See Table 12.

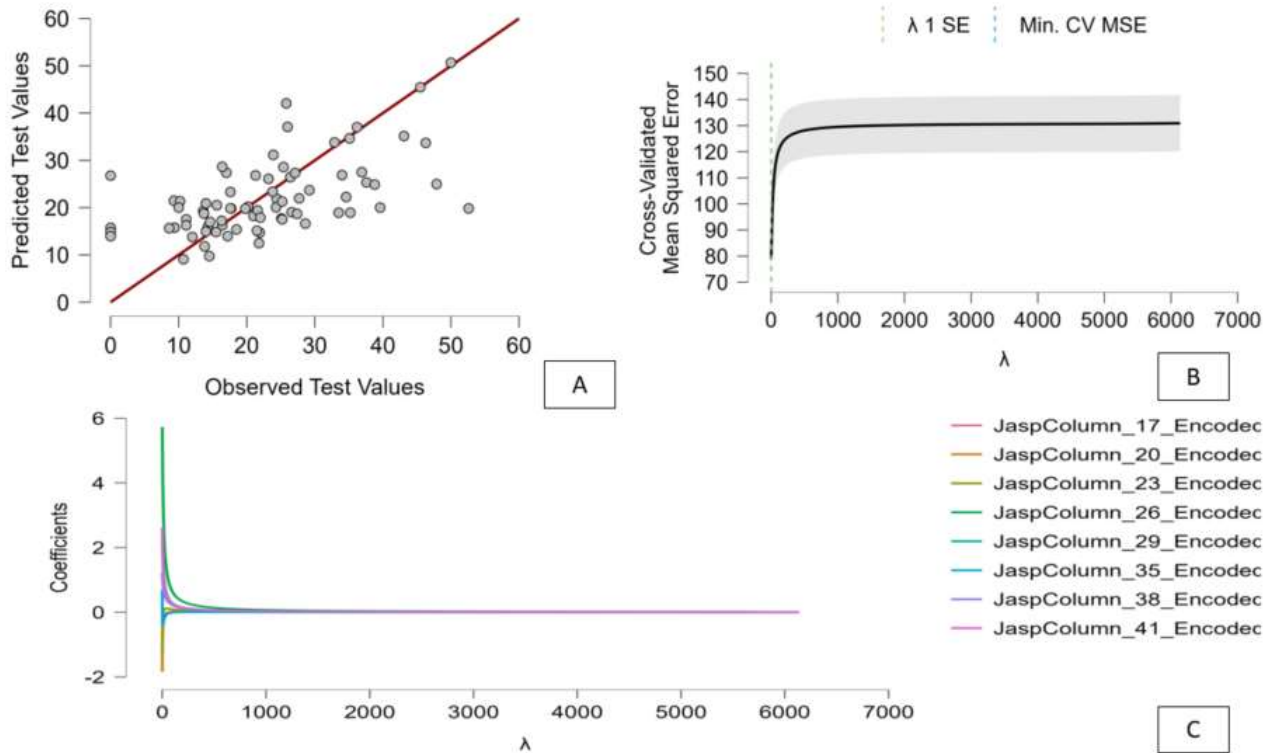
Table 12. Estimated Coefficients from the Regularized Linear Regression Model for PRC

	(Intercept)	SPAR	GTR	TJS	PICK	FOC	LISA	NFO	LDIS
Coefficient ( $\beta$ )	22.271	1.230	-1.841	-1.258	5.726	2.210	0.700	1.237	2.624

Note. The table reports standardized coefficients from the regularized linear model, indicating the direction and relative magnitude of each predictor’s contribution to perceived crime risk while controlling for multicollinearity and overfitting.

The figure shows the key results from the regularized linear regression, providing supplementary information on how well it predicts, as well as how it compares to alternative models. In particular, in Panel A, it is demonstrated how well the model predicts by comparing the actual test values with their corresponding predictions. It is seen that there is a high level of concordance between the actual values and their predictions, with all points lying close to the line where they should lie, i.e., a 45-degree line. While there is some scatter, it is not systematic, indicating that there is no tendency to systematically over- or under-predict, with the model appearing to capture the systematic component of the dependent variable with no obvious systematic bias in the predictions. In Panel B, it is demonstrated how well the model predicts in cross-validation, with the mean squared error plotted against the regularization parameter  $\lambda$ . It is seen that there is a strong reduction in cross-validation error for small values of  $\lambda$ , with little reduction in error for larger values, indicating that there is a strong benefit to using a moderate level of regularization in linear regression, with little to gain from going beyond that level. In addition, the position of the vertical dashed lines at the minimum cross-validation error, as well as one standard error above that minimum, indicates that there is little sensitivity to the level of regularization, with all three points lying close together, indicating that there is a strong balance between goodness of fit, complexity, and stability in the regularized linear regression model. In Panel C, it is demonstrated how the regression coefficients behave under regularization, with all coefficients being reduced towards zero, indicating that there is a strong benefit to using regularization in linear regression in controlling complexity and thus avoiding overfitting, with all coefficients behaving in a similar fashion, although at different rates, indicating that they have different relative importance in making predictions. See Figure 3.

Figure 3. Regularized Linear Regression Diagnostics: Prediction Accuracy, Cross-Validation, and Coefficient Shrinkage



Note. Panel A shows predicted versus observed values, Panel B reports cross-validated mean squared error across penalty parameters, and Panel C illustrates coefficient shrinkage paths, highlighting model stability and variable selection under regularization.

## 7. Results and Discussion

The above-reported results prove the complementarity of three different methodological approaches in achieving a complete picture of the determinants of Perceived Risk of Crime (PRC) in Italian regions from 2004 to 2022. Rather than yielding disparate information on a single topic, these methodological approaches converge to offer a more complete understanding of the determinants of PRC among the Italian population. The main goal of the econometric modeling approach, which includes various panel data models such as fixed effects models, random effects models, dynamic panel data models, and weighted least squares models, is to identify the determinants of PRC while controlling for unobserved time-varying heterogeneity across Italian regions. The results suggest that Perceived Risk of Crime increases with increases in pickpocketing (PICK), fear of crime (FOC), negative future outlook (NFO), and dissatisfaction with the local landscape (LDIS), while it decreases with increases in general trust (GTR) and trust in the judicial system (TJS). Moreover, the results suggest that perceptions are slow to change over time with past levels of insecurity having a positive effect on current Perceived Risk of Crime. The results also suggest that perceptions of insecurity are driven by both socio-psychological/environmental factors and by experience of routine crimes. Perceived Risk of Crime positively relates to PICK, which suggests a strong relationship with high-profile crimes involving predation. Perceptions of security are also negatively related to GTR and TJS, which suggests a strong

relationship with trust. The difference in the sign of social participation between the static and dynamic model can be an indication of a complex relationship between short-term risk awareness and long-term security perceptions, possibly involving the effect of social capital. In the machine learning analysis, the primary goal is prediction, along with the evaluation of an extensive range of models to achieve optimal performance. Under the machine learning approach, the best performing model is the regularized linear model that offers the best balance of low levels of predictive error along with high levels of explanatory power; the Random Forest model offers the highest R<sup>2</sup> while suffering from high levels of error; the Neural Networks model performs poorly overall. This suggests that the relationship between PRC and its covariates is primarily linear, while the nonlinear relationship offers limited levels of explanatory power. The variable importance measures along with the use of dropout loss indicate that PICK, LDIS, and FOC are the most important predictors of PRC, similar to the results of the econometric analysis. This is of particular interest since the machine learning approach, while differing from the econometric analysis, again identifies the key drivers of PRC while offering improved levels of predictive power. In the clustering analysis, an additional dimension is introduced that allows for the identification of regional profiles based on combinations of crime exposure, perception, trust, and well-being. The identification of eight different clusters indicates that the varying conditions of the covariates can lead to different levels of PRC that result in different levels of perceptual outcomes for different levels of the covariates. The differentiating dimensions of the clusters are PICK, FOC, GTR, TJS, and LDIS, similar to the variables identified as the most important predictors of PRC using the econometric and machine learning analysis, again highlighting the fact that PRC is driven by multiple dimensions. The overarching conclusion that can be drawn from the integrated analysis is that the combined use of econometric methods, machine learning methods, and clustering methods offers a more comprehensive examination of PRC than what could be achieved with any one of these methods in isolation. See Table 13.

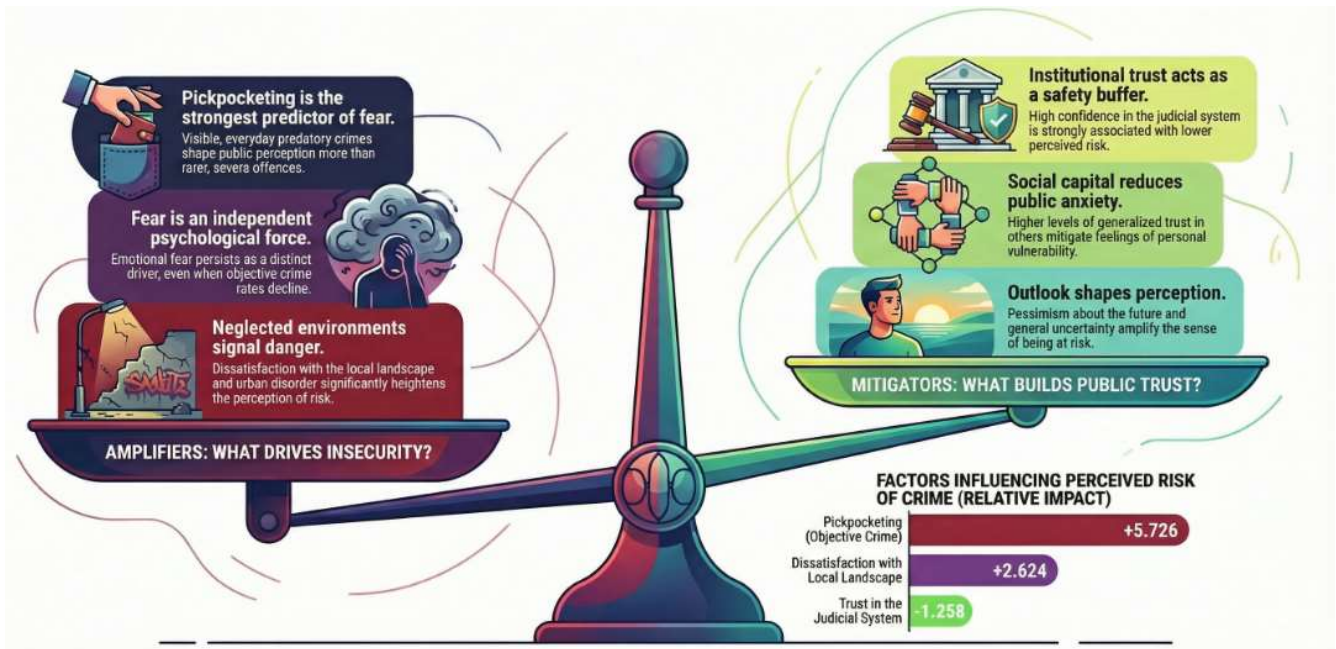
Table 13. Integrated Summary of Econometric, Machine Learning, and Clustering Results on PRC

Approach	Method	Objective	Main results on PRC	Key variables	Added value
Econometric (panel data)	Fixed Effects, Random Effects (GLS), Dynamic Panel, WLS	Explain the determinants of PRC while controlling for regional heterogeneity and time dynamics	PRC increases with PICK, FOC, NFO, and LDIS, and decreases with GTR and TJS. SPAR is positive in static models but turns negative in the dynamic specification. PRC shows significant persistence over time	PICK (strong positive), FOC (positive), TJS (negative), GTR (negative), NFO (positive), LDIS (positive)	Provides structural interpretation of relationships and robustness across different specifications
Machine Learning	Boosting, Random Forest, SVM, KNN, Decision Tree, Neural Network, Regularized Linear	Maximize predictive accuracy of PRC	The Regularized Linear model achieves the best trade-off between low prediction error and high R <sup>2</sup> . Random Forest reaches the highest R <sup>2</sup> but with higher errors, while Neural Network performs worst	PICK, LDIS, and FOC emerge as the most important predictors according to variable importance and dropout loss	Enhances predictive performance and ranks variables by their contribution to prediction
Clustering	Model-based clustering, k-means, hierarchical, fuzzy c-means	Identify latent regional profiles in terms of crime, perceptions, trust, and well-being	Eight clusters are identified, characterized by different combinations of crime exposure, fear, trust, and quality of life. Similar levels of PRC can arise from different configurations of covariates	Clusters differ mainly along PICK, FOC, GTR, TJS, and LDIS dimensions	Reveals heterogeneity and typologies of regional profiles beyond average regression effects

Note. The table compares three complementary analytical approaches, summarizing objectives, key findings, and main variables to illustrate how explanation, prediction, and classification jointly contribute to understanding regional differences in perceived crime risk.

The figure provides an excellent and easily comprehensible summary of the key empirical findings by conceptualizing the perceived risk of crime as the outcome of a balance between the forces that amplify it and those that reduce it. On the left, the “amplifiers” pinpoint three different ways in which insecurity is amplified. Firstly, the figure clearly shows that pickpocketing is the strongest predictor of PRC, which emphasizes the significance of visible, daily predatory crimes relative to less frequent but more serious crimes. This figure supports the findings of the econometric and machine learning analysis, which showed that PICK has the highest positive coefficient and highest predictive importance. Secondly, the figure shows that fear is an independent psychological force, which emphasizes the significance of the psychological effects of crime, even when objective crime conditions are improving. This reflects the notion that the fear of crime is not just the outcome of objective crime rates, but it is an independent determinant of PRC. Thirdly, the figure shows that neglected environments and dissatisfaction with the local landscape are signals of danger, which supports the theories of disorder and the broken windows perspective, as well as the positive relationship between LDIS and PRC. On the right, the “mitigators” section shows how social and institutional factors can mitigate, emphasizing the protective effect of institutional trust, particularly trust in the judicial system, which is depicted as a protective buffer, consistent with its strong negative coefficient in the regression models, implying that trust can mitigate perceived risks even in the presence of crime. Social capital, measured by generalized trust, is also depicted as mitigating public concern by mitigating personal vulnerability, supporting the idea that social capital can mitigate risk perception. The importance of outlook is also highlighted, implying that pessimism and ambiguity about the future can increase perception of risk, while more optimistic outlooks may create a sense of security. The scale at the bottom of the figure, which includes figures such as +5.726 for pickpocketing, +2.624 for dissatisfaction with the local landscape, and -1.258 for trust in the judicial system, serves to give a quantitative dimension to the conceptual discussion. The figure clearly communicates the idea that perception of crime risk is generated by the dynamic interplay between more tangible exposure and emotional/ environmental cues on one side, and institutional and social resources on the other, providing a compelling visual summary of the study’s key findings. See Figure 4.

Figure 4. Amplifiers and Mitigators of Perceived Crime Risk: A Conceptual and Empirical Synthesis



Note. The figure contrasts drivers increasing perceived insecurity with protective factors, combining regression evidence and conceptual insights to show how everyday crime, environmental disorder, fear, trust, and outlook jointly shape public perceptions of risk.

## 8. Policy Implications

The results of the study imply that the process of crime prevention policy formulation with regard to the reduction of the perceived crime risk in Italian regions should not be based on the narrow concept of crime control. Rather, it should be based on a multidimensional concept that simultaneously considers security, institutional credibility, social cohesion, and the quality of the living environment. Moreover, the significant effect of pickpocketing on the perception of crime risk may imply that more visible and more widespread forms of predatory crime can play an important role in shaping perceptions of crime risk. Therefore, crime prevention strategies focused on reducing the incidence of more common forms of public space crime, such as police deployment in transportation hubs, tourist areas, or city centers, may have a significant effect on not only security, but also security perceptions. At the same time, the negative relationship between trust in the judicial system and the perception of crime risk may imply that the institutional environment plays an important role in shaping security perceptions. Therefore, investments in improving the efficiency of the judicial system may have a significant effect on security perceptions, even with no change in the objective security situation. The importance of the fear of crime variable and the pessimistic future outlook may imply that it is necessary to develop strategies to deal with the emotional and psychological aspects of security. Therefore, public communication strategies, prevention strategies, and strategies to create positive narratives about crime trends may help to reduce the effect of the fear of crime on security perceptions. Moreover, macro-level socio-economic strategies to reduce uncertainty and increase positive expectations about the future may help to reduce the effect of pessimistic future outlook on security perceptions. The positive relationship between local landscape

dissatisfaction and perceptions of insecurity threats underscores the importance of urban environment quality. Urban regeneration, street maintenance, street lighting, cleanliness, and disorder control can have significant spillover effects on perceptions of security. These measures are relatively inexpensive in comparison to traditional security policies, with additional benefits for subjective well-being, social interaction, and urban livability. The results on social participation show inconsistency, underlining that policies on social capital should be evaluated from a long-run perspective. While high participation levels can have a positive impact on problem awareness in the short run, stronger social capital is expected to have a positive impact on informal social control in the long run. In this regard, these policies can be considered to have positive spillovers on both perceived and real security. The identification of different regional profiles, with clustering, underlines that a single solution is not likely to be effective in all regions. For example, regions in which insecurity perceptions are mainly related to crime exposure can benefit significantly from security policies, whereas regions in which insecurity perceptions are related to feelings of distrust, pessimism, or local landscape dissatisfaction can benefit from comprehensive policies addressing these issues. In conclusion, the results strongly support that an integrated approach to security is necessary, in which crime control, institution building, social cohesion, and quality of life policies are implemented together to produce significant reductions in insecurity perceptions.

## **9. Conclusions**

The research question addressed in this research is: What are the determinants of perceived crime risk in Italian regions from 2004 to 2022, with a mixed approach that integrates panel data econometrics, machine learning, and clustering in a single framework? What is new in this research is that it shows that, in addition to objective crime trends, there is evidence that perceived security outcomes are determined by complex interactions between crime exposure, emotional responses, institutional trust, social participation, and quality of life in general. The research is conducted with ISTAT-BES data, from which it is found that there is robust evidence of the simultaneous impact of both objective and subjective dimensions on perceptions of crime risk in Italy. From an econometric point of view, it is found that, in Italy, exposure to pickpocketing, fear of crime, generalized trust, trust in the judiciary, pessimism regarding the future, and dissatisfaction with local environment are all relevant to perceptions of crime risk, thus supporting the hypothesis that exposure to crime, emotional responses to crime, trust, pessimism regarding the future, and dissatisfaction with local environment are all relevant to perceptions of crime risk in Italy. Moreover, it is found that there is persistence in perceptions of crime risk, thus supporting the hypothesis that changes in security outcomes occur gradually, with shocks in the short term having permanent effects on perceptions of crime risk in Italy. The function of the machine learning part is to extend these findings by focusing on predictive performance instead of causal explanation. Among the models considered, the regularized linear model presents a good trade-off between accuracy and interpretability, while the Random Forest model presents the highest  $R^2$  but also increases prediction error. In any case, with regard to the importance of the variables, we can confirm that, across all models, pickpocketing, fear of crime, and satisfaction with local landscape occupy the top three positions, followed by trust-related variables, with regard to their relative importance for predictive accuracy. Finally, clustering analysis introduces a further perspective by showing how different combinations of social, institutional, emotional, and environmental factors contribute to similar levels of perceived insecurity. The analysis distinguishes between eight different regional profiles, which again highlights the diversity of the Italian context and, at the same time, underlines that perceived insecurity is not a unidimensional phenomenon. It is worth mentioning that clusters with high levels of perceived insecurity also present high levels of crime exposure and fear, while other clusters reveal high levels of perceived

insecurity even with relatively low levels of crime exposure. On the contrary, clusters with adverse conditions but with low levels of perceived insecurity indicate a process of adaptation or normalization. The implications of these findings are relevant with regard to both academic and policy-related issues. From a theoretical perspective, our results indicate that insecurity should be considered a multidimensional phenomenon, including different dimensions and methodological approaches, while policy implications indicate that, beyond reducing levels of crime, perceptions of insecurity require a series of interventions that also involve improvements in institutional trust, social cohesion, landscape quality, and expectations about the future. Improvements in institutional quality, landscape, and trust could be at least as important as improvements in crime reduction for increasing security perceptions. Despite all of these important contributions, it must be noted that the study has certain limitations. The regional level of analysis used in this study, although useful to analyze structural and institutional heterogeneity, does not lend itself well to differences at the micro-level. Future research should attempt to incorporate survey data at the micro-level with territorial data. Moreover, although dynamic panel techniques offer certain advantages, issues of endogeneity and measurement error remain. This suggests that alternative methodological strategies should be pursued in future research. However, the evidence offered here presents a coherent and robust picture of what drives perceptions of crime risk in Italy and provides a good base upon which more all-encompassing and holistic approaches to understanding social insecurity can be developed.

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