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Wildfire Crime and Social Vulnerability in Italy: A Panel Investigation

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Abstract

In this paper, we analyse the socio-economic determinants of wildfire crime in Italy using panel data at regional level. Using fixed effect Poisson models and fixed effect quantile panel regression analysis it is found that social vulnerability factors such as poverty, organised crime and income inequality play an important role in driving wildfire crime. The quantile regression analysis highlights a significant heterogeneity of the effects of driving factors across the Italian peninsula. Finally, we also extend our analysis to investigate the effect of economic downturns on wildfire crime and we find a positive correlation between a deterioration of per capita income and wildfire crime.

Keywords: wildfire crime, socio-economic factors, fixed effect Poisson, Quantile analysis.

JEL Classification: C21, C33, Q5, Q54

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1. Introduction

Wildfires constitute a significant threat to the environmental ecosystems as the occurrence of fire can change the physical and structural characteristics of the landscape, thus producing significant variations of forests vegetation, soil and fauna. Affected forestlands suffer from the loss of vegetation cover for long periods. During this time, the soil is exposed to erosion by atmospheric agents that can contribute to the degradation of the nutrient cycling which are essential for vegetation and therefore for wildlife as a byproduct (see Di Fonzo *et al*., 2015). There are several causes of forestlands fires, however, human fire ignition is worldwide recognized to be the single most important cause of forests fire (see for example Ganteaume, 2013). This is particularly the case in European Mediterranean countries where it is estimated that more than 90% of forestland fire is caused by human action (see for example Leone *et al*., 2002; Velez, 2009).

Against this background, the objective of this study is to identify significant socio-economic factors related to wildfire crime in Italy. The country constitutes an ideal setting to explore quantitatively the relationship between socio vulnerability factors and this specific type of environmental crime, for several reasons. First, the area of forestland is substantial in Italy as more than 35% of total area was reported as natural forestland in 2019, according to the World Bank collection of development indicators. Second, like as in many other Mediterranean countries in Europe, wildfires have been recognized as one of the most significant environmental threats giving rise to a multitude of environmental, social and economic impacts. However, wildfires are in most cases not originating from natural causes such as lightning, spontaneous ignition, volcanic eruptions, but are rather an anthropogenic phenomenon (see for example Lovreglio *et al*., 2010). Third, unlike other countries in the European Union, from the economic point of view Italy is a country profoundly divided. As it appears from Figure 1A in Appendix, gross domestic per inhabitant in some regions of Northern Italy is among the highest in the European Union, whereas most of the Southern regions have the lowest GDP in the European Union. The historical North-South economic divide sharply increased during the recent sovereign debt crises where a worsening of all the main socio-economic indicators of the Southern regions was observed (see for example Musolino, 2018).

In the crime literature, the relationship between social vulnerability factors and the incidence of crime has for long been an important subject of study. Theoretical models on the determinants of crime point to rational-choice factors that influence the likelihood of environmental crime. For example, in literature pioneered by Becker (1968) criminal's choice is modelled as a standard microeconomic problem of expected utility where an individual chooses whether to commit a crime by comparing its expected benefits with its costs, which can also include an opportunity cost, usually represented by income from a legal activity. Ehrlich (1973) expanded the basic analytical setting of the Becker's model by introducing the interaction between potential offenders (crime supply), deterrence and prevention (government intervention). In Ehrlich (1973) theoretical framework any factor that modifies agents' opportunity cost of legal activities can be included in the analysis of the determinants of crime. The results of empirical research support the prediction of theoretical models that socio-economic factors play a major role in establishing incentives for engaging in crime (see for example Enamorado *et al*., 2016; Coccia, 2017; Fajnzylber *et al.*, 2002; Gould *et al*., 2002).

Accordingly, in this paper, we are interested in addressing the following questions. First, if human induced wildfire is such an important cause of fire ignition, are the types of socio-economic factors that have been found relevant in the crime literature also pertinent for the type of environmental crime considered in this work? In other words, are factors such as poverty, income inequality and unemployment important drivers of wildfire crime? Also, as Italy is a country historically plagued by organized crime, does organised crime play a role? Or is this type of environmental crime more the result of individual perpetrators? In principle according to theoretical crime models (see for example Fajnzylber *et al*., 2002; Ehrlich, 1973), we should see a stronger relationship between socio-economic determinants and wildfire crime in Southern Italian regions with respect to the relatively wealthier Northern regions. Therefore, the second related question we address in this work is the following: Do socio vulnerability factors play a greater role in driving wildfire crime in more deprived regions? In other words, does the North-South economic divide pave the way for wildfire crime? Finally, consensus crime literature agrees that crime rate has a countercyclical behaviour, trending upward during recessions and downward during economic expansions (see for example Bushway *et al*., 2019; Mehlum *et al*., 2006). The supporting arguments for this inverted relationship point at several, sometime contrasting, reasons. First, the quality and quantity of legitimate employment opportunities are procyclical. Higher unemployment rate associated with economic recessions may promote crime by lowering the opportunity cost of time spent in criminal activity (see Grogger, 1998; Gould *et al*., 2002; Machin and Meghir, 2004). Second, the literature has found empirical support that the use of criminogenic commodities such as alcohol or drug abuse are related to the business cycle (see for example Johansson *et al*., 2006, Cook and Moore, 1993; Cook and Durrance, 2013). Third, expenditures in criminal deterrents are also related to business cycles. Accordingly, our third research question is the following: Is wildfire crime also related to the economic cycle? In other words, does the countercyclical relationship found in the crime literature also hold for the type of environmental crime considered in this paper?

In order to answer the above questions, we conducted a three-step investigation. In the first step of the empirical analysis we shed light on the socio-economic drivers of wildfire crime in Italy by using panel data models. Traditionally, in the empirical literature, modellers have tried to identify which environmental and socio-economic factors influence fire occurrence by using linear or nonlinear models in the context of cross-sectional data. For example, Martinez *et al*. (2009) uses the logistic regression model to investigate the causes of human factors associated with high forest fire risk in Spain. Similarly, logistic models and Poisson logistic regression for predicting the number of human-caused fire occurrence have often been used in the literature (see for example Levi and Bestelmeyer, 2016; Marchal *et al.*, 2017). However, the use of pooled linear or nonlinear specifications may leave the estimated model exposed to the unobserved heterogeneity problem leading to biased and inconsistent estimators (see Cameron and Trivedi, 2013). Unlike most of the related literature in this paper we estimate a Poisson fixed effect model that allows controlling for unobserved heterogeneity. Moreover, the adopted model has the advantage of being robust to heteroskedasticity. In particular, by using Poisson panel-data estimation techniques we are able to account for time-invariant region-specific factors that are often omitted in related empirical works. Time-invariant heterogeneity is represented by all those unobservable but relevant components characterizing a region, which are expected to be correlated with observed factors. Examples of region-specific factors are wildfire deterrence mechanism, land use and type, the presence of organized crime. While these instances represent a persistent problem in cross-sectional analysis, using panel data estimation techniques allow us to control for the regional heterogeneity.

The analysis in the first step of our research reveals how the conditional mean of the wildfire crime distribution responds to unit changes of different risk factors. In the model selection procedure several model specifications have been considered and the most parsimonious models have been selected using commonly used model selection criteria. Focusing on the central moment of the wildfire distribution allows us to easily estimate a relatively large number of models and accordingly establish which of the model specifications best describe the data at hand. However, a possible drawback of this type of analysis is that the conditional-mean framework does not allow us to consider the noncentral location of the crime distribution, which may be of interest for the objective of this paper. Accordingly, in the second step of our empirical analysis we complement the estimation results obtained from the fixed effect Poisson model by employing the fixed effect quantile regression model suggested in Machado *et al.* (2019). Quantile regression models are procedures for estimating a functional relationship between the response variable and the explanatory variables for all portions of the probability distribution (see Koenker, 2004). Therefore, the quantile regression analysis allows us to investigate if the social-economic risk factors considered in this work have greater impact on lower or upper tails of the crime distribution function.

The estimation results in the first two steps of our investigation reveal that there is an important relationship between socio-economic factors and wildfire crime. In particular, we find a statistically significant positive relationship between poverty and wildfire crime. Also, risk factors such unemployment, organised crime and income inequality affect the probability of crime in the same direction. On the other side, a statistically significant negative relationship between the level of education, broadly defined, and wildfire crime has been found. The quantile regression analysis reveals that socio-economic risk factors are particularly binding in the poorer Southern regions. Accordingly, in the third phase of our research we proceed to investigate the relationship between the business cycle and wildfire crime by calculating the time varying correlation between income and wildfire crime. The results support our conjecture that economic downturns have a significant impact on the type of environmental crime considered in this paper, thus confirming the findings of other empirical works in the crime literature.

This paper contributes to the literature in several ways. First it provides an extensive analysis on how socio-economic risk factors affect wildfire crime. In the literature, despite the progress in knowledge made with studying the physical facets of the phenomenon, causes of human-related wildfire remain mostly unknown. While other variables associated to fire hazard such as climate change are increasingly investigated, empirical works on the socio-economic factors influencing wildland arson are quite limited. However, given the importance of human risk, any improvement in the modelling and assessment of factors that drive human-made ignitions is critical for fire prevention, planning and management. The proposed methodological approach is the second contribution of the paper. Poisson and quantile regression models allow the researcher to account for heterogeneous covariates effects, while the availability of panel data allows us to include fixed effects to control for unobserved covariates. Third, in this paper we make an attempt to investigate the relationship between business cycle and wildfire crime cycle. Almost all previous empirical work relating to the wildfire modelling is based on climate cycles, however, the well stablished literature on cyclical behavior of macroeconomic fundamentals suggests that the behavior of wildfire crime patterns should stem from the properties of socio-economic determinants such as unemployment, poverty or income inequality, which are all overwhelmingly cyclical.

The remainder of this paper is organised as follows. In Section 2, some theoretical background on the socio-economic determinants of crime is introduced. In Section 3, the results of several models relating to the socio-economic determinants of wildfire are presented. In Section 4, the results of quantile fixed effect regression are presented. In Section 5, the effects of economic downturns are considered. Finally, in Section 6, some concluding remarks are given.

2. Theoretical Background of the Determinants of Crime

The crime literature suggests that socio-economic factors play a major role in the decision by individuals of undertaking criminal activity. However, consensus view agrees that there is no single factor identifying the cause of crime, but rather a number of determinants that interacting induce a social actor in engaging in crime activity. In this paper, we consider few main drivers analyzed in previous studies which are likely to be correlated to other omitted factors: *i*) income inequality, *ii*) poverty, *iii*) unemployment and labour market conditions, *iv*) education, and *v*) organized crime. Below we analyze them in turn in the context of the related literature.

The study on the effect of income inequality on crime was pioneered in the seminal paper by Becker (1968). The author argues that for a given probability of apprehension and expected punishment, higher levels of inequality would increase the expected benefit of committing a crime for the relatively disadvantaged. In a similar theoretical framework Fajnzylber *et al*. (2002) suggest that the effect of income inequality in society is strongly related to the individual's relative income position. Fajnzylber *et al*. (2002) argue that in the case of the wealthy, it is unlikely that an increase in inequality induces them to commit crimes. However, for poorer social actors, an increase in inequality may be crime inducing. This is because such an increase implies a larger gap between the wages of the poor and those of the rich, thus reflecting a larger difference between the income from criminal and legal activities. The idea that inequality causes crime finds support in several theoretical works (see for example Ehrlich, 1973; Imrohoroglu *et al*., 2000). However, strong theoretical models are not always supported by empirical evidence. The results of empirical studies reveal mixed evidence of the positive relation between crime rate and inequality. While some have found evidence of a positive relationship between inequality and crime (e.g. Enamorado *et al*., 2016; Harris and Vermaak, 2015; Coccia, 2017; Fajnzylber *et al.*, 2002), others have failed to find any significant relationship (Bourguignon *et al*., 2000; Neumayer, 2005).

Coming to poverty, although there is little empirical work specifically related to wildfire crime, the literature on the effect of poverty on crime is relevant in this context. The economic theory of crime suggests that individuals are more likely to become involved in criminal activity when they experience a negative income shock. In his seminal work Grossman (1991) frames the relation between crime and poverty in terms of the opportunity cost framework. The author argues that decreasing income levels reduce the opportunity cost of engaging in crime with respect to other legal economic activities (see also Seter, 2016). Similarly, the literature on the socio-economic determinants of criminal behaviour suggests a strong relationship between labour market conditions and crime. Grogger (1998) estimates a structural model of time allocation between criminal, labour market, and other non-market activities and finds strong evidence that higher wages deter criminal activity. Grogger’s (1998) empirical findings show that young men are responsive to wage incentives and that the racial differential in crime rate is in part attributable to labour market. Similarly, Gould *et al*. (2002) find that labour market conditions and especially wages are strongly related to crime rate for those most likely to commit crime (i.e. less educated men).

The relationship between crime and labour market conditions is typically studied by looking at unemployment. In the theoretical literature the relationship between unemployment and crime is grounded in the notion the individuals respond to incentives. This view rests on the assumption that a rational offender should compare the costs and returns of engaging in illegal activities and make decisions accordingly. As rising unemployment reduces the opportunity cost of committing a crime, illegal income become more appealing. In this respect, theoretical models predict a strong positive relationship between unemployment and the propensity to commit crime (see for example, Grogger, 2000). Despite this compelling theoretical argument, empirical studies on the relationship between wildfire crime and unemployment have found mixed results. For example, Maingi and Henry (2007) found no relationship between fire occurrence and unemployment (see also Sebastian-Lopez et al. 2008; Martınez *et al*., 2009; and Lovreglio *et al*. 2010), whereas Prestemon and Butry (2005) showed that arson fires and unemployment were related. A recent strand of literature looks at an indirect relation between labour market and wildfire crime. This literature suggests that forests have been voluntarily set on fire to create firefighting jobs or to gain land for agriculture and pasture, which were retained more valuable than logging (Leone *et al*., 2002).

Looking now at education attainment, an individual's education level may impact on the decision to commit a crime in several ways. The literature has highlighted three main channels. First, there is an income effect that is positively related to education. Higher levels of education attainment may be associated to increasing returns of legitimate work and raising the opportunity costs of illegal behaviour (Lochner, 2004; Lochner and Moretti, 2004). Second, resources allocated to education create time constraints that work as deterrent for criminal offences. Tauchen *et al*. (1994) investigate this "self-incapacitation effect" and found that time spent in education is negatively correlated to the probability conviction among youngsters. Hjalmarsson (2008) looks at the impact of being arrested before finishing school on the probability of graduating from high school and find that the probability of a young person being convicted for crime greatly increase the likelihood of becoming a high school dropout. Third, a stream of literature also associates greater education with higher life satisfaction which in turn reduces the probability of committing a crime. For example, Oreopoulos (2007) and Lochner (2004) suggest that higher levels of education increase risk aversion, thus lowering crime. In an interesting paper Usher (1997) argues that education promotes a "civilization effect" which contributes to reduce the incidence of criminal activity. The author argues that education conveys a civic externality, a benefit to society over and above the benefit to the student in enhancing his future earning power.

Despite the paucity of empirical studies in the environmental crime related literature, the relation between education attainments and wildfire crime appears to be supportive of findings in mainstream crime research. For example, Michetti *et al*. (2019) analysed the determinants of monthly variations in forest fire for Italian regions between 2000 and 2011 and concluded that education attainment played an important role in preventing fraudulent activity. Similarly, De Torres Curth *et al*. (2012) found that the areas with fewer fires tend to be characterized by population with higher levels of education.

As far as organized crime is concerned, studies on the relationship between organized crime and wildfire crime are rare. This is probably due to poor data availability. One of the few empirical works considering this relationship is the EFFACE (2016) report where evidence is found of a positive relation between organized crime (i.e., mafia-like organizations) and number of fire crimes. The influence of organized crime is reported to be stronger in Italy's Southern regions, where the government's ability to enforce the law is weaker. The literature on environmental crime mainly concentrates on the growing role of organized crime on other types of environmental crimes. This is particularly the case of illegal dumping and international illegal trafficking of hazardous waste, where it was found that organised mafia-like criminals play a significant role in the environmental criminality (see for example Germani *et al*., 2018).

3. Model Specification

Let WF_{it} be the wildfire crime count in the region i at time t. Consistent with the relevant literature (see for example Ganteaume *et al*., 2013 and the references therein) we partition the $k \times 1$ vector of risk factors, Z_{it}, as

$$Z'_{it} = [X'_{it} \quad Y'_{it}], \tag{1}$$

where the entry elements of the vector X_{it} are the covariates for social vulnerability risk factors and Y_{it} is a vector of control variables that includes demographic and environmental risk factors. In particular, the vector X_{it} includes risk factors related to income inequality, poverty, violence, educational attainments and labor market conditions. Below, we describe the risk factors in Eq. (1) in turn.

Starting with income inequality two proxies for this covariate were considered: *i*) the Gini coefficient, ($GINI_{it}$) and *ii*) the disposable income inequality, ($INER_{it}$). The Gini coefficient has often been used in the literature to investigate the relationship between crime and income inequality (see for example Fajnzylber *et al*., 2002), however this index may be biased toward the central part of the income distribution. Therefore, in addition to the Gini coefficient, the income quintile share was also considered as a proxy for income inequality. The variable $INER_t$ is defined as the ratio of total income received by the 20% of the population with the highest income to that received by the 20% of the population with the lowest income. According to ISTAT, the variable was calculated using an income equivalent factor to account for the heterogeneity of family compositions such as different needs between children and adults for example or economies of scale generated by sharing the same dwelling. Therefore, it may be suitable to reflect the regional heterogeneity of income inequality on wildfire crime rate.

Closely related to income inequality is poverty risk. In this case two proxy variables for poverty were considered: *i*) proportion of household in economic distress, and *ii*) the proportion of household leaving in severe material deprivation. However, due to the high correlation between these two variables (the calculated correlation coefficient is above 80%), and with the aim of reducing the number of regressors in the estimation, we used principal component analysis over these two indicators to construct a composite measure of poverty risk. The resulting risk factor is referred to as POV_{it}.

Household wealth and labour market conditions were considered inserting in the model covariates for unemployment rate, $UNEM_{it}$, per capita disposable income, INC_{it}, and employment rate in non-agricultural sector, $EMPL_{it}$. To capture the effect of educational attainment on wildfire crime two covariates were used: *i*) the rate of population with a upper secondary level of education, $EDUC_{it}$, and *ii*) the rate of population with tertiary education, $UNIV_{it}$. The rational for including two proxy variables for education attainment is that we expect the return of education on income to be higher for individuals with a university degree. Accordingly, analysing the effect of these two covariates allow us to investigate the magnitude of the "civilization effect" on wildfire hazard described in Usher (1997).

The last risk factor considered is the level of violence. Also in this case, two proxies for violence were considered: *i*) homicide rate, ($HOMR_{it}$), and *ii*) organized crime, ($ORGC_{it}$) defined as the conviction rate for organized and mafia-related crime. The rationale for including homicide rate as well as organized crime convictions is that the latter variable is likely to suffer from a significant measurement error. Organized crime is a difficult phenomenon to capture and using the number of trials for organized crime as the sole covariate to capture the impact of organized crime on wildfire crime may not be informative. In this respect, the inclusion of the covariate "homicide rate" may be useful to signal a significant presence of organized crime in a region. Clearly, the overall homicide rate does not distinguish between homicides committed by criminal organizations and other homicides. On the other hand, it is unlikely to suffer from measurement error and it allows us to test the hypothesis that the degree of violence in a region has an effect on the occurrence of wildfire crime.

Coming to the control variables, the entry elements of vector Y_{it} in Eq. (1) are weather related and demographic risk factors:

$$Y_{it} = [RAIN_{it}, TEMP_{it}, AGRI_{it}, DEN_{it}],$$

where $RAIN_{it}$ is the annual precipitation in mm, $TEMP_{it}$ is the temperature, measured as average highest temperature, DEN_{it} is the population density, and $AGRI_{it}$ is the proportion of population in agricultural employment.

In general weather conditions that cause downward changes in fuel moisture and, consequently, upward changes in fuel availability are expected to increase the probability of wildfire occurrence (see Albertson *et al.* 2009; Plucinski, 2014; Guo *et al.* 2016). Similarly, higher mean and maximum temperatures are expected to have a positive relation with wildfire (see Preisler *et al.* 2004; Carvalho *et al.* 2008; Vilar *et al.* 2010). In the fire related literature an increase of population density has been positively related to wildfire crime. For example, Catry *et al*. (2007) observed that the large majority of the fire ignitions in Portugal occurred in the municipalities with the highest population densities. Gonzalez-Olabarria *et al*. (2015) found that the distribution of arson in North Eastern Spain occurred near coastal areas, where the population density was higher. Similarly Romero-Calcerrada *et al*. (2008) found evidence of a positive relationship between the intensive use of the territory and the ignitions in forest areas in Spain (see also Padilla and Vega-Garcıa, 2011).

Finally, socio-economic transformations in rural areas such as rural exodus, reduction in agricultural employment and abandonment of agricultural land may contribute to wildfire crime occurrence. In the related literature several empirical studies have found positive relation between fire occurrence and agricultural activities (see for example Martınez *et al.*, 2009; Rodrigues *et al.*, 2016 among others). Accordingly, a covariate for the level agriculture employment in the region, $AGRI_{it}$, was included in the model.

3.1. Data

For the empirical investigation we use annual data for the period 2006-2015 for the twenty Italian regions. We calculated crime rates on the basis of population data and the number of crimes reported by Italian Office for National Statistic (ISTAT) for the twenty Italian regions. In particular, the wildfire crime variable is the number of reported cases of deliberate wildfire with known offender plus the total cases of unknown offender. We decided to exclude unintentional forest fires to concentrate on the most severe form of deliberate wildfires.

The time period under consideration was selected according the quality of the available data and by the availability of at least seven consecutive observations. Table 1 reports a description of the acronyms used and some descriptive statistics.

Table 1. Variable list and descriptive statistics.

Variable Name	*Description*	*Mean*	*Standard Deviation*
WF_{it}	Arsons crime rate (per 100,000 persons)	10.63	13.37
$INER_{it}$	Quintile share ratio (S80/S20) for disposable income: ratio between average income of the top quintile and average income of the bottom quintile	5.04	1.08
$GINI_{it}$	Gini index of household disposable income	0.31	0.02
$ORGC_{it}$	Organized crime and mafia-related crime rate (per 100,000 persons)	2.07	1.51
$HOMR_{it}$	Homicides rate per 100,000 inhabitants.	0.84	0.59
$EDUC_{it}$	Percentage of the population aged 25–64 with secondary education attainment	41.12	4.71
$UNIV_{it}$	Percentage of the population aged 25–64 with tertiary education attainment	15.26	2.67
$EMPL_{it}$	Employment in non-agricultural sector for the working-age population	825458.7	802060.3
INC_{it}	Per Capita Income	17462.4	3445.02
POV_{it}	Principal component analysis of: *i*) proportion of household in economic distress, and *ii*) proportion of household leaving in severe material deprivation.	9.75	1.00
$UNEM_{it}$	Total unemployment rate	9.70	4.95
DEN_{it}	Population density	183.99	111.63
$RAIN_{it}$	Total precipitation in mm in a given year	826.67	201.88
$TEMP_{it}$	Average maximum temperature in Celsius in a year	17.30	4.09
$AGRI_{it}$	Percentage of employment rate in the agricultural sector	4.57	2.49

Source: ISTAT: The National Institute for Statistics and authors' calculations.

3.2. Poisson Fixed Effect Analysis

To investigate the effect of risk factors in Eq. (1) we consider a Poisson fixed effect panel model (for an excellent review see Cameron and Trivedi, 2013). In the cross-section context, Poisson-type models have been used to investigate many problems in criminology and criminal justice (see for example Osgood, 2000 and the references therein). The advantage of using Poisson regression models is that the hypothesis of linearity is relaxed in the sense that a function of the mean of the observations is nonlinear in some set of covariates. The hypothesis of normality is also relaxed to the assumption that the distribution belongs to the exponential family. In the context of longitudinal data, the application of Poisson-type models is still limited. However, Poisson fixed effect models have been used for predicting the number of human-caused wildfire in Prestemon and Butry (2005); see also Levi and Bestelmeyer (2016); Marchal *et al*. (2017).

Let WF_{it} be the wildfire crime count in the region *i* at time t. The conditional density function of WF_{it} is defined as

$$f(WF_{it}|Z_{it}) = \frac{e^{-\mu_{it}}\mu_{it}^{WF_{it}}}{WF_{it}!}, \qquad (2)$$

where Z_{it} is a vector of *k* risk factors and

$$\mu_{it} \equiv E[WF_{it}|Z_{it}, \alpha_i] = \alpha_i \lambda_{it} = \alpha_i exp(Z'_{it}\beta), \tag{3}$$

where α_i is the regional individual effect. The regional fixed effect controls for unobserved region-level heterogeneity, but α_i may be potentially correlated with the regressors Z_{it}. However, consistent estimation of the parameters β is possible by eliminating α_i (for more details see Cameron and Trivedi, 2013).

In Eq. (2) we assume that the arson outcome, in a region *i* at time *t*, is a count of arson crime, WF_{it}. Because wildfire crime count are discrete and nonnegative events, for each region *i*, the stochastic process $\{WF_i, t \geq 0\}$ satisfies the property that $WF_i(s) \leq WF_i(t)$ if $s < t$, and $WF_i(t) - WF_i(s)$ is a number of events in the interval $(s, t]$.

Under the assumption that the observations are independent, the conditional density function in Eq. (2) can be expressed as

$$Pr(WF_{it} = wf_{it}|Z_{it}) = exp\{-\exp(\alpha_i + Z_{it}\beta)\}exp(\alpha_i + Z_{it}\beta)^{wf_{it}}/wf_{it}!. \tag{4}$$

Since the sum of n_i Poisson independent random variables, each with parameter λ_{it} for $t = 1, \ldots, n_i$ is distributed as Poisson with parameters $\sum_t \lambda_{it}$, the likelihood function can trivially be calculated from Eq. (4). Thus, the model in Eq. (2) can be estimated by maximizing the conditional log likelihood

$$L = log \prod_{i=1}^{n_i} \left[\left(\sum_{t=1}^{n_i} wf_{it}\right)! \sum_{t=1}^{n_i} \frac{exp(Z_{it}\beta)^{wf_{it}}}{wf_{it}!\left\{\sum_{l=1}^{n_l} exp(Z_{il}\beta)^{wf_{it}}\right\}} \right]^{\vartheta_i}, \tag{5}$$

where ϑ_i is the weight for region *i*. Assuming gamma heterogeneity the log likelihood function Eq. (5) reduces to

$$L = \sum_{i=1}^{n} \vartheta_i \left\{ \log \Gamma\left(\sum_{t=1}^{n_i} wf_{it} + 1\right) - \sum_{t=1}^{n_i} log\Gamma(wf_{it} + 1) + \sum_{t=1}^{n_1} wf_{it} log\pi_{it} \right\},$$

where

$$\pi_{it} = \frac{exp(wf_{it}\beta)}{\sum_l exp(wf_{it}\beta)}.$$

Model Selection Procedure

In Eq. (1) more than one proxy variable for a given socio-economic risk factor is considered. Accordingly, to estimate the expression in Eq. (2) we proceed following a general-to-specific modelling criteria and select the subset of best fitting models from a set of candidate specifications. Throughout the model selection procedure, the possible presence of multicollinearity was assessed using the eigenvalues of the different covariance matrices and computing the conditioning index (CI). Following Pena and Renegar (2000) the CI index is calculated as

$$CI = \sqrt{\frac{\lambda_{max}}{\lambda_{min}}} \tag{6}$$

where λ_{max} is the largest eigenvalue and λ_{min} the smallest eigenvalue of the variance covariance of the risk factor matrix Z_{it}. If $CI = 1$, then there is no evidence of collinearity between the covariates in the estimated model. However, as collinearity increases, the eigenvalues in Eq. (6) becomes both greater and smaller than 1 and the CI number increases. Pena and Renegar (2000) suggests $CI < 10$ for a well-defined matrix as opposite to $11 < CI < 30$ for moderate multicollinearity. Accordingly, the condition we imposed for introducing a covariate in the final model specification was a calculated CI number less than 10.

To select the best model specification, for each model, we calculated the Akaike's Information Criterion (AIC) scores and the Bayesian information criterion (BIC). AIC is an estimate of the relative Kullback–Leibler (KL) information loss in a specific model based on the data and is appropriate for model comparisonss. A lower AIC score indicates less KL information loss, and therefore a better specified model. AIC includes a penalty for the number of estimated parameters, which diminishes overfitting. The BIC criterion has a similar interpretation but is calculated using a different penalty for the number of parameters (see Burnham and Anderson 1998 for more details). Using these information criteria, we identified as the most plausible models the specification with the lowest AIC and BIC scores, among all models meeting the CI index condition.

Coming to the model misspecification tests, the assumption of serially uncorrelated structure of the error term has been assessed by testing the null hypothesis that there is no serial correlation in residuals using the Hausman and Newey (1984) test. The test is based on the off-diagonal elements of the residual correlation matrix and is asymptotically χ^2-distributed. Failure to reject the null hypothesis of no first order autocorrelation indicates that the model is not well specified.

3.3. Empirical Results

In Table 2 the estimated coefficients of the four best fitting models are reported. We label the models as M1, M2, M3 and M4, respectively. The estimated coefficients, along with the related robust standard errors, are reported in columns 2, 4, 6 and 8, respectively. An asterisk next to the estimated parameter indicates the level of statistical significance of the estimated coefficients. For easy of interpretation, the incidence rate ratios (IRR) are also reported in columns 3, 5,7, and 9. To avoid clutter, the CI index for each estimated model is reported in Table 1A.

In Table 2, model M1 and M3 include POV_{it} as risk factor, whereas in models M2 and M4 the risk factor $UNEM_{it}$ is included in the model, but the covariate POV_{it} is excluded. The reason for this specification is that these two covariates were found to be highly correlated and therefore only one risk factor at the time was considered. Similarly, the covariates $EDUC_{it}$ and $UNIV_{it}$ produced an high CI index. Accordingly, the former covariate was included in model M1 and M3, but excluded from model M2 and model M4. Surprisingly, the two proxies for violence, $ORGC_{it}$ and $HOMR_{it}$, were not found to be highly correlated (the correlation coefficient is 0.31) and the CI index in all the estimated models was found to be less than 10. For this reason, both risk factors were included in the models.

Table 2. Risk factors of wildfire crime rate.

Risk Factors	M1		M2		M3		M4	
	$Coef$	*IRR*	$Coef$	*IRR*	$Coef$	*IRR*	$Coef$	*IRR*
$INER_{it}$	0.073** (0.362)	1.076	0.012* (0.034)	1.122	-	-	-	-
$GINI_{it}$	-	-	-	-	1.611* (0.060)	5.010	1.380** (0.697)	3.973
$ORGC_{it}$	0.070* (0.008)	1.072	0.064* (0.011)	1.067	0.063* (0.006)	1.065	0.067* (0.011)	1.070
$HOMR_{it}$	0.239** (0.222)	1.270	0.071 (0.090)	1.074	0.188** (0.806)	1.207	0.082 (0.110)	1.085
$EDUC_{it}$	-0.084* (0.029)	0.919	-	-	-0.013 (0.035)	0.986	-	-
$UNIV_{it}$	-	-	-0.079* (0.028)	0.923	-	-	-0.074** (0.029)	0.929
$EMPL_{it}$	-	-	-	-	-2.608* (0.804)	0.074	-	-
INC_{it}	-	-	-	-	-	-	-3.587** (1.192)	0.027
POV_{it}	0.092** (0.041)	1.096	-	-	0.093** (0.041)	1.097	-	-
$UNEM_{it}$	-	-	0.031* (0.009)	1.031	-	-	0.041** (0.012)	1.042
DEN_{it}	0.031 (0.032)	1.031	0.026 (0.020)	1.026	0.022 (0.024)	1.023	0.021 (0.021)	1.021
$RAIN_{it}$	-0.001* (0.000)	0.998	-0.001* (0.000)	0.998	-0.001* (0.000)	0.998	-0.001* (0.000)	0.998
$TEMP_{it}$	0.109*** (0.098)	1.115	0.135** (0.061)	1.145	0.121 (0.086)	1.129	0.139** (0.051)	1.149
$AGRI_{it}$	-0.610*** (0.357)	0.543	-0.626*** (0.373)	0.534	-0.504*** (0.308)	0603	-0.583*** (0.245)	0.557
Pseudo Lik.	-288.69		-298.13		-282.37		-298.37	
Serial Corr.	0.567		0.452		0.891		0.826	
AIC	595.39		614.26		817.30		614.97	
BIC	622.42		641.93		846.18		645.69	

Note: The table report the estimated coefficients of the Poisson fixed effect panel (robust standard errors are presented in parentheses below their corresponding coefficients) with dependent variable WF_{it}. Asterisks *), **), ***) denote statistical significance at 1%; 5%; and 10%, respectively.

From Table 2 it appears that there is a positive relation between income inequality and wildfire crime as the estimated signs for $INER_{it}$ and $GINI_{it}$ in models M1-M4 are uniformly positive and the estimated coefficients are statistically significant. Following the theoretical model in Becker (1968) the positive effect of income inequality on the wildfire crime can be interpreted according to the cost-benefit framework where the magnitude of the income inequality coefficient measures the impact of the difference between the returns to crime and its opportunity cost (as measured by the legal income of the most poorer individuals). However, this argument purely based on rational behavior of agents, in the case of environmental crime may underestimate the importance of the social-economic environment in which social actors interact. Following Fajnzylber (2002), an alternative interpretation of the positive link between inequality and crime is that in regions with higher income inequality, individuals have lower expectations of lifetime improvement of their social-economic status through legal economic activities, which would decrease the opportunity cost of participating in illegal endeavors more generally.

The estimated coefficients of the income inequality covariates are not only statistically significant, but they are also important in magnitude. This is particularly the case for the Gini coefficients estimated in models M3 and M4. The incidence rate ratios indicate that the probability of fire crime occurrence is between four (model M3) and five time (model M4) higher in regions with higher income inequality with respect to regions that enjoy a lower Gini coefficient.

Coming to the effect of violence, the estimated coefficients for $ORGC_{it}$ are positive and statistically significant throughout the estimated models, whereas the estimated parameters for $HOMR_{it}$ are of the expected sign, but significant only in models M2 and M3. The magnitude of the estimated coefficient for $ORGC_{it}$ does not varies much throughout the estimated models and the incidence rate ratios indicate that in regions with higher rate of arrest for organized crime the probability of wildfire crime is also approximately 1.07 higher than regions with lower rate of arrest for organized crime. This result is significant since according to a report by the Italian Antimafia Directorate environmental crime is currently one of the most profitable forms of criminal activity and eco-mafia has become a big business in the waste sector in Italy (see Savona and Riccardi, 2018). Previous literature has found that organized criminal networks are involved in the illegal disposal of commercial, industrial and radioactive waste (see for example Germani *et al*., 2018). However, the relation between organized crime and wildfire crime has not been previously investigated. Bearing in mind that organised crime is deeply rooted in Italy this result may have important implications on crime deterrence policy.

Looking at the role of education, the results in Table 2 suggest that there is a negative relationship between education attainment and wildfire crime count throughout the estimated models. In model M1 a percentage increase in secondary education leads to a decrease of 8% in wildfire crime, which translate to an incidence ratio rate of approximately 0.92. This reduction increases to 13% in model M3 and the incidence ratio falls to 0.08, accordingly. This result suggests that the "civilization effect" discussed in the crime literature is also an important deterrent for wildfire crime. Looking at the effect of tertiary education in models M2 and M4, the estimated coefficients are not very different in magnitude with respect to those in model M1 and M3. A negative relation between education level and fire risk is also found to be significant in De Torres Curth *et al.* (2012).

Coming to unemployment, the estimated parameters in models M2 and M4 support the view that a worsening of labour market conditions increase the probability of wildfire crime count. In general, the findings in Table 2 confirm previous empirical results in the related literature that unemployment is an important risk factor in causing wildfire crime (see Mercer and Prestemon, 2005; Prestemon and Butry, 2005; Martınez *et al*., 2009). More specifically, in model M2 a percentage decrease in unemployment leads to a decrease about 3% in wildfire crime; model M3 reports similar results. Similarly, an increase in per capita income reduces the incidence of wildfire crime rate in model M3.

Looking now at the demographic risk factor, we do not find evidence that an increase of population density increases the probability of crime count, as the estimated coefficients are not significant in all the estimated models. This result may be due to the fact that the nonlinear specification of the Poisson model may not be the best specification to capture the influence of this covariate.

Coming to the weather related factors, from Table 2 it appears that weather conditions play a significant role in the wildfire crime count as the estimated coefficients are significant and of the expected sign. It is well known that the Mediterranean summer weather conditions (high temperature, prolonged drought periods and strong winds) facilitate wildfire occurrence; see for example Vasilakos *et al*. (2008) among others. In this respect, the results in Table 2 mainly confirm the results in the related literature.

Finally, looking at the estimated coefficient for $AGRI_{it}$, it appears that an increase of agricultural employment strongly reduces the probability of wildfire crime. This may be due to the conservation and land management role that farmers play in rural areas. These results are in agreement with Martinez *et al*. (2009) where land abandonment and rural exodus were found to be positively related to wildfire occurrence.

The bottom panel of Table 2 reports the *p*-values for the serial correlation test discussed in the previous section. The results show that all the estimated models pass the misspecification test, as the null hypothesis of serial correlation is rejected in all cases. Furthermore, the AIC and BIC information criteria suggest that the best fitting specifications are model M1 and M2, since they have the lower score than models M3 and M4.

To summarize, the estimation results provide evidence that supports theoretical prediction in Section 2. In particular, we found a statistically significant and positive relationship between poverty and wildfire crime. Risk factors such unemployment, organized crime and income inequality affect the probability of crime in the same direction. On the other side, a negative and statistically significant relationship between the level of education, broadly defined, and wildfire crime has been found. These findings are important since they are in line with the results for other type of environmental crimes examined in the literature (see for example Sedova, 2016).

4. Quantile Based Estimation of Wildfire Crime and Socio-Economic Factors

Above the relationship between wildfire crime and social-economic factors has been investigated. However, we consider an heterogeneous group of Italian regions with quite different economic performance over time (see Figure 1A in Appendix). The North-South divide has been a distinctive feature of the Italian economic development since the beginning of the 20th century. Historically, the gap in term of GDP growth was relatively small just after the country unification in 1861, but it increased steadily over time so much so that by the 1950s it was close to 50% of the GDP per capita in the Centre-North, and it never significantly changed thereafter, ranging from 55% to 60% until the present day (see Musolino, 2018). Labour productivity has also historically been significantly lower in Southern Italy. Similarly, high unemployment rate has contributed to maintain a significant gap in income inequality and poverty rate with respect to the Northern and Central regions. Not only the North-South divide constitutes a main source of heterogeneity, but differences in term of economic development and economic performance are quite remarkable also within the macro-regions. Notably, Central and Northern regions have been the core of Italian economic development since the end of Second World War, but the development model was quite different. On one side, the North-Western regions had a development model based on Fordist organization heavily relying on large firms and heavy industry. On the other side, economic growth in the North Eastern regions was based on the industrial district model (see for example A'Hearn and Venables, 2013). Different models of economic developments have brought about important differences in term of income distributions and inequality.

Against this background, a number of questions naturally arise. Is there a regional effect of wildfire crimes in Italy? Has the heterogenous distribution of wealth across regions affected the occurrence of environmental crimes such as wildfire? In other words, if socio-economic factors are important drivers of crime, we should see greater crime level in poorer and more inequal regions. A related question is therefore, does an increase of risk factors analyzed in the previous section have similar impact across Italian regions?

To tackle the research questions above we consider the properties of the cumulate distribution functions of wildfire crime and the related socio-economic determinants. To be more specific, we consider the distribution function of each element of the vector

$$\tilde{X} = [WF, INER, ORGC, HOMR, EDU, POV, UNEM, INC\ ].$$

Note that, to simplify the notation, the *i* and *t* subscripts for each variable have been dropped below. Let j (for $j = 1, \dots, 8$) be an element of the vector $\tilde{X}$, then for any j we can define $F_j(\tilde{X}) = Pr\{\tilde{X} \leq x\}$ as the distribution function of X_j and the quantile function as

$$Q_j(p) = F^{-1}(p) = \inf\{x|F(x) \geq p\},$$

with $p \in [0,1]$. For each element of $\tilde{X}$ let the proportion of total outcome that falls into the quantile interval $(Q_{j,p_{l-1}}, Q_{j,p_l})$, for $p_{l-1} \leq p_l$ be

$$S_j(p_{j,l-1}, p_{j,l}) = \frac{\int_{-\infty}^{Qp_l} xdF(x) - \int_{-\infty}^{Qp_{l-1}} xdF(x)}{\int_{-\infty}^{\infty} xdF(x)}. \qquad (7)$$

The expression in Eq. (7) defines the quantile shares and it allows us to investigate the shares of total outcome pertaining to the population segment from relative rank $Q_{j,p_{l-1}}$ to relative rank Q_{j,p_l} in the list of ordered outcomes.

Table 3 reports the estimates of the quantile shares of each element of the vector $\tilde{X}$ and the related estimated standard errors. In particular, the fist column reports the factors of the vector $\tilde{X}$, whereas in columns 2-11 the estimated proportion of the total outcome that falls into each quantile are described. For ease of interpretation, the proportions are reported in percentage and the quantile are expressed in term of percentile shares.

Table 3. Estimated proportions of total outcome by percentile share in percentage.

Risk Factors	*Quantiles*									
	10%	20%	30%	40%	50%	60%	70%	80%	90%	100%
WF	0.73	1.54	2.25	3.30	4.89	6.57	9.43	12.29	17.22	41.73
	(0.110)	(0.183)	(0.249)	(0.377)	(0.469)	(0.538)	(0.689)	(0.707)	(0.817)	(2.782)
INER	7.66	8.18	8.58	8.90	9.21	9.56	10.12	10.86	12.03	14.85
	(0.112)	(0.111)	(0.112)	(0.109)	(0.101)	(0.127)	(0.111)	(0.127)	(0.195)	(0.474)
ORC	2.39	4.88	5.75	6.79	7.75	8.88	10.55	12.40	15.44	25.14
	(0.474)	(0.255)	(0.297)	(0.307)	(0.305)	(0.348)	(0.437)	(0.452)	(0.551)	(2.140)
HOMR	1.89	4.32	6.05	7.13	7.67	9.13	10.48	12.10	14.69	26.52
	(0.427)	(0.504)	(0.319)	(0.340)	(0.331)	(0.344)	(0.362)	(0.445)	(0.471)	(1.764)
EDU	7.93	8.52	9.12	9.64	10.03	10.34	10.64	10.88	11.17	11.67
	(0.064)	(0.087)	(0.123)	(0.086)	(0.047)	(0.057)	(0.055)	(0.064)	(0.070)	(0.102)
POV	2.89	3.84	4.79	5.74	6.96	8.62	11.89	15.07	18.09	22.08
	(0.141)	(0.200)	(0.210)	(0.208)	(0.307)	(0.359)	(0.735)	(0.455)	(0.484)	(0.822)
UNEM	3.48	4.92	5.95	7.24	8.43	9.75	11.24	12.84	14.90	21.19
	(0.171)	(0.216)	(0.266)	(0.249)	(0.242)	(0.263)	(0.255)	(0.250)	(0.564)	(0.596)

From Table 3 it appears that wildfire crime density function is highly skewed, since approximately 60% of wildfire crimes are concentrated in regions that are located in the higher quantiles of the cumulate distribution function. Namely, regions in the top 30th quantile account for approximately 60% of the proportion of the wildfire crime in the sample under consideration. On the other side, regions in the bottom 30th quantile only get less than 5% of wildfire crime. It is interesting to note that the distributions of $ORGC$ and $HOMR$ and most of the other socio-economic indicators seem to follow a similar pattern. In particular, from Table 3 it appears that the regions in the in top 30th quantiles have 52.98% of organized crime convictions and 53.31% of homicides out of the total crimes, respectively. This contrast with regions in the bottom 30th quantile where the percentile shares decreases to 13.02% for organized crime convictions and 12.26% for homicide prosecutions, respectively. Similarly, the distribution of poverty and unemployment are highly skewed, with the top 30% worst performing regions in the sample receiving 55.24% and 48.93% of the total share in term of poverty and unemployment, respectively. Looking at $INER$, the ratio between average income of the top quintile and the average income of the bottom quintile is also a left tailed distribution with 37.74% of the share being in the higher top 30th quantiles. Finally, the education distribution seems to be quite uniform across Italian regions, with only marginal differences between top and worst performing regions.

4.1. Quantile Fixed Effect Regression Analysis

In the previous section we have investigated the role of socio-economic risk factors and other control variables on the probability of wildfire crime occurrence. With this target in mind, we have considered the effects of the risk factors in the $k \times 1$ vector Z_{it} of Eq. (1) on the conditional mean of WF_{it}. The econometric model used to estimate Eq. (2) allows us to answer the question of whether a given risk factor considered on the right hand side of the equation affects the conditional mean of WF_{it}. However, in the light of the results in Table 3, the focus on the conditional mean of the WF distribution may hide important features of the relation between the socio-economic risk factors under consideration and the level of observed crime. Accordingly, in this section we are interested in answering a related question: Does a one unit increase of a given risk factor of vector Z_{it} in Eq. (1) affects regions with lower wild crime rate differently from regions with higher fire crime rate? In other words, do risk factors have a different impact on the probability of wildfire crime occurrence in regions at the bottom quantile with respect to regions in the top quantile?

To consider if the marginal effects of vulnerability factors in vector Z are different for regions that are in the top quantile of the WF distribution with respect to regions that are in the bottom quantile we focus on the estimation of $Q_{WF_{it}}(p \mid Z_{it})$. Unlike the relationship in Eq. (2), where only the conditional distribution of $E(WF_{i,t}|Z_{i,t})$ was considered, we now take into account the functional relationship between wildfire crime and socio-economic risk factors for each portion of the probability distribution function. With this target in mind we estimate the conditional quantiles $Q_{WF}(p \mid Z_{i,t})$ using a model of the form

$$WF_{i,t} = \alpha_i + Z'_{i,t}\beta + (\delta_i + M'_{it}\gamma)\varepsilon_{it},$$

with $\Pr(\delta_i + M'_{it}\gamma > 0)$, and M is a ζ-vector of known differentiable (with probability 1) transformations of the components of Z with element l given by $M_l = \phi_l(Z)$. The p-th conditional quantile function of the response $WF_{i,t}$ can be represented as

$$Q_{WF_{i,t}}(p|Z_{i,t}) = (\alpha_i + \delta_i Q(p)) + Z_{i,t}'\beta + M'_{i,t}\gamma Q(p). \qquad (8)$$

where the parameters (α_i, δ_i), $i = 1, \ldots, n$, capture the i-region fixed effects so that the scalar coefficient $\alpha_i(p) \equiv \alpha_i + \delta_i Q(p)$ the quantile-p fixed effect for region i.

The model in Eq. (8) can be estimated using the method of moment-quantile regression as suggested in Machado and Santos Silva (2019). The proposed estimation method is closely related to that of Chernozhukov and Hansen (2008) in the sense that under suitable regularly conditions it identifies the same structural quantile function, but it has the advantage of being computationally simpler to estimate. Moreover, the estimation method allows the individual effects to affect the entire distribution, rather than being just location shifters as in the earlier models in Koenker (2004) and Canay (2011); see Machado and Santos Silva (2019) for more details.

Table 4 reports the estimated parameters for the quantiles $p \in \{0.1, \ldots, 0.90\}$ along with the associated standard errors. Note that the results in Table 4 only relate to models M1 and M2 as these two models beat the specification in models M3 and M4 according to the BIC and AIC information criteria. In Table 4, column 2-10 report the estimated coefficients and the relative robust standard errors.

Looking at the results in Table 4 it appears that, the estimated coefficients of income inequality are positive and significantly different from zero only for regions above the 40th and 50th quantile of the *WF* distribution, for model M1 and M2 respectively. Therefore, the effect of income inequality on wildfire crime only becomes a risk factor when the difference between the average income of the top quintile of the population and average income of the bottom quintile is relatively high. This effect is also reflected in the magnitude of the estimated coefficients for $INER_{it}$, as the estimated parameters are relatively low for regions below the median quantile of the *WF* distribution; but increase sharply for those regions located in the top quantile. Therefore, the marginal effect on *WF* of one unit increase of *INER* in regions in the top quantile is much greater than the marginal effect in regions that enjoy the desirable position at the bottom quantile. Coming to the impact of unemployment and poverty, the positive signs of the estimated parameters confirm the results in Table 2. However, it appears that, in this case, these risk factors are important even for regions that are at the bottom quantile of the *WF* distribution, as the estimated parameters for both POV_{it} and $UNEM_{it}$ are statistically significant for all, but the 90th quantile. Note that very high (low) quantiles are notoriously difficult to estimate accurately since there are relative fewer observations in the tails of the distribution. This is probably the reason why the estimated coefficient of $UNEM_{it}$ for the 90th quantile is found to be not significantly different from zero.

Looking at the effect of organized crime and homicide rates, once again, in Table 4 the estimated coefficients have positive signs denoting a positive relation between wildfire crime and violence, broadly defined. However, while the estimated coefficient for $ORGC_{it}$ is significant only for regions that are above the 30th and 40th quantile of the wildfire crime distribution (for model M1 and M2 respectively); the covariate $HOMR_{it}$ presents estimated parameters that are significant throughout the estimated quantiles. This result highlights the fact that wildfire crime is strongly related to local criminal organizations, thus confirming the literature findings for other types of environmental crimes (see for example Germani *et al*., 2018).

Considering the effect of education on wildfire crime, the results are mixed. From Table 4a it appears that $EDUC_{it}$ has the expected negative signs throughout the estimated quantiles when model M1 is considered. However, the estimated parameters are not statistically significant. For model M2, in Table 4b, the estimated coefficients have the expected signs for the higher quantiles, but the estimated coefficients are not significantly different from zero. These results contrast with the findings in Table 3 where the level of education was found to be significant and of negative sign. One reason for the result in Table 4 is that the linearity assumption made in Eq. (8) may be less suitable to describe the relation between this covariate and the dependent variable. Similarly, the control factor $RAIN_{it}$ has the correct sign, but the estimated coefficients are not significantly different from zero throughout the estimate quantiles. This result is probably due to the fact that the heterogeneity of the rain distribution across Italian regions makes the relation between wildfire occurrence and rain genuinely nonlinear.

The estimated coefficients of DEN_{it} have negative signs and are statistically significant. These results contrast with the findings in Table 2 where the estimated parameters for this covariate were found to be not significantly different from zero. However, the estimated coefficients for population density change very little across quantiles, both in Table 4a and Table 4b. Moreover, the magnitude of the estimated parameters is between 0.004 and 0.005, meaning that a unit increase in population density increase the wildfire crime between 0.4% and 0.5%. Such small estimated parameters cast some doubts on the actual impact of this covariate on wildfire crime for the data at hand. Finally, the effect of employment in the agricultural sector present mixed results as it is not significant in model M1, but significant up to the 80th quantile and with the correct sign for model M2.

Table 4. Wildfire crime and vulnerability factors using fixed effect quantile estimation.

Risk Factors	*Quantiles*								
	10	20	30	40	50	60	70	80	90
$INER_{it}$	0.116	0.128	0.147	0.159^{***}	0.174^{**}	0.188^{**}	0.198^{**}	0.210^{**}	0.232^{***}
	(0.153)	(0.133)	(0.103)	(0.089)	(0.080)	(0.083)	(0.091)	(0.105)	(0.140)
$ORGC_{it}$	0.110	0.111	0.115^{***}	0.116^{**}	0.119^{***}	0.120^{**}	0.122^{**}	0.124^{**}	0.127^{***}
	(0.091)	(0.078)	(0.061)	(0.052)	(0.047)	(0.049)	(0.054)	(0.062)	(0.084)
$HOMR_{it}$	0.759^{*}	0.691^{*}	0.582^{*}	0.511^{*}	0.424^{*}	0.341^{*}	0.290^{**}	0.219^{***}	0.083^{*}
	(0.186)	(0.159)	(0.127)	(0.111)	(0.100)	(0.103)	(0.112)	(0.129)	(0.169)
EDU_{it}	-0.056	-0.048	-0.036	-0.028	-0.018	-0.008	-0.002	-0.005	0.020
	(0.042)	(0.036)	(0.028)	(0.025)	(0.022)	(0.023)	(0.025)	(0.029)	(0.039)
POV_{it}	0.304^{**}	0.296^{**}	0.283^{*}	0.274^{*}	0.262^{*}	0.252^{*}	0.245^{*}	0.237^{**}	0.220^{***}
	(0.151)	(0.131)	(0.102)	(0.088)	(0.079)	(0.081)	(0.090)	(0.103)	(0.140)
DEN_{it}	-0.004^{*}	-0.004^{*}	-0.004^{*}	-0.004^{*}	-0.004^{*}	-0.004^{*}	-0.004^{*}	-0.004^{*}	-0.004^{*}
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
$RAIN_{it}$	-0.003	-0.003	-0.003	-0.004	-0.003	-0.002	-0.002	-0.003	-0.003
	(0.008)	(0.007)	(0.005)	(0.005)	(0.003)	(0.004)	(0.004)	(0.005)	(0.007)
$TEMP_{it}$	0.025	0.030	0.037^{*}	0.042^{*}	0.047^{*}	0.053^{*}	0.057^{*}	0.061^{*}	0.071^{*}
	(0.028)	(0.242)	(0.018)	(0.016)	(0.014)	(0.015)	(0.016)	(0.019)	(0.025)
$AGRI_{it}$	-0.305	-0.267	-0.207	-0.167	-0.119	-0.073	-0.039	-0.005	-0.070
	(0.441)	(0.381)	(0.297)	(0.256)	(0.230)	(0.228)	(0.263)	(0.301)	(0.409)

Table 4 (Continue). Wildfire crime and vulnerability factors using fixed effect quantile estimation.

Risk Factors	*Quantiles*								
	10	20	30	40	50	60	70	80	90
$INER_{it}$	0.012	0.029	0.063	0.086	0.110^{***}	0.136^{***}	0.170^{***}	0.203^{**}	0.229
	(0.147)	(0.131)	(0.106)	(0.093)	(0.051)	(0.091)	(0.081)	(0.101)	(0.158)
$ORGC_{it}$	0.062	0.069	0.082	0.091^{**}	0.100^{**}	0.110^{**}	0.123^{**}	0.135^{***}	0.146
	(0.086)	(0.078)	(0.062)	(0.055)	(0.051)	(0.053)	(0.054)	(0.079)	(0.093)
$HOMR_{it}$	0.699^{*}	0.662^{*}	0.587^{*}	0.534^{*}	0.481^{*}	0.423^{*}	0.290^{*}	0.275^{***}	0.216
	(0.171)	(0.150)	(0.123)	(0.111)	(0.103)	(0.107)	(0.112)	(0.155)	(0.182)
EDU_{it}	0.012	0.010	0.007	0.004	0.019	-0.008	-0.002	-0.008	-0.010
	(0.037)	(0.033)	(0.023)	(0.023)	(0.022)	(0.023)	(0.025)	(0.034)	(0.040)
$UNEM_{it}$	0.187^{*}	0.178^{*}	0.160^{*}	0.148^{*}	0.136^{*}	0.122^{*}	0.245^{*}	0.087^{***}	0.074
	(0.055)	(0.049)	(0.039)	(0.035)	(0.033)	(0.034)	(0.090)	(0.050)	(0.059)
DEN_{it}	-0.004^{*}	-0.004^{*}	-0.005^{*}	-0.004^{*}	-0.005^{*}	-0.004^{*}	-0.004^{*}	-0.005^{*}	-0.005^{*}
	(0.001)	(0.001)	(0.001)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.001)
$RAIN_{it}$	-0.001	-0.003	-0.002	-0.001	-0.001	-0.002	-0.002	-0.001	-0.002
	(0.007)	(0.005)	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.006)	(0.007)
$TEMP_{it}$	-0.006	0.001	0.011^{*}	0.019^{*}	0.028^{*}	0.036^{**}	0.057^{**}	0.059^{**}	0.068^{**}
	(0.026)	(0.023)	(0.019)	(0.017)	(0.016)	(0.016)	(0.016)	(0.024)	(0.028)
$AGRI_{it}$	-0.602^{**}	-0.586^{***}	-0.555^{**}	-0.533^{**}	-0.511^{**}	-0.487^{**}	-0.039^{***}	-0.426	-0.402
	(0.359)	(0.322)	(0.258)	(0.227)	(0.213)	(0.221)	(0.263)	(0.326)	(0.386)

Note: The table reports the estimated parameters and the robust standard errors (in brackets) of the quantile regression with dependent variable WF_{it}. * Significant at 1%; ** Significant at 5%; *** Significant at 10%.

5. Business Cycles and Wildfire Crime

In his influential paper Becker (1968) specified a crime production function where the decision of engaging in crime is a negative function of the probability of being caught and a negative function of income-equivalent loss experienced by the offender for being caught and convicted. According to Becker's model anything that raises the crime production cost, lowers the expected utility of the crime. In this respect, we expect the opportunity cost of crime to be lower during contraction phases of the business cycle. This is because GDP growth contractions are usually accompanied by an increase in unemployment, lower income, and greater deprivation. Also, reduced central and local income tax during contraction periods may result in budgets cuts for crime prevention policy which in turn reduce the probability of being held accountable for the crime committed. Given the reduction of crime production costs, we therefore expect higher correlation between income and wildfire crime over contraction periods and lower correlation during expansion periods.

As other Southern European countries, Italy has undergone a prolonged recession period due to the sovereign debt crisis that started in 2009. The dip contraction in economic growth led to an increase in inequality and poverty by hitting the bottom of the income distribution more severely. The Southern regions were particularly affected by the economic crisis as they experienced a contraction in income transfer coupled with a sharp increase in unemployment rate. In this respect, a deterioration of economic fundamentals in a region may play a role in human-induced forest fires. A study by Leone *et al*. (2002) found that forests in the South of Italy were voluntarily set on fire to create firefighting jobs. Similarly, Lovreglio *et al*. (2010) report that in Southern regions fires were ignited by seasonal workers in order to force or maintain employment.

Against this background, a natural question arises. Is wildfire crime related to the business cycle? In other words, do prolonged contractions in economic growth or sustained expansion periods have a relevant effect on wildfire crime patterns? Answers to these questions are important since knowledge of crime behaviour patterns in relation to the economic cycle may inform environmental policy makers on the correct course of action to take in order reduce the devastation caused by arsons.

With this target in mind we calculate a time varying correlation coefficient between wildfire crime and income. The hypothesis we are testing is that if it is the case that a contraction in income (and other economic fundamentals such as unemployment) reduces the crime production cost, as Becker theoretical model suggests, we should see the correlation between income and wildfire crime being higher during contraction periods of the business cycle. Also, if it is the case that a lower opportunity cost increases the probability of crime, we should observe greater persistence in the correlation over time in regions with lower income (i.e. greater unemployment level).

To investigate this hypothesis, we first rank each region in the sample according to the degree of wildfire crime rate. To do so we consider the quantile distribution function of the wildfire distribution for each region over time. Namely, each region i at time t was classified as belonging to the 25th, 50th, 75th or the 100th percentile of the wildfire distribution by assigning a code from 1 to 4 to each percentile; the 25th percentile being code 1 and the 100th percentile being code 4. In doing so we were able to classify each region, in each year, as belonging to a given group according to the code assigned. Finally, the twenty Italian regions were classified in four groups according to the gravity of the wildfire crime occurrence. Table 2A in Appendix reports the classification of the regions by code. From Table 2A it appears that, with the noticeable exception of the Northern region of Liguria, all the regions in the top quantile are in the South of Italy, where per capita income is the lowest. Figure 1 reports the average per capita income over time for each group of regions. From Figure 1 it appears that the ranking of the Italian regions in term of wildfire crime in Table 2A exactly matches the level of per capita income.

Figure 2 shows the time varying coefficients between WF_t and INC_t by code. In particular, Figure 2a), 2b), 2c) and 2d) report the time varying correlation coefficients between WF_t and INC_t for regions in code 1, 2, 3 and 4, respectively. For each code, the time varying correlation coefficients between the WF_t and INC_t have been calculated using a 3 year-moving window as follows

$$\rho_t = \frac{\sum_{t-8}^{T}(WF_t - \overline{WF_t})(INC_t - \overline{INC_t})}{\left(\sqrt{\sum_{t-8}^{T}(WF_t - \overline{WF_t})^2}\right)\left(\sqrt{\sum_{t-8}^{T}(WF_t - \overline{WF_t})^2}\right)}.$$

From Figures 2 a)-d) it appears that the correlation between WF_t and INC_t changes overtime quite substantially, no matter the region code taken into consideration. There is clear evidence that the recession that started in 2009 had an impact in wildfire crime rate in Italy. Indeed, regardless of the code under consideration, the correlation coefficients in Figure 2 are positive and greater in magnitude in correspondence of income throughs in 2010 and 2014, thus confirming the predictions of the theoretical model in Becker (1968). Also, it appears that opportunity cost mechanism has a greater impact for regions classified in Code 3-4 which have a lower income. Indeed, for these regions, the correlation coefficient is mostly positive. Also, in these regions the calculated coefficients ρ_t show greater persistence over time and fail to revert to the negative sign over the period under consideration. On the other side, it appears that for regions in Code 1-2 the signs of ρ_t show the feature of a mean reverting process.

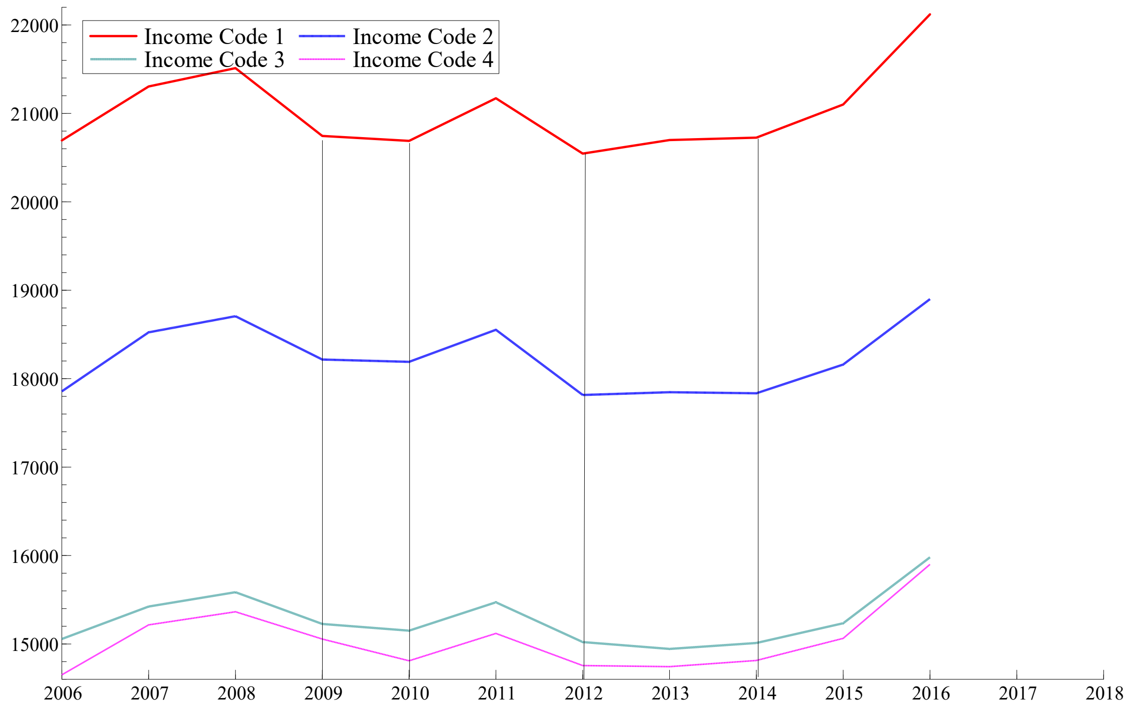

Figure 1. Per capita income during the sample under consideration by region code. Note: the vertical line relates to income turning points. See Table 2A for code classification.

Figure 2. Time-varying correlation coefficients between wildfire and per capita income by region code. Note: Time-varying correlation coefficients in the *y*-axes. See Table 2A for code classification.

To summarize the results in this section, a simple analysis of the time varying correlation coefficients reveals that economic downturns have a significant impact on the probability on the type of environmental crime rate considered on this paper. These results are in line with the literature, where it is found that the business cycle has important effects on the crime rate (see for example Grogger, 1998; Machin and Meghir, 2004).

Discussion

Before concluding this section, a question is in order: What do we learn from the application of Poisson and quantile fixed effect panel models to the data at hand? First, looking at the results in Table 3, it is clear that wildfire crime data do not lend themselves to be easily estimated using models that do not take into account fat tails, such as ordinary least squared regressions. This is because least squared methods do not have bounded influence and are not able to accommodate for the heterogeneity that is an important characteristic of the data considered in this paper. Heavy tails and outliers can make the estimators inconsistent, and even when the estimator itself is consistent, the standard errors require higher moments to exist (see Cameron and Trivedi, 2013). Also, when modelling the impact of socio-economic factors on wildfire crime, it is crucial to take the unobserved individual heterogeneity and distributional heterogeneity into consideration. In this respect, the econometric procedures used in this paper allow us to predict the conditional density function of the wildfire crime variable under weak assumptions.

Second, from the results in Table 4 it appears that quantile regression estimation in the environmental crime context is a potentially fruitful area of new research. This is because the use of quantile regression models allows the investigator to move away from the central moment of the crime distribution and consider the tails of the distribution where Italian regions with the highest and the least level of crime rates are located. The advantage of quantile regression models is that estimators are calculated to each quantile. This is certainly interesting from a policy perspective, since policy makers are more interested in knowing what happens at the extremes of a distribution than the center. However, the theoretical literature on quantile regression in the context of longitudinal data is still at the developing stage and these types of models are still rarely used in empirical applications. The modelling framework suggested in Machado and Santos Silva (2019) looks promising since it allows an investigator to control for individual specific heterogeneity via fixed effects and at the same time to explore heterogeneous covariate effects within the quantile regression framework. Overall, the model offers a more flexible approach to the analysis of panel data than that afforded by the classical Gaussian fixed and random effects estimators. Looking forward, it would be interesting to use quantile regression methods in the context of longitudinal count data. However, to the best of our knowledge, consistent estimators for quantile fixed effect Poisson-type regression models are still not available. The estimation of conditional quantiles with count data is notoriously difficult because of the conjunction of a non-differentiable sample objective function with a discrete dependent variable and the usual strategies based on Taylor expansions cannot be used to obtain the asymptotic distribution of the conditional quantiles (see Machado and Santos Silva, 2005). For this reason, in this paper the linear model suggested in Machado and Santos Silva (2019) was adopted for the quantile analysis.

6. Conclusion

In this paper we analyze the contributions of socio vulnerability factors in explaining wildfire crime across Italian regions. It is found that socio-economic factors are important determinants of wildfire crime. Higher levels of poverty increase wildfire crime rate. Also, risk factors such as unemployment, and income inequality affect the probability of crime in the same direction. On the other side, a negative relationship between the level of education and wildfire crime has been found. The results on the business cycle and the quantile regression analysis support our conjecture that economic downturn have a significant impact on the probability on wildfire crime and that the effect is particularly binding in the Southern regions where unemployment and income inequality are greater. We also find evidence of a positive correlation between organized crime and wildfire crime. Once again, the grip of organized crime appears to be stronger in Southern regions.

The results of this paper are important since according to the Italian environmental group Legambiente (2010) more than half of all Italy's fires are started deliberately. Despite of the fact that anthropogenic factors are responsible for most forest fires, socio-economic drivers behind wildfires are still poorly understood. In this respect, due to the heterogeneity of the economic performance of Italian regions, data used in this paper constitutes an ideal setting since they allow the investigator to get as close to a lab designed case-control-type experiment as it can possibly be done in the context of social sciences.

Our results highlight several research needs. First, the analysis in this paper relates to wildfire crime in Italy. However, there are other countries in Europe that are plagued by high wildfire crime and great socio-economic divide, Spain is a case in point (see Figure 1A in Appendix). Therefore, new research should explore whether the risk factors that we identify in this work also hold for other countries in similar situation. Second, the issue of the impact of business cycles on wildfire crime, and environmental crime in general, is virtually unexplored. However, in the light of the results in this paper more research is needed on the effect of the state of the economy on environmental crime. In this respect, the paucity of suitable data is certainly a problem since a proper analysis on this issue requires longer time span than the period considered in this work and currently the availability of these data is rather limited. Third, crime deterrence policies are not considered in this paper. However, the nonparametric analysis in this work reveal that more than 50% of fire crime areas were concentrated in the four Italian regions where the presence of mafia clans is highest. This result calls for further work on the role on the deterrence policy that can be put in place to contrast criminal action in the affected areas.[1] Finally, policy and fire management measures are being implemented in Italy to minimize the negative economic, social and environmental impacts of wildfire crime. However, lack of information on the socio-economic drivers of wildfire crime may result in ill-informed policy decisions and may lead to the misallocation of financial and organizational resources. In this respect, a better understanding of factors driving human-made ignitions is crucial for future fire prevention policies.

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[1] The impact of wildfire deterrence policies in Italy is considered in a companion work; see Drogo (2020).

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Appendix

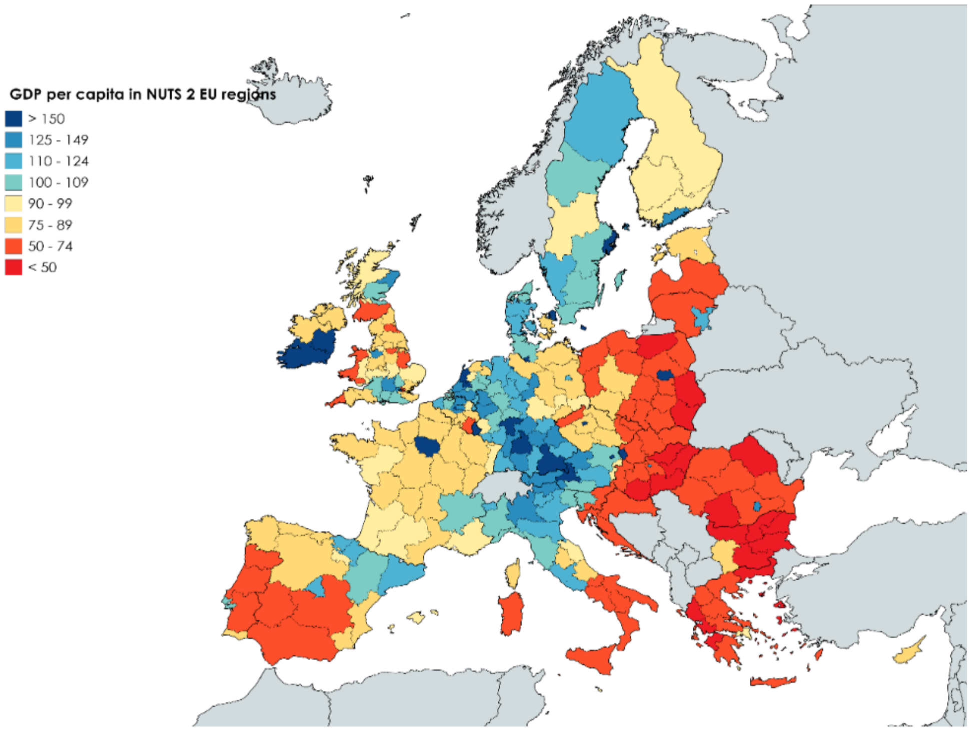

Figure 1A. Gross domestic product (GDP) per inhabitant in purchasing power standards in relation to the EU-28 average by European region (NUTS 2) in 2017. Source: Eurostat.

Table 1A. Condition index for the estimated models in Table 2.

	M1	M2	M3	M4
$INER_{it}$	1.00	1.00	-	-
$GINI_{it}$	-	-	1.00	1.00
$ORGC_{it}$	1.56	1.35	1.32	1.51
$HOMR_{it}$	1.92	1.97	1.86	2.08
$EDUC_{it}$	2.24	-	2.22	-
$UNIV_{it}$	-	2.11	-	2.33
$EMPL_{it}$	-	-	2.31	-
INC_{it}	-	-	-	2.37
POV_{it}	2.31	-	2.47	-
$UNEM_{it}$	-	2.16	-	2.74
DEN_{it}	2.58	2.50	2.93	3.05
$RAIN_{it}$	2.78	2.75	3.33	3.96
$TEMP_{it}$	3.53	3.5	4.32	5.66
$AGRI_{it}$	5.27	5.25	5.61	7.44

Table 2A. Classification of Italian regions by quantile according to the degree wildfire crime rate.

CODE 1	*CODE 2*	*CODE 3*	*CODE 4*
Trentino Alto Adige	Valle Aosta	Umbria	Molise

Veneto	Marche	Toscana	Basilicata
Emilia Romagna	Friuli Venezia Giulia	Puglia	Liguria
Piemonte	Abruzzo	Sicilia	Sardegna
Lombardia	Lazio	Campania	Calabria

Note: Codes 1, 2,3 and 4 correspond to the 25th, 50th, 75th and 100th percentale of wildfire distribution (WF), respectively.