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Contents

List of Figures **III**

List of Tables **IV**

Introduction **1**

1 Environmental crimes in Italy: deterrence and socioeconomic determinants **3**

1.1 Introduction . . . 3
1.2 Literature Review and Hypotheses Development . . . 5
1.3 Dataset construction and descriptive statistics . . . 8
1.3.1 Dependent variables: crime rates . . . 8
1.3.2 Deterrence and socioeconomic variables . . . 11
1.3.3 Descriptive statistics . . . 13
1.4 Model specification . . . 17
1.5 Results . . . 18
1.5.1 Waste crimes . . . 18
1.5.2 Wastewater . . . 20
1.5.3 Building violations . . . 21
1.5.4 Robustness checks . . . 23
1.6 Conclusions . . . 25

2 Is the enforcement of forest protection laws capable of preventing wildfires? Evidence from Italian provinces **28**

2.1 Introduction . . . 28
2.2 Literature review . . . 29
2.2.1 Crimes and forest fires in Italy . . . 31
2.3 Model specification and the dataset . . . 32
2.3.1 Model specification . . . 32
2.3.2 Dependent variable: forest fires . . . 32
2.3.3 Deterrence . . . 32
2.3.4 Weather and socioeconomic factors . . . 34
2.3.5 Descriptive statistics . . . 34
2.4 Results . . . 35
2.4.1 Regional-level analysis . . . 37
2.4.2 Arsons and unintentional forest fires . . . 39
2.4.3 Sensitivity analysis . . . 41
2.5 Conclusions . . . 43
2.6 Appendix . . . 44

3 Carbon emissions and the cost of debt financing: what role for policy commitment, firm disclosure and corporate governance? 47
3.1 Introduction 47
3.2 Literature review and hypotheses development 49
3.3 Research design 55
3.3.1 Data and sample construction 55
3.3.2 Empirical model and variable definitions 58
3.3.3 Dependent variable: the cost of debt 58
3.3.4 Independent variables 58
3.3.5 The econometric models 61
3.4 Results 63
3.4.1 Descriptive statistics and correlation 63
3.5 Multivariate analysis 68
3.5.1 The effect of carbon risk on the cost of debt 68
3.5.2 The Post-Paris Agreement effect: a sectorial analysis 68
3.5.3 The role of disclosure: reporting through the CDP questionnaire 71
3.5.4 Third-party verification of emissions and governance 74
3.6 Conclusion 77

Conclusions 78

Bibliography 80

List of Figures

1.1 Criminal prosecution simplified scheme. Own elaboration on Vagliasindi et al. (2015) 10
1.2 Waste and wastewater violations trend. Note: Own elaboration on ISTAT data. . 15
1.3 Building violations trend. Note: Own elaboration on ISTAT data. 15
1.4 Clearance rates. Note: Own elaboration on ISTAT data. 16
1.5 Trial rates. Note: Own elaboration on ISTAT data. 16
1.6 Conviction rates. Note: Own elaboration on ISTAT data. 17

2.1 Trend of clearance and trial rates Note: Own elaboration on ISTAT data. 36
2.2 Map of forest fires Note: Own elaboration on EFFIS data. 46

List of Tables

1.1 Description of variables 12
1.2 Descriptive statistics 14
1.3 Regression results - Waste-related crimes 20
1.4 Regression results - Wastewater crimes 21
1.5 Regression results - Building violations 23
1.6 Regression results - Waste and wastewater crimes 2006-2014 25
1.7 Laws considered in the analysis 27

2.1 Descriptive statistics 35
2.2 Regression results 37
2.3 Regression results - Regional analysis 39
2.4 Regression results - Arsons and unintentional forest fires 41
2.5 Regression results - Sensitivity analysis 43
2.6 Correlation matrix 45

3.1 CDP Database 2010-2018 – Firm distribution per year 54
3.2 Sample selection process 56
3.3 Sample distribution per year 57
3.4 Sample distribution by ICB Industry (firm-year observations) 59
3.5 Sample distribution by country (firm-year observations) 60
3.6 Sample descriptive statistics 64
3.7 Correlation matrix 67
3.8 Regression results - Carbon risk 69
3.9 Regression results – Post-Paris effect and High versus Low emitters 70
3.10 Sample distribution by sector - Carbon intensity statistics 72
3.11 Regression results – The effect of disclosure: answering the CDP questionnaire 73
3.12 Regression results – Third-party verification of emissions, board oversight of climate issues, and emissions reduction target 75

Introduction

The main objective of this dissertation is to investigate two different aspects of the environmental pollution caused by human activities: environmental crimes and corporate carbon risk. In particular, the first objective of the thesis is to assess the effectiveness of enforcement activities in deterring environmental crimes, building upon the economic analysis of crime developed by Becker (1968) with a focus on the Italian case. The second objective of the thesis is to assess whether policies aimed at limiting climate change have been incorporated by the European financial markets. In particular, the objective is to investigate the relationship between the cost of debt and corporate carbon risk, as proxied by the carbon intensity, trying to understand if lenders charge an additional risk premium to more polluting firms.

The first chapter aims at contributing to the research on environmental enforcement by analysing the main environmental crimes in Italy over the period 2006-2016. The study investigates whether deterrence effects vary across different crime categories, where enforcement activities appear to be more efficient and where they need to be enhanced. The analysis considers crimes related to waste management, wastewater discharge, and building violations. To account for enforcement levels, we compute crime-specific proxies for the main probabilities that are likely to affect offenders: the probability of being apprehended (measured by the clearance rate), the probability of standing trial once apprehended (trial rate), and the probability of being convicted once a suspect is standing trial (conviction rate). Simultaneously considering these enforcement factors allows us to assess the enforcement effectiveness without the risk of omitting relevant prosecution elements likely to restrain potential offenders from engaging in a criminal activity.

The second chapter explores the relationship between deterrence and forest fires. Despite the global diffusion of forest fires, few studies analysed the effectiveness of enforcement activities. In addition, the frequency and intensity of forest fires is predicted to increase in the near future because of climate change. The fact that the majority of forest fires is human-ignited makes the analysis of enforcement activities all the more relevant. The predominance of human-caused wildfires suggests that there might be more space for policy makers to restrain the number of occurrences with respect to a situation in which fires' causes are natural. Using the ISTAT dataset on environmental charges, the chapter analyses forest fires in the Italian provinces (NUTS 3 level) over the period 2009-2015. An additional objective of the chapter is to understand how deterrence works with different degrees of punishments, that is according to whether the forest fire being prosecuted is deliberate or unintentional.

The third chapter investigates the relationship between the cost of debt and the carbon risk on a sample of non-financial firms belonging to the Euro area over the period 2010-2018. The aim of the chapter is to assess whether firms with a higher carbon risk, as proxied by a higher carbon intensity, are charged a higher risk premium by lenders. In addition, we test whether the carbon risk premium increased in the aftermath of the 2015 Paris agreement. A further objective is to explore whether the disclosure of climate-change information through the Carbon Disclosure Project (CDP) questionnaire mitigates the relationship between carbon emissions and the cost of debt. Finally, we consider the effect of corporate actions to tackle climate risks on the cost of debt. In particular, we explore the relationship between the cost of debt and the presence of i) an external verification of GHG emissions, ii) the board-oversight of climate-related issues, and iii) an internal emissions reduction target.

Chapter 1

Environmental crimes in Italy: deterrence and socioeconomic determinants

FEDERICO DROGO

Abstract

Environmental crimes are among the most diffused illegal activities and are increasing in the recent years. Beyond harming directly the ecosystems they also disturb the functioning of markets, as in the waste sector. Despite the relevance of environmental crimes, very few studies investigated environmental crimes in the European context, and the existing one focus especially on the waste sector. This paper analyzes environmental crimes in the Italian regions over the period 2006-2016. Using new data from the ISTAT database of criminal charges we investigate the relationship between deterrence and crime rates for some of the most diffused environmental crimes: waste-, wastewater-, and building-related violations. Differently from our studies we compute crime-specific proxies for i) the probability of being apprehended, ii) the probability of standing trial and iii) the probability of being convicted once a suspect is standing trial. Our results provide evidence of a significant deterrence effected especially through the probability of being convicted. This outcome indicates that offenders respond to the threat of punishments that are farther in time. The deterrent effect is stronger for crimes regulated by the Code of the Environment, such as waste- and wastewater-related crimes.

1.1 Introduction

According to a recent report of the United Nations Environment Programme environmental crimes represent a big share of illegal activities and their number increased in recent years (Nellemann et al., 2016). Indeed, environmental misconducts are among the most profitable criminal activity. Their monetary value has been estimated to be around $ 91-259 billion per year, representing the fourth largest criminal area (UNEP, 2018).[1]

Common environmental unlawful acts comprehend poaching and illegal wildlife

[1]The first three criminal areas are: drugs, counterfeits, and human trafficking.

trade, illegal logging, illegal shipping of waste, arsons, and fishery crimes, to name a few. These crimes damage the environment by increasing the level of pollution, killing animal species, and destroying the flora. Contamination of aquifers and agricultural land, besides harming ecosystems, imposes also significant impacts on human health. The so-called "triangle of death" in the Italian region of Campania is one of the latest examples of health damages caused by illegal waste disposal. Moreover, environmental crimes often disturb the functioning of markets, as in the case of waste management firms operating without permit and creating which lower the market price of waste management and create unfair competition in the industry, or in the case of public funding misallocation due to presence of mafia-controlled firms. The crowding out of firms that operate legally leads also to a reduction in the tax revenues.[2] The increasing trend of environmental crimes has also been observed in Italy, with a peak in 2013.[3] Despite the global environmental, economic and social importance of environmental crime, most of the empirical literature on the relationship between deterrence and environmental offences focuses on US samples (Shimshack, 2014). Relatively few empirical studies consider European countries (Germany and Italy), and the existing Italian studies consider predominantly the waste sector. There is a significant gap of knowledge concerning the effectiveness of monitoring and enforcement and the role played by socioeconomic determinants on environment-related infractions beyond the waste sector – wastewater violations, arsons and involuntary fires, building and landscape violations.

This paper aims to contribute to the empirical literature on environmental monitoring and enforcement by extending the analysis of the effects of deterrence to some of the most diffused environmental crimes in Italy: waste- and wastewater-related crimes and building violations. Differently from other studies, we do not focus only on the waste sector, but we also consider other unlawful acts which produce considerable externalities on the environment and the population: waste-water and building violations. Considering the main environmental crimes allow us to compare the relative effectiveness of enforcement activities according to the typology of environmental crime under investigation. For the purpose of the present analysis we build an innovative dataset by matching ISTAT data about environmental criminal proceedings to their respective crime-specific clearance rate, trial rate, and conviction rate obtained from the ISTAT dataset on crime charges (ISTAT, 2018).

Differently from other studies that employ as explanatory variables proxies of the general level of deterrence, like police officers per capita or aggregate clearance rate (e.g. Buonanno (2006)), the crime-specific matching adopted in this work allows us to take into account the specificity of the enforcement effort with respect to different crime categories. In this way we are also able to jointly consider aspects of deterrence related to the different phases of the criminal procedure: i) the probability of being caught (clearance rate), ii) the probability of being brought to trial (trial rate), and iii) the probability of being convicted once a suspect is standing trial. The present chapter does not considers arsons, a crime category for which the economic

[2] EnviCrimeNet and Europol, 2015, p.26 - IPEC Report on Environmental Crime in Europe: "*As the Italian examples perfectly illustrate, criminals have already used the current financial crisis, with a high cost pressure on many businesses, to their advantage. In the waste industry, it is particularly easy for criminals to undercut honest competitors, which is affecting the important market of waste and recycling. Criminal proceeds can be as high as in illegal drugs trafficking and enable OCGs to further infiltrate into the legal economy.* (EnviCrimeNet and Europol, 2015)

[3] (ISTAT, 2018)https://www.istat.it/it/archivio/218648

motive is not always the predominant one Prestemon and Butry (2008); Legambiente (2010), and whose frequency is explained also by concurrent meteorological and biophysical variables. Arsons will be analysed in more detail and with a deeper geographical level of disaggregation in the second chapter.
The paper is organized as follows. Section 1.2 introduces the relevant literature on deterrence and on environmental crimes. Section 1.3 explains the construction of the dataset as well as the descriptive statistics and section 1.4 the estimation method. Section 1.5 presents the results. Section 1.6 concludes.

1.2 Literature Review and Hypotheses Development

The seminal work of Becker (1968) is the starting point for each analysis dealing with crimes. He developed a model in which a potential offender decides to commit a crime if the benefits from the misconduct outweigh the expected costs. That model has been subsequently expanded to investigate theoretically and empirically the relationship of crime rates with many factors, ranging from deterrence to socioeconomic indicators such as education or the level of inequality. The main objective of this stream of literature has been to understand the mechanism of deterrence, which in the words of Nagin (2013, p.204) can be defined as "*..the behavioural response to the perception of sanction threats*", in order to identify the best crime-preventing legal tools or policies. Following the review of Chalfin and McCrary (2017), studies belonging to the economics of crime can be subdivided in three main areas, that investigate the responsiveness of crime to changes in i) the probability that an individual is apprehended, ii) the severity of criminal sanctions, and iii) labour market conditions. Overall, the empirical evidence agrees on points i) and iii): on average crime rates decrease when the apprehension probability increases and the economic conditions improve. On the other hand, evidence on the impact of the severity of sanctions points to a small deterrent effects produced by enhancing punishments. Indeed, individuals seem to be more threatened by the probability of being caught than by the heaviness of prospected fines or imprisonment (Nagin, 2013b).

Since Becker's crucial contribution (1968) and the subsequent applications, a strand of literature has tried to apply this framework to conducts which are unlawful according to environmental laws (Cohen, 2000). The definition what is an environmental crime from a legal point of view is not univocal because of different legal definitions in different countries. However, using the definition of the European Union, an environmental crime might be defined as crime that "*covers acts that breach environmental legislation and cause significant harm or risk to the environment and human health*".[4] According to Shimshack's (2014) review of the literature on environmental monitoring and enforcement, the empirical evidence shows that environmental enforcement is effective in reducing firms' pollution and violations. Environmental inspections and sanctions produce two typologies of deterrence: specific and general. The former occurs when an increase in monitoring and enforcement improves environmental performance at the specific facility (that is the one which is evaluated or punished), the latter occurs when deterrence activities by police or regulators are able to affect also firms or production facilities not

[4]European Commission (2020) `https://ec.europa.eu/environment/legal/crime/`

directly targeted by inspections or sanctions.
Despite the abundant evidence of environmental deterrence related to US and Canadian firms, the European context has been less investigated. One of the few empirical studies to apply Becker's framework to environmental crimes in the European context is the study by Almer and Goeschl (2010). Using environmental crimes data from 15 German states over the period 1995-2005, they find a deterrent effect of enforcement. In particular, the trial rate and the imprisonment rate appear to deter environmental unlawful acts more than the clearance, conviction, fine, and arrest rates. Changing perspective, the same authors also analyse environmental violations focusing on the institutions involved in the criminal justice system: police, prosecutors, and courts (Almer and Goeschl, 2011). Specifically, they study the determinants at each stage of the enforcement process trying to control for political economy factors. They show that a pro-industry government tends to decrease the amount of cleared, tried, and convicted cases while citizens' environmental awareness increases cleared and convicted cases. In addition, the amount of cleared, tried, and convicted cases is negatively related to the aggregate number of crimes (other than environmental crimes), suggesting that an increase in the overall rate of criminality diverts resources from the management of environmental crimes.

In a subsequent study, Almer and Goeschl (2015) focus on waste disposal crimes. Using a panel dataset of 44 counties in the German Land of Baden-Wüttenberg they find evidence of deterrence. Similarly to their previous analyses they test different types of enforcement instruments: prison rate, fine rate, clearance rate, and trial rate. In line with their previous work on the broader category of environmental offences, the imprisonment appears to be the most effective variable.

Environmental crimes have been studied also in the Italian context and in relation to the presence of organized crime. Specifically, the majority of studies which consider the role of deterrence focus on the waste sector, looking both to illegal waste disposal (crimes related to illegal management and non-fulfilment of waste regulations) and to illegal trafficking of waste.[5] D'Amato and Zoli (2012) develop a theoretical model of the role played by mafia in illegal waste disposal. In particular, they allow for the presence of a criminal organization which extorts a rent from agents willing to perform illegal disposal. One significant, counterintuitive conclusion of their work is that, under certain conditions, the presence of mafia could increase the level of economic activity and lead to less enforcement from public authorities. One potential explanation of this outcome put forward by the authors is that the demand for waste management must be fulfilled someway and, in the face of high monitoring and enforcement costs, governments might find it preferable to decrease the level of enforcement and leave the waste management task to mafia groups, whose methods may ultimately result in lower management costs. Using data from the "*First report on the fight against environmental illegality*" they provide stylized facts of their theoretical results through environmental enforcements statistics related to the number of crimes, enforcement levels, and the presence of mafia (Ministero dell'Ambiente, 2010). For instance, they point out that level of enforcement, proxied by the number of inspections per km^2, is lower

[5]According to art. 260 of the EC is considered to be held liable for illicit trafficking of waste "*whoever, in order to achieve an unfair profit, with multiple operations and through the establishment of means and continuing organised activities, sells, receives, transports, exports, imports or otherwise improperly handles large quantities of waste*". Vagliasindi et al. (2015), p. 21

in Sicily, despite the presence of a strong criminal organization, than in Tuscany. Germani et al. (2015b) analyse the determinants of the illegal trafficking of waste in the Italian regions over the period 2002-2013. In order to proxy for the enforcement by public authorities they use the charge rate (the share of charged suspects out of the recorded suspects) and the arrest rate. The control variables related to enforcement are included linearly and with the respective squared term. Results do not show a strong deterrent effect, as suggested by the negative and significant coefficient of the squared deterrence variables. Interestingly, the major determinants differ between North and South: in Northern regions, education is positively related with crime while in Southern regions the opposite pattern is observed.

D'Amato et al. (2015) study how waste tariffs and the mafia affect waste disposal. Using municipal solid waste data for the period 1999-2008 from the ISPRA database they find that the presence of mafia reduces legal waste management.

In a related paper, D'Amato et al. (2018) expand the framework of the previous study to analyse empirically the role of monitoring and enforcement in the waste sector. They use a dataset of waste crimes (violations, charges, and requisitions) and inspections carried out by the former State Forestry Corp (CFS) for 86 Italian provinces from 2005 to 2010. They find that the adoption of the new tariff in Italian municipalities increased illegal waste disposal and that CFS inspections deter crimes only once a certain threshold is reached. Specifically, they test the role of deterrence by introducing two regressors: the inspection rate and the inspection rate squared. Across the various specifications they find the inspection rate coefficient to be positive and its squared term negative. These outcomes point to the fact that waste crime rates start to decrease – that is deterrence becomes effective – only when the inspection rate reaches a sizeable level (analogously to Germani et al.'s, 2015 results). For this reason, as far as environmental violations are concerned, they point to the Italian system of inspections as "relative deterrent".

Summarizing, whereas the empirical evidence indicates a deterrent effects of police forces on general crime rates, in the case of environmental crimes the existing evidence, particularly in the Italian context, is more limited. German empirical studies document a deterrent effect both for the waste sector and when all environmental crimes are jointly considered. The available evidence for Italy concerns mainly the waste sector and suggests a weak deterrent effect for this subset of environmental crimes. With this work we thus try to fill this gap with a new dataset and considering (besides inspection, clearance and arrest rates as done in previous studies) also crime-specific clearance, trial, and conviction rates. In this way, we aim to account for deterrence probabilities ranging from the beginning of the criminal prosecution process to the end.

Considering the abovementioned literature, to the purpose of this paper's analysis of deterrence we formulate the following first hypothesis:

- *H1: An increase in the level of deterrence, as proxied by the i) clearance rate, ii) trial rate, and iii) conviction rate, is expected to reduce the reported environmental crime rate.*

Moreover, provided the heterogenous effects produced by different legal tools to deter crimes, and in particular the greater deterrent effect of convictions often found for environmental crimes we formulate our second hypothesis as follows:

- *H2: An increase in the conviction rate is expected to reduce the reported environmental crime rate more with respect to the trial rate and the clearance rate.*

Moving to the socio-economic determinants of crime, there are three factors generally found to affect the probability of being involved in criminal behaviour: differential wages between legal and illegal activities, wage inequality, and the level of education (Buonanno, 2003).
Empirical studies focussing on Italy confirm a negative relationship between crime rates and socioeconomic conditions. For instance, Marselli and Vannini (2000) use the CRENoS dataset to study the effect of unemployment on three typologies of crime: homicide, theft, and extortion over the time span 1970-1994. They find that the unemployment rate is positively related with crimes. According to their estimates a one percentage point increase in the unemployment rate elicits an increase of 118 thefts, 12 robberies, and 0,2 voluntary homicides per 100,000 inhabitants. Along the same line, Buonanno (2006) studies the effects of labour market opportunities on crime rates in the Italian regions from 1993 to 2002 considering the property crime rate, the theft rate, and the total crime rate. Explanatory variables are divided in four main subgroups: unemployment, the clearance rate as a proxy for deterrence, demographic variables, and socioeconomic variables. Using a GMM approach he finds that the determinants of crime appear to be differentiated between the North-Centre and the South of Italy. In the North-Centre the lagged crime rate and deterrence variables are strongly related with crime, while in the South the most important role is played by socio-economic indicators, particularly unemployment and wages. In a related study, Buonanno and Leonida (2006) analyse the relationship between education and crime rate, using a panel data of Italian regions from 1980 to 1995. Using as a proxy of education the average years of schooling of the population they find a negative and statistically significant effect of education on crime.

Considering the established findings in the literature on the socio-economic determinants of general crime, we thus formulate the third hypothesis as follows:

- *H3: An increase in the unemployment rate is expected to increase the rate of reported environmental crimes.*

1.3 Dataset construction and descriptive statistics

1.3.1 Dependent variables: crime rates

Our main source is the ISTAT database of crimes against the environment and the landscape, whose original source is the Public Prosecutors' archive. This dataset contains information about environmental crime cases and the related convictions over the years 2006-2016. The focus of this study is on three categories of crimes: waste-, wastewater-, and building-related crimes.[6] Waste and wastewater crimes are

[6]The new types of offences introduced by law 68/2015 about environmental crimes, which prescribes more severe penalties, are not included in the analysis for lack of sufficient statistics due to the recent introduction.

mainly regulated by the Code of the Environment. In 2006 the decree n. 152/2006, known as "Codice dell'ambiente" (Code of the Environment - hereinafter EC) was introduced in the Italian legal system. The EC regulates several issues: Environmental Impact Assessment, protection of soil and water, regulation of the waste and wastewater sectors, and decontamination of polluted sites (Ferrara et al., 2018).
The first category of crimes considered in the present analysis comprehends all the violations related to the disposal of waste, committed by both firms and private citizens. Specifically, the following illegal practices are considered: abandonment, unauthorized disposal, illegal trafficking and illegal burning of waste, as well as missed decontamination of sites[7] Collecting, managing, disposing, selling waste without the necessary authorizations are violations sanctioned as misdemeanours. Organized traffic and illegal burning of waste are considered felonies and give rise to heavier sanctions, including arrest.
Wastewater violations constitute the second category of Environmental code violations. They include illegal conducts such as discharging wastewater from an illegal industrial plant or simply by not respecting the maximum pollution loads set by the law.
The third category includes building violations, which are regulated according to a double sanctionatory regime. Indeed, these violations can be punished through both administrative and penal sanctions. In the present analysis only building violations considered as felonies – therefore sanctioned through penal law – are considered. There exist fundamentally three typologies of building violation misdemeanours (de Biase and Losco, 2017). First, non-compliance with rules set by the DPR 380/2001. In this case, only fines up to €10,329 apply. The second case is the execution of construction works without the necessary permit or non-compliance with the permit rules. Such building violations can be sanctioned with the arrest up to 2 years and a fine from €5,164 to €51,645. Finally, the third case is the illegal allotment of land. For such case, sanctions provided for by law are the arrest up to 2 years and the payment of a fine from a minimum of €15,493 to a maximum of €51,645. The Italian Statute of limitations establishes a maximum time of 4 years for misdemeanours after which the offence is extinguished. Moreover, there is the possibility to extinguish the violation before the trial with the payment of a sum of money, the so-called *"oblazione"*[8]. For each one of the crime categories introduced above we compute specific crime rates and deterrence variables.
Before turning to the details of the construction of the dependent and deterrence variables, with Figure 1.1 we provide a simplified scheme of the phases involved in the prosecution of a generic crime, which also applies to environmental crimes.

[7] Regulated by EC articles 255, 256, 257, 260, and 256 bis respectively.

[8] *"Oblazione"* is an out-of-court settlement for which a request to settle is made through the payment of a sum of money.

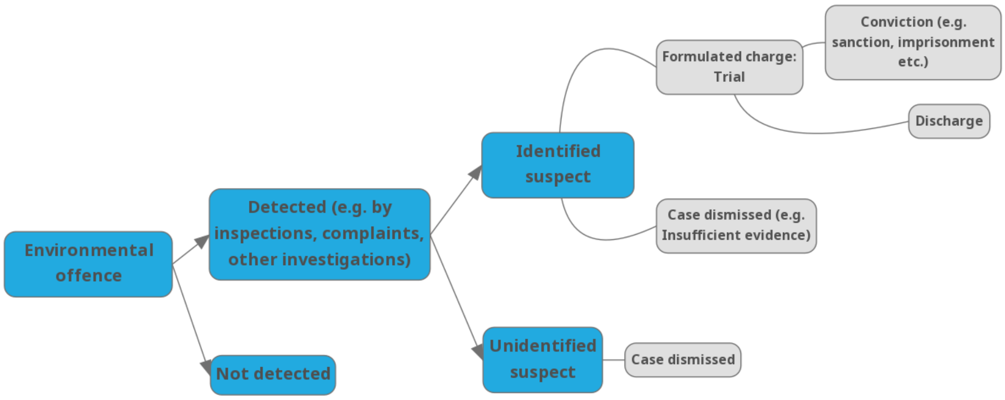

Figure 1.1: Criminal prosecution simplified scheme. Own elaboration on Vagliasindi et al. (2015)

A violation might be detected by police forces' inspections (which can be random or planned according to the evidence collected during investigation activities) or by citizens' warnings or complaints. Once a violation is detected, the preliminary investigation phase starts. From this point there are three possibilities according to whether a suspect has been identified. If the offenders have been identified and there is no sufficient merit to further conduct the prosecution phase, the prosecutor asks the judge to dismiss the case. On the contrary, if there is merit and evidence, the prosecutor formulates the charge and she fills a request to put the case before a judge, that is the suspected offender will be standing trial. Alternatively, if police forces do not identify the offender, the case is dismissed.
These three possible outcomes constitute the information used to build the dependent variable and the deterrence variables. In detail, the ISTAT dataset provides the following statistics at the region-year level: i) the number of cases with a known offender for which at the end of the preliminary investigation phase a formal charge is formulated, ii) the number of cases with a known offender which get dismissed, and iii) the number of cases for which the author remains unknown and which are dismissed. For region i and year t we define the reported number of environmental offences of type x as:

$$\begin{gathered} reported\_crime_{x,i,t} = (n.\ of\ cases\ brought\ to\ trial)_{x,i,t} + \\ (n.\ of\ cases\ dismissed\ known)_{x,i,t} + (n.\ of\ cases\ dismissed\ unknown)_{x,i,t} \end{gathered} \tag{1.1}$$

In order to account for differences in reported crimes due to the size of regional population we express the dependent variable as the rate of reported environmental crime per 100,000 inhabitants:

$$crime\_rate_{x,i,t} = \frac{(reported\_crime)_{x,i,t}}{(population)_{x,i,t}} \times 100,000 \tag{1.2}$$

1.3.2 Deterrence and socioeconomic variables

In Becker's framework the expected utility of a potential offender is defined as:

$$EU = pU(Y - f) + (1 - p)U(Y) \tag{1.3}$$

where Y is the generic benefit of success in committing a crime, f is the sanction if apprehended, and p is the probability of being apprehended. Hence Y represents the expected benefit, while f and p are the expected costs. In Becker's model, f *"is to be interpreted as the monetary equivalent of the punishment"* (Becker, ibid., p.177). However, as remarked by Chalfin and McCrary (2017), f could be also interpreted as a function of many phases of the judiciary process, for instance the probability of being convicted once a potential offender had to stand trial.[9] In the present analysis the expected costs are represented by the probabilities of being discovered (clearance rate), the probability of being brought to trial once an offender has been apprehended (trial rate), and the probability of being convicted once a case has been brought to trial (conviction rate).

The three different outcomes introduced in the previous section allow us to compute proxies for these three probabilities for each category of crime. In particular, the *clearance rate* is computed as the ratio between the number of cases for which a suspect has been identified and the total number of reported cases. The clearance rate is a proxy for the probability of being apprehended. It is considered a better measure with respect to arrest rates because the number of arrests is mechanically higher in regions with more crimes and they do not represent a probability of being caught (Curry et al., 2016). Similarly to Almer and Goeschl (2010, 2011, 2015) we define the *trial rate* as the ratio between the number of cases for which a charge is formulated and the number of cases for which a suspect has been identified. More specifically, starting from ISTAT data on environmental criminal proceedings, we compute the clearance and trial rate as follows:

$$clearance\_rate_{x,i,t} = \frac{(n.\ of\ cases\ with\ an\ identified\ suspect)_{x,i,t}}{(total\ n.\ of\ cases)_{x,i,t}} \tag{1.4}$$

$$trial\_rate_{x,i,t} = \frac{(n.\ of\ cases\ brought\ to\ trial)_{x,i,t}}{(n.\ of\ cases\ with\ an\ identified\ suspect)_{x,i,t}} \tag{1.5}$$

Finally, as a proxy for the probability of being convicted we compute the *conviction rate* in the following way:

$$conviction\_rate_{x,i,t} = \frac{(n.\ of\ convictions)_{x,i,t}}{(n.\ of\ cases\ brought\ to\ trial)_{x,i,t}} \tag{1.6}$$

[9] Footnote 2 of Chalfin and McCrary (2017) literature review: *"In principle, f can be a function of many different characteristics of the sanction including the length of the sentence, the conditions under which the sentence will be served, and the degree of social stigma that is attached to a term of incarceration, all of which are likely heterogeneous among the population."*

Due to differences in the data collection processes for cases and convictions the conviction rate is computed as a ratio of individual convictions to cases. The difference is due to the fact that the conviction is always referred to a single suspect, while the case might include more suspects.

The ISTAT dataset is then merged with other socioeconomic variables from the same dataset and from the Italian Institute for Environmental Protection and Research (ISPRA).

The amount of opportunities available in the legal market makes criminal activity more or less profitable. We use the unemployment rate, previously found to affect crime rates Raphael and Winter-Ebmer (2001); Buonanno (2006), as a proxy for labour market conditions. The majority of waste produced in Italy are special waste deriving from firms' production activities (Massarutto, 2009). In order to account both for different level of economic activities across Italian regions and for the potential amount of waste produced, we include the logarithm of firms' revenues (Almer and Goeschl, 2015). Moreover, considered that mafia-type organizations are often involved in the waste disposal sector and in unauthorized building (or building abusivism) (Corona and Sciarrone, 2012; De Leo, 2017; Berruti and Palestino, 2019; Chiodelli, 2019), we use the rate of organized crime, defined as the rate of organized crime and mafia-related crimes per 100,000 inhabitants, as a control variable. The organized crime rate includes the following types of offence: criminal conspiracy, mafia-related conspiracy, conspiracy for production and trafficking of drugs, conspiracy for dealing drugs.

As an additional control we include the number of waste treatment plants and the urban waste recycling rate to account for the availability of legal sites to manage and dispose of waste and for different levels of efficiency of regions in managing sorted waste (Germani et al., 2015b). Table 1.1 shows a description of the variables used in the analysis along with the respective acronyms.

Table 1.1: Description of variables

Acronym	**Variable description**
Dependent variable	
Crime rate	Reported environmental crimes per 100,000 inhabitants
Deterrence variables	
Clearance	Share of cases for which a suspect has been identified
Trial	Share of cases that go to trial
Conviction	Ratio of convictions to the number of cases that go to trial
Socioeconomic and crime-specific controls	
Unem	Unemployment rate
Org_crime	Organized crime and mafia-related crime rate (per 100,000 persons)
Plant	Number of waste treatment plants
Rev_firms	Logarithm of the firms' revenues
Recycling	Share of urban waste recycled

1.3.3 Descriptive statistics

Table 1.2 presents the descriptive statistics of the dataset. Data pertain to the 20 Italian regions for 10 years, from 2006 to 2016. Building violations are the most diffused crime category, with an average of 78 cases per 100,000 inhabitants. The second category is waste-related crimes, with 21 cases. Wastewater violations are the less common among the infractions considered with a crime rate of about 4 cases per 100,000 inhabitants.

Considering only crimes sanctioned by the EC, waste-related infractions are the most diffused, representing 84% of EC crimes. The clearance rate is particularly high for building violations, with an average of 94% of cases for which a suspect has been identified. The relative higher difficulty in finding the offender is demonstrated by the lower clearance rates for waste (72%) and wastewater (80%) misconducts. The ranking found for the clearance rate is reversed when the probability of standing trial is considered. In fact, waste and wastewater violations have an average of 68% of cases going to trial once the suspect has been identified, while the share for building violations is considerably lower, with 36% of cases going to trial. One potential explanation for this difference might be the different time of the preliminary investigation phase. For instance, in 2015 the median number of days of the preliminary investigation phase was 337 for crimes regulated by EC but 539 for building violations. As this phase is prolonged, the likelihood of dismissals of the case due to the expiry of statute limits increases.

The conviction rate is higher for waste-related crimes, with an average of 42 convictions per 100 cases, while the average for the other two categories is 35. Differently from the clearance and trial rate, maximum values of *conviction* exceeds unity for two reasons. First, as mentioned in the previous section, the conviction rate is the ratio between individual convictions to cases that go to trial. A single case might aggregate more investigated persons. In addition, it is not possible to link the convictions to the year in which the crime has been committed. Due to this temporal mismatch it is therefore possible to observe conviction or trial rates above unity, in line with similar studies based on aggregate data, without the possibility to link convictions to the related processes Almer and Goeschl (2015).

Table 1.2: Descriptive statistics

	count	mean	sd	min	max
Waste-related crimes					
Crime rate	220	21.06	12.29	1.17	72.61
Clearance	220	0.72	0.15	0.22	0.97
Trial	220	0.68	0.11	0.30	1.00
Conviction	220	0.42	0.33	0.00	1.87
Recycling	220	0.36	0.18	0.05	0.73
Plant	220	26.39	16.27	0.00	80.00
Wastewater-related crimes					
Crime rate	220	3.71	2.83	0.00	18.60
Clearance	216	0.80	0.14	0.00	1.00
Trial	215	0.68	0.17	0.00	1.00
Conviction	212	0.35	0.34	0.00	2.00
Building-related crimes					
Crime rate	220	78.38	42.12	14.76	242.18
Clearance	220	0.94	0.04	0.80	1.00
Trial	220	0.36	0.13	0.09	0.68
Conviction	220	0.35	0.19	0.04	1.17
Socioeconomic controls					
Unem	220	9.70	4.95	2.75	23.42
Rev_firms	220	18.11	1.27	15.48	20.57
Org_crime	220	2.07	1.51	0.00	14.92

Figure 1.2 illustrates the trend of reported crimes for the crimes considered in the EC. The left panel shows the trend of waste-related violations. Starting from 2006 there is a clear increasing trend till 2014, which is the peak year with about 15,000 cases. The right panel shows wastewater violations, with a peak in 2010 followed by a decreasing trend with some fluctuations.
Figure 1.3 shows the trend of building violations. For this violation category there is a monotonically decreasing trend, starting with almost 50,000 violations in 2006 to less than 35,000 in 2016.

Figure 1.4 shows the trends of the average clearance rates of the different crime categories. In general the trend is increasing, indicating a slow improvement in the ability of police forces to identify suspects. Figure 1.5 shows the trend of the average trial rates for the different crime typologies. One key aspect that emerges from the trial rate trend is a marked drop after 2015 for waste and wastewater crimes. This pattern is due to the introduction of article 318bis, which allows offenders to settle the violation through the payment of a fine (ISTAT, 2018). Finally, figure 1.6 shows the conviction ratio. The share of convictions to the cases that go to trial is increasing for EC crimes, while is essentially stable for building violations.

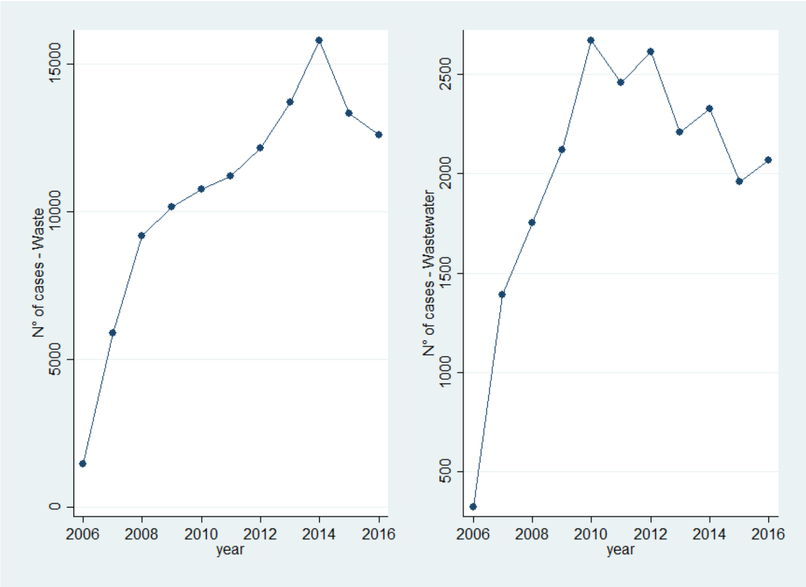

Figure 1.2: Waste and wastewater violations trend.
Note: Own elaboration on ISTAT data.

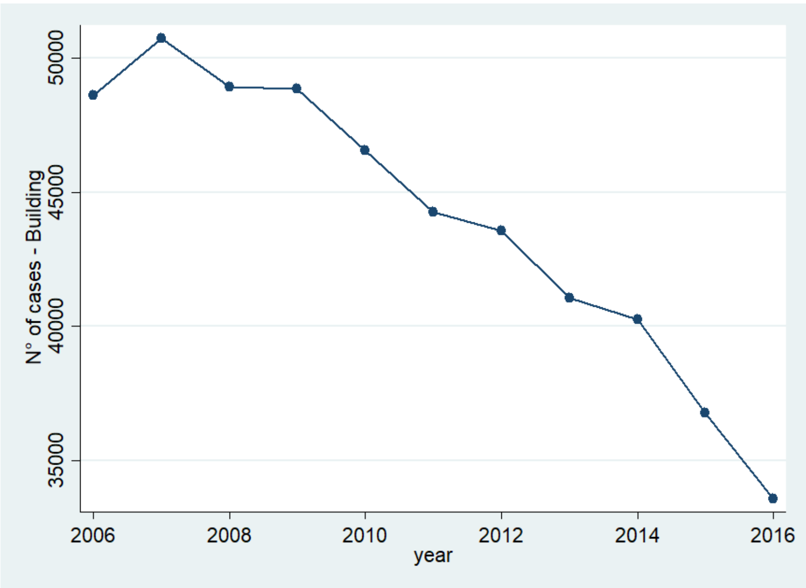

Figure 1.3: Building violations trend.
Note: Own elaboration on ISTAT data.

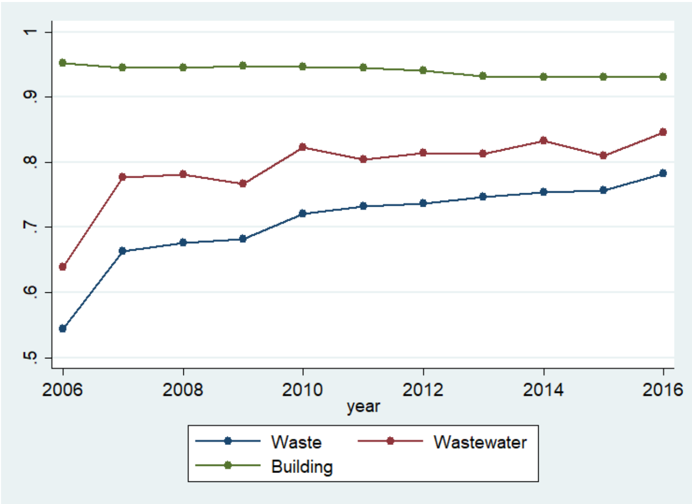

Figure 1.4: Clearance rates.
Note: Own elaboration on ISTAT data.

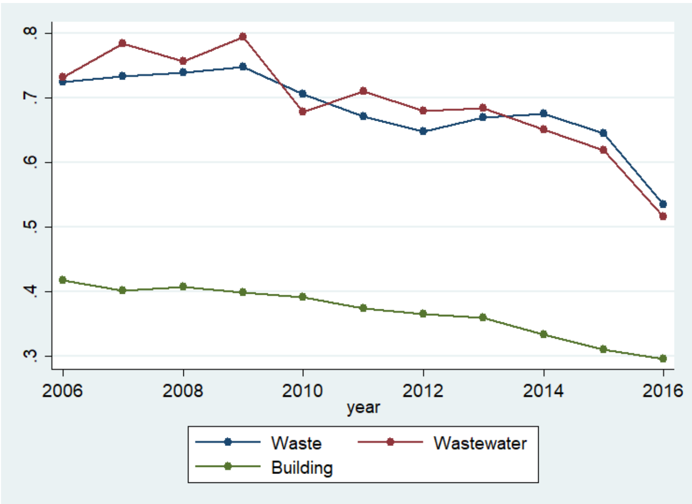

Figure 1.5: Trial rates.
Note: Own elaboration on ISTAT data.

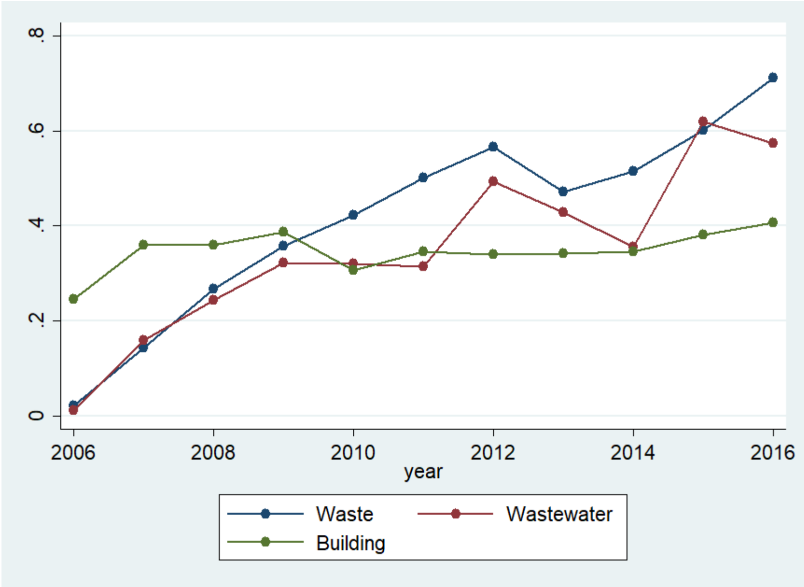

Figure 1.6: Conviction rates.
Note: Own elaboration on ISTAT data.

1.4 Model specification

We model the crime rate as a function of its own first lag, a vector of deterrence variables, and a vector of socioeconomic controls according to the following specification:

$$\begin{aligned} ln(Crime_{i,t}) = Con + \alpha ln(Crime_{i,t-1}) + \beta Deterrence_{i,t} + \\ + \delta Socioeconomic_{i,t} + T_t + \epsilon_{i,t} \end{aligned} \tag{1.7}$$

where $Crime_{i,t}$ is the crime rate in region i and year t and $Crime_{i,t\text{-}1}$ its lag. We follow the literature in using logarithms of crime rates in order to lessen measurement error problems stemming from the typical reporting bias of crime, as well as to reduce the effect of outliers Buonanno et al. (2018). *Deterrence* is a vector including crime-specific clearance, trial, and conviction rates. Vector Z includes crime-specific controls. *Socioeconomic* is a vector of socioeconomic controls including the unemployment rate, the natural logarithm of firms' revenues, and the organized crime rate.
One trickiest issues faced by studies in the economics of crime is the endogeneity of deterrence or enforcement variables due to simultaneity (Levitt and Miles, 2007). A traditional example of simultaneity is when a higher number of crimes in a region leads to a greater effort by its authorities which might decide to increase the number of inspections leading to more discoveries of violations. In order to deal with endogeneity of deterrence and the presence of a lagged dependent variable as a regressor we use the System GMM approach developed by Blundell and Bond (1998), which is particularly suitable in situations with more endogenous regressors (Bond, 2002; Bun et al., 2019). Indeed, in the presence of an unobserved individual effect both the OLS estimator and the Within Groups estimator are not able to eliminate the correlation between the lagged dependent variable and the transformed error (Bond, 2002). For this reason, OLS estimates tend to be upward biased and the Withing

Groups estimator downward bias. Maintaining the System GMM as our preferred specification, we also estimate the regression equation using both the OLS and the Within Groups estimator to check that GMM coefficients remain withing the OLS-Within Groups estimator range and for a sensitivity check to compare results across different estimation methods. In line with the literature we consider the lag of the crime rate and the three deterrence-related variables to be endogenous, and as such, they are instrumented using their own lags but starting from their second lag (*t-2*).
Despite the advantages, the System GMM estimator is vulnerable to the problem of "too many instruments" (Roodman, 2009b,a). This problem is particularly relevant for System GMM where lagged levels of a variables are used as instruments in the differenced equation and lagged differences are used in the level equation. Moreover, the problem is worsened as the number of time periods increases, leading to a situation in which the number of instruments tends to the number of observations in the dataset. This condition of instruments proliferation causes essentially two problems: overfitting bias of instruments in the direction of OLS estimates and a decrease of the power of the Sargan-Hansen test of overidentifying restrictions in small samples (Bowsher, 2002).
In order to deal with the abovementioned problem two common approaches have been implemented in the analysis as a robustness check of results. The first one is to collapse the matrix of instruments in order to avoid reduntant moment conditions[10]. The second one is to estimate the regression equation reducing the number of lags (Bond, 2002) to be used as instruments from 4 to 1 to check the sensitivity of results to different choices of the number of instruments. In addition, we estimate the model separately for each type of crime to avoid the aggregation bias typical of crime rates (Cherry and List, 2002). That is, the effect of the probability of arrest, or the probability of going to trial might be particularly different among crime categories and not taking that into account might bias the deterrence coefficients hiding crime-specific patterns.

1.5 Results

1.5.1 Waste crimes

Table 1.3 presents the OLS, FE, and System GMM estimates for waste-related violations. The lagged crime rate is positive and statistically significant in all the specifications, indicating crime persistency for this typology of violations.
Overall, the results provide evidence of a deterrence effect, hence confirming the first hypothesis. However, the deterrent effect is produced mainly by the conviction rate, which displays the predicted negative signs in all specifications, with p-value <0.05 in columns 1-3. Column 4 displays the result for the GMM specification with

[10]Following Roodman (2009a, 2009b), the standard matrix of instruments

$$\begin{bmatrix} 0 & 0 & 0 & 0 & 0 & 0 & \cdots \\ y_{i1} & 0 & 0 & 0 & 0 & 0 & \cdots \\ 0 & y_{i2} & y_{i1} & 0 & 0 & 0 & \cdots \\ 0 & 0 & 0 & y_{i3} & y_{i2} & y_{i1} & \cdots \\ \vdots & \vdots & \vdots & \vdots & \vdots & \vdots & \ddots \end{bmatrix} \text{ is transformed to the collapsed form } \begin{bmatrix} 0 & 0 & 0 & \cdots \\ y_{i1} & 0 & 0 & \cdots \\ y_{i2} & y_{i1} & 0 & \cdots \\ y_{i3} & y_{i2} & y_{i1} & \cdots \\ \vdots & \vdots & \vdots & \ddots \end{bmatrix}$$

reduced number of instruments. Interestingly in this case *Conviction* has a higher p-value, while the clearance rate's p-value decreases (p-value = 0.086).
Moving to the socioeconomic controls, it can be noticed that our main regressors of interest, the unemployment rate, has the predicted positive sign in all the specifications – but with high p-values considerably above the usual thresholds with the exception of the OLS specification. Similarly, the variables specifically related to waste crimes – *waste_plant* and *recycling_rate* – have high p-values in line with the study of Germani et al. (2015b) on the specific typology of illegal trafficking of waste. Firms' revenues have a negative coefficient in all specifications, with a low p-value < 0.001 in the OLS and GMM, indicating that more economically developed regions experience less waste-related crimes. Finally, the organised crime rate has a positive coefficient in specifications 2-4, although with a low p-value only in the GMM specification with reduced number of instruments.

Table 1.3: Regression results - Waste-related crimes

	(1) OLS	(2) FE	(3) Sys-GMM	(4) Sys-GMM
Lag Crime_rate	0.515***	0.340***	0.424***	0.566***
	(0.000)	(0.000)	(0.000)	(0.000)
Clearance	0.318	0.215	-0.568	-0.935*
	(0.165)	(0.544)	(0.153)	(0.086)
Trial	-0.166	-0.239	-0.583**	0.201
	(0.486)	(0.285)	(0.031)	(0.792)
Conviction	-0.368***	-0.482***	-0.397**	-0.0916
	(0.000)	(0.000)	(0.024)	(0.741)
Unem	0.0274***	0.0192	0.00313	0.00314
	(0.000)	(0.118)	(0.819)	(0.881)
Waste_plant	-0.00174	0.00183	-0.00337	-0.00227
	(0.141)	(0.688)	(0.319)	(0.604)
Recycling_rate	0.230*	-0.0371	0.163	-0.0121
	(0.063)	(0.933)	(0.649)	(0.982)
Rev_man	-0.113***	-0.00625	-0.149***	-0.152**
	(0.000)	(0.973)	(0.001)	(0.036)
Org_crime	-0.00282	0.000453	0.0111	0.0512*
	(0.762)	(0.971)	(0.402)	(0.058)
N. of Observations	200	200	200	200
N. of Groups	20	20	20	20
N. of Instruments			64	28
Adj. R2	0.850	0.700		
AR1(p-value)			0.0066	0.0026
AR2(p-value)			0.7895	0.7055
Sargan-Hansen(p-value)			0.0595	0.3625
Kleibergen-Paap rk LM statistic (p-value)			0.009	0.0001

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5.2 Wastewater

Table 1.4 displays the results for the wastewater violations. The persistency of this environmental crime is confirmed by the always positive sign and low p-values of the lagged crime rate. The clearance rate has a positive coefficient but a high in all the four specifications. Conversely, the trial and the conviction rates have the expected negative coefficient in all the specifications, with the trial rate displaying low p-values in column 3 (p-value = 0.014) and column 4 (p-value = 0.076). A similar pattern is found for the conviction rate in the OLS and FE specifications (p-value < 0.01) as well as in column 3 (p-value = 0.083). On the whole, findings show that for this crime category there is ~~robust~~ evidence of a deterrence effect which operates through the probability of standing trial and the ensuing probability of being convicted. Surprisingly, the socioeconomic controls do not seem to explain much of the variation in wastewater crime rate. One possible explanation is that the

wastewater crime rate does not distinguish among urban, domestic, and industrial wastewater. In fact, firms found guilty of wastewater illegal management are likely to respond to an economic rationale to a certain extent different from that of city's public officials. Hence the inability of separating cases related to domestic, urban, and industrial might hinder a more thorough analysis of the underlying socioeconomic determinants.
Another plausible explanation is the absence of clear-cut differences between social and economic factors. Italy has been failing to comply with the EU regulation on wastewater treatment for many years, as the last referral to the EU Court of Justice in March 2019 exemplifies EC (2019). Specifically, as the EU press release explains, the inadequacy of the urban wastewater system concerns 16 out of the 20 Italian regions over a time period of 13 years.[11]

Table 1.4: Regression results - Wastewater crimes

	(1) OLS	(2) FE	(3) Sys-GMM	(4) Sys-GMM
Lag Crime_rate	0.659***	0.490***	0.524***	0.309*
	(0.000)	(0.000)	(0.000)	(0.069)
Clearance	0.697	1.655	3.033	6.815
	(0.499)	(0.210)	(0.116)	(0.107)
Trial	-1.221	-1.518	-2.908**	-6.303*
	(0.153)	(0.149)	(0.014)	(0.076)
Conviction	-0.463***	-0.429***	-0.339*	-0.795
	(0.000)	(0.002)	(0.083)	(0.104)
Unem	0.00974	-0.00566	0.0297	0.0251
	(0.115)	(0.832)	(0.150)	(0.631)
Org_crime	0.0148	-0.00538	-0.00185	-0.00215
	(0.338)	(0.825)	(0.939)	(0.956)
Rev_firm	-0.0173	-0.276	0.120	-0.0886
	(0.518)	(0.338)	(0.309)	(0.666)
Observations	192	192	192	192
Adj_R2	0.755	0.470		
AR1(p-value)			0.0042	0.0047
AR2(p-value)			0.1744	0.0965
Sargan-Hansen(p-value)			0.1064	0.2741

p-values in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5.3 Building violations

Table 1.5 displays the results for the building violations crime rate. In line with the EC crimes estimates also this crime category shows persistency in the crime rates. The evidence in support of a deterrent effect, however, is in this case weaker than for waste and wastewater violations. The trial rate displays a negative coefficient with low p-values only in the OLS and FE specifications and the conviction rate

[11] https://ec.europa.eu/commission/presscorner/detail/en/MEMO_19_1472

only in the OLS. However, the GMM specifications that treat deterrence variables as endogenous do not show evidence of deterrence. Among the socioeconomic variables, the unemployment rate has the expected positive coefficient in all the specifications, with a low p-value (0.017) in the GMM specification of column 3 – which however does not pass the Sargan-Hansen test of overidentifying restrictions (p-value = 0.0250).
The lack of deterrence for building-related violations is nonetheless consistent with the deterrence theory of an offender who weighs benefits and costs. On the benefits side, illegal building allows to bypass property taxes and construction levies as well as saving by building on agricultural plots, which are much less valuable than plots on which building is allowed (Chiodelli, 2019). As far as costs are concerned, in Italy building violations have been perceived as a relatively less serious unlawful act, which was also object of three amnesties by the government in 1985, 1994, and 2003 (Zanfi, 2013). Moreover, the most deterrent tool, which is the demolition of the unauthorized building foreseen by the law, is rarely applied. The Italian environmental NGO *Legambiente* reports that only 19% of the demolition orders issued in the period 2004-2018 have been executed (Legambiente, 2018). The relatively high benefits compared with the low social stigma and the low probability of being convicted and having the illegal building demolished make the deterrence for this crime category rather difficult.

Table 1.5: Regression results - Building violations

	(1) OLS	(2) FE	(3) Sys-GMM	(4) Sys-GMM
Lag Crime_rate	0.918***	0.506***	0.773***	0.776***
	(0.000)	(0.000)	(0.000)	(0.000)
Clearance	-0.0295	-0.207	0.513	0.278
	(0.924)	(0.611)	(0.447)	(0.828)
Trial	-0.228*	-0.875**	-0.163	0.795
	(0.082)	(0.016)	(0.670)	(0.336)
Conviction	-0.170**	-0.0782	-0.0696	-0.159
	(0.039)	(0.666)	(0.594)	(0.458)
Unem	0.0108***	0.00118	0.0207**	0.00522
	(0.004)	(0.912)	(0.017)	(0.721)
Org_crime	-0.00355	-0.00367	-0.00765	-0.000145
	(0.691)	(0.626)	(0.376)	(0.992)
Rev_firm	-0.0113	-0.268	-0.0462	-0.0333
	(0.354)	(0.285)	(0.240)	(0.567)
Observations	200	200	200	200
Adj. R2	0.926	0.591		
AR1(p-value)			0.0012	0.0021
AR2(p-value)			0.5228	0.4510
Sargan-Hansen(p-value)			0.0250	0.2281

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.5.4 Robustness checks

Our findings provide evidence of the presence of significant deterrence in the fight against environmental crimes regulated by the EC, with the exception of building violations. Our estimates considered considered the time frame from 2006 to 2016. In 2015, however, a key reform for environmental crimes entered into force, law 68/2015 *"Dispositions concerning crimes against the environment"*. Law 68/2015 introduces in the criminal code new types of felonies with increased penalties and statute of limitations, e.g. art. 452-bis "*Environmental Pollution*", art. 452-quarter "*Environmental Disaster*", and "*Trafficking and neglect of highly radioactive material*" among others. These new provisions provide investigators with an enhanced set of legal instruments to prosecute environmental crimes. The new framework plausibly represents an increased deterrent effect raising the expected costs of undertaking an illegal act against the environment.

Law 68/2015 along with the EC can be seen as an example of a normative evolution at the EU level according to which member states start to use criminal law to punish environmental crimes per se, and not only as violations of administrative rules (Faure, 2017a,b). Secondly, such evolution is characterized by the use of a '*toolbox*' approach (Faure, 2017b) which entails the use of different sanctioning instruments, from the less severe administrative sanctions to imprisonment. In the Italian context, EC and the new environmental crimes introduced in the Penal Code embody

such toolbox.
The introduction of the new law might have induced expected increase in the level of deterrence, and the results reported in our analysis could be driven by that recent normative change. In order to rule out the possible effect of the new law, we rerun our preferred GMM specification with a reduced number of instruments (corresponding to columns 4 in Tables 1.3 and 1.4) dropping years 2015 and 2016. Table 1.6 displays the results, with column 1 referring to waste-related crimes and column 2 to the wastewater category.
The results confirm our previous findings for the whole period. As far as waste violations are concerned, the conviction rate has the expected negative sign with a low p-value = 0.026. With respect to wastewater crimes, deterrence acts through the probability of standing trial (p-value = 0.031). The clearance rate for wastewater crime is positive with a p-value = 0.094. Positive coefficients of police officers per capita or inspections are commonly found in the literature (Cherry, 1999). For instance, in the domain of environmental infractions, a positive coefficient of the clearance rate is found by Almer and Goeschl (2010, 719) for generic environmental crimes (not disaggregated by typology) when considering all the German States. They ascribe this finding to the fact that "*detection and clearance are joint products of police effort*", or to "*economies of scale in clearing cases*". The signs and p-values of the control variables are qualitatively the same with respect to the estimates obtained over the period 2006-2016, hence confirming the importance of organized crime and firm revenues in explaining waste crimes rates.

Table 1.6: Regression results - Waste and wastewater crimes 2006-2014

	(1) Waste	(2) Wastewater
Lag Crime rate	0.494***	0.245
	(0.004)	(0.148)
Clearance	-0.350	7.504*
	(0.574)	(0.094)
Trial	-0.219	-7.470**
	(0.594)	(0.031)
Conviction	-0.524**	-0.326
	(0.026)	(0.550)
Unem	0.00632	0.0459
	(0.693)	(0.348)
Rev_firm	-0.135*	0.0328
	(0.061)	(0.778)
Org_crime	0.0355**	0.00121
	(0.027)	(0.979)
Waste_plant	-0.00208	
	(0.646)	
Recycling_rate	0.0850	
	(0.879)	
N. of Observations	160	154
N. of Groups	20	20
N. of Instruments	26	23
AR1(p-value)	0.0032	0.0007
AR2(p-value)	0.8252	0.8785
Sargan-Hansen(p-value)	0.0915	0.8225
Kleibergen-Paap rk LM statistic (p-value)	0.0005	0.0073

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

1.6 Conclusions

This paper analyses the relationship between environmental crime rates and deterrence in the Italian regions over the period 2006-2016. Illegal actions that affect the environment are particularly relevant in Italy. The focus of our analysis is on three crime types related to: waste, wastewater, and building violations. Although they do not represent the whole range of illegal acts against the environment they are nonetheless among the most important and diffused. Despite the importance of the issue, the literature on environmental crime and deterrence is rather limited with respect to the Italian case and it mainly focuses on the waste sector.

This study contributes to the literature by testing the prediction of the Becker model for the particular category of environmental crimes in Italy by using a new ISTAT dataset of environmental crime charges. Specifically, we contribute by shedding light on which specific elements of deterrence works. To do so, we build a detailed dataset with crime-specific deterrence variables covering the main phases of criminal prosecution. Differently from other studies, which focus only on single aspects of deterrence like the inspection rate, we consider jointly all the key phases which are predicted to affect offenders' decision of committing a crime according to deterrence theory: the clearance, trial, and conviction rates. Taking into account all the prosecution phases allows us to understand which elements of the criminal proceeding is more likely to deter potential environmental offenders.

Overall our findings confirm the considerable role of deterrence factors in order to explain variation in environmental crime rates across Italian regions. Our results show that there is evidence of deterrence particularly for the crimes regulated by the Code of the Environment, that is illegal acts in the waste and wastewater sectors. Waste and wastewater crimes are deterred, specifically, by the probability of standing trial and being convicted. This is an interesting difference with respect to the empirical literature on non-environmental crimes: here, the clearance rate is no longer the main deterrent tool.

Socioeconomic factors, and namely unemployment as a proxy of income inequality across Italian regions, do not appear to explain variations in wastewater and building violations. The significant role played by organized crime is, instead, confirmed in determining the differential incidence of illegal waste management. Overall, our findings confirm the predominant role of deterrence factors in explaining environmental crime rates in Italy, pointing to the importance of enforcement activities as the major tool to hinder unlawful behaviour in the environmental domain.

Appendix

Table 1.7: Laws considered in the analysis

Law	Article	Crime
D. Lgs. 152/2006[1]	133	Wastewater
D. Lgs. 152/2006	134	Wastewater
D. Lgs. 152/2006	137	Wastewater
D. Lgs. 152/2006	255	Waste
D. Lgs. 152/2006	256	Waste
D. Lgs. 152/2006	257	Waste
D. Lgs. 152/2006	259	Waste
D. Lgs. 152/2006	260	Waste
D. Lgs. 152/2006	260 ter	Waste
D. Lgs. 152/2006	261	Waste
D. Lgs. 152/2006	261 bis	Waste
D. Lgs. 152/2006	296 ter	Waste
D.P.R. 380/2001[2]	10	Building
D.P.R. 380/2001	44	Building
L. 47/1985[3]	20	Building
D.L. 146/1985[4]	3	Building
L. 298/1985[5]	3	Building
D.P.R. 380/2001	44, c. 1, lett. C	Building
L. 47/1985	20, c. 1, lett. C	Building

Chapter 2

Is the enforcement of forest protection laws capable of preventing wildfires? Evidence from Italian provinces

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Abstract

This paper analyzes the effect of enforcement on forest fires in Italian provinces (NUTS 3 level) in the period 2009-2015. Despite the relevance of the phenomenon and the related social and environmental costs, the link between forest fires and deterrence remains a relatively unexplored issue. Using recent public prosecutors' offices data on forest fires-related criminal proceedings, we test whether an increase in the enforcement level reduces the number of forest fires. Results show a statistically significant deterrent effect of the clearance and trial rates. In particular, deterrence is higher in the case of unintentional forest fires. Moreover, forest fires are more responsive to changes in the clearance rate, indicating that enforcement in the short term has a higher deterrent effect with respect to legal actions farther in the future.

2.1 Introduction

Forest fires represent a major threat for humans and ecosystems. Due to climate change, the frequency, intensity, and severity of wildfires are predicted to increase in the near future (Abatzoglou and Williams, 2016; Boegelsack et al., 2018; Price et al., 2013). More frequent and intense fire episodes will cause major adverse effects on human health. With an increased severity and intensity of forest fires also a higher number of fire-related casualties have been observed (Koplitz et al., 2016), especially in fire prone areas like southern Europe (Molina-Terrén et al., 2019). In addition, wildfires are associated to respiratory diseases and, to a lesser extent, to cardiovascular diseases (Reid et al., 2016). Beyond damages caused directly to humans, burning of wide forested areas create further damages to ecosystems, for instance land degradation (Olsson et al., 2019). A related risk particularly relevant for the Italian territory is hydrogeological instability, typically occurring 5 or 6

years after a mountain forested area has been hit by fires (Comitato Capitale Naturale, 2018). Wildfires also constitute one of the causes of biodiversity loss, both directly, by harming wildlife, and indirectly through the destruction of habitats, territories, shelters, and nourishment (Dennis et al., 2001).
Forest fires demand considerable human and financial resources, first in direct fire-extinguishment operations and secondly to restore forested and non-forested damaged areas (Anderson, 1999; Di Fonzo M., P.M. Falcone, et al., 2015).

A very low share of forest fires is due to natural causes. The majority are human-caused, either unintentional or deliberate acts (San-Miguel-Ayanz et al., 2017). The human origin of the phenomenon makes the analysis of policies aimed at preventing and prosecuting wildfires crucial. Despite the relevance and worldwide extension of forest fire events, however, the analysis of the deterrent effect of police forces and legal systems is still limited. This paper contributes to the literature by investigating the relationship between forest fires and deterrence in Italy, one of the most affected European countries both in terms of occurrences and of burnt surface. In order to investigate deterrence, we use a new dataset of criminal prosecution cases at the provincial level for both arsons and unintentional forest fires. Criminal proceedings data allow us to compute proxies for the probability of being apprehended as well as for the probability of standing trial for the two typologies of crime at the provincial level. In addition, we complement the analysis based on provinces testing the main model with regional level data covering all Italian regions on a longer time frame. Results point to a significant deterrent effect especially through the probability of being apprehended for unintentional forest fires.
The remainder of the paper is as follows. Section 2.2 reviews the relevant literature and introduces the hypotheses. Section 2.3 describes the dataset and the research method. Section 2.4 presents the results and section 2.5 concludes.

2.2 Literature review

The idea that individuals weigh costs and benefits before engaging in criminal activities was modelled formally for the first time by Becker (1968). His model started a specific branch of research with the aim of better understanding the relationship between crime, deterrence, and socioeconomic factors both theoretically and empirically. As pointed out in Chalfin and McCrary's (2017) literature review, studies belonging to this stream of research can be further divided into three main subgroups. The first group includes studies focusing on how crimes respond to changes in the probability of being apprehended, which is often measured through different indicators like the number of police officers per inhabitant or the share of cases solved (e.g. Corman&Mocan (2000)). The aim of the second group is instead to investigate the response of crime rates to changes in the severity of the sanctioning regime, like increases in fines or the years to be spent in prison. The third group focuses on the relationship between crime and labour market conditions, considering for instance the unemployment rate or the level of income inequality (e.g. Kelly (2000); Fajnzylber et al. (2002)). Overall, the evidence over fifty years of research in this domain confirms the presence of a deterrent effect of increases in police presence (Nagin, 2013a). Empirical evidence also confirms a strong link between labour market opportunities and crime. Consensus about the effectiveness of sanction and sentence enhancement is more limited, and in general the deterrence effect

of sanctions enhancement is smaller with respect that of monitoring (proxied by police manpower) (Chalfin&McCrary, 2017). In other words, individuals tend to be deterred from an illegal act more by the probability of punishment, in particular the probability of apprehension, than by its severity (Nagin, 2013b). The predictions of Becker's model and the deterrent effect of enforcement have been also found with respect to illegal acts against the environment (see Cohen (2000) and Shimshack (2014) for an overview of environmental monitoring and enforcement studies).
Considering the above-mentioned literature, and in particular the presence of a deterrent effect of enforcement as well as the higher effect of forms of punishment closer in time, we formulate the following hypotheses:

- H1: *An increase in the level of deterrence is negatively associated to the number of forest fires.*

- H2: *An increase in the clearance rate exerts a greater deterrent effect with respect to increases in the trial rate and in the conviction rate. The following coefficients' ordering is expected:* $|\beta_{clear}| > |\beta_{trial}| > |\beta_{conv}|$

The majority of empirical studies concerned with acts against environmental law mainly focus on the pulp and paper industry (e.g. Magat&Viscusi, 1990), air and water quality regulations, oil spills, and the waste sector (see for instance Almer&Goeschl, (2015), and D'Amato et al. (2018)), leaving forest fire crimes as a relatively unexplored crime category. In addition, the few available studies focus on US data.
Donoghue and Main's (1985) paper is one of the first attempts to relate forest fires with the level of enforcement. The authors analyse annual forest fires from 27 US states over the period 1970-1981. As an indicator of law enforcement they use the sum of the annual number of prosecutions, convictions, and settlements for the forest fire felony. Their results suggest a weak relationship between enforcement and arsons, while in the case of forest fires caused by debris-burning the relationship is not significant. A first application of the economic model of crime to forest fires data is in Prestemon and Butry (2005). Using yearly wildland arson ignition data from Florida over the time frame 1995-2001 they find a negative and statistically significant coefficient for police forces per capita in the fixed effect specification. In addition, poorer areas are associated to more arsons. In a later work, Prestemon and Butry (2008) expand their previous research to test whether the factors found to influence other categories of crime (e.g. murder, rape, and assault among others) have similar explanatory power in the case of arson wildfires. Their findings confirm that arsons are affected by the same main control variables as other types of crime. In line with their previous study, there is evidence of a deterrent effect of police per capita rate. Interestingly, the magnitude of the deterrent effect is higher in the case of arsons with respect to the other crime categories. One proposed explanation for the high sensitivity of arsons with respect to the wage rate is that arsons are mainly committed by youths, who tend to be more responsive to labour market conditions. Another possible reason is that arson is a typology of crime narrowly defined, while other categories of crime include different illegal acts under a single classification name. This feature of arsons could attenuate the errors-in-variables bias. In a recent study, Prestemon et al. (2019) investigate the effect of arrests on intentional fires in the Spanish region of Galicia. Using daily fires data at the municipality level they

estimate a model of forest fires as a function of arrests, socioeconomic and weather variables. Their results show that "all temporal and spatiotemporal lags of arrests were highly statistically significant and negatively related to counts of intentional wildfires at all spatiotemporal lags tested". In particular, agricultural wildfires are more elastically related to arrests. Contrarily to previous studies, the unemployment rate is not statistically significant, and income changes have an unexpected significant and positive sign for non-agricultural and for total intentional fires.

Considering the findings related to a differential deterrence effect according to the motivation behind the ignition we formulate our third hypothesis:

- H3: *The deterrent effect is higher for unintentional forest fires.*

2.2.1 Crimes and forest fires in Italy

Crimes have been also analysed with respect to the Italian context. For instance, Buonanno (2006) finds a deterrent effect, as proxied by a negative and significant coefficient of the clearance rate, for property crimes and thefts. In addition, the deterrent effect is more incisive in the North. Focusing on illegal trafficking of waste, Germani et al. (2015a) measure the deterrent effect using the charge rate and the arrest rate as well as their squared terms, finding evidence of deterrence only for very high level of enforcement. D'Amato et al. (2018) consider the crime of illegal disposal of waste and they find a similar result using as a proxy the rate of inspections of the State Forestry Corp. The association between forest fires, weather, and socioeconomic factors has been also investigated in the Italian context. Pazienza and Beraldo (2004) analyse the relationship between unemployment and forest fires in the area of Gargano National Park in the Italian region of Apulia, pointing to the adverse effect of the former law governing fire-fighting funds which created a perverse incentive for temporary fire-fighters to intentionally ignite fires in order to increase their chances of having their job reconfirmed in the next seasons. Mancini et al. (2018) study the relationship between 39 weather and socioeconomic factors that are generally considered to affect forest fires at the municipality level for the years 2007-2013. In particular, through different estimation models they test the effect of these variables on three dependent variables: fire occurence, fire size, and fire density. Their results suggest that disadvantaged and poorer areas with high levels of unemployment and income inequality experience more forest fires. In a recent study, Michetti and Pinar (2019) analyse forest fires in Italian regions from 2000 to 2011 both daily and yearly. In particular, their yearly model includes also socioeconomic factors like the percentage of employment in agriculture, the relative poverty rate, the education level, and the rate of extortion per 100,000 inhabitants. Results show that the education is statistically significant with a negative sign, while the extortion rate is significant and positively associated to fire occurrence only in the Southern regions.

2.3 Model specification and the dataset

2.3.1 Model specification

The count of forest fires, $y_{i,t}$, is assumed to follow a negative binomial distribution (NB) (Cameron and Trivedi, 2013) with the following probability mass function:

$$f(y_{i,t}, \lambda_{i,t}, \theta_{i,t}) = \frac{\Gamma(\lambda_{i,t} + y_{i,t})}{\Gamma(\lambda_{i,t})\Gamma(y_{i,t} + 1)} \left(\frac{\theta_i}{1 + \theta_i}\right)^{y_{i,t}} \left(\frac{1}{1 + \theta_i}\right)^{\lambda_{i,t}} \tag{2.1}$$

where Γ is the gamma function, $\lambda_{i,t} = \exp(\beta \mathbf{x}_{i,t})$ and θ_i is the overdispersion parameter. The mean and the variance are $E(y_{i,t}) = \theta_i \lambda_{i,t}$ and $var(y_{i,t}) = (1 + \theta_i) \theta_i \lambda_{i,t}$ respectively.

Differently from the Poisson distribution, which assumes the equality of the mean and the variance, the NB allows the variance to exceed the mean in order to account for data overdispersion, that is when var(y) > E(y). The choice of using an NB model rests on the result of an overdispersion test (ibid., 77-79), which rejects the null hypothesis of the equality of the variance and the mean, H_0: $\theta = 0$, against H_1: $\theta > 0$. The vector of covariates $\mathbf{x}_{i,t}$ includes three main categories of factors representing a) deterrence, b) weather, c) and socioeconomic factors. The next subsections will describe in detail both the dependent and independent variables.

2.3.2 Dependent variable: forest fires

Data on forest fires have been collected from the database of the European Forest Fire Information System (EFFIS), which was officially established by the European Commission in 2003 (San-Miguel-Ayanz et al., 2013). The EFFIS database gathers data on the number of fires, the average burnt surface, and weather forecasts from both EU member states and non-EU states. Our dependent variable is the number of forest fires in province *i* in year *t*. Provinces corresponds to geographical units at the NUTS 3 level of the European territorial subdivisions. Provinces belonging to autonomous regions with special statute[1] are not considered in the provincial-level analysis because they did not send complete data to the EFFIS database after 2012. However, they are considered in the region-level (NUTS 2) analysis in section 2.4.1. The final sample comprehends 489 province-level observations from the 15 Italian ordinary statute regions over the period 2009-2015.

2.3.3 Deterrence

The original model developed by Becker (1968) assumes that individuals are utility maximizers who assess the benefits and costs of engaging in illegal activities. In particular the expected utility of a potential offender is formalized as follows:

$$EU = pU(Y - f) + (1 - p)U(Y) \tag{2.2}$$

where *Y* is the generic benefit from committing a crime, *f* is the monetary equivalent of punishment, and *p* is the probability of being apprehended. Benefits

[1] Aosta Valley, Trentino-Alto Adige, Friuli Venezia Giulia, Sardinia and Sicily

can be for example the money which could be obtained from a theft, while the costs might be the amount of an issued fine or the time to be spent in prison. In particular, f can be a function of different phases of the criminal prosecution (Chalfin and McCrary, 2017), like the probability of being apprehended, tried, or convicted. The empirical literature uses different indicators like police officers per inhabitant rates, clearance and trial rates, or arrest rates. Overall, empirical findings suggest that crime rates are negatively correlated to the level of enforcement. According to the limited available empirical literature, forest fires respond to enforcement efforts by public authorities similarly to other crime categories. For instance, Prestemon and Butry (2008) find that arsons in Florida are negatively related to the police per capita rate. In a recent study, Prestemon et al. (2019) find that the count of arrests is negatively related to wildfires in the Spanish region of Galicia. However, aggregate measures such as general police force rate might undermine their ability to correctly measure enforcement levels (Curry et al., 2016). In fact, police officers might be allocated to patrol urban areas or specific typologies of crime, which are different from the felony analysed by the researcher. As far as the number of arrests is concerned, as remarked by Curry et al. (2016), this specific measure does not represent a probability of apprehension (and therefore an index of efficiency of prosecution) and tends to be automatically higher in areas with more crimes. In order to avoid such drawbacks, we proxy for the level of deterrence using crime-specific clearance and trial rates at the provincial level.
We use the ISTAT dataset on criminal proceedings to calculate deterrence variables (ISTAT, 2018). For each crime category, the ISTAT dataset provides the following statistics: i) the number of cases with an identified suspect that go to trial, ii) the number of cases with an identified suspect which get dismissed, and iii) the number of cases for which a suspect has not been identified and which are consequently dismissed. Specifically, for province i in year t we define the *clearance rate* as the share of forest fire-related legal proceedings with an identified suspect out of the total recorded cases:

$$Clear_{i,t} = \frac{(n.\ of\ cases\ with\ an\ identified\ suspect)_{i,t}}{(total\ n.\ of\ cases)_{i,t}}, \tag{2.3}$$

The *trial rate* is defined as the share of forest-fire related cases that go to trial out of the cases with an identified suspect:

$$Trial_{i,t} = \frac{(n.\ of\ cases\ brought\ to\ trial)_{i,t}}{(n.\ of\ cases\ with\ an\ identified\ suspect)_{i,t}}, \tag{2.4}$$

In addition, in the regional-level analysis we will also consider forest fire-related convictions by introducing the conviction rate computed in the following way:

$$Conv_{i,t} = \frac{(n.\ of\ convictions)_{i,t}}{(n.\ of\ cases\ brought\ to\ trial)_{i,t}}, \tag{2.5}$$

This ratio gives an approximation for the probability of being convicted once a suspect has been brought to trial. Considering also the rate of convictions allows us to control for the deterrent effect produced by the probability of being punished by the issue of a fine or an imprisonment sentence.

2.3.4 Weather and socioeconomic factors

Weather and socioeconomic factors affect the occurrence of forest fires. Climate conditions affect especially the fuel load – that is the amount of live and dead vegetation – available for ignition and propagation. To control for weather factors we include the natural logarithm of the average level of precipitation – *prec* – and the average maximum temperature obtained from the *Osservatorio Agroclimatico* of the Italian Ministry of Agricultural, Food and Forestry Policies. In fact, the level of precipitation and the temperature influence the flammability of the fuel load (Russo et al., 2017; García-Llamas et al., 2019).
In Europe forest fires are mainly human-caused and different socioeconomic factors play a role (Ganteaume et al., 2013), with unemployment and agricultural activities among the most important (Martínez et al., 2009). For instance, unemployment has been found to be related to forest fires because seasonal fire-fighters have the incentive to ignite fires in order to be hired in the following years (Lovreglio et al., 2010). To account for labour market conditions and the general level of economic development of the provinces we include the unemployment rate (*unem*) and the natural logarithm of per capita GDP (*gdp*) as control variables. The general level of criminality is another factor which has been positively associated to forest fires occurrence (Michetti and Pinar, 2019). As a proxy for delinquency we use the rate of theft per 100,000 inhabitants. Agricultural activities have been also identified as causes of forest fires. Indeed, a common cause is the use of fires by farmers to get rid of stubbles (Lovreglio et al., 2010). To control for the potential risk factor due to agricultural activities we use the share of agricultural employment. In addition, more densely populated areas are also associated to a higher number of wildfires (Romero-Calcerrada et al., 2008; Martínez et al., 2009; Costa et al., 2011). We use population density defined as the number of inhabitants per square kilometer to control for human pressure.

2.3.5 Descriptive statistics

Table 2.1 displays the descriptive statistics of our sample. On average, there are about 58 forest fires per year in each Italian province. However, there is considerable variability as the number of wildfires ranges from 0 to the maximum of 705 forest fires recorded in the Cosenza province in 2015. Figure 2.2 in the appendix presents the geographical distribution of forest fires. Provinces particularly affected by forest fires are concentrated in the South (Calabria, Campania, and Apulia) and in the northern region of Liguria. The average clearance rate is 0.27, which means that around 1 case out of 4 is cleared by police forces. The average trial rate is 0.42, indicating that 42% of cleared cases are then brought to trial. The clearance and trial rates computed separately according to the typology of criminal charge, unintentional or arson, provide a more thorough account of the forest-related enforcement. Indeed, the average probability of apprehension is higher for unintentional igniters

(0.77) with respect to arsonists (0.21). A similar pattern is observed for the probability of standing trial, with an average value of 0.64 for unintentional forest fires and 0.34 for arsons. Figure 2.1 displays the trend of the clearance and trial rates. The left panel shows the trend considering all typologies of forest fires, while the right panel the clearance and trial rates separated according to the typology of fire charge (unintentional vs arson). The clearance rate slowly decreased from 2008 to 2012, then it considerably raises for two consecutive years, to return in 2015 at about the initial level. The trial rate follows a slightly increasing trend, which is mainly led by arson-related charges.

Table 2.6 in the appendix shows the correlation matrix. Clearance rates, both for intentional and unintentional forest fires, are negatively and significantly correlated with forest fires. Trial rates, instead, are not significantly correlated. The weather controls, temperature and precipitation, have the predicted sign and are significantly correlated with the dependent variable.

Table 2.1: Descriptive statistics

	count	mean	p50	sd	min	max
fires	298	73.97	37.00	106.03	0.00	705.00
clearc	298	0.82	1.00	0.25	0.10	1.00
clearn	298	0.19	0.12	0.19	0.01	1.00
trialc	298	0.64	0.78	0.39	0.00	1.00
trialn	298	0.38	0.33	0.33	0.00	1.00
temp	298	17.84	18.40	2.88	6.60	23.30
prec	298	6.76	6.75	0.21	6.27	7.38
unem	298	10.49	9.31	5.11	2.85	31.46
lngdp	298	10.09	10.12	0.26	9.58	10.85
den	298	269.62	185.50	364.74	49.50	2681.60
agr	298	0.05	0.04	0.04	0.00	0.18
theft	298	21.18	19.93	9.19	5.95	53.58

2.4 Results

Table 2.2 displays the results of the main model. Columns 1 and 2 refer to the full sample while columns 4 and 5 to the North-Central and Southern provinces respectively. Column 1 displays the result of the control variables. The coefficients of *temp* and *prec* have the expected positive and negative sign respectively, confirming the importance of weather factors in explaining forest fires. Surprisingly none of the socioeconomic controls show a strong relationship with the dependent variable. The absence of a clear relationship between *unem* and wildfires is consistent with previous researches (Prestemon et al., 2019; Prestemon and Butry, 2005). The other socioeconomic factors, despite the predicted positive sign of *den* and *theft* and the negative sign of *gdp* and *agr*, are not strongly related to wildfires (p-values > 0.1).

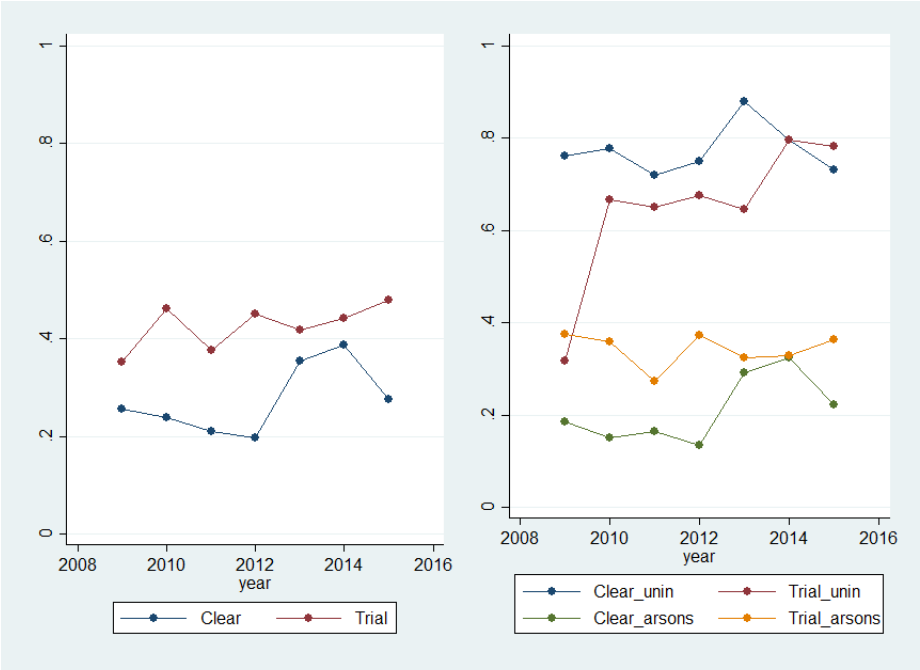

Figure 2.1: Trend of clearance and trial rates
Note: Own elaboration on ISTAT data.

Column 2 displays the results once deterrence is considered. On the one hand *clear* has the expected negative sign with a p-value = 0.001, indicating that an increase in the identification of suspects of forest-fire cases is related to a reduction in the number of wildfires. On the other hand, there is no evidence of deterrence by the probability of standing trial. Indeed, the *trial* rate coefficient has an unexpected positive sign but with a relatively high p-value (0.086). These results hence point to the relevance of deterrence for this crime category.
However, forest fires seem to be mainly counteracted by the probability of being discovered rather than the probability of standing trial.

Considering the full sample might hide regional patterns of forest fires linked to deterrence and socioeconomic factors. This is particularly relevant for Italy, a country with an historical North-South divide (Musolino, 2018). Columns 3 and 4 display the results for North-Central and Southern provinces separately. Weather factors maintain their relevance, with the exception of the level of temperature in the South, in line with Michetti and Pinar (2019). Interestingly, by splitting the sample into North-Center and South some socioeconomic factors acquire importance. As far as the North-Center is concerned, the population density is negatively related to forest fires (p-value = 0.057) in line with other studies which focus on large urban areas (Beccari et al., 2016; Costafreda-Aumedes et al., 2018). Similarly, the share of agricultural employment (p-value = 0.059) is negatively related to forest fire occurrence indicating the risk-reduction role of fuel-management activities performed by farmers. In the South sample, the *theft* rate is strongly related to forest fires (p-value = 0.005), pointing to the general level of criminality as an important element to explain forest fire occurrence. This result confirms the findings of Michetti and Pinar (2018), who find a positive relationship between the extortion rate and forest fires in the South of Italy using regional-level data. The clearance rate maintains its significance once we split the sample. The coefficient for southern provinces, however is approximately three times higher in magnitude with respect to northern-central provinces. Interestingly, the greater elasticity of forest fires to the clearance rate goes in the opposite direction with respect to of Buonanno's (2006) findings. In fact, for property crimes, thefts, and total crimes Buonanno finds that on average clearance rate coefficients are higher in the Northern regions.

Table 2.2: Regression results

	(1) Full	(2) Full	(3) North-Center	(4) South
Clear		-0.556***	-0.426**	-0.999***
		(0.001)	(0.016)	(0.008)
Trial		0.132*	0.127	0.0833
		(0.086)	(0.133)	(0.579)
Temp	0.0582*	0.0550*	0.110***	-0.00399
	(0.051)	(0.065)	(0.003)	(0.953)
Prec	-0.791***	-0.760***	-0.778**	-1.612***
	(0.000)	(0.000)	(0.010)	(0.000)
Unem	-0.0114	-0.0129	-0.0423*	-0.0117
	(0.437)	(0.372)	(0.091)	(0.521)
Gdp	0.157	0.218	0.687	0.491
	(0.767)	(0.675)	(0.390)	(0.620)
Den	0.196	0.314	-1.188*	0.484
	(0.593)	(0.418)	(0.057)	(0.353)
Agr	-0.0261	-0.0288	-0.118*	-0.0349
	(0.336)	(0.284)	(0.059)	(0.287)
Theft	0.00261	0.000472	-0.000956	0.0626***
	(0.810)	(0.965)	(0.940)	(0.005)
_cons	4.699	4.056	-0.417	7.823
	(0.402)	(0.461)	(0.960)	(0.454)
Observations	489	489	340	149
Wald test	783.3***	804.1***	633.0***	394.0***

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.1 Regional-level analysis

Province-level results provide evidence of a deterrent effect of wildfire prosecution steps. This effect is most notably present in the activities related to the discovery of unintentional wildfires suspects. However, the coverage of provincial-level data is limited to regions with ordinary statute. Such data limitation entails the omission of the five autonomous regions, including Sardinia and Sicily, which are among the most hit both in terms of number of fires and forestry burnt surface. Moving to regional-level data allows us to check provincial-level results including all the 20 Italian regions for a longer time period, ranging from 2007 to 2016. Moreover, at the regional level we can also observe the rate of convictions of forest fires is available. Considering also the conviction rate allows us to introduce one additional and relevant prosecution step.

Table 2.3 displays the results of the regional-level model. Column 1 shows the result for the full sample, while columns 2 and 3 the estimates for the North-Center and South regions respectively. With respect to the weather factors, the results for the full sample point to a reduction in the importance of *temp* (p-value = 0.681) and, to a lesser extent, of *prec* (p-value = 0.144). This might be due to the fact that the regional aggregation of weather factors is not sufficient to introduce enough variability across regions for temperature and precipitation as in the provincial-level analysis.

The socioeconomic controls do not play a significant role in explaining the variation of forest fires, in line with the full sample provincial-level estimates. Differently from the provincial-level results, now all deterrence variables have the expected negative coefficient and low p-values (with the exception of the clearance rate in the North-Center with a p-value = 0.067). Moreover, considering all the three prosecutions steps makes it possible to compare their relative dimension. The order of magnitude of the coefficients in all the three specifications confirms our initial hypothesis of a relatively higher deterrent effect for the probability of being apprehended. Such deterrence effect decreases as the potential cost of the unlawful acts is shifted farther in time. Overall, the regional-level results support the provincial-level ones, confirming the importance of deterrence factors in explaining yearly variations of forest fires. In addition, results provide evidence of a deterrent effect from all enforcement steps, with the clearance rate in a prominent role, followed by the trial rate, and lastly by the conviction rate.

Table 2.3: Regression results - Regional analysis

	(1) Full	(2) North-Center	(3) South
Clear	-2.246***	-1.164*	-3.240***
	(0.000)	(0.067)	(0.000)
Trial	-0.841***	-0.714***	-0.661***
	(0.000)	(0.007)	(0.006)
Conv	-0.178***	-0.117**	-0.250***
	(0.000)	(0.039)	(0.001)
Temp	0.0179	0.0354	0.00983
	(0.681)	(0.636)	(0.904)
Prec	-0.292	-0.279	-0.310
	(0.144)	(0.570)	(0.262)
Unem	-0.0130	-0.130*	0.0462*
	(0.558)	(0.076)	(0.086)
Gdp	0.106	-0.0204	0.496
	(0.684)	(0.964)	(0.430)
Den	0.962	0.745	1.351
	(0.657)	(0.833)	(0.756)
Agr	-0.0625	-0.0924	-0.0974*
	(0.236)	(0.547)	(0.085)
Theft	-0.0207	0.00702	0.0178
	(0.151)	(0.748)	(0.598)
_cons	5.283	5.640	1.571
	(0.120)	(0.386)	(0.849)
Observations	171	94	77
Wald test	575.8***	353.2***	476.2***

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.2 Arsons and unintentional forest fires

The results of both the provincial-level and regional-level analyses point to an effective role played by the deterrence variables in contrasting forest fires. Overall, the wildfires crime rates vary negatively with increases in the enforcement variables, and is even more sensitive to variations in the clearance rate, the proxy for the probability of being apprehended. Until now we have considered deterrence variables related to forest fire crime as sanctioned by article 423-bis of the Italian Penal Code. This law foresees two differentiated punishments according to the igniter's motivation. If the forest fire is the outcome of a negligent behaviour, then the punishment may entail imprisonment from 1 to 5 years. Differently, in case of a deliberate act, the imprisonment period is increased from a minimum of 4 to a maximum of 10 years. The motivations underlying the decision to lit a fire are heterogeneous and context-specific (Ganteaume et al., 2013). For instance, as discussed above, in southern Italy forest fires are often lit in order to burn stubbles, for agricultural uses, or by seasonal fire-fighters (Lovreglio et al., 2010). In southern

France common causes are “arsons with undetermined motivations” and “workers’ negligence” (Ganteaume and Guerra, 2018). In the North of Portugal wildfires are mainly caused by negligent agricultural practices while in the South the most relevant cause is related to crop harvesting machinery (Lourenço et al., 2013). For the Italian case, ISTAT data on forest fires judicial cases allow us to compute clearance and trial rate according to the two main categories of forest fires: deliberate (arson) and unintentional. This allows us to investigate the role of deterrence in the two cases In this way it is possible to assess whether forest fires vary more or less elastically according to the typology of forest fires (deliberate or unintentional) being prosecuted.

Table 2.4 displays the results for the specification with clearance and trial rates according to the igniter’s motivation. Column 1 displays the results for the full sample. The number of observations decreases with respect to the estimates presented in Table 2.2 due to the low number of unintentional forest fires, which in some cases does not allow us to compute the clearance or trial rates. Weather and socioeconomic factors are qualitatively the same as in the results displayed in the previous tables. With respect to deterrence variables, the clearance rates for unintentional fires (*clear_unin*, p-value = 0.002) and arsons (*clear_arsons*, p-value = 0.055) are both negatively related to forest fires. The trial rate of unintentional wildfires (*trial_unin*) has the expected negative sign but with a high p-value = 0.519. Similarly, the arson trial rate has a high p-value = 0.206 but with an unexpected positive coefficient. A positive coefficient of the trial rate has been also found in German environmental crime prosecution data (Almer and Goeschl, 2011).

Columns 2 and 3 display the results for the North-Center and Southern provinces respectively. Once the motivations of forest fire are considered, the p-values of deterrence variables increase for the North-Center sample. Interestingly, the results for the South show that deterrence works mainly for unintentional wildfires, and that in this case both the probability of being identified (p-value = 0.063) and the probability of standing trial (p-value = 0.060) point to a crime-prevention effect of the enforcement activities. The use of motivation-specific clearance and trial rates provides a more complete and detailed framework of the relationship between this crime category and its related prosecution activities. Overall, an increase in the clearance rate is more effective in reducing the count of forest fires. Such pattern is especially valid for unintentional forest fires in the South. A greater deterrence effect for unintentional forest fires is in line with the findings of Prestemon et al. (2019) concerning the higher deterrence found for agricultural wildfires with respect to non-agricultural ones. The explanation put forward by the authors is that farmers respond to a profit-maximizing behaviour and the threat of a fine is more compelling for them because it would directly undermine their income.

A possible reason for the lower deterrent effect in the case of arsons might be due to the very low share of apprehended arsonists, which is in line with other countries (Cozens and Christensen, 2011). The probability of identifying an arsonist and then bring her to trial is lower with respect to unintentional forest fires, suggesting first the difficulty of finding the culprit and then to bring sufficient evidence to prosecute her. In other words, increases in the probability of finding arsonists might be not efficient unless the share of identified suspects reaches a considerable level, that is a level able to increase considerably the expected costs of the ignition and therefore to discourage potential future arsonists.

Table 2.4: Regression results - Arsons and unintentional forest fires

	(1) Full	(2) North-Center	(3) South
Clear_unin	-0.375***	-0.257	-0.309*
	(0.002)	(0.132)	(0.063)
Clear_arson	-0.447*	-0.360	-0.667
	(0.055)	(0.118)	(0.226)
Trial_unin	-0.0475	0.0566	-0.171*
	(0.519)	(0.523)	(0.060)
Trial_arson	0.112	0.133	0.127
	(0.206)	(0.174)	(0.395)
Temp	0.0893**	0.119**	0.211***
	(0.019)	(0.011)	(0.009)
Prec	-0.692***	-0.465	-1.656***
	(0.002)	(0.211)	(0.000)
Unem	-0.0164	-0.0395	-0.00573
	(0.298)	(0.162)	(0.759)
Gdp	-0.706	-1.107	-0.363
	(0.237)	(0.287)	(0.728)
Den	0.00876	-1.685**	1.552
	(0.987)	(0.028)	(0.265)
Agr	-0.0132	-0.209***	0.0126
	(0.699)	(0.007)	(0.751)
Theft	0.0104	0.00746	0.0122
	(0.434)	(0.631)	(0.700)
_cons	12.55*	16.24	12.67
	(0.051)	(0.142)	(0.233)
Observations	295	190	105
Wald test	573.7***	404.9***	346.1***

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.4.3 Sensitivity analysis

To further check the robustness of our results we run a sensitivity analysis. We consider the full sample specification and we rerun the estimates using alternative estimation models. In particular we estimate the main specification using a Fixed Effects Panel Poisson model with robust standard errors and the System Generalized Method of Moments (System GMM). According to the review of Costafreda-Aumedes et al. (2018) the Poisson regression is the most used technique to analyse the number of humanly induced forest fires when the time span considered is annual or longer. In addition, comparing Poisson regression and negative binomial allows us to check the sensitivity of the results according to whether data overdispersion has been taken into account. Finally, in line with the crime economics empirical literature (see among others (Fajnzylber et al., 2002; Almer and Goeschl, 2015; Bun et al., 2019)), we use the System GMM (Blundell and Bond, 1998) treating de-

terrence variables as endogenous. In the latter, in line with the literature (e.g. Curry et al. (2016), the dependent variable has been normalized by expressing it in the natural logarithm of the forest fire rate per 100,000 inhabitants.
Table 2.5 presents the results for the four specifications. In order to make the comparison easier, column 1 repeats the results of the first column of Table 2.4. Column 2 displays the results of the Poisson fixed effects model. Columns 3 and 4 display the GMM estimates, with the former treating deterrence variables as exogenous and the latter considering them as endogenous. Overall the results confirm that unintentional forest fires are deterred by increases in the clearance rate. In particular, the clearance rate for unintentional forest fires has a p-value < 0.001 in the FE Poisson and a p-value = 0.07 in the GMM specification. Poisson results suggest that also the probability of standing trial for unintentional wildfires is able to restrain fire occurrence. The Poisson specification supports the relevance of weather factors, in particular *temp* and *prec*. Differently from NB and Poisson, the GMM specification underlines only the relevance of the clearance rate for unintentional forest fires, while the other controls have p-values > 0.1. Overall, the results of the sensitivity analysis underline that deterrence is mostly effective for unintentional forest fires. The positive effect of the probability of being identified and the absence of (or lower) effect of the probability of standing trial might be explained by the propensity of individuals to respond to incentives that are perceived to be closer in time. A possible explanation is that unintentional forest fires are often ignited by farmers, easier to identify than arsonists. Since one of the most commonly known motivations of forest fires in Italy is stubble burning (Lovreglio et al., 2010), it is likely that farmers or people who lit this kind of fires do so in the proximity of their dwellings, thus making the investigation phase shorter. This result is in line with the theoretical predictions of Lee and McCrary's model (2017), according to which impatient individuals are more responsive to immediate apprehension than to later punishments.

Table 2.5: Regression results - Sensitivity analysis

	(1) NB	(2) Poisson	(3) Sys GMM	(4) Sys GMM
Clear_unin	-0.375***	-0.580***	-1.292***	-0.973*
	(0.002)	(0.000)	(0.001)	(0.055)
Clear_arson	-0.447*	-0.378	-0.883	-0.660
	(0.055)	(0.180)	(0.210)	(0.412)
Trial_unin	-0.0475	-0.186**	-0.0399	-0.242
	(0.519)	(0.047)	(0.805)	(0.496)
Trial_arson	0.112	0.127	0.340	0.208
	(0.206)	(0.207)	(0.174)	(0.593)
Temp	0.0893**	0.188**	0.177	0.0347
	(0.019)	(0.042)	(0.139)	(0.665)
Prec	-0.692***	-0.617**	-0.989**	-0.722
	(0.002)	(0.011)	(0.036)	(0.211)
Unem	-0.0164	-0.00529	0.0664	0.100
	(0.298)	(0.696)	(0.248)	(0.107)
Gdp	-0.706	0.0782	-1.039	-0.372
	(0.237)	(0.941)	(0.674)	(0.877)
Den	0.00876	-2.545	0.0745	0.0926
	(0.987)	(0.593)	(0.943)	(0.933)
Agr	-0.0132	0.00551	-0.120	-0.00448
	(0.699)	(0.888)	(0.383)	(0.967)
Theft	0.0104	0.0394*	-0.0133	0.0149
	(0.434)	(0.075)	(0.727)	(0.697)
L.lnfires			0.155	0.169
			(0.205)	(0.184)
_cons	12.55*		18.47	10.63
	(0.051)		(0.486)	(0.682)
Observations	295	295	258	258
Wald test	573.7***	1147.7***		
Sargan-Hansen test			(0.2737)	(0.1813)
Autocorrelation				
First order			(0.0051)	(0.0076)
Second order			(0.7631)	(0.8446)

p-values in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2.5 Conclusions

This paper analyses the relationship between deterrence and forest fires on a sample of Italian provinces (NUTS 3 level) belonging to the 15 ordinary statute regions, from 2009 to 2015. Wildfires are destructive phenomena that each year provoke huge damages to humans, animals, and plants. With the acceleration of the climate emergency forest fires will increase in numbers and destructive potential. Fire suppression and reconstruction activities entails relevant economic costs. The monetary burden caused by forest fires and the fact that the majority of ignitions are human-induced makes the analysis of the effectiveness of enforcement actions particularly relevant. Despite the importance of the issue, there are very few empirical studies on the link between deterrence and forest fires especially with respect to the European context.

This study contributes to the literature in providing new evidence of the presence of deterrence of enforcement activities from a sample of Italian provinces. Using a novel ISTAT dataset about forest fires charges, we compute proxies for the efficiency of the prosecution system at the provincial level. By using clearance and trial rates we contribute to the literature by shedding light on the role of the probability of apprehension and the probability of standing trial once apprehended.

Our results provide evidence that deterrence variables are negatively related to the occurrence of forest fires. In particular, wildfires are more responsive to increases in the clearance rate with respect to increases in the trial rate. Such relationship is stronger in Southern provinces. Moreover, we analyse the relationship between forest fires and deterrence at the regional level on a longer time frame and including all the 20 Italian regions, along with the conviction rate. In this way, all three main steps of the prosecution process are considered. Results confirm the provincial-level analysis and indicate that (i) deterrence operates mainly for unintentional forest fires and that (ii) wildfires are more elastically related to increases in the clearance rate rather than to increases in the probability of standing trial or being convicted confirming that for this crime category threats which are closer in time are more effective in deterring potential igniters with respect to enforcement actions farther in time. Another aim of the paper was to assess whether prosecution activities are more or less decisive according to the typology of wildfire investigated (deliberate or unintentional). With respect to this research question, our findings show that deterrence is effective mainly in preventing unintentional forest fires. Finally, our results are consistent across different estimation models.

The outcomes of the analyses presented in this work convey policy implications that may be useful to a more effective targeting of wildfire control efforts. In particular, territorial monitoring, for example through a capillary deployment of forest police forces on the most affected territorial units, as identified here, would appear to be a more effective use of resources, in relative terms, than increases in investigative and prosecution efforts, which are enforcement activities farther in time and therefore less likely to deter future igniters.

2.6 Appendix

Table 2.6: Correlation matrix

	(1)											
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
fires(1)	1.00											
clearc(2)	-0.28***	1.00										
clearn(3)	-0.35***	0.22***	1.00									
trialc(4)	0.02	-0.00	0.08	1.00								
trialn(5)	-0.09	0.08	0.03	-0.12*	1.00							
temp(6)	0.29***	-0.09	-0.15**	0.05	-0.13*	1.00						
prec(7)	-0.15**	0.10	0.17**	-0.01	0.04	-0.15**	1.00					
unem(8)	0.39***	-0.09	-0.20***	0.13*	-0.14*	0.50***	-0.11	1.000				
lngdp(9)	-0.47***	0.09	0.35***	-0.01	0.08	-0.46***	0.15**	-0.737***	1.00			
den (10)	-0.05	0.14*	0.08	0.00	-0.08	0.10	0.04	0.05	0.199***	1.00		
agr (11)	0.42***	-0.22***	-0.299***	0.028	-0.070	0.49***	-0.21***	0.630***	-0.79***	-0.34***	1.00	
theft(12)	-0.21***	0.11	0.33***	0.00	-0.01	-0.08	-0.00	-0.29***	0.64***	0.36***	-0.53***	1.00

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

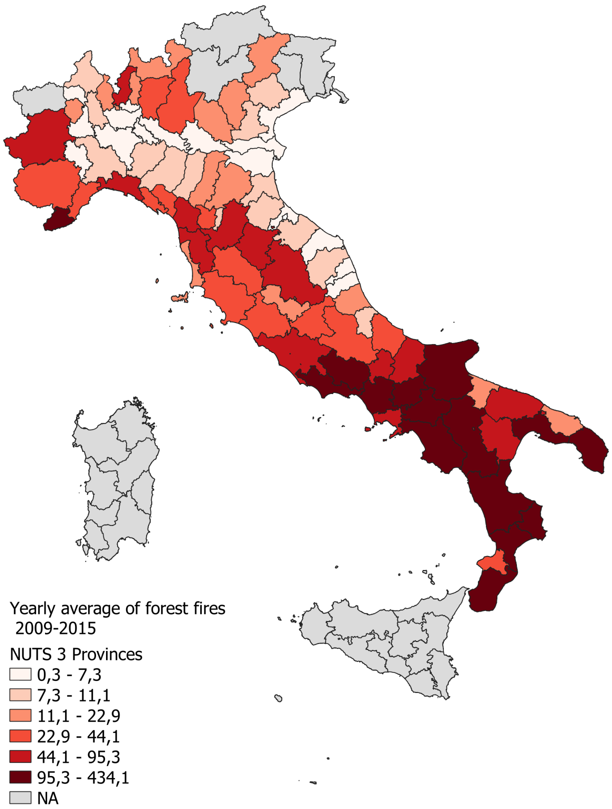

Figure 2.2: Map of forest fires
Note: Own elaboration on EFFIS data.

Chapter 3

Carbon emissions and the cost of debt financing: what role for policy commitment, firm disclosure and corporate governance?

FEDERICO DROGO AND VERA PALEA

Abstract

Over time, investors have become increasingly aware of the risks associated with a transition to a low-carbon economy. This study investigates the association between carbon emissions and the cost of debt financing for a sample of firms from the Eurozone in the period 2010 – 2018. Results provide evidence that the risk premium required by lenders increases with carbon emissions. However, while the most polluting sectors were already charged before the Paris Agreement, and not further penalized in the subsequent period, our results indicate that the less polluting sectors started being charged a higher spread for their emissions only in the period after the Agreement. The Paris Agreement appears to be a turning point around which lenders have become aware of the strong commitment taken by policymaker in fighting climate change. Our findings also suggest that increased levels of disclosure on climate-related issues can mitigate corporate carbon risk. On the other hand, results are not compelling when we consider the effect of control mechanisms, such as external verification for emissions, board oversight of carbon risk and the presence of emission reduction targets, on the cost of debt.

3.1 Introduction

In the last few years, financial investors have become increasingly aware of climate change as an emerging risk. According to the World Economic Forum (2020), environmental-related risks - including extreme weather events, failure of climate-change mitigation and adaptation, natural disaster and ecosystem collapse - are the top 5 risks in terms of likelihood and impact. The frequency and severity reached by extreme weather events show that there is substantial support for considering climate change as the gravest threat for economic activities (Pachauri et al., 2014).

Several initiatives have been taken both at an international and national level to tackle global warming and to incentivize economic actors to undertake steps in order to accelerate the transition to a low-carbon economy. The 2015 Paris Agreement (also Agreement hereafter) represents a milestone in such a process. The Paris Agreement was signed in December 2015 and entered into force in November 2016 (UNFCCC, 2019) with the main objective of limiting the average temperature increase to 2 C° above the preindustrial level. Ratifying members, among which there is the European Union (EU hereafter), have committed themselves to submit a plan to reduce emissions and to make financial flows consistent with a low-carbon transition.

The EU has always played a leadership role in climate policy (Rayner and Jordan, 2016). Energy and industrial policies are two competences of the EU. Accordingly, the European Commission has incorporated climate change mitigation into its actions, setting a variety of policies to boost investment in infrastructure, such as energy, transport, and communication, along with smart and green manufacturing (European Commission, 2018). Estimates of the needs for such investments in the EU are very significant. The overall infrastructure investment gap is estimated at roughly EUR 403 billion, while investment in research would require an annual investment of EUR 140 billion (European Investment Bank, 2018).

Due to a high average public-sector debt, budgeting consolidation is set to continue at a national level. Thus, an upturn in investments cannot be based only on the public sector or classic budgetary stimulus programs. The investment portfolios of financial institutions need to be mobilized and directed toward financing the transition toward a low-emissions economy (European Central Bank, 2018; European Commission, 2013).

With this aim, in 2018 the European Commission published the "Action plan for financing a sustainable growth" (2018; also "Action Plan" hereafter), which is intended to reorient capital flows toward sustainable investments, to help investors manage financial risks stemming from climate change, and to promote transparency and long-termism in investment decisions. With this purpose, the Commission has started working on a taxonomy for sustainable economic activities based on their contribution to climate change mitigation and adaptation. Moreover, the Action Plan considers incorporating climate risk into prudential requirements. A green supporting factor, which gives banks capital relief for their green lending, is currently under discussion at the EU level. Finally, the "Guidelines on reporting climate-related information" (2019) issued by the European Commission provide a list of key-performance indicators, such as greenhouse gas (GHG) emissions, useful to assess a company's exposure to climate change risks.

Central banks and supervision authorities, too, have started analyzing the impacts of climate change on banks' portfolio and the stability of the financial system (NGFS, 2019). Climate change affects the financial system through three main channels. The first involves physical risks, such as floods, landslides, hurricanes, and wildfires, which can destroy relevant fixed assets, thus imposing losses on firms that impair their ability to operate and to repay their debt (NGFS, 2019). Faiella and Natoli (2018), for instance, indicate that over the last years Italian banks have reduced their credit supply to firms in risky areas. The second channel involves transition risk, which refers to the additional costs or devaluation of assets due to changes in the regulation made with the purpose of reducing GHG emissions and adjusting to low-carbon economy (Batten et al., 2018). The introduction of a carbon tax is a typical example of transition risk. Another is the phasing out of coal, already announced by eight EU countries, which is expected to significantly affect coal-based utilities (EURACTIV, 2019). The third channel involves liability risk, which is more specific to insurance companies and arises from firms that are damaged from climate change and consequently try to recoup their losses suing other parties or through their insurances. The Netherlands Central Bank (Vermeulen et al., 2019), by combining different climate policy responses and energy technologies into four economic scenarios, finds that Dutch insurance might experience losses of around 11% of their total assets.

This being the context, understanding whether and how higher carbon emissions result in a higher cost of capital is a key issue for all the market players - both capital providers and borrowers - as well as policymakers. To our knowledge, this study is the first to investigate the relationship between the cost of debt financing and corporate carbon risk for a sample of non-financial listed companies from the Eurozone for the period 2010-2018. We define carbon risk as any corporate risk related to carbon emissions likely to restrict managers' ability to conduct business (Hoffmann and Busch, 2008). The focus is on non-financial firms, as they represent the backbone of the EU economy, and on loans, which are the main corporate financing source in the EU (European Central Bank, 2018). Importantly, data availability allows us to investigate whether the Paris Agreement has changed the way lenders incorporate carbon risk in their investment decisions.

Complementing prior analyses, our study documents that a positive relationship between carbon risk and the cost of debt holds in the context of the Eurozone. Interestingly, findings indicate that lenders started charging low emitters a higher risk premium for their carbon risk only after the Paris Agreement, when fighting climate change became a stronger commitment at the EU level. Higher emitters, instead, were already charged before the Agreement, and not further penalized in the subsequent period. Taken as a whole, our results suggest that the Paris Agreement represents a turning point after which capital providers started incorporating carbon risk into their lending decisions, both for low and high emitters. As such, they provide support to the European Commission's initiatives aimed at driving the financial system to incorporate climate-related issues into asset allocation. They also show that lenders assess carbon risk on the basis of sector analyses rather than broader industry classifications.

Furthermore, our study indicates that increased levels of climate-related disclosure can mitigate carbon risk. Results, on the other hand, are not compelling when we consider specific control mechanisms of carbon risk such as external validation of carbon emissions, board oversight of carbon risk and the existence of emissions reduction targets. The remainder of the paper is as follows. Section 3.2 reviews the relevant literature and develops the research hypotheses. Section 3.3 explains the dataset construction and the econometric models, while Section 3.4 presents the results. Section 3.6 concludes.

3.2 Literature review and hypotheses development

In the wake of the Paris Agreement and the European Commission's Action Plan, there has been a growing interest in the relationship between corporate carbon risk and investors' decisions. As mentioned above, the adoption of carbon pricing policies represents one important factor that could affect corporate risk, affecting borrowers' future cash flows and, therefore, their ability to repay debts and maintain regular dividend payments. Some studies have also highlighted possible reputational risks for capital providers financing high carbon-risk borrowers, which could lower their capacity to attract future customers and their subsequent ability to generate revenues (e.g., Coulson & Monsk, 1999; Subramamnian et al., 2015; Thompson, 1998; Thompson & Cowton, 2004).

In general, research documents that capital providers take corporate carbon risk into consideration when they analyze a company's risk profile and define their investment strategies (e.g., Matsumura et al., 2014; Weber, 2012). Carbon risk is usually operationalized as carbon intensity, which is computed as carbon emissions over revenues or total assets (Hoffmann and Busch, 2008). Some studies have investigated the relationship between carbon intensity and the cost of equity capital. Kim et al. (2015) as well as Trinks et al. (2017), among others, document that the cost of equity increases in carbon risk. Interestingly, results from Trinks et al. (2017) reveal that the relationship between the cost of equity and carbon emissions holds only when both scope 1 and 2 are considered, suggesting that capital providers take both direct and indirect emissions into consideration. Other studies have examined the effect of carbon emissions on the cost of debt. Results generally indicate that higher carbon emitters are considered riskier and thereby pay a higher cost of debt (e.g., Chen & Gao, 2012; Goss & Roberts, 2011; Jung et al., 2018; Kleimeier & Viehs 2018; Weber, 2012). Furthermore, Gianfrate and Peri (2019) document that green bonds are more financially convenient than non-green ones, supporting the view that green projects are considered less risky than the others.

As a first step for our analysis, we test whether a positive relationship between historical data on carbon emissions and the cost of capital also holds in the Eurozone context. We expect higher polluters to be charged an additional carbon risk premium for the higher uncertainty associated with the transition to a low-carbon economy, which may affect their future cash flows. Accordingly, our first hypothesis (in alternative form) states as follows:

- H1: *Firms that exhibit a higher carbon risk pay a higher cost of debt.*

A consistent regulatory framework may play a key role in driving lending policies. With this purpose, the EU has set over time a variety of policies aimed at reorienting the economy towards low-emissions targets (European Commission, 2018, 2019). Research indeed suggests that after the Paris Agreement banks have started taking into account the risk associated to stranded assets. De Greiff, Delis, and Ongena (2018), for instance, find that since 2015 banks have charged a higher loan spread to fossil fuel firms with higher fossil fuel reserves. Capasso and Gianfrate (2019) show that in the aftermath of the Paris Agreement the exposure to climate change decreases the distance to default for an international sample of companies. Monasterolo and De Angelis (2020) report that the level of systemic risk for low-carbon stock indexes from the US, EU and global financial markets has significantly declined since the Paris Agreement. Coherently, our hypothesis is that after the Paris Agreement investors have increased their awareness of climate change issues, becoming more sensitive to carbon risk. Our hypothesis (in alternative form) states as follows:

- H2: *The effect of carbon risk on the cost of debt is higher in the years following the Paris Agreement.*

Improving corporate disclosure on climate-related risks is one key point of the European Commission's Action Plan (2018). In 2019, the European Commission issued the "non-binding guidelines on reporting climate-related information", which include guidance on reporting of climate-related information related to business models, key performance indicators, risks and their management. By providing this kind of information, companies can better incorporate carbon risk in their operations, while investors can better assess a company's overall risk (Financial Stability Board, 2017). Understanding whether a relationship exists between increased levels of corporate disclosure on climate-related risks and the cost of capital is therefore key for well-informed policymaking.

According to the European Commission (2019), increased levels of disclosure of climate-related risks can provide important benefits to firms, including a potentially lower cost of capital. In the presence of increased levels of disclosure, a lower cost of capital could be ascribed to a reduction, for capital providers, of the uncertainty associated with the investment and thereby to a decrease in the risk premium component associated with information asymmetry. Lemma et al. (2019) indeed document that voluntary carbon disclosure is associated with a lower overall cost of capital for a sample of South African firms over the period 2010 – 2015. Kleimeier and Viehs (2018) find similar evidence for an international sample, while Jung et al. (2018) document this relationship for a sample of Australian firms. Gianfrate et al. (2015) however show that the effect of environmental information on the cost of debt varies according to geographical area. In contrast, a few studies point out that increased levels of carbon information come with proprietary costs and could result in revealing information with possible negative repercussions on firms (Guidry & Patten, 2012; Peters & Romi, 2014; Verrecchia, 1983).

This being the context, we consider it important to provide further insight into this issue, thus verifying whether a negative relationship between increased levels of disclosure on carbon risks and the cost of debt holds within the specific context of the Eurozone. Consistent with prior research (Jung et al., 2018; Kleimeier and Viehs, 2018), we measure increased levels of transparency on climate-related issues as the willingness of a firm to respond to the Carbon Disclosure Project's (CDP) questionnaire. CDP is a UK-based not-for-profit organization that targets listed companies with an annual survey concerning their carbon emissions and actions to mitigate climate change risk. The CDP survey is acknowledged worldwide as a leading source of a firm's activity regarding climate change mitigation (Luo et al., 2012; Luo and Tang, 2014). For this reason, it represents one important data source for the European Commission (2017). Table 3.1 reports, per each year, the number of firms targeted and responding to the CDP survey - displayed by geographical area – along with the number of firms having verified emissions, board oversight of climate-related issues and emission reduction targets. Our CDP database covers the period 2010-2018 (CDP, 2019).

We assume that increased levels of climate-related disclosure reduce information asymmetry and thereby the risk premium component associated with it. Our third hypothesis therefore states (in alternative form) that:

- H3: *Firms that increase the level of transparency on their carbon risk pay a* *lower cost of debt.*

Emissions data may be prone to measurement errors (Kaspereit and Lopatta, 2018; Busch et al., 2018). Asking a third party to verify the firm's carbon emission according to an accepted and recognized emissions accounting standard should solve this problem, thus increasing data reliability. For the same reason, the European Commission's guidelines on climate-related information (2019) recommend companies disclosing whether their carbon emissions are externally verified.
Prior research suggests an important role for external certification in accessing both bank and equity financing (Kleimeier and Viehs, 2018; Trinks et al., 2017). Table 3.1 shows that the companies responding to the CDP survey have adopted virtuous behaviors over time in this respect. External verification of scope 1 emissions increased from 26% in 2010 to 56% in 2018, whereas external verification of scope 2 emissions increased from 22% in 2010 to 55% in 2018. In Europe, this trend has been particularly relevant for emission-intensive industries (Green and Zhou, 2013). Our fourth hypothesis aims at verifying whether the existence of a third-party validation for at least scope 1 or scope 2 emissions exerts a mitigating effect on the cost of debt financing in the specific context of the Eurozone. Our hypothesis (in alternative form) therefore states as follows:

- H4: *Firms whose carbon emissions are not verified by a third party pay a higher cost of debt.*

According to the European Commission (2018), corporate governance can significantly contribute to a more sustainable economy, allowing companies to take the strategic steps necessary to manage carbon risk by developing new technologies, adjusting business models toward circular economy and improving environmental performance. Moreover, the presence of adequate board oversight into climate change issues would give evidence of the firm's commitment to address environmental issues, thus improving corporate reputation and legitimacy among stakeholders. The European Commission's non-binding guidelines (2019) therefore suggest that companies should disclose whether there is board insight of climate-related issues.
Table 3.1 shows that, over time, companies responding to the CDP questionnaire increased board insight of climate change issues from 51% in 2010 to 71% in 2018. Evidence on the role of corporate board on carbon risk, however, is quite mixed. Some studies suggest a positive association between board environmental orientation and carbon performance (e.g., Moussa et al., 2020). In contrast, other studies show that boards generally do not fulfill their monitoring roles (e.g., Prado & Garcia, 2010). Environmental governance mechanisms focus more on avoiding reputational and/or regulatory harm than taking responsible actions (Bansal and Kistruck, 2006; Cho et al., 2012; Neu et al., 1998; Patten, 2005; Rodrigue et al., 2013).
Consistent with the European Commission (European Commission, 2019), we assume that board monitoring can mitigate the corporate carbon risk, thus lowering the cost of debt. Coherently, our hypothesis (in alternative form) states as follows:

- H5: *Firms that have board oversight of carbon risk pay a lower cost of debt.*

So far, our analysis has focused on the relationship between the cost of debt and historical data on carbon emissions. Nonetheless, carbon risk may impact firms to varying degrees depending on the actions that firms are undertaking to confront or even pre-empt the risks and challenges caused by carbon emissions (Labatt and White, 2011). For this reason, the non-binding guidelines of the European Commission recommend firms disclosing whether they have processes associated with activities that meet the criteria for substantially contributing to mitigation of or adaptation to climate change. Firms with emission reduction targets increased from 38% in 2010 to 64% in 2018.
This being the context, we test whether the capital providers consider forward-looking information on carbon emissions as well. In doing this, we assume that Eurozone firms having carbon emission reduction targets in place pay a lower cost of debt. Our last hypothesis therefore states (in alternative form) as follows:

- H6: *Firms that have carbon emission reduction targets pay a lower cost of debt.*

Table 3.1: CDP Database 2010-2018 – Firm distribution per year

	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Firms targeted by CDP	6,221	6,557	7,071	7,455	7,167	6,302	5,815	6,028	6,083	58,699
Asia	2,013	2,185	2,203	2,287	2,495	2,084	1,937	2,007	2,030	19,241
America	1,757	1,336	1,685	1,816	1,734	1,337	1,275	1,485	1,454	13,879
Africa	131	150	155	162	134	130	97	122	123	1,204
Oceania	263	282	306	321	291	271	263	264	269	2,530
Europe	2,056	2,604	2,721	2,869	2,513	2,480	2,243	2,149	2,207	21,842
Firms answering to CDP	2,434	2,464	2,534	2,700	2,575	2,776	2,506	2,756	2,372	23,117
Asia	525	562	594	618	619	683	649	748	641	5,639
America	770	656	688	746	726	791	683	776	703	6,539
Africa	70	84	86	89	86	89	69	84	67	724
Oceania	111	115	119	122	102	117	103	108	89	986
Europe	958	1,047	1,047	1,125	1,042	1,096	1,002	1,039	872	9,228
Firms with scope 1 emissions externally verified	630	805	995	1,051	1,139	1,217	1,193	1,358	1,333	9,721
Firms with scope 2 emissions externally verified	546	729	915	1,001	1,091	1,174	1,152	1,316	1,297	9,221
Firms with board oversight of climate-related issues	1,238	1,137	1,286	1,359	1,442	1,538	1,472	1,737	1,686	12,895
Firms with emission reduction targets	927	1,030	1,198	1,280	1,370	1,456	1,410	1,662	1,529	11,862

3.3 Research design

3.3.1 Data and sample construction

To examine the relationship between the cost of debt financing and corporate carbon risk, we merge data from the CDP and Thomson Reuter's ASSET4 databases. We start from the CDP dataset, which contains the information about external validation of carbon emissions, board insight of climate change issues and carbon emission reduction targets that we need for our analysis.

Table 3.2 displays the sample selection process. We first select the companies from the Eurozone targeted by the CDP questionnaire. We focus on the Eurozone to avoid problems related to different currencies and monetary policies. We exclude firms from the financial sector, which are subject to specific regulatory requirements. Moreover, their liabilities are different in nature and thereby difficult to compare with other industries (Jung et al., 2018; Pittman and Fortin, 2004; Rajan and Zingales, 1995). We collect financial data from the Thompson Reuters database. We use this data provider for carbon emissions as well. In this way, we avoid self-selection bias. In fact, Thompson Reuters' ASSET4 collects emission data from a variety of sources, including companies' reports. As a result, it reports emissions also for firms that are targeted, but not responding to the CDP questionnaire. The CDP database, instead, contains only emission data released by the respondent firms, which may be more virtuous in tackling climate change than the others. Furthermore, our choice allows investigating whether increased levels of disclosure on climate-related issues, operationalized as the willingness to respond to the CDP survey, can mitigate carbon risk. Finally, ASSET4 corrects emissions data in case of ex-post adjustments by reporting companies (Busch et al., 2018), which enhances analysis reliability. Correlation between CDP and ASSET4 is nonetheless very high, i.e. 95% for scope 1 and 90% for scope 2 emissions (Busch et al., 2018). We exclude from our sample firms delisted, failed, or with zero debt. We finally drop observations for which the cost of debt is below the 5% or above the 95% percentile. Our final sample consists of 1,469 firm-year observations.

Table 3.3 shows our sample distribution over time, divided into firms targeted by the CDP survey, firms responding to the questionnaire, and firms having verified emissions, board oversights, and emission reduction targets. As one can notice, the number of firms targeted by the CDP survey increased by 86% from 118 in 2010 to 220 in 2018. The response rate varies from 69% in 2015 to 84% in 2011. The response rate is 83% in 2016 and 80%, both in 2017 and 2018. If compared to the lowest level of 69% in 2015, this data may suggest that after the Paris Agreement firms consider improving climate-related disclosure as beneficial. The lowest percentage of firms with an external validation for carbon emissions is 74% for scope 1 and 59% for scope 2, both in 2010, while the highest percentage is 94% for scope 1 and 92% for scope 2, both in 2015. The highest percentage of firms with board oversight (91%) and emission reduction targets (93%) is in 2015, whereas the lowest percentage is in 2018 (74% for board insight and 71% for emission reduction targets). While the number of firms answering the questionnaire increased in the period following the Paris Agreement, the percentage of firms with external validation for emissions, board oversight and emission reduction targets has decreased compared to 2015. The reason for this could be that firms answering the question-

Table 3.2: Sample selection process

	Firm-year observations
Firm-year observations for the Eurozone	11,253
- Financial institutions	(1,296)
- Missing data (carbon intensity or control variables)	(8,132)
- Failed or delisted companies	(109)
- Firms with zero debt	(17)
- Outliers (trimmed 5-95%)	(230)
Final sample	1,469

naire for the first time were not sufficiently skilled in tackling climate change issues compared to those already involved in the program for many years. If this was the case, it would suggest that disclosing climate-related information may provide a good incentive for firms to adopt more virtuous behavior in this respect.

Table 3.3: Sample distribution per year

	2010	2011	2012	2013	2014	2015	2016	2017	2018	Total
Firms targeted by CDP	118	127	148	160	163	170	176	187	220	1,469
Firms answering to CDP	111	119	136	147	145	142	146	150	175	1,271
Firms with scope 1 emissions externally verified	70	89	106	115	113	111	116	119	129	968
Firms with scope 2 emissions externally verified	56	81	99	112	108	109	115	117	128	925
Firms with board oversight of climate-related issues	85	84	98	107	106	107	111	117	129	944
Firms with emission reduction targets	77	91	96	114	111	110	109	116	124	948

Table 3.4 displays the sample distribution according to industry classification.

As Table 3.4 shows, the industrials group is the most represented, accounting for 29% of observations. The industrial group includes very different sectors: aerospace and defense, construction and materials, electronic and electrical equipment, general industrials, industrial engineering, industrial support services, and industrial transportation. Since very different business models may correspond to very different carbon intensity, we will also account for such heterogeneity in our analysis. Consumer discretionary, which includes 15% of observations, also comprehends very different sectors such as car producers, media, and leisure goods. The other two relevant groups, which account for 10% of observations each, are basic materials, including chemicals and industrial materials, metals and mining, and utilities.

Table 3.5 shows the geographical distribution of our sample. The most represented countries are France and Germany, which together account for 44% of the observations. Finland, Spain, Italy, and the Netherlands are the other most represented countries, accounting for 46% of the observations.

3.3.2 Empirical model and variable definitions

We use ordinary least square regression to estimate the effect of the carbon risk on the cost of debt.

3.3.3 Dependent variable: the cost of debt

The dependent variable in our analysis is the logarithm of the cost of debt. We compute the cost of debt as the ratio between interest expense on the average debt (expressed in basis point). We use the logarithm to linearize the relationship between risk and return (Belsley et al., 1980). Specifically, the cost of debt for firm *i* in year *t* is computed as follows:

$$cod_{i,t} = [(interestexpense_{i,t})/((totdebt_{i,t-1} + totdebt_{i,t})/2)] \tag{3.1}$$

Interest expense includes interest expense on short- and long-term debt, while total debt is the sum of short- and long-term interest-bearing financial obligations. We truncate the dependent variable at the 5% and 95% percentiles of the distribution (Pittman and Fortin, 2004).

3.3.4 Independent variables

Carbon risk

We use carbon intensity as an indicator of corporate carbon risk (e.g., Hoffmann & Busch, 2008; Jung et al., 2018; Lewandowski, 2017). We compute carbon intensity as the ratio between scope 1 and scope 2 emissions and net sales (Jung et al., 2018; Lewandowski,2017; Capasso & Gianfrate, 2019). Scope 1 includes direct emissions that originate from plants or sources owned or directly controlled by a company, whereas scope 2 includes emissions originating from the purchase of the electricity needed for a firm's production activities (GHG Protocol, 2019). Considering both scope 1 and scope 2 emissions provides a more comprehensive view of

Table 3.4: Sample distribution by ICB Industry (firm-year observations)

	Frequency	Percentage	Cumulated
Basic Materials	149	10.14	10.14
Consumer Discretionary	231	15.72	25.87
Consumer Staples	110	7.49	33.36
Energy	98	6.67	40.03
Health Care	84	5.72	45.75
Industrials	429	29.20	74.95
Technology	91	6.19	81.14
Telecommunications	127	8.65	89.79
Utilities	150	10.21	100
Total	1,469	100	

companies' effectiveness in reducing carbon risk. Companies' ability to decrease carbon intensity in the short term, for instance, relies more on scope 2 rather than scope 1 emissions. In fact, buying energy from a sustainable energy producer is easier than investing in emissions reduction technologies, which are likely to be more expensive and require more time to be fully implemented (Busch & Lewandowski, 2018). We do not instead consider scope 3 emissions, which include all the indirect emissions that originate from a firm's value chain (GHG Protocol, 2019). Scope 3 emissions are difficult to quantify and subject to material errors (Matisoff et al., 2013; Busch et al., 2018). As a result, both the quantity and quality of scope 3 emissions reporting remain highly uncertain (Matisoff et al., 2013; Busch et al., 2018).

We scale carbon emissions by revenues in order to account for different firm size and industry (Hoffmann and Busch, 2008). Unlike prior research (Jung et al., 2018; Kleimeier and Viehs, 2018), we test the cost of debt against one year-lagged carbon intensity in order to avoid endogeneity and to increase the robustness of our results with regard to the direction of the relationship between the cost of capital and carbon emissions. By using lagged carbon intensity, we also account for carbon emission data being available with a certain delay. Similarly, firms reap financial benefits from carbon emission mitigation over time (Brzobohatỳ and Janskỳ, 2010; Trumpp et al., 2015). We also perform our analysis for a two year-lagged carbon intensity but correlation with the cost of debt is weaker.

Table 3.5: Sample distribution by country (firm-year observations)

	Frequency	Percentage	Cumulated
Austria	40	2.72	2.72
Belgium	44	3.00	5.72
Finland	161	10.96	16.68
France	355	24.17	40.84
Germany	295	20.08	60.93
Greece	22	1.50	62.42
Ireland	62	4.22	66.64
Italy	136	9.26	75.90
Luxembourg	24	1.63	77.54
Netherlands	134	9.12	86.66
Portugal	38	2.59	89.24
Spain	158	10.76	100
Total	1,469	100	

Control variables

There is no doubt that a close relationship exists between investors' expected returns and financial performance of the firms in which they are investing (e.g., Altman et al., 2017; Modigliani & Pogue, 1974) We therefore include companies' financial ratios as control variables in our regressions. After a wide review of the literature (e.g., Almamy et al., 2016; Altman et al., 2017; Tian & Yu, 2017), we select the following financial ratios: operating profit, leverage, working capital ratio and size. Operating profit, computed as the ratio of operating income over net sales, accounts for a firms' profitability. We expect a negative relationship between this variable with the cost of debt as the more profitable firms are, the lower the probability to go bankrupt (e.g., Tudela & Young, 2005). Leverage is computed as total debt over total assets and controls for the level of indebtedness (Altman et al., 2017). The working capital ratio, computed as working capital over total asset, accounts for liquidity (Altman et al., 2017). We expect firms that are more indebted, or less liquid, to pay a higher spread on the cost of debt. Finally, we include the logarithm of total assets to proxy for firms' size (Jung et al., 2018; Kleimeier and Viehs, 2018). Since larger companies are less likely to go bankrupt (i.e., Bernanke et al., 1996, 1999), we expect a negative correlation of this variable with company size (e.g., Jung et al., 2018). To control for monetary policy, we include the yearly average of the 6 months Euribor. Indeed, the cost of debt adjusts in line with the Euribor interest rate variation (Arce at al., 2013; Goss & Roberts, 2011; Moccero et al., 2014). As for carbon intensity, control variables are lagged by one year in order to avoid endogeneity (Du et al., 2017; Liu et al., 2017). Moreover, lending decisions likely incorporate a company's financial performance with a certain delay. We finally control for differences in industry and country. Industry classification is based on the Industry Classification Benchmark (ICB) taxonomy. In each regression, standard errors are clustered by firm and year (Petersen, 2009).

3.3.5 The econometric models

The econometric model used to test our first hypothesis is the following:

$$
\begin{aligned}
ln(cod_{i,t}) = \alpha_0 + \alpha_1 carbon\_int_{i,t-1} + \sum_{i=1}^{k} \alpha_k financial\_controls_{i,t-1} \\
+ \alpha_3 industry_i + \alpha_4 country_i + \alpha_5 euribor_{t-1} + \epsilon_{i,t}
\end{aligned}
\tag{3.2}
$$

where *ln($cod_{i,t}$)* is the natural logarithm of the cost of debt for firm *i* in year *t*; carbon˙int is the carbon intensity for firm *i* in year *t-1*; *financial_controls* is a vector of financial ratios for firm *i* in year *t-1*; industry is the industrial sector for firm *i*; country is the country for firm *i*; and *euribor* is the euribor in year *t-1*.
The presence of a post-Paris effect is tested with the following model:

$$
\begin{aligned}
ln(cod_{i,t}) = \alpha_0 &+ \alpha_1 carbon\_int_{i,t-1} + \alpha_2 carbon\_int_{i,t-1} \\
&\times post_{2015} + \alpha_3 post_{2015} + \sum_{i=1}^{k} \alpha_k financial_{controls_{i,t-1}} \\
&+ \alpha_4 industry_i + \alpha_5 country_i + \alpha_6 euribor_{t-1} + \epsilon_{i,t}
\end{aligned}
\tag{3.3}
$$

where *post_2015* is a dummy equal to one after 2015, and zero otherwise, while *carbon_int x post_2015* is an interaction term between the dummy variable and the carbon intensity. The other variables are defined as in model (1).
To test the effect of increased level of disclosure on climate-related issues through answering the CDP questionnaire, we use the following model:

$$
\begin{aligned}
ln(cod_{i,t}) = \alpha_0 &+ \alpha_1 carbon\_int_{i,t-1} + \alpha_2 carbon\_int_{i,t-1} \\
&\times CDP + \alpha_3 CDP + \sum_{i=1}^{k} \alpha_k financial_{controls_{i,t-1}} \\
&+ \alpha_4 industry_i + \alpha_5 country_i + \alpha_6 euribor_{t-1} + \epsilon_{i,t}
\end{aligned}
\tag{3.4}
$$

where *CDP* is a dummy is equal to one if the firm answers the CDP questionnaire, and zero otherwise. *Carb_int x CDP* is the interaction term between the dummy and the carbon intensity. The other variables are defined as in model (1).

The following regression is run in order to test for external verification of emissions:

$$
\begin{aligned}
ln(cod_{i,t}) = \alpha_0 &+ \alpha_1 carbon\_int_{i,t-1} + \alpha_2 carbon\_int_{i,t-1} \times verified_{i,t-1} \\
&+ \alpha_3 verified_{i,t-1} + \sum_{i=1}^{k} \alpha_k financial_{controls_{i,t-1}} \\
&+ \alpha_4 industry_i + \alpha_5 country_i + \alpha_6 euribor_{t-1} + \epsilon_{i,t}
\end{aligned}
\tag{3.5}
$$

where *verified* is a dummy variable equal to one if the firm has an external verification of emission either for scope 1 emissions or for scope 2 emissions, and zero otherwise. *Carbon_int x verified* is the interaction term between the dummy and the carbon intensity. The other variables are defined as in model (1).

To investigate the role of the effect of board oversight on the cost of debt, the model is:

$$
\begin{aligned}
ln(cod_{i,t}) = \alpha_0 + \alpha_1 carbon\_int_{i,t-1} + \alpha_2 carbon\_int_{i,t-1} \times board_{i,t-1} \\
+ \alpha_3 board_{i,t-1} + \sum_{i=1}^{k} \alpha_k financial_{controls_{i,t-1}} \\
+ \alpha_4 industry_i + \alpha_5 country_i + \alpha_6 euribor_{t-1} + \epsilon_{i,t}
\end{aligned}
\tag{3.6}
$$

where *board* is a dummy variable equal to one if the firm has board oversight of climate-related issues, and zero otherwise. *Carbon_int x board* is the interaction term between the dummy and the carbon intensity. The other variables are defined as in model (1).
We finally run the following regression to investigate the role of carbon emission reduction targets in reducing the cost of debt:

$$
\begin{aligned}
ln(cod_{i,t}) = \alpha_0 + \alpha_1 carbon\_int_{i,t-1} + \alpha_2 carbon\_int_{i,t-1} \times target_{i,t-1} \\
+ \alpha_3 target_{i,t-1} + \sum_{i=1}^{k} \alpha_k financial_{controls_{i,t-1}} \\
+ \alpha_4 industry_i + \alpha_5 country_i + \alpha_6 euribor_{t-1} + \epsilon_{i,t}
\end{aligned}
\tag{3.7}
$$

where *target* is a dummy variable equal to one if the firm has emission reduction targets, and zero otherwise. *Carbon_int x target* is the interaction term between the dummy and the carbon intensity. The other variables are defined as in model (1).

3.4 Results[1]

3.4.1 Descriptive statistics and correlation

Table 3.6 displays descriptive statistics for the variables included in our regressions. The average value of carbon intensity is 0.41 tonnes of carbon dioxide per EUR 1,000 of revenues, with a maximum value of 8.76. Data are consistent with other statistics (e.g., Jung et al. 2018). Firm leverage is, on average, 63% of the total assets, which is also in line with other analyses for EU companies (e.g., ECB 2018). Operating margin is, on average, 10%. 93% of our sample verify either direct or indirect emissions, while 89% have board-oversight of climate-related issues, and 90% set a carbon emission reduction target.

[1]This Section describes and comments on statistical results in compliance with the American Statistical Association Statement on Statistical Significance and P-values (Wasserstein and Lazar, 2016; Wasserstein et al., 2019). Accordingly, we report p-value for regression coefficients, while abandoning the dichotomization of results into “significant” and “not significant”. This approach treats statistical results as being much more incomplete than the norm, thus acknowledging that uncertainty exists everywhere in research and that this is exploratory in nature.

Table 3.6: Sample descriptive statistics

Variable	Count	Mean	p25	Median	p75	SD	Minimum	Maximum
Ln(cod)	1,469	5.95	5.71	6.00	6.24	0.40	4.78	6.85
Carbon_int	1,469	0.41	0.02	0.06	0.37	1.00	0.00	8.76
Lev	1,469	0.63	0.53	0.63	0.72	0.15	0.17	1.44
Op_marg	1,469	0.10	0.04	0.09	0.14	0.1	-0.41	0.54
Wc_ta	1,469	0.07	-0.02	0.05	0.14	0.13	-0.45	0.51
Size	1,469	16.21	15.30	16.08	17.15	1.29	13.09	19.81
Euribor	1,469	0.48	-0.16	0.31	1.08	0.64	-0.26	1.64
CDP	1,206	0.88	-	-	-	0.33	0.00	1.00
Verified	1,044	0.93	-	-	-	0.26	0.00	1.00
Board	1,059	0.89	-	-	-	0.31	0.00	1.00
Target	1,053	0.90	-	-	-	0.30	0.00	1.00

List of Variables: *Ln(cod)* is the dependent variable defined as the natural logarithm of the ratio between interest expense on debt and average total debt; *Carbon_int* is the carbon intensity computed as the ratio between scope 1 and scope 2 emissions over revenues. *Lev* is the leverage defined as total liabilities over total assets. *Op_marg* is the operative margin defined as the ratio between operating income and revenues. *Wc_ta* is the ratio of working capital over total assets. *Size* is the natural logarithm of total assets. *Euribor* is the yearly average of the 6-months Euribor. *CDP* is a dummy variable equal to 1 if the firms answers the CDP questionnaire. *Verified* is a dummy variable equal to 1 if the firm has either scope 1 or scope 2 emissions externally verified. *Board* is a dummy variable equal to 1 if the firm has board oversight of climate-related issues. *Target* is a dummy variable equal to 1 if the firm has an emissions reduction target.

Table 3.7 displays the correlation matrix for the regression variables. As expected, *carbon_int* is positively correlated with the cost of debt, with a p-value $<$ 0.001. *Lev* and the *op_margin* are also correlated with the cost of debt with the predicted positive and negative sign, respectively, and p-values < 0.001. The correlation coefficient on the *wc_ta* is negative but with a p-value = 0.341. Contrary to our expectations, the coefficient on size is positive with a p-value < 0.001. As expected, the existence of an external verification of emissions is negatively correlated with the cost of debt, with a p-value < 0.001. Both the dummies board and target are negatively correlated with the cost of debt, although with larger p-values = 0.373 and = 0.501 respectively.
Collinearity diagnostics (not reported) show that the variance inflation factors for the explanatory variables are far below critical levels (e.g., Belsley et al. 1980; Greene 2008; Marquardt, 1970).

Table 3.7: Correlation matrix

	Ln(cod)	Carbon_int	Lev	Op_marg	Wc_ta	Size	Euribor	CDP	Verified	Board	Target
Ln(cod)	1.000										
Carbon_int	0.122	1.000									
	(0.000)										
Lev	0.185	-0.063	1.000								
	(0.000)	(0.015)									
Op_marg	-0.184	-0.001	-0.108	1.000							
	(0.000)	(0.984)	(0.000)								
Wc_ta	-0.025	-0.024	-0.461	-0.032	1.000						
	(0.341)	(0.368)	(0.000)	(0.213)							
Size	0.080	0.105	0.201	0.014	-0.309	1.000					
	(0.002)	(0.000)	(0.000)	(0.602)	(0.000)						
Euribor	0.354	0.032	0.062	0.033	-0.022	0.052	1.000				
	(0.000)	(0.226)	(0.017)	(0.201)	(0.397)	(0.045)					
CDP	0.041	-0.005	0.152	0.019	-0.098	0.227	0.134	1.000			
	(0.151)	(0.871)	(0.000)	(0.506)	(0.001)	(0.000)	(0.000)				
Verified	-0.098	0.089	0.002	-0.082	-0.103	0.273	-0.143	0.151	1.000		
	(0.001)	(0.004)	(0.940)	(0.008)	(0.001)	(0.000)	(0.000)	(0.000)			
Board	-0.027	0.064	-0.014	-0.052	0.004	0.077	-0.126	0.061	0.120	1.000	
	(0.373)	(0.036)	(0.654)	(0.092)	(0.908)	(0.012)	(0.000)	(0.069)	(0.000)		
Target	-0.021	0.098	0.033	0.047	-0.007	0.191	-0.143	0.114	0.238	0.151	1.000
	(0.501)	(0.001)	(0.284)	(0.125)	(0.818)	(0.000)	(0.000)	(0.001)	(0.000)	(0.000)	

Note: P-values in parentheses

List of Variables: *Ln(cod)* is the dependent variable defined as the natural logarithm of the ratio between interest expense on debt and average total debt; *Carbon_int* is the carbon intensity computed as the ratio between scope 1 and scope 2 emissions over revenues. *Lev* is the leverage defined as total liabilities over total assets. *Op_marg* is the operative margin defined as the ratio between operating income and revenues. *Wc_ta* is the ratio of working capital over total assets. *Size* is the natural logarithm of total assets. *Euribor* is the yearly average of the 6-months Euribor. *CDP* is a dummy variable equal to 1 if the firms answers the CDP questionnaire. *Verified* is a dummy variable equal to 1 if the firm has either scope 1 or scope 2 emissions externally verified. *Board* is a dummy variable equal to 1 if the firm has board oversight of climate-related issues. *Target* is a dummy variable equal to 1 if the firm has an emissions reduction target.

3.5 Multivariate analysis

3.5.1 The effect of carbon risk on the cost of debt

Table 3.8 displays results from the regression model (1). Column (1) reports results from the regression with the control variables only, whereas column (2) includes carbon intensity. Column (1) and (2) refers to the full sample.

Column (1) shows that, consistent with our prediction, the coefficient on *Lev* is positive with a p-value = 0.004, indicating that the more firms are indebted, the higher the spread on debt. The coefficient on op˙marg is negative with a p-value < 0.001. Contrary to our expectations, the coefficient on *wc_ta* is positive with a p-value = 0.040, which suggests that firms with higher values for this ratio are considered riskier. Indeed, a higher level of working capital on total assets could signal inefficient management of inventories or difficulties in collecting credits. The coefficient on Size is positive but with a high p-value = 0.201. The constant is positive with a p-value < 0.001 (Jung et al., 2018; Capasso & Gianfrate, 2019).
The adjusted R^2 in column (1) is equal to 25.7%, indicating that a substantial variation in the cost of debt financing is left unexplained by the variables included in the regression. The low adjusted R^2 is in line with empirical literature showing that accounting data have lost value-relevance overtime (Lev and Gu, 2016) and provides consistent support to the European Commission's claim (2018) that more non-financial disclosure is needed to better understand corporate risk both in absolute and relative terms. Residual analysis (not reported) suggests that results are not affected by omitted variable bias. Regression in column (2) includes carbon intensity. When we introduce the latter, the adjusted R^2 increases to 26.7% indicating that carbon intensity adds to explaining variation in the cost of debt financing. As expected, the coefficient on *carbon_int* is positive and statistically robust, with a p-value = 0.001.
We then split the observations and run the regression for the pre- and post-Paris Agreement period, separately. In the post-Paris Agreement period, we include observations from 2016 to 2018. Column (3) shows the results from the regression for the pre-Paris Agreement period, while column (4) reports the results for the post-Paris Agreement period. The coefficients on carbon˙int are positive in both the regressions, with a p-value = 0.093 for the Pre-Paris Agreement and a p-value < 0.001 for the post-Paris Agreement. A higher magnitude of the coefficient on *carbon_int* in column (4) suggests increasing lenders' awareness to carbon risk in the aftermath of the Paris Agreement. Our results are robust to different model specifications. We also perform a regression by excluding the top polluting sectors (i.e., electricity, and gas, water and multi-utilities) in order to check whether the "carbon intensity effect" on the cost of debt financing is led by the highest emitters. Results (not tabulated) are qualitatively similar to Table 3.8.

3.5.2 The Post-Paris Agreement effect: a sectorial analysis

Table 3.9 reports results from regression model (2).

Column (1) displays the results for the full sample. In this column, the coefficient on *carbon_int x post_2015* is positive with a p-value = 0.059, which suggests an increased lenders' sensitivity to corporate carbon risk in the aftermath of the Paris Agreement. The coefficient on *post_2015*, instead, is negative, with a p-value

Table 3.8: Regression results - Carbon risk

	(1) Full Sample	(2) Full Sample	(3) Pre-Paris Agreement	(4) Post-Paris Agreement
Carbon_int		**0.0449**	**0.0345**	**0.0521**
		(0.001)	**(0.093)**	**(0.000)**
Lev	**0.360**	**0.418**	**0.309**	**0.563**
	(0.004)	**(0.001)**	**(0.032)**	**(0.000)**
Op_marg	**-0.708**	**-0.693**	**-0.837**	**-0.537**
	(0.000)	**(0.000)**	**(0.000)**	**(0.002)**
Wc_ta	**0.308**	**0.334**	**0.291**	0.370
	(0.040)	**(0.021)**	**(0.084)**	(0.135)
Size	0.0182	0.0162	0.00682	0.0257
	(0.201)	(0.250)	(0.637)	(0.144)
Constant	**5.576**	**5.552**	**5.843**	**5.299**
	(0.000)	**(0.000)**	**(0.000)**	**(0.000)**
Industry fixed effects	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes
Euribor	Yes	Yes	Yes	Yes
Observations	1,469	1,469	886	583
Adjusted R2	0.257	0.267	0.205	0.202

p-values in parentheses

In bold variables of specific interest for the analysis. List of Variables: *Ln(cod)* is the dependent variable defined as the natural logarithm of the ratio between interest expense on debt and average total debt; *Carbon_int* is the carbon intensity computed as the ratio between scope 1 and scope 2 emissions over revenues. Lev is the leverage defined as total liabilities over total assets. *Op_marg* is the operative margin defined as the ratio between operating income and revenues. *Wc_ta* is the ratio of working capital over total assets. *Size* is the natural logarithm of total assets. *Euribor* is the yearly average of the 6-months Euribor. *CDP* is a dummy variable equal to 1 if the firms answers the CDP questionnaire. *Verified* is a dummy variable equal to 1 if the firm has either scope 1 or scope 2 emissions externally verified. *Board* is a dummy variable equal to 1 if the firm has board oversight of climate-related issues. *Target* is a dummy variable equal to 1 if the firm has an emissions reduction target. *Industry* is the 2-digits ICB industry code.

Robust standard errors clustered by firm and year.

Table 3.9: Regression results – Post-Paris effect and High versus Low emitters

	(1) Full Sample	(2) HE Group	(3) LE Group
Carbon_int	0.0270	**0.0362**	-0.0211
	(0.156)	**(0.049)**	(0.519)
Carbon_int x Post_2015	**0.0418**	0.0182	**0.103**
	(0.059)	(0.433)	**(0.018)**
Post_2015	**-0.149**	**-0.142**	**-0.144**
	(0.002)	**(0.005)**	**(0.001)**
Lev	0.386	0.224	0.463
	(0.001)	(0.185)	(0.001)
Op_marg	-0.712	-0.737	-0.668
	(0.000)	(0.000)	(0.002)
Wc_ta	0.246	-0.427	0.475
	(0.078)	(0.028)	(0.007)
Size	0.0106	0.0115	-0.00186
	(0.423)	(0.628)	(0.934)
Constant	5.528	6.168	5.434
	(0.000)	(0.000)	(0.000)
Industry fixed effects	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes
Euribor	Yes	Yes	Yes
Observations	1,469	599	870
Adjusted R2	0.335	0.361	0.353

p-values in parentheses

In bold variables of specific interest for the analysis. List of Variables: *Ln(cod)* is the dependent variable defined as the natural logarithm of the ratio between interest expense on debt and average total debt; *Carbon_int* is the carbon intensity computed as the ratio between scope 1 and scope 2 emissions over revenues. Lev is the leverage defined as total liabilities over total assets. *Op_marg* is the operative margin defined as the ratio between operating income and revenues. *Wc_ta* is the ratio of working capital over total assets. *Size* is the natural logarithm of total assets. *Euribor* is the yearly average of the 6-months Euribor. *CDP* is a dummy variable equal to 1 if the firms answers the CDP questionnaire. *Verified* is a dummy variable equal to 1 if the firm has either scope 1 or scope 2 emissions externally verified. *Board* is a dummy variable equal to 1 if the firm has board oversight of climate-related issues. *Target* is a dummy variable equal to 1 if the firm has an emissions reduction target. *Industry* is the 6-digits ICB industry code.

Robust standard errors clustered by firm and year.

= 0.002, indicating that, on average, the risk premium has decreased since 2015. Such a finding is consistent with well-established literature showing that the negative facility rate set by the European Central Bank starting from 2014 has increased risk-taking in the Eurozone (e.g., Heider et al., 2019). Surprisingly, the positive coefficient on the *carbon_int* is no more statistically robust (p-value = 0.156).
To get more insight into this issue, we split the sample into two groups, "high emitters" (also HE hereafter) and "low emitters" (also LE hereafter), according to their sector carbon intensity. Carbon risk varies significantly across sectors (UNEP, 2006) and may not be captured by the two-digit standard industry classification used in our previous regression. Battiston et al. (2017), for instance, document a similar problem for NACE2 and NAICS classifications.
Table 3.10 displays our sample distribution by sectors based on a six-digit industry code. Sectors are listed in descending order of carbon intensity median. Our HE group includes sectors having carbon emissions greater than 0.10 tonnes per EUR 1,000 of sales, which are: electricity, gas water and multi-utilities, travel and leisure, chemicals, industrial materials, industrial metals and mining, energy, general industrials, and construction and materials. The Task Force on Climate-related Financial Disclosure (Financial Stability Board, 2017) considers these sectors particularly vulnerable to climate risks. The HE group represents about 40% of the sample.
Column (2) and (3) in Table 3.9 display the results from the regressions for the HE and LE groups, respectively. Interestingly, the coefficient on *carbon_int* for the HE group is positive with a p-value = 0.049, whereas the coefficient on *carbon_int x post˙2015* is positive with a p-value = 0.433. In contrast, the coefficient on *carbon_int* for the LE group is negative with a p-value = 0.519, whereas the coefficient on *carbon_int x post_2015* is positive with a p-value = 0.018. Taken as a whole, these findings suggest that high emitters in the Eurozone were already charged a carbon risk premium before the Paris Agreement, but not further penalized thereafter. On the contrary, low emitters started being charged for their carbon risk only in the aftermath of the Agreement. According to our analysis, the Paris Agreement represents a turning point, in proximity of which lenders have become aware of the strong commitment taken by policymakers in fighting climate change and adopting consistent actions. Accordingly, they have started taking carbon risk into account for both high and low emitters. The regulatory framework therefore appears to have the potential to drive the financial system toward incorporating carbon risk into investment decisions.
Importantly, our findings are robust to alternative criteria for splitting the sample into HE and LE groups, including a classification that is based on firm, rather than sector, carbon intensity. Results are not tabulated for the sake of parsimony.

3.5.3 The role of disclosure: reporting through the CDP questionnaire

Table 3.11 displays the results from the regression model (3), which tests the effect of increased levels of disclosure on the cost of debt. Column (1) shows the results for the full sample, column (2) for the HE group, and column (3) for the LE group. Column (4) and (5) report the results for the HE group in the pre- and post-Paris Agreement period, respectively.

As column (1) shows, the coefficient on the interaction term *carbon_int x CDP*

Table 3.10: Sample distribution by sector - Carbon intensity statistics

	Median	Mean	Min	Max	Sd	N.
Electricity	1.18	1.37	0.01	5.60	1.13	89
Gas, Water and Multi-utilities	0.94	1.23	0.22	3.62	1.02	61
Travel and Leisure	0.58	0.66	0.00	1.44	0.53	30
Chemicals	0.52	0.71	0.02	4.81	0.76	80
Industrial Materials	0.46	0.51	0.34	0.76	0.16	16
Industrial Metals and Mining	0.36	0.45	0.00	1.10	0.25	53
Energy	0.36	0.48	0.00	3.42	0.51	98
General Industrials	0.30	0.34	0.02	0.86	0.28	29
Construction and Materials	0.11	1.22	0.01	8.76	2.33	143
Food Producers	0.10	0.19	0.06	0.74	0.19	29
Beverages	0.07	0.06	0.00	0.12	0.04	33
Automobiles and Parts	0.06	0.07	0.00	0.19	0.04	59
Health Care Providers	0.05	0.04	0.03	0.05	0.01	8
Electronic and Electrical Equipment	0.04	0.05	0.02	0.15	0.03	42
Pharmaceuticals and Biotechnology	0.04	0.36	0.01	3.21	0.88	56
Industrial Transportation	0.04	0.16	0.00	7.28	0.73	98
Personal Care, Drug and Grocery Stores	0.04	0.04	0.00	0.10	0.02	48
Household Goods and Home Construction	0.04	0.04	0.01	0.05	0.01	11
Telecommunications Service Providers	0.04	0.04	0.00	0.18	0.03	110
Retailers	0.04	0.03	0.00	0.08	0.02	16
Medical Equipment and Services	0.03	0.12	0.01	0.72	0.22	20
Aerospace and Defense	0.02	0.03	0.01	0.14	0.03	38
Industrial Engineering	0.02	0.02	0.01	0.06	0.01	42
Technology Hardware and Equipment	0.02	0.07	0.01	0.38	0.10	32
Telecommunications Equipment	0.01	0.02	0.01	0.03	0.01	17
Industrial Support Services	0.01	0.02	0.00	0.03	0.01	37
Software and Computer Services	0.01	0.01	0.00	0.04	0.01	59
Media	0.01	0.02	0.00	0.12	0.02	79
Leisure Goods	0.01	0.01	0.01	0.01	0.00	8
Personal Goods	0.01	0.01	0.00	0.02	0.00	28
Total	0.06	0.41	0.00	8.76	1.00	1,469

Table 3.11: Regression results – The effect of disclosure: answering the CDP questionnaire

	(1) Full Sample	(2) HE Group	(3) LE Group	(4) HE Group Pre-Paris Agreement	(5) HE Group Post-Paris Agreement
Carbon_int	**0.0920**	**0.0692**	0.0486	-0.498	**0.0695**
	(0.000)	**(0.000)**	(0.240)	(0.253)	**(0.000)**
Carbon_int x CDP	**-0.0582**	-0.0407	0.424	0.524	-0.0479
	(0.086)	(0.128)	(0.209)	(0.230)	(0.304)
CDP	0.0192	**-0.190**	0.0603	-0.0943	**-0.319**
	(0.686)	**(0.034)**	(0.298)	(0.405)	**(0.000)**
Lev	0.491	0.187	0.583	0.0483	0.552
	(0.000)	(0.337)	(0.000)	(0.814)	(0.009)
Op_marg	-0.697	-0.778	-0.753	-0.977	-0.375
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Wc_ta	0.249	-0.476	0.539	-0.347	-0.343
	(0.013)	(0.006)	(0.000)	(0.328)	(0.280)
Size	0.0236	0.0291	0.00624	0.00747	0.0693
	(0.087)	(0.242)	(0.810)	(0.804)	(0.006)
Constant	5.102	5.939	5.015	6.363	5.199
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Industry fixed effects	Yes	Yes	Yes	Yes	Yes
Country fixed effects	Yes	Yes	Yes	Yes	Yes
Euribor	Yes	Yes	Yes	Yes	Yes
Observations	1,132	474	658	281	193
Adjusted R2	0.389	0.417	0.414	0.383	0.443

p-values in parentheses
In bold variables of specific interest for the analysis. List of Variables: *Ln(cod)* is the dependent variable defined as the natural logarithm of the ratio between interest expense on debt and average total debt; *Carbon_int* is the carbon intensity computed as the ratio between scope 1 and scope 2 emissions over revenues. Lev is the leverage defined as total liabilities over total assets. *Op_marg* is the operative margin defined as the ratio between operating income and revenues. *Wc_ta* is the ratio of working capital over total assets. *Size* is the natural logarithm of total assets. *Euribor* is the yearly average of the 6-months Euribor. *CDP* is a dummy variable equal to 1 if the firms answers the CDP questionnaire. *Verified* is a dummy variable equal to 1 if the firm has either scope 1 or scope 2 emissions externally verified. *Board* is a dummy variable equal to 1 if the firm has board oversight of climate-related issues. *Target* is a dummy variable equal to 1 if the firm has an emissions reduction target. *Industry* is the 6-digits ICB industry code.
Robust standard errors clustered by firm and year.

is negative, with a p value = 0.086, which suggests that increased levels of transparency on carbon risk can contribute to mitigating corporate carbon risk. The coefficient on *CDP* is positive but not statistically robust (p-value = 0.686). When we split the sample into high and low emitters, regression estimates indicate that high emitters disclosing through CDP pay, on average, a lower cost of debt compared to high emitters not disclosing. The coefficient on *carbon_int x CDP* in column (2) is negative with a p value = 0.034. In column (3), instead, both the coefficients on *carbon_int x CDP* and *CDP* for low emitters are positive, but with large p-values = 0.209 and 0.298, respectively. When we further split the observations for the HE group into a pre- and post-Paris Agreement period, the positive effect of disclosing for the HE group appears to hold only in the aftermath of the Paris Agreement. The coefficient on CDP is negative, with a p-value < 0.001 only in column (5).
Taken as a whole, our analysis suggests that increased levels of climate-related disclosure started playing a role in carbon risk assessment only in the aftermath of the Paris Agreement and for high emitters. Results from Table 3.11 provide support to findings from Table 3.9, which indicate that high emitters have not been further penalized for their emissions in the period after the Paris Agreement. In fact, an increased level of disclosure might have contributed to mitigating their carbon risk. Results from Table 3.11 are also consistent with research showing that since 2015 banks have become aware of the risk of stranded assets for high polluters (e.g., De Greiff, Delis & Ongena, 2018). Accordingly, banks may have started considering climate-related information in order to better assess corporate carbon risk.

3.5.4 Third-party verification of emissions and governance

Table 3.12 displays results from regression models (4), (5) and (6). For each model, we run the regression for the full sample (column 1), for the HE group (column 2), for the LE group (column 3), for the period before the Paris Agreement (column 4), and for the period after the Paris Agreement (column 5). For the sake of parsimony, we report only the coefficients of interest.

Results from Table 3.12 do not provide a clear picture of how lenders view external verification of emissions, board oversight of carbon risk and emission reduction targets. The top panel of the table shows the results for third-party verification. As expected, the coefficient on *carbon_int x verified* and *verified* for the full sample is negative. However, the large p-values = 0.194 and 0.311, respectively, are not statistically robust to make inference. When we split observations into HE and LE groups, the coefficient on verified for the HE group is still negative and with a p-value = 0.047, whereas the coefficient on *carbon_int x verified* is negative, yet with a large p-value = 0.617. For the LE group, the coefficient on *verified* is also negative but with a p-value = 0.255, whereas the coefficient on *carbon_int x verified* becomes positive with a p-value = 0.081. Taken as a whole, third-party verifications appear to be important in decreasing the cost of debt for high polluting firms. Surprisingly, they would instead lead to a higher cost of debt for low emitters. When we split the observations into the pre- and post-Paris Agreement period, we find that the coefficient verified is negative, with a p-value = 0.032 only in the period before the Paris Agreement. In the post-Paris period, the coefficient is positive with a very high p-value of 0.364. Further analysis, not reported, indicates that the pre-Paris effect is led by high emitters, which is consistent with low emitters not being charged

Table 3.12: Regression results – Third-party verification of emissions, board oversight of climate issues, and emissions reduction target

	(1) Full Sample	(2) HE Group	(3) LE Group	(4) Pre-Paris Agreement	(5) Post-Paris Agreement
Panel A: Third-party emissions verification					
Carbon_int x Verified	-0.0337	-0.0151	**0.974**	-0.0292	-0.482
	(0.194)	(0.617)	**(0.081)**	(0.331)	(0.396)
Verified	-0.0719	**-0.197**	-0.0844	**-0.126**	0.118
	(0.311)	**(0.047)**	(0.255)	**(0.032)**	(0.364)
Control variables, industry, and country indicators	Yes	Yes	Yes	Yes	Yes
Euribor	Yes	Yes	Yes	Yes	Yes
Observations	1,037	494	543	662	375
Adjusted R2	0.387	0.381	0.438	0.347	0.428
Panel B: Board oversight of climate-related issues					
Carbon_int x Board	0.123	-0.0495	1.625	0.0678	**0.514**
	(0.132)	(0.590)	(0.680)	(0.251)	**(0.052)**
Board	**-0.100**	0.00328	-0.141	-0.0711	**-0.0833**
	(0.043)	(0.985)	(0.165)	(0.142)	**(0.000)**
Control variables, industry, and country indicators	Yes	Yes	Yes	Yes	Yes
Euribor	Yes	Yes	Yes	Yes	Yes
Observations	1,052	496	556	677	375
Adjusted R2	0.385	0.371	0.433	0.333	0.438
Panel C: Emissions Reduction Target					
Carbon_int x Target	0.0537	-0.00222	**2.987**	-0.0193	-0.226
	(0.452)	(0.977)	**(0.000)**	(0.785)	(0.399)
Target	-0.0364	-0.0161	**-0.123**	0.00683	-0.0724
	(0.517)	(0.841)	**(0.064)**	(0.905)	(0.483)
Control variables, industry, and country indicators	Yes	Yes	Yes	Yes	Yes
Euribor	Yes	Yes	Yes	Yes	Yes
Observations	1,046	496	550	676	370
Adjusted R2	0.382	0.370	0.438	0.329	0.439

p-values in parentheses

In bold variables of specific interest for the analysis. List of Variables: *Ln(cod)* is the dependent variable defined as the natural logarithm of the ratio between interest expense on debt and average total debt; *Carbon_int* is the carbon intensity computed as the ratio between scope 1 and scope 2 emissions over revenues. Lev is the leverage defined as total liabilities over total assets. *Op_marg* is the operative margin defined as the ratio between operating income and revenues. *Wc_ta* is the ratio of working capital over total assets. *Size* is the natural logarithm of total assets. *Euribor* is the yearly average of the 6-months Euribor. *CDP* is a dummy variable equal to 1 if the firms answers the CDP questionnaire. *Verified* is a dummy variable equal to 1 if the firm has either scope 1 or scope 2 emissions externally verified. *Board* is a dummy variable equal to 1 if the firm has board oversight of climate-related issues. *Target* is a dummy variable equal to 1 if the firm has an emissions reduction target. *Industry* is the 6-digits ICB industry code.

Robust standard errors clustered by firm and year.

for carbon risk in the pre-Paris period.
The second panel of the table displays results for board oversight of climate-related issues. The coefficient on *board* in column (1) is negative with a p-value = 0.043, which suggests that companies with board oversight pay, on average, a lower spread on the cost of debt. Columns (4) and (5) further indicate that lenders have started considering board oversight only in the aftermath of the Paris Agreement. In column (5), the dummy *board* has a p-value < 0.001, while *carbon_int x board* a p-value = 0.052. Both the coefficients are statistically robust. However, while the negative coefficient on *board* in column (5) suggests a mitigating effect of board oversight on the cost of debt, the positive, and larger, coefficient on *carbon_int x board* indicates that the sensitivity to carbon risk in the presence of board oversight has increased after the Paris Agreement and results in a higher spread on debt. Indeed, the presence of board oversight could signal a firm's higher exposure to climate-related risk, which requires more control. Results for the LE group and for the pre-Paris period have very large p-values, which do not support robust conclusions.
Findings are also unclear when we test the existence of carbon emission reduction targets. The third panel of the table reports results from the regression model (3). The variables of interest have very large p-values in both the regressions for the full sample and the HE group. In column (3), which refers to the LE group, the coefficient on target has a p-value = 0.064, while the coefficient on *carbon_int x target* has a p-value < 0.001. This occurrence may be consistent with high emitters from the Eurozone already participating in an Emission Trading System (ETS), which set a mandatory cap to their emissions decreasing over time. Under ETS, high emitters are already well monitored and driven by public authorities to low emissions. For instance, during the fourth ETS phase, which will last from 2021 to 2030, the overall number of emission allowances will further decline at an annual rate of 2.2% compared to the current 1.74% (European Commission, 2020). In such a context, investors could consider emission reduction targets set at a firm level less relevant, thus ignoring them in credit risk assessment. However, while the negative coefficient on the dummy variable in column (3) indicates that the presence of emission reduction targets mitigates corporate carbon risk for low emitters, the positive coefficient on carbon˙int x target suggests that lenders charge a higher spread to borrowers that have a reduction target in place. Again, the presence of emission reduction targets could signal that a certain firm, despite belonging to a low-polluting sector, is highly exposed to carbon risk compared to its peers, and therefore needs to take action. Inconclusive results in this respect have also been found by Kleimeier and Viehs (2018).
As is clear, results from Table 3.12 are not compelling. From a statistical point of view, this occurrence could be due to the size of our sub-samples. Sample size is an important input to the calculation of confidence limits for measures of effect, and smaller samples can contribute to reducing the statistical test's power (Betensky, 2019). From an economic point of view, findings could be consistent with a context in which carbon risk assessment by lenders as well as the release of climate-related information by firms are something relatively new. Table 3.8 indeed suggests that lenders have started considering carbon risk for all borrowers, both low or high emitters, after the Paris Agreement. Similarly, Table 3.11 shows that climate-related information has started being incorporated in risk assessment processes only in the aftermath of the Agreement. As a result, it might take some time for investors to

incorporate corporate control mechanisms of carbon risk into credit risk assessment practices. Further evidence is needed in this respect.

3.6 Conclusion

This study analyses the relationship between corporate carbon risk and the cost of debt for a sample of listed firms from the Eurozone for the 2010-2018 period. The geographic area under analysis is particularly interesting, as the EU has set sustainable development as one of its main objectives (European Union, 2007). Since the Paris Agreement, the European Commission has taken an increasing number of actions to rapidly adjust the economic system to low-emission targets. In 2018, the European Commission launched the Action Plan for financing sustainable growth, which is intended to reorient financial market participants toward sustainable investments and to help them better assess climate risk. In 2019, it released updated guidelines and recommendations on climate-related disclosures, which should provide investors with better information on corporate carbon risk. The period covered by our analysis allows the examination of the effects of carbon emissions on lending policies in the period immediately subsequent to the Paris Agreement.

Our results provide evidence that higher carbon emissions are associated with a higher cost of debt financing. However, while high emitters were already charged a carbon risk premium before the Paris Agreement, low emitters started being charged a higher spread only in the subsequent period. According to our analysis, in the period surrounding the Paris Agreement, lenders changed the way they consider corporate carbon risk. It is likely that lenders have become aware of the strong commitment taken by policymakers in fighting climate change and adopting consistent actions, thus starting to price carbon risk for all the borrowers, despite being either high or low emitters.

When we investigate the role of disclosure, results indicate that increased levels of climate-related disclosure exert a mitigating effect on the cost of debt. Such evidence, however, holds only for high emitters and in the period after the Paris Agreement, which can explain why high emitters appear not to have been further penalized in the aftermath of the Agreement. In fact, increased levels of disclosure might have reduced the risk premium component associated to information asymmetry.

Our results, instead, are not compelling as far as investors view external validation of emissions, board oversight of climate-related issues and the existence of emission reduction targets. Further evidence is needed in this respect.

To conclude, this study provides robust evidence that a strong policy commitment to keep global warming under control can lead investors to consider corporate carbon risk in their investment decisions. As such, our analysis supports the proactivity of the European Commission on these issues. With the same aim, further research into the relationship between corporate carbon risk and probability of default would be useful. If a robust relationship could be empirically proved, then regulators should differentiate between high and low emitters for capital requirement purposes so as to further incentivize financial institutions' investments in the transition to a low carbon economy.

Conclusions

The objective of this dissertation has been to contribute to the comprehension of the drivers and the relative effectiveness of policy options in the two domains of environmental crimes and of corporate carbon risk. With respect to the first topic, the objective of the thesis has been to assess whether the predictions of the Becker's model that individuals respond to deterrence are verified also in the case of Italian environmental crimes. Related studies mainly focused on the waste sector, using as a proxy for enforcement activities the inspection rate or the charge rate. We tried to fill this gap by extending the analysis to the most diffused environmental crimes in Italy and by measuring deterrence with detailed crime-specific enforcement variables, covering all the steps of the prosecution process. The second concern of the thesis has been the climate change transitions risks associated with carbon intensity faced by private companies. More polluting firms are likely to show more volatile cash-flows and therefore they are more likely to be charged a higher interest rate by lenders. We tried to contribute to this stream of research by providing new evidence that carbon risk has started to be priced by financial markets in the Euro area over the period 2010-2015.

The first chapter analysed environmental crimes in Italy over the period 2006-2016 and showed that there is evidence of deterrence by enforcement activities. In particular, deterrence works especially in the waste and wastewater sectors, which are regulated by the Code of the Environment. Enforcement efforts are instead less effective in reducing building and landscape violations crime rates. Moreover, our results show that deterrence works mainly through the probability of conviction, that is the last and the most severe step of the prosecution phases. Socioeconomic factors do not explain much of the variation in crime rates. Overall, the results show that enforcement variables, rather than socioeconomic factors, are the most important elements to explain Italian environmental crimes.

Following the deterrence theory framework used in the first chapter, the second chapter investigates the role of enforcement with respect to forest fire crimes in Italian provinces over the period 2009-2015. Our results provide evidence of a deterrent effect of enforcement activities. However, differently from the findings of the first chapter, in this case deterrence works especially through the probability of being apprehended rather than the probability of standing trial or the probability of being convicted. This result indicates that forest fires igniters tend to respond to incentives that are closer in time, while offenders related to the crime categories in the waste and wastewater sectors are much more deterred by the probability of conviction. When we consider the deterrence variable taking into account the type of wildfire – deliberate or accidental – our results provide evidence that deterrence works especially for accidental forest fires. Finally, our findings are consistent across different estimation models.

In the third chapter of the thesis we have studied the relationship between corporate carbon risk and the cost of debt on a sample of non-financial firms in the Euro area over the period 2010-2018. Our results provide evidence that higher levels of carbon emissions are associated with a higher cost of debt. However, not all firms have been equally affected by the Paris Agreement. In fact, while high emitters were already charged a carbon risk premium before the Paris Agreement, low emitters started to be charged a higher premium only in the aftermath of 2015, indicating that lenders started to be increasingly aware of the carbon risk and, as a consequence of the increased awareness, they started to price carbon risk for all borrowers. As far as disclosure is concerned, the results indicate a mitigating role of disclosing through the CDP questionnaire. However, this relationship holds only for the high emitters in the aftermath of the Paris agreement. With respect to external validation of emissions, board oversight, and the presence of an emission reduction target our results are instead not compelling.

Overall, the dissertation provides evidence that enforcement activities are effective in deterring environmental crime. Enforcement is more efficient when at least one of the prosecution phases is able to produce a deterrent effect, either actual or perceived. A deterrent effect has been found for waste, wastewater, and forest fire crimes. For the first two categories the most important crime-inhibiting factor is the probability of being convicted, whereas in the case of arsons is the probability of being apprehended. One limitation of the analyses conducted is the impossibility to match a criminal charge to its actual outcome, due to data limitations. More detailed data about the single criminal charge would enable a deeper investigation of the time lag between the apprehension and the conviction phase.

With respect to wildfire crimes, the provincial level of analysis has included only ordinary regions, whereas a more thorough assessment of deterrence should include also autonomous regions. This would represent a useful extension of the current research, once forest fires data will become available for all Italian regions.

A further avenue for future research would be investigating whether deterrence for this type of crime has changed after the State Forestry Corp was dissolved in 2017. The redeployment of the State Forestry Corp personnel is a potential exogenous shock which might have impacted on the efficiency in prosecuting forest fires. Such institutional change could provide an interesting opportunity to investigate the causal effect of police forces redeployment on forest fire crime rates.

With respect to the relationship between the cost of debt and carbon risks, our results indicate that lenders have started to charge a risk premium to firms that have higher levels of carbon emissions, thus suggesting that a policy commitment to mitigate climate change may be able to redirect investors to consider corporate carbon risk in their lending decisions. Future research could investigate the relationship between the cost of debt and carbon risk on a longer time frame after the Paris Agreement, in order to better assess the impact of the last European Commission's measures related to climate reporting, which might have sent stronger signals to the market concerning climate risks.

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