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ENFORCEMENT AND AIR POLLUTION: AN ENVIRONMENTAL JUSTICE CASE STUDY

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ABSTRACT. This paper provides an environmental justice empirical analysis on the relationship between income, demographic characteristics and concentrations of air industrial pollutants within the Italian provinces. Two general conclusions can be drawn from the empirical results. First, the estimates obtained are consistent with an inverse U-shaped environmental Kuznets curve: air pollution releases increase with income up to a turning point, where the relation reverts. Second, there is evidence that air releases tend to be higher in provinces with high concentration of females as households' head and with high concentration of children. Since our findings do not point to environmental discrimination on the basis of ethnicity, this suggests that environmental justice issues in Italy are not likely to manifest themselves along racial and ethnic terms but instead in terms of social categories and gender composition. We also find that judicial inefficiency (a measure of the inefficiency of law enforcement) is associated with higher levels of pollution. In terms of policy implications, this result suggests the need to strengthen, all through the territory, the local enforcement of environmental laws in order to possibly reduce the negative effects on ambient air pollution.

Keywords: Environmental justice, social inequalities, air pollution emissions
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1. INTRODUCTION

Environmental justice is a movement that emerged in the United States in the 1980s[1] and has become a concern in the U.S. federal policy agenda in the early 1990s. In 1994, in fact, environmental justice was institutionalized at federal level through an Executive Order[2] which focused attention on human health and environmental conditions in low-income and minority communities. The key concept of environmental justice issues is that low-income groups and ethnic minorities bear disproportionate environmental burdens, in the form of polluted air and water, unsafe jobs, under-enforcement of environmental laws, etc. (Ringquist, 1997; Evans and Kantrowitz, 2002).

As argued by Ringquist and Clark (1999), environmental equity involves an equal distribution of environmental risk across all social classes, races and geographic areas. The concept of environmental equity is substantially similar to environmental justice, with the only difference that the latter has a stronger nuance in terms of environmental policy. Environmental justice, thus, deals mainly with the question of whether disadvantaged population groups, such as racial and socioeconomic minorities, are disproportionately exposed to pollution and whether demographic composition influences the amount of pollutants. However, while environmental groups continue to focus their attention on environmental justice problems, the evidence from empirical studies has been ambiguous. There is no general agreement on whether minorities or disadvantaged population groups are exposed to more pollution, and if so which minorities (racial, age, socioeconomic) are more at risk.

In the United States it has been widely shown that socioeconomic status and ethnicity are associated with exposures to environmental hazards (Brown, 1995; Arora and Cason, 1999). In particular, minorities and people with low income often tend to live closer to contaminated sites, thus suffering more than the general population from adverse environmental risks. Contrary to the United

[1] More exactly, the environmental justice movement was launched in 1982, when residents of Warren County (North Carolina) protested the construction of a hazardous waste landfill in their predominantly African-American community.
[2] Title VI of the Civil Rights Act of 1964 prohibits discrimination on the basis of race, color, or national origin. Environmental justice as a national policy goal was first through Executive Order 12898.

States, as far as we know in Italy the impact of socioeconomic factors on environmental outcomes has been rarely studied. Empirical analyses on Italian data with focus on social inequalities in exposures to traffic emissions have only been done with regard to the city of Rome (Forastiere *et al*., 2007), and on waste generation and landfill diversion (Mazzanti *et al*., 2009).

This work aims to cover this gap in the empirical literature by investigating whether income and the ethnic and social composition of population in Italy may have a role in explaining air emissions. The analysis is conducted at the provincial level[3] to investigate the existence of provincial differences in the determination of environmental pollution. Air pollution emissions data (from 2005 data) were combined with data from the latest available Italian Census (the 2001 Italian Census). The main objective of this paper is twofold: first we assess whether the economic characteristics (such as income levels, percentage of foreigners, percentage of children, etc.) of provinces help to explain the level of emissions in the air; secondly, we test the social inequality hypothesis linked to air pollution. The results obtained show no evidence of environmental inequity against the foreign component of the population but provide evidence that releases are higher in provinces with higher percentage of both children and female-headed households. These first results imply that, in Italy, environmental injustices are more likely to be observed in terms of social conditions that in terms of racial discrimination.

The environmental justice issue is closely linked to the enforcement issue. In fact, the enforcement of environmental quality regulations is an important element of any environmental policy: only a coherent and homogeneous enforcement of laws guarantees the inexistence of social or ethnic inequalities in exposure to environmental risk. In order to account for the enforcement issue, we consider the number of pending proceedings in the courts located in the Italian provinces as a measure of the inefficiency of law enforcement. Arguably pollution will be lower in provinces with efficient courts and efficient enforcement, since

[3]In Italy, a province is an administrative sub-division of a region, which is an administrative sub-division of the State. A province consists of several administrative sub-divisions called "comune". Italy was divided into 103 provinces at the time we collected our data; as of 2011, there are 110 provinces. Provinces are equally distributed on the territory between north west, north east, centre and south, even though the level of urbanization is higher in the northern part of the country.

long trials are likely to postpone the timing of punishment (Becker, 1968) and this could be an important factor inducing firms to commit illegal activities.

The remainder of the paper is organized as follows. Section two presents a review of the key conceptual issues that are addressed by the environmental justice literature. Section three presents the theoretical framework. In sections four and five, respectively, the model specifications and the datasets used in the analysis are discussed, while in section six the results from the estimations are presented. Section seven concludes with some final considerations in which are discussed, in particular, the potential implications (if any) between enforcement of air emissions regulation and low-income groups in Italy.

2. KEY REFERENCES IN LITERATURE

The relationship between the distribution of environmental pollution and the population characteristics has been studied by a substantial body of literature. In the next two sections, the main U.S. and E.U. empirical contributions on this issue are reviewed.

2.1. U.S. EMPIRICAL EVIDENCE

In the United States, the pioneering study on race and environmental quality *Toxic Wastes and Race in the United States* was conducted by the United Church of Christ's (UCC) Commission for Racial Justice (1987). Race is found to be the most significant variable associated with the location of hazardous waste sites since communities with the greatest number of hazardous waste facilities had the highest composition of racial and ethnic population. The study also found that three out of every five African Americans lived in communities with abandoned toxic waste sites and that 60 percent of African Americans lived in communities with one or more waste sites.[4] Twenty years after the release of *Toxic Wastes and Race*, the recent results by Bullard *et al.* (2010) are still very similar to the

[4] More precisely, the report found that zip code areas with one hazardous waste facility had twice the nonwhite population (24%) than those without such facilities, and that communities with more than one waste facility had an average 38% of nonwhite population (the national average nonwhite population was 16%.).

findings from 1987. They confirm that significant racial and socioeconomic disparities persist today since Hispanics or African Americans are concentrated in neighbourhoods with the greatest number of hazardous waste facilities.

Over the last two decades, environmental justice literature has grown very rapidly. However, mixed evidences were obtained by various studies. Numerous studies document inequities in the spatial distribution of environmental quality (e.g., Bullard, 1983; Bullard and Wright, 1987, 1989; Goldman, 1991; Nieves and Nieves, 1992; Hamilton, 1993, 1995) and many others find limited support for the existence of environmental inequities (e.g., Anderton *et al*., 1994; Been and Gupta, 1997). Anderton *et al*. (1994) and Been and Gupta (1997) use binary response models to analyze plant location decisions, comparing neighbourhoods with industrial plants to neighbourhoods without a plant. Anderton *et al*. (1994), using the 1980 U.S. census data and employing multivariate regression techniques to investigate environmental equity in the demographics of dumping, find that education and occupation, but not race, are significant indicators of waste facilities in a region. Been and Gupta (1997) using 1990 U.S. census data investigated, through multivariate techniques, whether waste facilities were placed in minority communities or minorities moved in afterwards. They obtain mixed evidence on environmental inequities: while waste disposal sites proved to be correlated with race and income, neither the percentage of poor nor the percentage of African Americans were significant factors in deciding the siting of waste sites.

Mohai and Bryant (1992) reviewed fifteen various environmental inequity studies conducted between 1971 and 1992 and concluded that nearly all the studies showed evidence of inequities, based on income and race, in the distribution of environmental hazards. The fifteen studies varied substantially in terms of geographic areas considered. About half of the studies focused on a single urban area, while the rest focused on a region, an aggregation of urban areas, or the U.S. as a whole. Eleven of the studies examined the distribution of air pollution, four examined the distribution of solid or hazardous waste facilities, while one focused on toxic fish consumption. The scale and the statistical methods employed cannot always be determined from the Mohai and Bryant review. They also suggest that factors such as housing discrimination and the location of jobs may have led poor and racial minorities to move closer to hazardous facilities due to the cheapest available housing and potential job opportunities.

More recently, Cory and Rahman (2009) studied the association between income, race and hazardous levels of arsenic concentrations in Arizona and found no supporting evidence that selective enforcement of the arsenic standard could disadvantage minority or low-income groups. They use data on arsenic water concentration and socioeconomic data from 2000 U.S. Census. Out of 359 zip-code areas, 121 were found to be exposed to arsenic levels greater than the maximum level of arsenic allowed in water, while the other 238 were not exposed. They use logistic regression models to estimate the relationship between the likelihood of arsenic contamination at zip-code level and its associated demographic and economic characteristics. The dependent variable is arsenic exceedance in respect to the maximum level and the explanatory variables are the following: percent of white population, percent of black population, percent of Hispanic population, percent of minority (black and Hispanic population), per capita family income, average value of house and average income per household. If a particular zip-code had average arsenic concentration greater than the maximum limit allowed it was assigned the value of 1, otherwise it was assigned the value of 0. Their results support the conclusion that selective enforcement of arsenic standard is unlikely to have disadvantaged minority or low-income groups in Arizona.

In another work, however, Aradhyula *et al.* (2006) found the existence of disproportionate environmental risk in low-income and minority communities for the Phoenix metropolitan area in Arizona. Using data from 1990 and 2000 U.S. Census and from the Toxic Release Inventory (TRI), [5] they estimate a simultaneous equations model to explain jointly firms' siting decisions and minorities' decision to move. Their results suggest two main conclusions. First, there is a positive and highly significant relationship between TRI exposure and

[5] The U.S. Toxics Release Inventory is a database compiled and maintained by the EPA since 1981. Over 75,000 companies are required to report their emissions to the EPA by chemical and amount released. So through the TRI the EPA collects data on toxic chemical releases and waste management activities.

minority communities. Second, the presence of a TRI facility increased the minority share in a community by nearly 10%.

As a matter of fact, notwithstanding the U.S. well-established literature, there is still significant disagreement whether race and social class generate environmental inequities in the United States. This is partially explained by the sensitivity of Environmental Justice results to the type of contaminant considered, its geographical location, and the spatial unit of analysis.

2.2. E.U. Empirical Evidence

The environmental justice debate is only beginning to develop at the European Union level. This approach can be dated from the drafting of the UNECE Convention on Access to Information, Public Participation in Decision-making and Access to Justice in Environmental Matters, adopted at the Fourth Ministerial Conference in the *"Environment for Europe*" process in Aarhus (1998). In its Article 1, the Convention states as an objective to "guarantee the rights of access to information, public participation in decision-making, and access to justice in environmental matters in accordance with the provisions of this Convention."

However, especially in the U.K. the environmental justice debate has started to expand by integrating environmental issues and social justice perspective. In Europe, in fact, the majority of the empirical studies took place in U.K. In England and Wales, McLeod *et al.* (2000) investigate the relationship between particulate matter (PM_{10})[6], nitrogen dioxide (NO_2) and sulphur dioxide (SO_2), and a vector of socioeconomic indicators. They found that higher social

[6] Particulate matter of solid or liquid matter suspended in the atmosphere; PM_{10} particles (<10 μm) and $PM_{2.5}$ particles (<2.5 μm) are of major health and environmental concern. Fine particulates (PM_{10} and $PM_{2.5}$) together with nitrogen dioxide (NO_2), sulphur dioxide (SO_2), carbon monoxide (CO) and benzene are part of the Air Quality Strategy (AQS) (DETR 2000) developed in response to the 1995 Environment Act and the EU Air Quality Framework Directive (96/62/EC). Each of these pollutant can have potential effects on health. Short-term and long-term exposure to ambient levels of particulate matter are associated with respiratory and cardiovascular illness and mortality as well as other ill-health effect (DEFRA, 2007; World Health Organization, 2005; Committee On the Medical Effects of Air Pollutants, 2007). At high levels NO_2 causes inflammation of the airways. Long term exposure may affect lung function and respiratory symptoms (DEFRA, 2007). Carbon monoxide substantially reduces capacity of the blood to carry oxygen to the body's blocking important biochemical reactions in cells (DEFRA, 2007). SO_2 causes constriction of the airways of the lung. Benzene is a recognized human carcinogen (DEFRA, 2007).

classes were more likely to be exposed to greater air pollution. In contrast, Brainard *et al.* (2002) found that the level of NO_2 and carbon monoxide (CO) in Birmingham was higher in communities with a greater proportion of black people and deprived classes. They found that the average carbon monoxide and nitrogen dioxide emissions for districts with poor populations are higher than in wealthy ones. The averages of these pollutants were also higher among districts with high proportion of blacks than among more white districts. Wheeler and Ben-Shlomo (2005) also found that air quality is poorer among households of low social class. More recently, social inequalities in NO_2 levels in Leeds were confirmed by Namdeo and Stringer (2008) at the detriment of poorer groups. Naess *et al*. (2007) using a number of socioeconomic indicators (income, education, living in a flat or in a crowded household) showed that in Oslo (Norway) the most deprived areas were exposed to higher particulate matter emission levels. In contrast, no association between nitrogen dioxide emission levels and education or occupation was found in a cohort of Norwegian men.

Environmental inequalities were explored also in Helsinki (Finland) by Rotko *et al.* (2000) and Rotko *et al*. (2001): levels of NO_2 decreased with a higher level of education. Much greater contrasts in exposure were observed between socio-economic groups for men than for women, both for NO_2 and $PM_{2.5}$. In Sweden, two studies showed evidence of social inequalities related to NO_2. Stroh *et al*. (2005) found that the strength of the association between the socio-economic status and NO_2 concentrations varied considerably between cities. In another study, Chaix *et al.* (2006) found that children from areas with low neighbourhood socio-economic status were more exposed to NO_2 both at home and at school.

Four other European studies explored social inequalities related to air pollution. In Rijnmond (Netherlands), according to Kruize *et al*. (2007), lower income groups live in areas with higher levels of NO_2 than greater income groups. In Germany, Schikowski *et al*. (2008) revealed the existence of a social gradient with higher PM_{10} exposures among subjects with less than 10 years of schooling than among those with higher education. By contrast, in Rome, Forastiere *et al.* (2007) found that the higher social classes appear to reside in areas with high traffic emissions. This disparity is even stronger when socio economic status rather than income is considered. Havard *et al.* (2009), using a French deprivation index (Havard *et al.* 2008), found that in Strasbourg the mid-level deprivation areas were the most exposed to NO_2, PM_{10} and CO.

From this review, it is clear that in Europe the empirical literature that investigates the relationship between exposure to environmental pollution and socio-economic status is a relatively novel topic compared to the USA. European studies (similarly to the U.S. literature) also generate mixed findings regarding exposure disparities. Italy is one of the less investigated countries. In what follows we aim to cover this gap by trying to establish the existence or not of environmental injustices.

3. THEORETICAL FOUNDATIONS

The environmental justice literature has its own theoretical roots in the "inverse U" relationship, commonly referred to as the *Environmental Kuznets Curve* (EKC), which suggests that the level of per capita income has a negative effect on environmental quality measured by the levels of pollution, but, beyond a certain level, per capita income has a positive effect on environmental quality. A crucial issue becomes the existence of a turning point in the relationship between income and pollution. The EKC assumes that the relationship between environment and income might be similar to that suggested by Kuznets (1955) between income inequality and economic development. Since the pioneering works by Grossman and Krueger (1991, 1993, 1995) on the environmental Kuznets curve, there has been a large amount of both theoretical and empirical studies.[7] A comprehensive review of the literature on EKC is provided by Brock and Taylor (2005) whose analysis aims to underline how a non-monotonic

[7] In particular, Grossman and Krueger analyse the EKC through the discussion of three different mechanisms: scale effect, composition effect and technique effect. Scale effect shows that even if the structure of the economy and technology does not change, an increase in production will result in an increase of pollution and environmental degradation. Thus, economic growth through scale effect has a negative impact on the environment. On the other hand, the authors argue that composition effect may have a positive impact on the environment. Pollution increases in the earlier stages of development, while in the later stages of development pollution decreases as the economic structure moves towards services and light manufacturing industries. Therefore, composition effect could lower environmental degradation through this change in the structure of production. Finally, technique effect captures improvements in productivity and adaptation of cleaner technologies, which will lead to an increase in environmental quality.

inverted U-shaped curve may emerge from the relationship between income and pollution emissions.

The so-called environmental justice approach aims to expand the structural factors assumed to drive the environmental Kuznets curve relationship, in order to better integrate economic and social issues with environmental issues. Ethnic diversity and race have been the most significant variables which have been neglected in empirical studies (for example, Cole *et. al.* 1997; Selden and Song, 1994) on the EKC, but that have started to be used by the environmental justice literature to investigate the possible causal relationship between income inequalities and pollution levels. The EKC function usually takes the form $E_{it} = \alpha + \beta Y_{it}/pop + \gamma(Y_{it}/pop)^2 + \varepsilon$ (Stern and Common, 2001) where E is environmental degradation, Y is real income, *pop* is population, ε is an error term, i is location, t is time and α, β and γ are parameters to be estimated.

Grossman and Krueger (1994) argue that knowledge of the shape of the relationship between environment and income could help policy makers in improving or developing new environmental policies. However, as de Bruyn *et al.* (1998) point out, studies on EKC are based on reduced-form models. This means that the endogenous variable (environmental quality) is expressed only as a function of predetermined variables, and no indication about the direction of causality (whether growth affects the environment or vice versa) is known. As stated by Cole *et. al.* (1997, p. 401) reduced-form relationship “reflect correlation rather than causal mechanism”.

To motivate this empirical analysis, we adopt the theoretical framework developed by Hamilton (1995) in which he puts forward three alternative explanations to account for the pollution patterns examined in environmental justice studies: *i)* pure discrimination related to race/gender, *ii)* the Coase Theorem, and *iii)* the theory of collective action (Olson, 1965).

Under the race/gender discrimination hypothesis, facility operators are assumed to look at the racial composition of communities surrounding polluting facilities and decide to locate or increase releases in areas with higher concentrations of minority or low-income groups. Hence, race is perceived to be a factor behind such decisions, that prevails compared to other economic factors (i.e., costs, efficiency) that would be of greater importance to a rational profit-maximizing firm. Mohai and Bryant (1992) have identified a number a possible relationships between race/gender composition and facilities' siting decisions, such as *(a)* lower costs of doing business (due to the availability of lower land values and lower incomes in minority communities); *(b)* lack of conflict in poor areas due to weak political power or insufficient community resources; and *(c)* limited mobility of minorities due to poverty and housing discrimination.

The second explanation applies the standard version of the Coase theorem, suggesting that, in a world without transaction costs, a polluting firm will locate (or increase pollution) in areas in which the releases will cause the least damage. Looking for the lowest damage can be translated, from the polluting firm's perspective, in locating in areas where potential compensation demands (i.e., for adverse health impacts and property loss caused by exposures to pollution) and liability costs are expected to be lower. Areas with higher incomes and property values will increase the potential damages from releases in an area, so polluting firms will attempt to conduct these activities in areas with low income residents and associated lower property values.

Finally, under the last explanation, firms may decide to increase releases in minority and poor communities areas because they face less (political) collective actions. In an ideal Coasean world, the "victim" would be able to negotiate compensation directly with the polluter. However, the compensation demands, in reality, are typically negotiated at community level through the political process. This could lead to results that appear similar to the pure race/gender discrimination hypothesis: firms will decide to locate or increase releases in areas where they face the lowest political opposition to their actions. To the extent that minority communities are less likely to be politically active, then these communities will be more likely to experience higher levels of pollution.

These alternative theories predict that certain variables should explain pollution levels. The race/gender discrimination hypothesis tests whether factors such as the race and the gender composition of the population predict releases. The Coase theorem hypothesis tests whether economic factors such as income levels and unemployment rates explain releases. The political/collective action tests whether the political activity of local residents influences environmental quality. Factors such as age, education and the number of households with children are expected to influence the incentives to undertake political actions (Filer, Kenney and Morton, 1993).

4. Model Specifications

The main objective of this work is to test whether air releases generated by the industrial sector could be explained using socio-economic-and demographic variables. However, a methodological issue that arises in the environmental justice literature is that regressing pollution levels on demographic characteristics can introduce endogeneity problems. In fact, when investigating if pollution amounts may be determined by a number of factors such as income, gender, education levels and other demographic variables, it must be considered that firms may be attracted to locate in minority and low-income areas (Hamilton 1993, 1995), but also some groups (minorities or low-income) may choose to live in or nearby polluted areas for social or economic reasons (e.g., cheaper rents) or other social factors. Hence, there is a problem of reverse causality,[8] due to the fact that *(a)* firms can decide to locate in a minority or low-income area, or *(b)* minority and low-income groups decide to live in polluted areas.

We collected some of the measures that have been employed in prior environmental justice studies and, in order to minimize possible bias due to this endogeneity problem, we developed our investigation through two steps of analysis. In the first step, in a standard ordinary least-squares linear regression, per-capita income is estimated as a function of a vector of fairly standard variables (the set of explanatory variables comprise different classes of population's ages, sex, different types of levels of education, entrepreneurial spirit, and geographical dummies). Predicted values from this regression are then used in the second step where an ordered probit is used to address the extent to which socio-economic

[8] Reverse causality is one of the main sources of endogeneity problems. Been (1994) also points out this endogeneity problem and resolves it by using pre-siting demographic data (i.e., data from before the industrial plants were built). Ringquist (1997) uses a control variable approach by controlling for housing prices; Gray and Shadbegian (2004) use instrumental variables.

factors influence air pollution levels.

Moreover, the values of the explanatory variables are observed at their 2001 Census values: thus, the 2001 socio-economic characteristics are used to explain air releases in 2005 (see Arora and Cason, 1999, on the use of lagged explanatory variables to avoid endogeneity bias). Hence, in our estimation model, we assume that the socio-economic conditions (pre-determined economic and demographic provincial data observed at time *t*) take some time (a four-years time lag) to exhibit their effects on the levels of air pollution (observed at time *t+1*).

Equation 4.1 presents the first auxiliary linear ordinary least-squares regression of per-capita income. Each of the variables will be discussed in more detail in the following sections.

(4.1)

$$pcincome = \alpha + \beta_1 pcenterpr + \beta_2 \inf rastructure + \beta_3 females + \beta_4 age15to34 + \beta_5 age35to49 + \\ + \beta_6 uni\deg ree + \beta_7 low\sec school + \beta_8 primschool + \beta_9 noedu + \beta_{10} north + \beta_{11} centre + \varepsilon_i$$

We, then, substitute the obtained predicted values of income in the second step of analysis (equation 4.2), where we estimate a standard ordered probit model (Greene, 2003) in which explanatory variables are used to predict the probabilities of being exposed to different levels of pollution emissions as shown below:

(4.2)

$$y_i^* = \beta_0 + \beta_1 \log pcincomehat + \beta_2 \log pcincomehat^2 + \beta_3 \log pcasia + \beta_4 \log pcafr + \\ + \beta_5 \log pcfemhead + \beta_6 \log children + \beta_7 \log elders + \beta_8 \log pendingproceedings + e$$

We will now discuss in more details the two-steps model here introduced and all variables will be properly defined.

4.1. Income Regression Analysis

The first step focuses on identifying the factors which are related to the determination of per-capita income. An OLS regression is estimated (for the year 2001) using equation 4.1, where *pcenterpr* is the number of registered firms at provincial level every 100 people, *infrastructure* is an indicator of the transportation infrastructure level, *females* is the number of population which is female, *age15to34* is the number of population aged between 15 and 34 years old, *age35to49* is the number of population aged between 35 and 49 years old, *unidegree* is the number of people with an undergraduate university degree, *lowsecschool* is the number of people with low secondary school diploma, *primschool* is the number of people with only primary school, *noedu* is the number of people with no education at all, *north* is a geographical dummy variable representing the Northern Italian provinces, *centre* is a geographical dummy variable representing the Central Italian provinces. Table 4 shows the results of coefficients and t-statistics.

4.2. AIR POLLUTION REGRESSION ANALYSIS

This second step of analysis aims to identify the demographic characteristics that could explain the distribution of the levels of air pollution. To accomplish this objective, in the ordered probit regression the dependent variable (air pollution emissions) is categorized into four levels and is coded 1 for low air emissions, 2 for medium-low air emissions, 3 for medium-high air emissions and 4 for high emissions.[9] To measure socioeconomic status, we use the variable (*lpcincomehat*), the logarithm of the predicted income values; we also considered the quadratic specification of the same variable (*lpcincomehat2*) which allows us to capture the presence of an inverse U-shaped relation between income and pollution. Regarding ethnic groups characteristics, the percentage of African population (*pcafr*) and the percentage of Asian population (*pcasia*) are used. The percentages of children and of family households with a female as the head of the household are considered to be groups that could suffer from possible environmental discrimination. As mentioned above, we control for a measure of

[9] The standard ordered probit is built around a latent regression of the form $y^* = x'\beta + \varepsilon$ where x is the vector of explanatory variables, β is the vector of estimated parameters, and ε is the error term, which is assumed to be normally distributed across observations and is normalized with the mean and variance of zero and one, with cumulative distribution denoted by $\Phi(\cdot)$ and density function denoted by $\phi(\cdot)$. The air pollution data, y, are related to the underlying latent variable y^*, through cut offs points or thresholds μ_n, where $n = 1\ldots3$. The probabilities are the followings: $Prob(y = n) = \Phi(\mu_n - \beta'x) - \Phi(\mu_{n-1} - \beta'x)$, $n = 1\ldots3$, where $\mu_0 = 0$ and $\mu_3 = +\infty$ and $\mu_1 < \mu_2 < \mu_3$ are defined as three thresholds between which categorical responses are estimated; ordered probit estimation will give the thresholds μ and parameters β. The thresholds μ show the range of the normal distribution associated with the specific value of the dependent variable; the parameters β represent the effect of changes in explanatory variables on the underlying scale. The marginal effects show how the probability of air pollution releases change with a small unit change in the explanatory variables.

law enforcement (*pending proceedings*). Table 5 includes the coefficients, their standard errors and *z*-ratios.

A multitude of different statistical approaches are employed in the environmental justice analysis, depending on the nature of the dependent variable. Multivariate analysis (for example, Been and Gupta, 1997; and Pastor *et al.* 2001), as well as logit (for example, Cory and Rahman, 2009; Hamilton, 1995; or Brooks and Sethi, 1997, where the dependent variable, i.e. the level of exposure to pollution levels, assumes the value of 1 if there was an increase of exposure in the zip code and 0 otherwise) and probit models (Ringquist, 1997; Aradhyula *et al.*, 2006) are used.

The advantage of the ordered probit model is that the marginal effects allow us to determine the impact of each explanatory variable (e.g., ethnicity, income and minorities) on the probability of each level of air pollution emissions. Even though this ranking approach to measure the amount of pollution has not been widely used in previous environmental justice studies, there are some precedents for using an ordered probit analysis. Sadd *et al.* (1999) estimate an ordered logit model on Los Angeles neighbourhoods. They constructed a dependent variable ordered according to the level of assumed health hazard, which takes a value of 0 if the tract has no air release, a value of 1 if it has an air release that does not contain carcinogen compounds, and a value of 2 if it contains carcinogen air release. Forastiere *et al.* (2007), in their investigation of the relationship between exposure to traffic emissions and socioeconomic conditions in Rome, grouped air pollution (i.e., particulate matter emissions, PM_{10}) into four categories: low, mid-low, mid-high, and high emissions, using the 20^{th}, 50^{th}, and 80^{th} percentiles as cut-off points.

To build our dependent variable in the ordered probit regression, beside using air pollution emissions raw data and simply aggregating together the fourteen different pollutants, we also defined a province-level index of air pollution. In order to do that, following Brooks and Sethi (1997),[10] we use Threshold Limit Values (TLVs) in order to adjust for toxicity: *"A threshold limit value is the amount of airborne concentration in mg/m^3 of a substance to which a*

[10] Brooks and Sethi (1997) created a weighted toxicity index using Threshold Limit Values (TLV), combined with a distance function, to develop an exposure measure for each U.S. zip code.

worker may be repeatedly exposed for a normal 8-hour workday and a 40-hour workweek without adverse health effect" (Brooks and Sethi, 1997: 236).

We employed both the Italian threshold limit values established by law for ambient pollution (D.P.C.M. 28/3/83,[11] D.P.R. 203/88,[12] D.Lgs. 351/99[13]) and the U.S. threshold values (see Table A2, in appendix) using the GESTIS-Substance Database which contains information for the safe handling of hazardous substances and other chemical substances at work.[14] In the U.S., the major providers of the Occupational Exposure Limits are the American Conference of Governmental Industrial Hygienists (ACGIH)[15], the Occupational Safety and Health Administration (OSHA), and the National Institute of Occupational Safety and Health (NIOSH). We considered the limit values released and enforced by the U.S. OSHA that sets workplace standard; where the OSHA threshold limit values were not available, we used the U.S. National Institute of Occupational Safety and Health (NIOSH)[16] values.

For example, under the Italian environmental law, sulphur dioxide has a threshold limit value of 80µg/m^3 (D.P.R. 203/88) into ambient air, while nitrogen dioxide has a limit value of 40µg/m^3 (D.P.R. 203/88). Thresholds available from the U.S. OSHA define, instead, the maximum concentration mg/m^3 of a substance to which a worker may be repeatedly exposed for a normal 8-hour workday and a 40-hour workweek without adverse health effects. For example, arsenic has a threshold limit value of 0.2 mg/m^3, while chromium has a threshold limit value of

[11] Decree of the President of the Council of Ministers.
[12] Decree of the President of the Italian Republic.
[13] Decree Law.
[14] The database provides an overview of the limit values from various E.U. member States, Canada (Québec), and the United States as of 2010. The GESTIS-Substance Database is maintained by the Institut für Arbeitsschutz der Deutschen Gesetzlichen Unfallversicherung (IFA, Institute for Occupational Safety and Health of the German Social Accident Insurance).
[15] The ACGIH is a professional organisation of occupational hygienists from universities or governmental institutions. The list of TLVs includes more than 700 chemical substances and physical agents, as well as dozens of biological exposure indices for selected chemicals. ACGIH threshold values do not have a legal force in the USA, but they are only recommendations. OSHA defines regulatory limits. However, ACGIH threshold values are a very common base for setting TLVs in the USA and in many other countries. ACGIH exposure limits are in many cases more protective than OSHA's (http://www.acgih.org).
[16] The U.S. National Institute of Occupational Safety and Health publishes recommended exposure limits (RELs) which OSHA takes into consideration when promulgating new regulatory exposure limits (http://www.osha-slc.gov/SLTC/pel/index.html). NIOSH's documents and threshold limit values list are available at http://www.cdc.gov/niosh/database.html.

1mg/m^3.

For the purpose of aggregating pollutants, our air pollution index was constructed in the following way. Let E^i_j define the emission of pollutant j from province i, and let T_j denote the threshold limit value associated with substance j. Then, the toxicity-weighted aggregated level of air pollution in province i is defined as: $AP^i = \sum_j \frac{E^i_j}{T_j}$. This procedure provides us with a measure of emission for each province, which represents our dependent variable in the ordered probit model. So, for every province in our data set, the sum of the fourteen hazardous substances considered, weighted by their associated threshold limit values (under both Italian and U.S. regulations), was calculated. This procedure allows us to get a more accurate measure of emissions for each Italian province.

On the basis of the different threshold limit values available, we were able to formulate nine different specifications of the dependent variable, that is: 1) E: raw data on emission levels; 2) NE: normalized raw data on emission levels; 3) zE: standardized raw data on emission levels;[17,18] 4) AWE: data on emission levels divided by the U.S. threshold limit values; 5) NAWE: normalized data on emission levels divided by the U.S. threshold limit values; 6) zAWE: standardized data on emission levels divided by the U.S. threshold limit values; 7) IWE: data on emission levels divided by the Italian threshold limit values; 8) NIWE: normalized data on emission levels divided by the Italian threshold limit values; 9) zIWE: standardized data on emission levels divided by the Italian threshold limit values. Except for the three specifications of the dependent variable in which the data are standardized and for the specifications where U.S. threshold limit values are employed, the remaining four specifications (E, NE, IWE and NIWE) yield very similar results both in terms of their statistical significance and of the signs of coefficients.

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[17] Standardization and normalization are the re-scaling techniques most frequently used to better compare a sample. To normalize the data, we used the following command on STATA: su E, meanonly gen NE = (E-r(min))/(r(max)-r(min)), where r(min) and r(max) are respectively the minimum and the maximum values of the data.

[18] To standardize the data, we use the formula $z = (x - \mu)/\sigma$ where x is the observation to be standardized, μ is the mean of the population, σ is the standard deviation of the population.

5. DATA

In order to assess whether air emissions are influenced by socioeconomic status at the Italian provinces level, and whether social inequalities are linked to air pollution, data from the latest available 2001 Census by the Italian Statistical Agency (ISTAT) are used (see Table A1 in the appendix), in which both socio-demographic characteristics (sex, age, type of family, nationality) and socio-economic variables (educational degree) are observed. These data are merged with data available at provincial level on household income (Istituto Tagliacarne).

5.1. THE ISPRA DATABASE

With regard to the environmental data, some papers in the literature use proximity to dangerous facilities as a proxy for environmental risk, [e.g. Anderson *et al.* (1994), Been (1994), Boer *et al.* (1997), Oakes *et al.* (1996), Pollock and Vittas (1995)] whereas other studies use actual pollution emissions levels [see Brooks and Sethi (1997), Daniels and Friedman (1999), Gray and Shadbegian (2004), Morello-Frosch *et al.* (2004), Ringquist (1997)]. In our analysis, given the lack of more disaggregated data, it was not possible to document the proximity and the exposure of poor and minority communities to sources of industrial air pollution. We are aware of the fact that the use of too broad a scale or unit of analysis has been discouraged (Anderton *et al.* 1994), but the most disaggregated available Italian data are only at provincial level.

We use the information on air pollution provided by the Italian Institute for Environmental Protection and Research (ISPRA)[19] which is responsible for the National Emission Inventory. The ISPRA dataset includes data on air emissions in all the Italian provinces (103 provinces distributed over 20 regions). This is a comprehensive database that collects all emission estimates of the major pollutants including greenhouse gases, ozone precursors, benzene, particulate matters, heavy metal and polycyclic aromatic hydrocarbon. The national inventory

[19] ISPRA is the Institute for Environmental Protection and Research established by Italian Law 133/2008. The Institute performs the functions of three former institutions: APAT (Agency for Environmental Protection and Technical Services), ICRAM (Central Institute for Applied Marine Research), INFS (National Institute for Wildlife).

is reported to the European Commission at the national aggregated level, but it is calculated at the regional level and then disaggregated at the provincial level. In the "*Disaggregation of the National Inventory 2005*" Report, data related to the disaggregation of the emissions of the national inventory at the provincial level are available, divided by activity according to the SNAP (Selected Nomenclature for Air Pollution) classification. [20] The SNAP classification consists of the following 11 groups of activities: 1) combustion in energy and transformation industry; 2) non-industrial combustion plants; 3) combustion in manufacturing industry; 4) production processes; 5) extraction and distribution of fossil fuels; 6) solvent and other product use; 7) road transport; 8) other mobile sources and machinery; 9) waste treatment and disposal; 10) agriculture; 11) other sources.

We use data relative only to macro-sector 1 (combustion in energy and transformation industry), macro-sector 3 (combustion in manufacturing industry) and macro-sector 4 (production processes), since we want to base our analysis on air pollution emissions released by the industrial sector and not also from agriculture or road, air, or sea transportation. Descriptive statistics relative to the fourteen contaminants selected for this analysis are provided in table 1. Air pollution emissions are expressed in megagrams: the average level of air releases is 3532766 megagrams with a minimum value of 131997.8 megagrams (Prato) and a maximum value of 2.86e+07 megagrams (Rome). The average per-capita air emission levels, instead, is 7.14 megagrams with a minimum value of 0.57 megagrams (Prato) and a maximum value of 41.04 megagrams (Taranto). Figure 1.1 and figure 1.2 (at the end of the paper) show, respectively, air emission levels and per-capita emission levels for the first twenty most polluted provinces.

5.2. Independent Variables

The primary source for the demographic data used in this analysis is

[20] This classification includes all activities which are considered relevant for atmospheric emissions. The ISPRA database is characterized by three different typologies of emissions: area, point and linear sources. For area emissions (emissions from sources distributed on the territory) a direct measurement is not feasible, and it is necessary, therefore, to estimate them from statistical data and specific emission factors. The approach that ISPRA has applied is based on a linear relation between source activity and emission, following this relation: $E_i = A * FE_i$, where: Ei = emission of the pollutant i (g year^{-1}); A = activity indicator (i.e. produced amount, fuel consumption, etc.); FEi= emission factor for the pollutant i (i.e., $g\ t^{-1}$ of product, kg/kg of solvent, g inhabitant^{-1}).

derived from the Italian Census 2005 Population and Housing by the Italian Statistical Agency. The variables selected and their summary statistics are provided in table 2. All tables are reported at the end of the paper.

The independent variables were chosen according to the most commonly used in environmental justice studies. Additional variables, such as the entrepreneurial spirit, the infrastructural endowment and the efficiency of the judicial system constitute an improvement upon previous studies.

Demographic data

Age/sex/race

In the first step of analysis (ordinary least square regression - OLS), following the traditional and conventional estimation of the Mincer (1958; 1974) equation, we regress income on a set of independent variables which include age, gender, educational attainment and geographical dummy variables. More specifically, the distribution of income among different working age group population is examined. The independent variable *age* (grouped into ranges of 5 years each) is categorized into two groups of age, namely (i) age range from 15 to 34 years and (ii) age range from 35 to 49 years. Another independent variable employed is *female* (percentage of population which is females) to examine female-based variations in the distribution of households income.

In the second step of analysis (ordered probit regression), *children* (percentage of population less than six years old) and *elders* (percentage of population more than 65 years old) are also examined as they are assumed to be inherently more susceptible to air pollution (Greenberg, 1993; Chaix *et al.*, 2006). Regarding racial characteristics, the percentage of *African* residents and the percentage of *Asian* residents are used. Moreover, the percentage of family households with a *female as the head of the household* is considered to be a group that could suffer from possible environmental discrimination (Arora and Cason, 1999).

Education

In the OLS regression, educational levels are considered as determinants of income and are classified into four categories corresponding to the International Standard Classification of Education: university degree, lower secondary education, primary education and no education at all.

Income

The Tagliacarne Institute and the Union of Italian Chambers of Commerce provide the data related to real household disposable *income* per capita in each province.

Territorial variables

In the OLS regression, we introduced two geographical dummy variables to reflect the territorial subdivision of Italy (Bagnasco, 1977): *North Italy* (comprehensive of North-eastern and North-western Italian provinces) and *Central Italy*. The dummy South Italy is left out as reference.

Other independent variables

In the OLS regression, two additional variables are included: provincial *entrepreneurial spirit* (number of registered firms every 100 people at the province level) and the level of *infrastructure* present in each province, measured as an indicator of the transportation infrastructure endowment (Guiso, Sapienza and Zingales, 2004). These data were drawn from the yearly report of data and social indicators on quality of life performed by the leading Italian financial newspaper, *Il Sole 24 Ore*.[21]

In the ordered probit regression, the demographic and economic data are implemented with the variable *pending proceedings* which is a measure of the inefficiency of law enforcement in terms of number of pending trials in each province (data collected from "*Il Sole 24 Ore*").[22] Pending proceedings have risen to almost 9 millions in the last few years in Italy, two thirds of which belong to the criminal sector, while the remaining are civil ones. Trial and appeal delays and the large number of pending proceedings are one of the major problems associated with the inefficiency of justice in Italy.

By merging the above described environmental, demographic and

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[21] *Il Sole 24 Ore* publishes this annual report on quality of life every year since 1989. The 103 Italian provinces are ranked according to a summary indicator of their quality of life constructed collecting official statistical data. The final quality of life indicator is based on 36 social indicators related to six main areas: consumption and wealth, labor and business, environment and services, justice efficiency and criminality, population, leisure. Even though the statistical robustness of these rankings is often criticized (Lun *et al*,. 2006; Vitali and Merlini, 1999), the results of the *Il Sole 24 Ore* report it constitutes a very regular collection and analysis of data on quality of life.

[22] The data on the number of pending proceedings by the *Il Sole 24 Ore* is an elaboration of the data released by the Italian Ministry of Justice.

economic data we produced a database that can contribute to extremely exiguous literature on environmental justice studies in Italy.

Table 2 provides the descriptive statistics for the economic and the demographic variables: these measures are the independent variables in our regressions. Average per capita income is in million liras; average income is 14.675 which varies from a minimum of 9.104 (province of Caltanissetta) to a maximum of 20.613 (province of Milan). Entrepreneurial spirit reflects the number of registered firms; the average number of firms on the territory is 23.970 with a minimum value of 9.85 (province of Vibo Valentia) and a maximum value of 37.93 (province of Verbania). The maximum value of the infrastructural index belongs to Trieste while its minimum value is 443 and belongs to Sondrio. On average, 10% of the population has an undergraduate university degree with a minimum value of almost 7% (province of Prato) and a maximum value of almost 18% (Rome). On average 35.8% of the population has a lower secondary school diploma, with a minimum value of 26.4% (Rome) and a maximum value of 45.7% (Bolzano). On average 1.2% of the population have no education at all, with a minimum value of 0.3% (Sondrio) and a maximum value of almost 3.6% (Crotone). About 0.27% of the population is Asian with a minimum value of 0.015% (Enna) and a maximum value of 2.09% (Prato). About 0.64% of the population is African with a minimum value of 0.07% (Taranto) and a maximum value of 2.19% (Modena). The average number of family households with a female as the head of the household is 11.7% with a minimum value of 7.7% (Nuoro) and a maximum value of 20.1% (Savona). The average percentage of children is 5.2 with a minimum value 3.69 (Ferrara) and a maximum value of 7.35 (Naples). On average, the 19.8% of the population is composed by elders with a minimum value of 12.5% (Naples) and a maximum value of 25.9% (Savona). The average number of pending proceedings is 41.14 every thousand people, but there is a high variability among the provinces. Some provinces have a number of 9.5 (Lecco) or 11.44 (Trento) pending proceedings, others go as high as 132.96 (Messina) or 158.06 (Reggio Calabria) per thousand people.

Table 3 reports the cross-correlations between the various socio-economic variables and the environmental variable. Limiting our comments on the strength of the relationship between the main independent variables of interest and the dependent variables, we can observe that there is a quite high collinearity between some of the independent variables. In particular there is a high positive correlation between the following independent variables: (i) between the number of firms and per-capita income (r = 0.84) and between the number of firms and North (r = 0.7); (ii) a high negative correlation between per-capita income and no education (r = - 0.73); (iii) a fairly high positive correlation between per-capita income and North (r = 0.6); (iv) there is also collinearity between the number of pending proceedings and North (r=0.71). However, given the model specifications presented in section 4.4, there is no high correlation between any of the independent variables that might pose a serious specification problem of collinearity.

6. RESULTS

6.1. INCOME REGRESSION ANALYSIS - RESULTS

In the first OLS regression, the dependent variable is per-capita income and is regressed over the above specified set of explanatory variables. Table 4 presents the OLS regression's results (obtained using STATA/SE 9.0). Overall, this model performs well in explaining the dependent variable with an R-squared value of 84.29%. Among all the independent variables, the entrepreneurial spirit (number of firm) and the infrastructure endowment have the strongest effect on per-capita provincial income level. Note that the coefficients on age classes are both statistically significant. The sign of the coefficient on people aged between 15 and 34 is negative, while the one on people aged between 35 and 49 is positive, suggesting that income profiles rise with age (experience). These outcomes are not new in literature. Gomez and Hernandez de Cos (2008), in fact, examined the role of the age structure of the population as a determinant of economic growth and they found that productivity peaks during the working ages of 35 and 54 when "*the balance between formal education and experiential human capital reaches its optimum*".

The coefficient on female participation to the determination of per-capita income is negative but it is not statistically significant. Almost all the education variables (except the lower secondary school diploma) are significant in explaining per-capita provincial income. We find that higher levels of education (undergraduate university degree) are positively related to per-capita provincial income; consistently, no education at all has a statistically significant and negative impact on per-capita income. Our findings also suggest that geography (Northern and Central Italian provinces) has a positive and significant effect on per-capita provincial income (relative to Southern provinces). Hence, population age, educational attainment and geographic factors seem to matter in explaining the variability of per-capita income across Italian provinces.

6.2. AIR POLLUTION REGRESSION ANALYSIS - RESULTS

Table 5 reports the results of the ordered probit model. For convenience we report in full details the results associated only to one specification of the independent variable (i.e., raw data). It should be noted that when the dependent variable is ordered, estimated parameters do not reflect a unit change of an independent variable on probability; thus, the estimated coefficients in an ordered probit have no direct interpretation. For this reason, we also calculate the associated marginal effects (see Greene, 2003, p. 738, for a discussion of calculating marginal effects). These can be interpreted as the change in the probability of attaining different levels of air pollution emissions as a result of a unit change in each explanatory variable. Notice that the sum of the marginal effects equals zero. The signs on the marginal effects of the significant variables do not remain constant: more specifically, in the third and the fourth air pollution categories, *Pr*(Y=3: medium-high emissions) and *Pr*(Y=4: high emissions), the statistically significant variables have opposite signs compared to the first and the second air pollution categories. In the fourth scenario, for example, a 1% increase in income is associated with a 35.92% increase in the probability of attaining high emission levels.

Tables from 4.5.1 to 4.5.5 report the marginal effects that each explanatory variable has on the four scenarios of air pollution – that is the impact that an increase of one unit of the explanatory variables has on the probability of attaining, respectively, low, medium low, medium high and high air pollution emissions. From table 5.4, the *income* variables (in their logarithmic linear and quadratic specifications) are both statistically significant, showing that an increase in income translates to an increase in the probability of attaining high levels of air pollution emissions. Moreover, the statistical significance of the squared term for income and its negative relationship with the dependent variable, allow us to identify an inverse U-shaped relationship between income and air releases. The interpretation of this environmental Kuznets curve is that an increase in economic activity leads to a higher probability of attaining high levels of air pollution, but beyond a turning point, as income increases further, the demand for a cleaner environment reduces the level of pollution. This outcome implies that in the richest Italian provinces industrial firms are more likely to invest in technology and innovation and to control air pollution.

We can notice that the percentages of Asian and African foreigners are never, in the four scenarios, statistically significant. Hence, the results provide no support for the contention that ethnicity could be associated with a disparate-impact discrimination for environmental harm. The results, however, indicate that a 1% increase in the number of family households with a female head translates into a 0.49% increase in the probability of attaining high levels of air pollution emissions: so, these estimates suggest that air releases are greater, on average, in provinces with greater proportion of female-headed households. The results for children are somewhat similar: a 1% increase in the percentage of resident children translates into an increase by 1.6 percentage points in the probability of attaining high levels of air pollution emissions. Those are key results: greater concentrations of females as household heads and of children are likely to be associated with increased levels of air pollution.

We can notice that the sign of the coefficient of judicial inefficiency is positive (although this variable is not statistically significant), implying that an increase in judicial inefficiency is associated with an increase in the probability of having high releases. In other words, provinces with high judicial inefficiency are more likely to experience more releases than provinces with lower judicial efficiency. We were motivated to refine the model and to capture potential interactions (which are the product of two independent variables) in influencing air pollution. To account for this, we tried out several possible interactions of judicial inefficiency with other explanatory variables but the only interaction term which was statistically significant (and improved the estimation results) was that between *pending proceedings* and *children* (hence, pending proceedings*children was included as an additional independent variable).[23] Intuitively, the interaction term reflects the possibility that the result could be influenced by this particular independent variables' combination.

The model incorporating the interaction is:

(4.3)

$$y_i^* = \beta_0 + \beta_1 \log pcincomehat + \beta_2 \log pcincomehat^2 + \beta_3 \log pcasia + \\ + \beta_4 \log afr + \beta_5 \log pcfemhead + \beta_6 \log children + \beta_7 \log elders + \\ + \beta_8 pendingproceedings + \beta_9 pendingproceedingschildren + e$$

Similar to the previous estimation model, the same explanatory variables remain significant and the levels of statistical significance of all the estimated coefficients improve overall. In table 6, the results of the ordered probit model with the interaction term are provided. Tables from 6.1 to 6.5 report the marginal effects that each explanatory variable has on the four scenarios of air pollution. The statistical significance of the income variables improves and the signs are confirmed, again validating the existence of an inverse U-shaped relationship between income and air releases. The key result from this model is, however, that pending proceedings not only are statistically significant but also that the interaction term shows a statistically significant impact on air releases.

When the variable pending proceedings is present in the regression also interacted with the proportion of children, its overall sign is given by the sum of the coefficients of the variable itself plus the product between the interaction coefficient and the proportion of children in each province. For instance, when the coefficient of pending proceedings is 5.66 and the interaction coefficient is -3.12, the overall effect will depend on the proportion of children in the province. If this proportion in a certain province is 0.10 (i.e., 10%), the net effect in this province

[23] The following interactions were also tried out: *pendingproceedings*incomehat, pendingproceedings*incomehat2, pendingproceedings*pcfemhead, pendingproceedings*pcasia, pendingproceedings*pcafr* .

is given by [5.66 – (3.12 * 0.10) = (5.66 - 0.312) = 5.348]; if the proportion of children in another given province is 0.20 (i.e., 20%), the net effect in this other province would be [5.66 – (3.12*0.20)= (5.66- 0.624) = 5.036], and, thus, the overall effect would be always positive even though it decreases at the increasing of the proportion of children.

From our results, therefore, an increase of judicial inefficiency (weaker law enforcement) is associated with an increase in the probability of air releases. The interaction term suggests that an increase of judicial inefficiency in the provinces with higher proportions of children leads to a decrease in the probability of having high levels of air pollution, even though the net effect is always positive.

More specifically, if we look at table 6.4, a 1% increase in the number of pending proceedings translates into a 1.6 percentage points increase in the probability of attaining high levels of air pollution emission. In general, therefore, it seems that wherever law enforcement is weak, firms pollute more implying that enforcement of law does matter, other conditions being equal, to explain air pollution. However, further investigation needs to be done to clarify the interpretation of the interaction between the effects of judicial inefficiency and the proportion of children.

We employed all the alternative model specifications (although the results are not reported in full detail) to estimate the same ordered probit models reported above for the five other alternative specifications of the dependent variable, as explained in section 4.4.2. Our results are substantially confirmed in both ordered probit models (with and without the interaction variables), in terms of statistical significance and coefficient signs, when using normalized raw data (NE) and when using Italian threshold limit values for ambient air pollution (in both forms, normalized and not normalized data), as one can see from tables 4.7 to 4.8.1. However, when using U.S. threshold limit values for hazardous substances, all the independent variables lose their statistical significance. So, while the estimated coefficients on some specifications of the dependent variable (i.e.: E, NE and IWE) were definitely robust (see table 9), on the remaining alternative specifications (NIWE, AWE and NAWE) they do not perform well under the same set of explanatory variables.

7. CONCLUSIONS

This paper presents a reduced form statistical analysis on the relationship between air pollution and socioeconomic characteristics across the Italian provinces. Our approach uses the level of air pollution emissions (fourteen types of pollutant substances from the industrial sector), released by industrial plants in 2005 as the measure of environmental quality, merged with 2001 data on socio-demographic characteristics at provincial level. The main objective is to ascertain whether income, ethnicity and gender composition of the population can help explain releases and whether environmental injustice arguments can be identified in Italy.

The estimates obtained by the ordered probit models indicate that an increase in income by one unit is expected to increase the probability of higher levels of air pollution releases, that is releases increase with income, but our estimates are also consistent with an inverse U-shaped environmental Kuznets curve: once income exceeds a turning point, air pollution decreases with increasing income.

Our search for environmental injustice finds evidence that releases tend to be higher in provinces with high concentration of females as households' head and with high concentration of children. Our findings do not allow identifying any environmental discrimination based on ethnicity suggesting that environmental justice issues are not likely in Italy to be perceived in racial and ethnic terms but in terms of social categories and gender composition.

We find also that greater judicial inefficiency (or lenient law enforcement) is associated with higher levels of pollution. This result suggests that a better implementation, all through the territory, of the local enforcement of environmental laws can play an important role in creating the conditions for better relationships between firms and judicial institutions improving, thus, the overall environmental quality.

Extension of the work and future research. Data on Italian air emissions releases are available for the years 1990, 1995, 2000 and 2005, so it would be possible, for future research, to use a panel data analysis using also the penultimate 1991 Italian Census data and the imminent release of the 2011 Census data. In the present paper, a cross-section regression was run on 2005 pollution emissions data. Estimating other cross-section regressions for each year would allow us to check for structural changes over time in the relationship between the variables, under both fixed effects and random effects.

One of the main limitations of the ISPRA dataset is that it is not possible to obtain information on the compliance trends and on the enforcement activities in each province. It would be desirable to have access to more detailed data sets on the number of inspections conducted by enforcement authorities, on compliance levels and on the implications of the different penalty means. The lack of accurate and incomplete information does not allow policymakers to understand how the Italian system of enforcing environmental laws work and what reforms may be needed.

Another interesting investigation for future research can be to estimate separate air pollution regressions for the local and the global pollutants. Sulphur dioxide (SO_2), carbon monoxide (CO) and nitrogen monoxide (NOX) are three major local air pollutants whereas carbon dioxide (CO_2) is the major global pollutant. With regard to the relationship between pollutants and income, while in the literature there is a general agreement on the existence of an inverted-U curve for local pollutants, there is less consensus on the shape of the curve for global pollutants (Lopez, 1994; Meers, 2000). Treating differently local and global pollutants, thus, might add important further insights into the empirical and theoretical debate.

Another area of improvement of the present work could be the measurement of the dependent variable. We examine toxicity (by employing threshold limit values), but risk exposure is not covered in this analysis: instead of using actual pollution levels, the use of spatial analysis using Geographical Information System (GIS) would allow to use proximity from hazardous facilities as a proxy for environmental risk.

Finally, concerning on the use of instrumental variables, instead of performing a two-steps regression model it may be useful to estimate the model in a single step. Modeling an ordered probit with instrumental variables in one single step, however, cannot be run by STATA software. We leave the programming of this model as our future task to be solved.

Table 1. Descriptive statistics of the air pollutants that compose the dependent variable in the ordered probit regression

Pollutants - descriptive statistics (N = 103 provinces)					
pollutants	mean	median	standard deviation	minimum value	maximum value
*sulphuric dioxide**	8557.90	1990.71	17423.36	0.303	96385.52
*nitrogen oxides**	8980.24	3946.46	11918.65	14.60	54407.96
*carbon monoxide***	16963.46	9025.16	38034.08	1502.72	376509.9
*carbon dioxide****	3493031	1848533	4561720	129135.4	2.85e+07
*nitrous oxide**	1381.87	848.42	2176.10	112.85	20518.56
*ammonia***	3847.59	2224.30	4817.7	14.25	28817.56
*arsenic*****	363.38	107.35	894.59	0.56	8076.338
*chromium***	508.68	185.51	810.91	0.65	4481.793
*copper***	405.63	126.35	1524.76	3.53	15151.66
*mercury***	69.95	34.18	138.26	1.58	1076.05
*nickel**	1332.13	564.34	1978.39	3.64	13554.87
*lead**	1943.42	695.85	4622.00	0.83	42187.82
*selenium**	109.11	30.93	215.34	0.36	1665.048
*benzene**	153.64	114.53	140.91	16.82	917.8066
total air emissions	3532766	1863494	4606910	131997.8	2.86e+07
per-capita air emiss.	7.140	4.468	8.137	0.5792	41.04

Notes: *substance measured in micrograms; **substance measured in milligrams; ***substance measured in megagrams; ****substance measured in nanograms. In the ordered probit regression analysis, all the different measurement units were converted into megagrams.

Figure 1. Air pollution emissions for the first twenty most polluted Italian provinces (in millions megagrams)

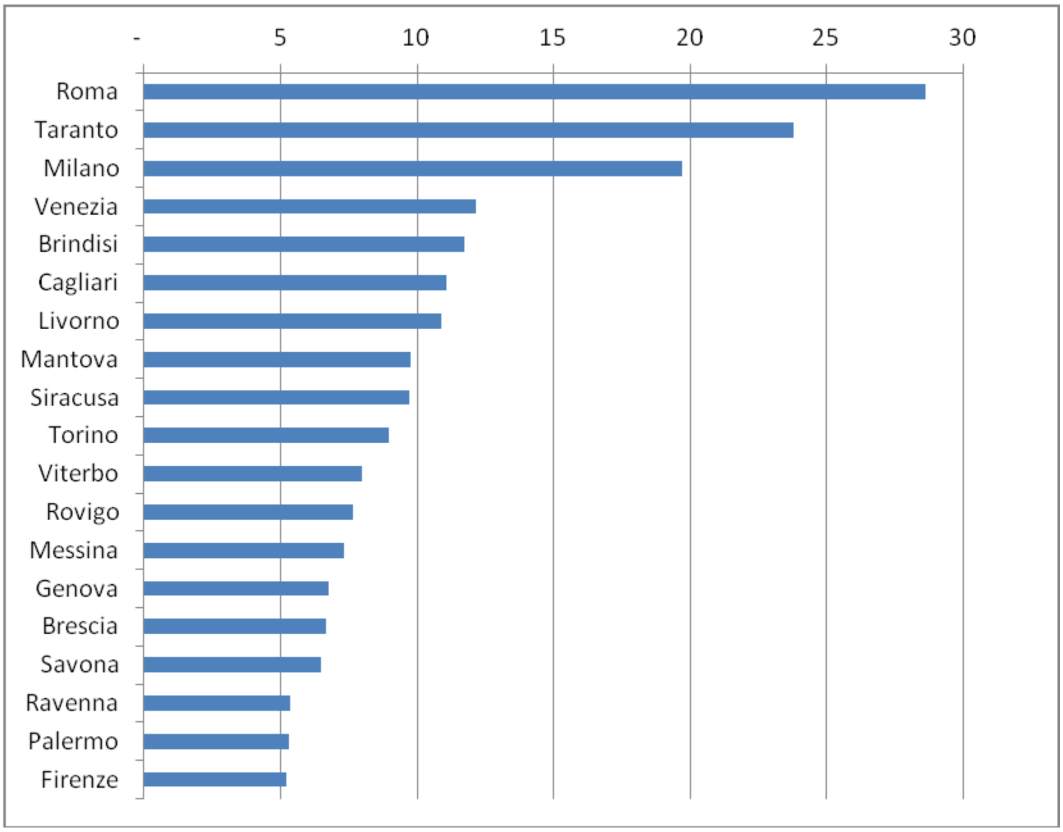

Figure 2. Per-capita air emissions levels for the first twenty most polluted provinces (per-capita megagrams)

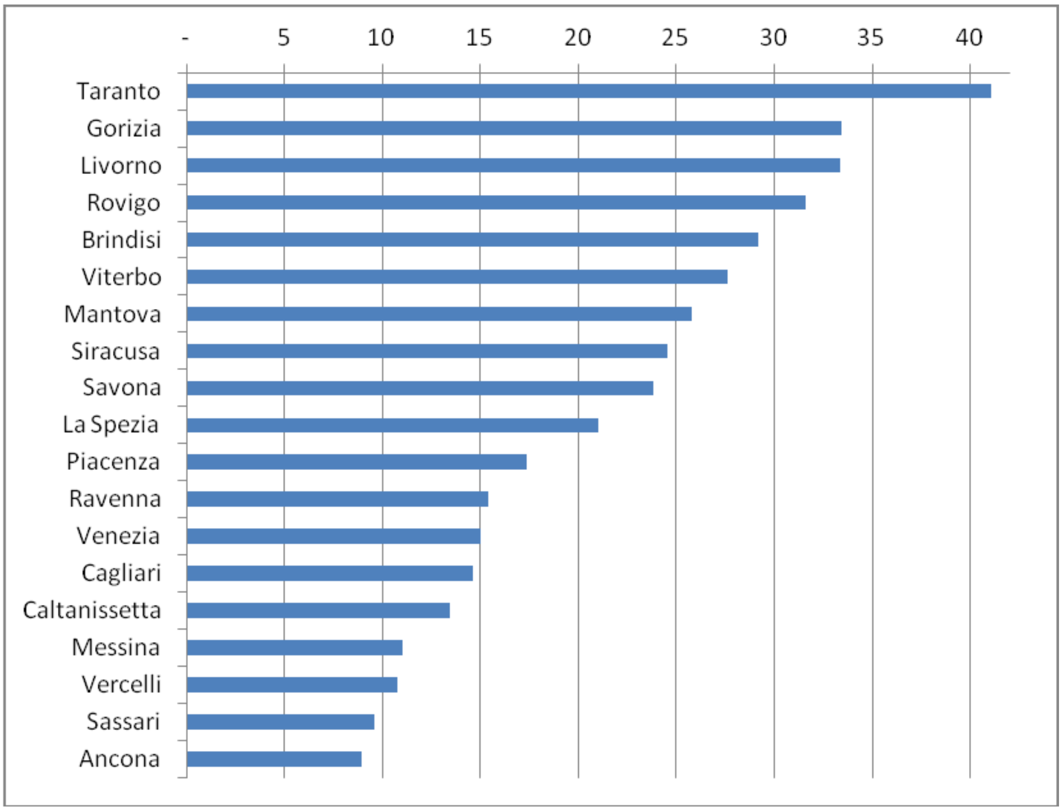

Table 2. Independent variables descriptive statistics (N = 103 provinces)

Variable	mean	standard deviation	minimum value	Maximum value
pcincome	14675.68	3024.42	9104.12	20613.52
entrepreneurial spirit	23.970	4.964	9.85	37.93
infrastructure	556.902	81.927	443	1000
females	247242	271537.8	39886	1696080
age15to34	90399.67	101921.6	12641	678961
age35to49	93498.53	106050.4	14172	714986
pcunivdegree	0.105	0.022	0.067	0.178
pclowsecschool	0.358	0.035	0.264	0.457
pcprimschool	0.116	0.022	0.046	0.161
pcnoedu	0.012	0.007	0.002	0.035
pcasia	0.0027	0.0031	0.00015	0.020
pcafr	0.0064	0.0048	0.0007	0.021
pcfemhead	0.117	0.023	0.077	0.201
children	5.27	0.75	3.69	7.35
elders	19.84	3.09	12.52	25.91
pendingproc	41.146	29.107	9.55	158.06

Note: The variables used in logs in the regression are presented in their original levels.

Table 3. Independent variables descriptive statistics – Correlation matrix (N = 103 provinces)

	pcemissions	Pcincome	# firms	Infrastructure	females	age15~34	age35~49	pcunidegree	pclowsec	pcprimary	pcnoedu	Pcasia	pcafr	pcfemhead	pcchildren	pcelders	pendingproc	north	centre
pcemissions	1																		
pcincome	0,050	1																	
# firms	0,087	0,848	1																
infrastructure	0,027	0,203	0,113	1															
females	-0,079	0,141	0,117	0,447	1														
age15~34	-0,082	0,167	0,156	0,427	0,993	1													
age35~49	-0,077	0,219	0,193	0,416	0,990	0,993	1												
pcunidegree	-0,089	-0,127	-0,204	0,468	0,463	0,392	0,414	1											
pclowsec	0,055	0,127	0,216	-0,250	-0,228	-0,157	-0,190	-0,794	1										
pcprimary	-0,185	-0,520	-0,560	-0,363	-0,269	-0,277	-0,310	-0,220	0,185	1									
pcnoedu	-0,085	-0,738	-0,758	-0,041	0,004	-0,036	-0,071	0,354	-0,304	0,652	1								
pcasia	-0,014	0,461	0,453	0,110	0,304	0,338	0,357	-0,073	0,099	-0,157	-0,332	1							
pcafr	-0,063	0,528	0,567	-0,137	0,073	0,140	0,143	-0,375	0,335	-0,167	-0,375	0,536	1						
pcfemhead	-0,077	0,251	0,092	0,292	0,154	0,118	0,151	0,294	-0,346	-0,150	-0,068	0,189	-0,107	1					
pcchildren	-0,245	-0,600	-0,477	-0,022	0,257	0,267	0,200	0,140	-0,017	0,325	0,602	-0,098	-0,069	-0,150	1				
pcelders	0,144	0,626	0,509	0,019	-0,321	-0,337	-0,272	-0,092	-0,089	-0,308	-0,529	0,096	0,151	0,228	-0,875	1			
pendingproc	-0,031	0,443	0,506	-0,194	-0,099	-0,039	-0,032	-0,547	0,504	-0,340	-0,578	0,173	0,531	-0,274	-0,182	0,176	1		
north	0,116	0,643	0,704	0,061	0,019	0,077	0,088	-0,404	0,399	-0,481	-0,606	0,241	0,609	-0,120	-0,283	0,304	0,711	1	
centre	-0,039	0,162	0,068	-0,060	-0,019	-0,041	-0,010	-0,008	-0,156	0,010	-0,220	0,219	-0,084	0,336	-0,301	0,286	-0,172	-0,455	1

Table 4. First-step regression with OLS estimation - dependent variable: *per-capita income*

per-capita income (dep. variable)	coefficients	standard errors	t	P>|t|	[95% Conf. Interval]	
entrepreneurial spirit	214.36	72.960	2.94	0.004	69.43	359.28
infrastructure	4.99	1.563	3.20	0.002	1.88	8.09
females	-0.003	0.004	-0.66	0.512	-.012	0.006
age15to34	-0.032	0.015	-2.17	0.033	-.063	-0.002
age35to49	0.039	0.008	4.71	0.000	.022	0.05
university education	36452.35	16535.96	2.20	0.030	3605.69	69299
lower secondary school	1622.864	6213.95	0.26	0.795	-10720.4	13966.13
primary school	36152.43	8619.007	4.19	0.000	19031.84	53273.03
no education	-97931.4	27214.3	-3.60	0.001	-151989.3	-43873.53
North	3554.092	696.63	5.10	0.000	2170.30	4937.88
Centre	2415.81	508.23	4.75	0.000	1406.25	3425.36
_cons	-2663.83	3427.3	-0.78	0.439	-9471.80	4144.12
num. of observations = 103						
F(11, 91) = 79.69						
prob > F = 0.0000						
R-squared = 0.84						
Root MSE = 1269.1						

Table 5. Second-step regression with ordered probit estimation - dependent variable: *air pollution emissions* – specification: raw data (E)

air pollution emissions (dependent variable)	coefficients	standard error	z	P>|z	[95% Conf. Interval]
lpcincomehat	123.11	63.30	1.94	0.052	-0.95 247.19
lpcincomehat2	-6.47	3.29	-1.96	0.050	-12.9 -0.011
lpcasia	-0.17	0.17	-0.96	0.339	-0.52 0 .17
lpcafr	-0.21	0.22	-0.95	0.340	-0.66 0.23
lpcfemhead	1.69	0.69	2.43	0.015	0.32 3.069
lchildren	5.51	1.93	2.85	0.004	1.72 9.30
lelders	2.73	1.65	1.65	0.098	-0.50 5.97
lpendingproceedings	0.26	0.28	0.93	0.350	-0.29 0.82
cut_1	601.25	305.05			3.35 1199.15
cut_2	602.06	305.06			4.14 1199.98
cut_3	602.87	305.07			4.93 1200.81
num. of observations = 103					
LR $chi^2(8)$ = 28.48					
prob > chi2 = 0.0004					
log likelihood = -128.53					
pseudo R2 = 0.099					

Table 5.1. Marginal effects of the ordered probit for *Pr* (Y =1: low air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	Z	P>|z
lpcincomehat	-34.84	15.31	-2.28	0.023
lpcincomehat2	1.83	0.79	2.30	0.021
Lpcasia	0.04	0.05	0.97	0.333
Lpcafr	0.06	0.06	0.96	0.338
Lpcfemhead	-0.48	0.20	-2.30	0.021
Lchildren	-1.56	0.55	-2.83	0.005
Lelders	-0.77	0.47	-1.63	0.102
lpendingproceedings	-0.07	0.08	-0.92	0.359

Table 5.2. Marginal effects of the ordered probit for *Pr* (*Y=2*: medium-low air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	Z	P>|z
lpcincomehat	-14.26	8.78	-1.62	0.104
lpcincomehat2	0.75	0.45	1.64	0.102
lpcasia	0.019	0.021	0.91	0.364
lpcafr	0.025	0.027	0.91	0.361
lpcfemhead	-0.196	0.103	-1.90	0.058
lchildren	-0.639	0.304	-2.10	0.035
lelders	-0.316	0.216	-1.46	0.143
lpendingproceedings	-0.03	0.034	-0.90	0.369

Table 5.3. Marginal effects of the ordered probit for *Pr* (*Y=3*: medium high air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	13.18	7.25	82	0.069
lpcincomehat2	-0.69	0.37	-1.83	0.067
lpcasia	-0.018	0.02	-0.92	0.359
lpcafr	-0.023	0.025	-0.92	0.359
lpcfemhead	0.181	0.099	1.82	0.069
lchildren	0.59	0.28	2.07	0.038
lelders	0.292	0.203	1.44	0.150
lpendingproceedings	0.028	0.032	0.88	0.381

Table 5.4. Marginal effects of the ordered probit for *Pr* (*Y=4*: high air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	35.92	15.79	2.27	0.023
lpcincomehat2	-1.89	0.82	-2.30	0.021
lpcasia	-0.05	0.05	-0.97	0.334
lpcafr	-0.06	0.06	-0.96	0.338
lpcfemhead	0.49	0.21	2.31	0.021
lchildren	1.60	0.56	2.86	0.004
lelders	0.79	0.48	1.64	0.101
lpendingproceedings	0.07	0.08	0.92	0.357

Table 5.5 Summary of marginal effects of significant variables for the ordered probit estimation (I) – dependent variable: *air pollution emissions* – specification: raw data (E)

Probability in air pollution levels	Coefficient	Marginal Effect
lpcincomehat		
	123.11	
Pr (Y=1)		-34.84
Pr (Y=2)		-14.26
Pr (Y=3)		13.18
Pr (Y=4)		35.92
lpcincomehat2		
	-6.47	
Pr (Y=1)		1.83
Pr (Y=2)		0.75
Pr (Y=3)		-0.69
Pr (Y=4)		-1.89
lpcfemhead		
Pr (Y=1)	1.69	
Pr (Y=2)		-0.48
Pr (Y=3)		-0.19
Pr (Y=4)		0.18
		0.49
lchildren		
Pr (Y=1)	5.51	
Pr (Y=2)		-1.56
Pr (Y=3)		-0.63
Pr (Y=4)		0.59
		1.60

*Notes:*Y =1: low air pollution; Y=2 : medium-low air pollution; Y=3: medium-high air pollution; Y=4: high air pollution.

Table 6. Ordered probit estimation with interaction variable - dependent variable: *air pollution emissions* – specification: raw data (E)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	153.58	65.45	2.35	0.019
lpcincomehat2	-8.06	3.41	-2.36	0.018
lpcasia	-0.16	.17	-0.93	0.354
lpcafr	-0.28	.23	-1.22	0.224
lpcfemhead	1.83	.70	2.58	0.010
lchildren	23.76	9.55	2.49	0.013
lelders	3.16	1.68	1.87	0.061
lpendingproceedings	5.65	2.77	2.04	0.041
*lpendproc*lchildren*	-3.12	1.59	-1.95	0.051
cut_1	780.39	319.84		
cut_2	781.22	319.86		
cut_3	782.04	319.87		
number of observations = 103				
LR chi2(9) = 32.37				
log likelihood = -126.58				
prob > chi2 = 0.0002				
pseudo R2 = 0.1134				

Table 6.1. Marginal effects of the ordered probit for *Pr*(*Y =1*: low air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	-42.74	18.23	-2.34	0.019
lpcincomehat2	2.24	0.95	2.36	0.018
lpcasia	0.04	0.05	0.93	0.353
lpcafr	0.07	0.06	1.21	0.227
lpcfemhead	-0.50	0.20	-2.53	0.012
lchildren	-6.61	2.70	-2.45	0.014
lelders	-0.88	0.47	-1.84	0.065
lpendingproceedings	-1.57	0.77	-2.02	0.043
*lpendproc*lchildren*	0.86	0.44	1.94	0.053

Table 6.2. Marginal effects of the ordered probit for *Pr*(*Y* = *2*: medium-low air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	-18.51	8.96	-2.07	0.039
lpcincomehat2	0.97	0.46	2.08	0.038
lpcasia	0.02	0.022	0.89	0.372
lpcafr	0.03	0.029	1.15	0.250
lpcfemhead	-0.22	0.11	-1.98	0.048
lchildren	-2.86	1.42	-2.01	0.044
lelders	-0.38	0.23	-1.64	0.101
lpendingproceedings	-0.68	0.38	-1.75	0.080
*lpendproc*lchildren*	0.37	0.22	1.70	0.090

Table 6.3. Marginal effects of the ordered probit for *Pr*(*Y* = *3*: medium high air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	16.76	8.35	2.01	0.045
lpcincomehat2	-0.88	0.43	-2.02	0.044
lpcasia	-0.01	0.020	-0.89	0.374
lpcafr	-0.03	0.027	-1.14	0.256
lpcfemhead	0.19	0.10	1.90	0.058
lchildren	2.59	1.32	1.96	0.049
lelders	0.34	0.21	1.58	0.114
lendingproceedings	0.61	0.35	1.72	0.085
*lpendproc*lchildren*	-0.34	0.20	-1.68	0.093

Table 6.4 Marginal effects of the ordered probit for *Pr*(*Y* = *4*: high air pollution emissions)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	44.48	19.07	2.33	0.020
lpcincomehat2	-2.33	0.99	-2.35	0.019
lpcasia	-0.04	0.05	-0.93	0.354
lpcafr	-0.08	0.06	-1.21	0.227
lpcfemhead	0.53	0.20	2.53	0.011
lchildren	6.88	2.83	2.43	0.015
lelders	0.91	0.49	1.86	0.063
lpendingproceedings	1.63	0.81	2.01	0.045
*lpendproc*lchildren*	-0.90	0.47	-1.92	0.055

Table 6.5. Summary of marginal effects of significant variables for the ordered probit estimation (II) with interaction variable – dependent variable: *air pollution emissions* – specification: raw data (E)

Probability in air pollution levels	Coefficient	Marginal Effect
lpcincomehat		
	153.58	
Pr (Y=1)		-42.74
Pr (Y=2)		-18.51
Pr (Y=3)		16.76
Pr (Y=4)		44.48
lpcincomehat2		
	-8.06	
Pr (Y=1)		2.24
Pr (Y=2)		0.97
Pr (Y=3)		-0.88
Pr (Y=4)		-2.33
lpcfemhead		
Pr (Y=1)	1.83	
Pr (Y=2)		-0.50
Pr (Y=3)		-0.22
Pr (Y=4)		0.19
		0.53
lchildren		
Pr (Y=1)	23.76	
Pr (Y=2)		-6.61
Pr (Y=3)		-2.86
Pr (Y=4)		2.59
		6.88
lpendingproceedings		
Pr (Y=1)	5.65	
Pr (Y=2)		-1.57
Pr (Y=3)		-0.68
Pr (Y=4)		0.61
		1.63
*lpendproc*lchildren*		
Pr (Y=1)	-3.12	
Pr (Y=2)		0.86
Pr (Y=3)		0.37
Pr (Y=4)		-0.34
		-0.90

Notes: Y =1: low air pollution; Y=2 : medium-low air pollution; Y=3: medium-high air pollution; Y=4: high air pollution.

Table 7. Ordered probit estimation without interaction variable (dependent variable: *air pollution emissions* – specification: *NE* – normalized raw data)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	137.92	63.65	2.17	0.030
lpcincomehat2	-7.25	3.31	-2.19	0.029
lpcasia	-0.24	0.18	-1.37	0.169
lpcafr	-0.18	0.22	-0.82	0.414
lpcfemhead	1.76	0.70	2.51	0.012
lchildren	5.32	1.92	2.76	0.006
lelders	2.52	1.64	1.54	0.125
lpendingproceedings	.26	0.28	0.95	0.342
cut_1	671.13	306.72		
cut_2	671.96	306.74		
cut_3	672.79	306.75		
number of observations = 103				
LR chi2(8) = 31.26				
prob > chi2 = 0.0001				
log likelihood = -127.14				
pseudo R2 = 0.1095				

Table 7.1 Ordered probit estimation with interaction variable (dependent variable: *air pollution emissions* – specification: *NE* – normalized raw data)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	169.74	65.87	2.58	0.010
lpcincomehat2	-8.90	3.43	-2.60	0.009
lpcasia	-0.24	0.18	-1.35	0.176
lpcafr	-0.25	0.23	-1.08	0.278
lpcfemhead	1.90	0.71	2.68	0.007
lchildren	24.09	9.56	2.52	0.012
lelders	2.96	1.68	1.76	0.078
lpendingproceedings	5.81	2.77	2.10	0.036
*lpendproc*lchildren*	-3.21	1.59	-2.01	0.045
cut_1	857.67	321.90		
cut_2	858.52	321.92		
cut_3	859.37	321.93		
number of observations = 103				
LR chi2(9) = 35.37				
prob > chi2 = 0.0001				
log likelihood = -125.08				
pseudo R2 = 0.1239				

Table 8. Ordered probit estimation without interaction variable (dependent variable: *air pollution emissions* – specification: *IWE* – Italian threshold limit values)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	106.91	62.83	1.70	0.089
lpcincomehat2	-5.58	3.27	-1.71	0.088
lpcasia	-0.27	0.17	-1.55	0.121
lpcafr	0.04	0.22	0.20	0.839
lpcfemhead	1.68	0.68	2.46	0.014
lchildren	4.38	1.88	2.32	0.020
lelders	1.83	1.63	1.12	0.261
lpendingproceedings	0.01	0.28	0.04	0.966
cut_1	521.28	302.64		
cut_2	522.06	302.65		
cut_3	522.85	302.66		
number of observations = 103				
LR chi2(8) = 22.11				
prob > chi2 = 0.0047				
log likelihood = -131.71				
pseudo R2 = 0.0774				

Table 8.1. Ordered probit estimation with interaction variable (dependent variable: *air pollution emissions* – specification: *IWE* – Italian threshold limit values)

air pollution emissions (dependent variable)	Coefficients	Standard error	z	P>|z
lpcincomehat	135.42	64.90	2.09	0.037
lpcincomehat2	-7.06	3.38	-2.09	0.037
lpcasia	-0.27	0.17	-1.56	0.119
lpcafr	-0.004	0.22	-0.02	0.986
lpcfemhead	1.81	0.69	2.62	0.009
lchildren	22.21	9.51	2.34	0.020
lelders	2.33	1.67	1.40	0.163
lpendingproceedings	5.26	2.75	1.91	0.056
*lpendproc*lchildren*	-3.03	1.58	-1.92	0.055
cut_1	690.53	316.96		
cut_2	691.32	316.97		
cut_3	692.14	316.99		
number of observations = 103				
LR chi2(9) = 25.82				
prob > chi2 = 0.0022				
log likelihood = -126.58				
pseudo R2 = 0.0904				

Table 9. Comparison among ordered probit estimations with interaction variable across alternative specification of the dependent variable

air pollution emissions (dependent variable)	coefficients (dep. var.: *E*)	P>|z	coefficients (dep. var.: *NE*)	P>|z	coefficients (dep. var.: *IW*E)	P>|z
lpcincomehat	153.58	0.019	169.74	0.010	135.42	0.037
lpcincomehat2	-8.06	0.018	-8.90	0.009	-7.06	0.037
lpcasia	-0.16	0.354	-0.24	0.176	-0.27	0.119
lpcafr	-0.28	0.224	-0.25	0.278	-0.004	0.986
lpcfemhead	1.83	0.010	1.90	0.007	1.81	0.009
lchildren	23.76	0.013	24.09	0.012	22.21	0.020
lelders	3.16	0.061	2.96	0.078	2.33	0.163
lpendingproceedings	5.65	0.041	5.81	0.036	5.26	0.056
*lpendproc*lchildren*	-3.12	0.051	-3.21	0.045	-3.03	0.055

Note: dependent variable: *air pollution emissions* specifications: *E* – raw data; *NE* – normalized raw data and *IWE* – data weighted by the Italian threshold limit values.

APPENDIX: DATA SOURCES AND VARIABLES DESCRIPTION

TABLE A1 – Variable Description and Data Sources

Variable	Description	Source
air pollution emissions	data on air emissions in all the Italian provinces	ISPRA – Air Emissions Provincial Inventory – year 2005
per-capita income	natural logarithm of per-capita income at provincial level, year 2001	elaborated from Institute Tagliacarne – our calculation
entrepreneurial spirit	number of registered firm at provincial level	Il Sole 24 Ore - Quality of Life Report data- year 2001
infrastructure	transportation infrastructural index	Il Sole 24 Ore - Quality of Life Report data- year 2001
females	number of female component the population	ISTAT data Census data, 2001
age15to34	number of people aged between 15 and 34 years old	ISTAT data Census data 2001
age35to49	number of people aged between 35 and 49 years old	ISTAT data Census data 2001
pcuniversitydegree	percentage of the population which has an undergraduate university degree	elaborated from ISTAT data Census data 2001
pclowersecondaryschool	percentage of the population which has a lower secondary school diploma	elaborated from ISTAT data Census data 2001
pcprimaryschool	percentage of the population which has a primary school diploma	elaborated ISTAT data Census data 2001
pcnoeducation	percentage of the population which has a no education at all	elaborated ISTAT data Census data 2001
pcfemalehead	percentage of family households with a female as the head of the household	elaborated from ISTAT data Census data 2001
pcasia	percentage of Asian residents	elaborated from ISTAT data Census data 2001
pcafr	percentage of African residents	elaborated from ISTAT data Census data 2001
children	percentage of children < 6 years old	elaborated from ISTAT data Census

		data 2001
elders	percentage of people >65 years old	elaborated from ISTAT data Census data 2001
pending proceedings	number of civil proceedings pending at courts located in a province every thousand inhabitants	Il Sole 24 Ore – Quality of Life Report data- year 2001
territorial dummies: northern provinces, central provinces	the geographical distinction in the three macro-areas it has been done following the definition of ISTAT. - North-west and north-east regions comprehend: Liguria, Lombardia, Piemonte, Valle d'Aosta, Friuli Venezia Giulia, Emilia R., Trentino, Veneto. - Central regions: Toscana, Marche, Umbria, Lazio. -Southern regions: Abruzzo, Basilicata, Calabria, Campania, Molise, Puglia, Sardegna, Sicilia.	ISTAT

TABLE A2 – Pollutants description and threshold limit values

In the following table the pollutants and their respective U.S. and Italian threshold limit values are reported

Pollutants description and threshold limit values			
Code	Pollutant	U.S. TLVs – eight hours mg/m3	Italian laws on air pollution – eight hours
001	SO2 – sulphur dioxide	13	80 μg/m^{3*}
002	NOX – nitrogen monoxide	30	40 μg/m3
005	CO – carbon monoxide	55	10 mg/m^{3**}
006	CO2 – carbon dioxide	9000	100.000t/year***
007	N2O – nitrous oxide (NIOSH)	30	50 μg/m3
008	NH3 – ammonia	35	10 mg/Nm3
M01	As – arsenic	0,2	6 ng/m3****
M03	Cr – chromium	1	0,05 mg/m3
M04	Cu – copper	1	1 mg/m3
M06	Ni - nichel	1	0,1 μg/m^3
M07	Pb - lead	0,05	0,5 μg/m^3
M08	Se - selenium	0,2	0,2 μg/m^3
P11	Benz - benzene (NIOSH)	0,32	5 μg/m^3

Notes: *substance measured in micrograms; **substance measured in milligrams; ***substance measured in megagrams; ****substance measured in nanograms. In the ordered probit regression analysis, all the different measurement units were converted into megagrams.

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