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November 2023

Working paper No. 2023-07

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"Coming to the nuisance": Unraveling the link between exposure to hazardous sites and poverty

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Abstract

This study analyzes the mechanisms behind the overexposure of poor households to environmental nuisances, with particular emphasis on the sorting mechanism – namely the "coming to the nuisance" phenomenon. Using an exposure profile based on polluting sites, and taking into account spatial heterogeneity due to population density, we assess whether environmental degradation leads to a sorting process within the population of poor households. Our findings show that environmental degradation triggers sorting processes in urban and peri-urban areas, characterized by a higher growth rate of poor households and a lower growth rate of non-poor households in newly exposed areas. This pattern suggests the presence of a "coming to the nuisance" phenomenon among poor households in these newly polluted areas.

Keywords: Environmental justice, poverty, pollution, E-PRTR.

JEL classification: O15, O13, Q53, Q56.

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1 Introduction

In 2020, 9 million individuals were categorized as poor in metropolitan France, representing 14.4% of the population (Gerardin, 2023). This relative measure of monetary poverty, commonly employed by the Institut national de la statistique et des études économiques (hereafter Insee), is derived from the population's overarching distribution of living standards. It entails establishing a threshold below which an individual is considered poor. This threshold is standardized at 60% of the median standard of living and corresponds, in 2020, to 1,120 euros per consumption unit (Gerardin, 2023). Despite integrating poverty alleviation and prevention measures into governmental reforms, as evidenced by the National Strategy for the Prevention and Combat against Poverty, launched in 2018, the poverty rate and its intensity in France have exhibited only marginal change since the late 1990s (Insee, 2021).

Beyond monetary deprivation and the associated social risks, a substantial body of literature highlights a disproportionate burden of environmental hazards supported by low-income households (e.g., Collins et al., 2016; Glatter-Götz et al., 2019; Zwickl, 2019). For instance, Fosse et al. (2022) and Salesse (2022) demonstrate that the least affluent households in France are the most affected by pollution. This overexposure of low-income households may exacerbate the social risks these households already face. Overexposure of low-income households can, as explained by Banzhaf et al. (2019b), contribute to perpetuating the phenomenon of poverty traps. Moreover, this overexposure may, according to Hajat et al. (2015), accentuate the risk of poor health, even as existing health disparities exist (see, for instance, McLean et al., 2014 and Schäfer et al., 2012).

The analysis of disparities in exposure to environmental hazards falls within the concept of environmental justice, a subject that has garnered extensive scholarly attention.² The concept of environmental justice originated in the United States in the 1980s, emanating from civil protests against installing a landfill in Warren County, which, among other factors, housed a significant proportion of low-income households. According to Banzhaf et al. (2019b), the pioneering work of the US General Accounting Office (1983), Bullard (1983), and United Church of Christ (1987) placed exposure disparities as a stylized fact in the social sciences.

Most studies approach the issue of environmental justice from the perspective of distributive justice (Collins et al., 2016; Glatter-Götz et al., 2019; Zwickl, 2019), corresponding to one of the four components of Kuehn (2000)'s taxonomy of environmental justice. Distributive justice refers to the notion that environmental burdens and amenities should be equitably distributed, with no segment of the population disproportionately exposed. In cases of disparities in exposure to environmental hazards, this concept advocates for reducing environmental burdens rather than reallocating among different populations. Timmons Roberts et al. (2018) summarize the concept of distributive justice as following: "Distributive justice refers to inequalities in the distribution of neighborhood environmental quality, both bad and good, such as the presence (or absence) of

¹Insee defines the intensity of poverty as the difference between the median standard of living of poor households and the poverty threshold.

²See Cain et al. (2023) and Di Fonzo et al. (2022) for literature reviews.

contaminated sites and air and water pollution in neighborhoods and the absence (or presence) of trees, parks, open space in them."

As proposed by Banzhaf et al. (2019b), understanding the causal mechanisms driving these environmental inequalities serves the dual purpose of identifying the origins of these disparities and informing the development of public policies aimed at addressing them. The literature underscores the "voting with their feet" mechanism in relation to environmental quality as one of the two phenomena that may explain the overrepresentation of low-income households near environmental hazards (see Banzhaf et al., 2019a,b; Mohai and Saha, 2015b). Specifically, the extension by Banzhaf et al. (2019b) of Tiebout (1956)'s "voting with their feet" hypothesis posits that households select their place of residence based on their willingness, or more precisely, their ability to pay for living in a healthier environment. According to Banzhaf et al. (2019b), neighborhoods offering a range of amenities (such as a clean environment, green spaces, quality schools, and safety) experience increased demand, which subsequently drives up property prices. In contrast, the presence of environmental disamenities, such as polluting sites, may diminish the attractiveness of these neighborhoods, thereby reducing property values and making them more accessible to low-income households. Consequently, two simultaneous phenomena may arise: low-income households moving towards environmental nuisances, and/or wealthier households fleeing from them. For instance, Banzhaf and Walsh (2008) document a decrease in population density and average income in California regions experiencing environmental quality decline. However, their study does not determine whether this is due to a "coming to the nuisance" phenomenon among low-income households, a "fleeing from the nuisance" effect among affluent households, or both processes occurring concurrently. Levasseur et al. (2021) identify a tendency among the highest income quintile in Southwestern Europe to "flee from the nuisance." To our knowledge, no study has explicitly evaluated the presence or absence of a "coming to the nuisance" phenomenon among poor households.

By focusing our analysis on newly exposed geographical areas and those that have never been exposed to polluting sites, we investigate the potential existence of a "coming to the nuisance" phenomenon among poor households in France. The study is conducted in four stages. Firstly, we evaluate the correlation between environmental degradation and both the proportion and intensity of poverty, comparing these areas to those that have never experienced such negative externalities. Secondly, we examine the growth rate of poverty across two periods to determine whether a sorting mechanism is present. To differentiate between "coming to the nuisance" and "fleeing from the nuisance" phenomena, we assess the impact of environmental degradation on the growth rate of both poor and non-poor households.

In this study, we utilize high-resolution gridded data (200 meters) published by Insee, which includes the proportion of poor households. This dataset represents the finest geographical scale available in France. By combining data from 2015 and 2019, we initially restrict our sample to geographical units observable in both periods. To address environmental degradation, we incorporate locations of sites listed in the European Pollutant Release and Transfer Register (E-PRTR) in metropolitan France for the period from 2010 to 2015. We apply a second restriction

to distinguish geographical units that hosted E-PRTR sites between 2011 and 2015, but not in 2010, from those that did not host such sites between 2010 and 2019. To account for the heterogeneity introduced by population density in the relationship between poverty and exposure, as highlighted by Neier, 2021 and Salesse, 2022, we interact the environmental degradation variable with the population density of the corresponding municipality.

The remainder of this paper is structured as follows. The next section presents a literature review of the main findings and challenges related to environmental justice. Section 3 presents the empirical strategy. Section 4 describes the data and presents descriptive statistics. Section 5 presents the results. Section 6 explores the sensitivity analysis, and Section 7 comments and concludes.

2 Literature review

The concept of environmental justice emerged in the United States in the 1980s from a social protest against installing a landfill contaminated with polychlorinated biphenyls in Warren County, where a significant proportion of low-income groups and some ethnic groups were concentrated. The seminal work of the US General Accounting Office (1983) and Bullard (1983) showed, for some counties, an over-representation of some ethnic groups and people with low incomes around landfills and waste incinerators. The first nationwide study, by the United Church of Christ (1987), confirms the previous findings. According to Banzhaf et al. (2019b), these three studies place inequalities in exposure to environmental nuisances as a stylized fact in social science. Since then, although the methodologies used to explore exposure to environmental nuisances have varied, the studies have identified a relationship between economic disadvantage and exposure to environmental hazards. Indeed, while some studies highlight an overexposure of low-income households to certain types of pollutants (e.g., Jbaily et al., 2022; Rosofsky et al., 2018; Salesse, 2022), others reveal an overrepresentation of poor households around environmental hazards (e.g., Neier, 2021; Schaeffer and Tivadar, 2019; Zwickl, 2019).

Highlighting the overexposure of low-income households to air pollution is of significant public interest, primarily due to the unequal health impacts associated with such exposure (see Lavaine, 2015 or Ouidir et al., 2017). Nevertheless, it appears that visible environmental nuisances, rather than the presence of air pollutants, exert a greater influence on residential choices. This tendency can be partially explained by the imperfect information available to households (Hausman and Stolper, 2021). A deeper recognition of disparities in exposure to these visible nuisances may provide a more comprehensive understanding of the mechanisms driving residential patterns. The literature highlights an overrepresentation of low-income households in proximity to various environmental hazards, such as waste treatment sites (e.g., Mohai and Saha, 2015a), fracking activities (e.g., Zwickl, 2019), industrial sites (e.g., Neier, 2021), and landfills (e.g., Baden and Coursey, 2002). Moreover, some studies also explore the unequal distribution of environmental amenities. In the Grenoble-Alpes metropolitan area in France, Schaeffer and Tivadar (2019) demonstrate that the poorest households are located farther from green spaces. Conversely, these households are situated closer to hazardous sites compared to the wealthiest households. The

investigation into the overrepresentation of poor households near environmental hazards is well documented in the United States and some European countries. However, studies addressing this issue in France are more sporadic and often concentrated on specific geographic areas. For instance, Hautdidier et al. (2021), focusing on the Aix-Marseille-Provence metropolitan area, and Viel et al. (2011), examining the Franche-Comté region, emphasize the overrepresentation of disadvantaged households around polluting sites. To our knowledge, the sole nationwide study exploring the relation between economic disadvantage and overrepresentation around hazardous sites is Laurian and Pottratz (2008) research.

As previously mentioned, the discernible presence of environmental nuisances significantly influences household residential decisions (Hausman and Stolper, 2021). Consequently, most environmental justice studies rely on residential proximity to potential pollution sources as a proxy for exposure to environmental hazards (e.g., Neier, 2021; Schaeffer and Tivadar, 2019; Zwickl, 2019). Shao et al. (2021) describe the three primary methodologies employed in the literature to investigate the correlation between economic disadvantage and exposure to environmental hazards. The first method, better suited for aggregated data, such as a municipality in France or a county in the United States, corresponds to the spatial coincidence method. In this approach, if a geographical area hosts at least one environmental hazard, it is considered an exposed unit. Although suitable for aggregated data, this methodology raises, among other issues, an "edge effect problem" (Chakraborty et al., 2011). A geographic area whose neighboring area hosts a site near its border will be considered an unexposed unit. The second methodology, considered as an alternative to the limitations of the first (Chakraborty et al., 2011; Mohai and Saha, 2006, 2007, 2015b,a), distinguishes three approaches to deploying it. In the context of the '50% areal containment approach, after delineating a buffer zone as the initial step, a geographical unit is deemed exposed if a minimum of 50% of its area falls within this designated buffer zone. For the "areal apportionment" approach, one deems a geographical unit exposed when it intersects the buffer zone (with socioeconomic characteristics weighted by the area of intersection). And in the 'boundary intersection' approach, we consider a geographical unit exposed if it intersects the buffer zone. Some studies, such as Neier (2021) or Rüttenauer and Best (2021), use the exact distance between the centroid of the geographical unit under study and the nearest source of nuisance. These approaches require having data at a relatively fine geographical scale. The third methodology involves accounting for pollutant emissions by weighting them according to their risks to human health. The assignment of the exposure status of a geographical unit can be accomplished by employing either of the two methodologies mentioned above or by employing pollution plume modeling.

Although there are numerous methodologies for approximating residential proximity to environmental nuisances are various, the conclusions drawn from the literature highlight an over-representation of disadvantaged households around environmental nuisances (e.g., Laurian and Pottratz, 2008; Mohai and Saha, 2015a; Neier, 2021). As noted in the introduction, understanding the causal mechanisms behind these exposure disparities would, according to Banzhaf et al. (2019b), help identify their origins, thereby improving public policies to reduce them. The literature primarily identifies two causal mechanisms (Banzhaf et al., 2019a,b; Mohai and

Saha, 2015b,a) without, however, establishing the superiority of one mechanism over the other, hence drawing an analogy to the "Chicken and the Egg" debate as noted by Mohai et al. (2009) in addressing this type of issue. The first mechanism, "disproportionate siting," describes the phenomenon wherein polluting sites predominantly install themselves in areas that concentrate low-income groups. Arguments presented in the literature (e.g., Banzhaf et al., 2019a; Glatter-Götz et al., 2019; Mohai and Saha, 2015b; Rüttenauer, 2018; Zwickl, 2019) assert that areas harboring a substantial concentration of disadvantaged households exhibit characteristics such as relatively lower land prices, an available labor force, diminished political influence, minimal opposition, and an abundant transportation network. These factors partly explain why hazardous sites focus on establishing themselves in these areas (see Wolverton, 2009).

The second mechanism, called a "post-siting demographic change" describes the phenomenon wherein pollutant sites' establishment or past presence induces demographic changes in exposed areas. Environmental nuisances potentially trigger a mechanism of "fleeing from the nuisance" for wealthier households, simultaneously leading to a mechanism of "coming to the nuisance" for low-income households. Both mechanisms originate from the extension of Tiebout (1956)'s "vote with their feet" mechanism, as developed by Banzhaf et al. (2019b). According to this theory, households make a trade-off between neighborhood amenities, including environmental quality, and consumption, which encompasses housing expenses. Environmental nuisances can generate negative externalities, such as noise, visual disruptions, or smelly emissions, which may diminish the area's attractiveness and contribute to a decline in land value. Indeed, as Currie et al. (2015) and Hanna (2007) highlight, hazardous sites can exert downward pressure on land prices. Although households, regardless of income, generally derive greater utility from a clean environment, not all are equally willing or able to pay for access to high environmental quality. Wealthier households are typically both more willing and able to pay relatively more than less affluent households for a clean environment, as suggested by Banzhaf et al. (2019b). Areas affected by environmental nuisances may, therefore, prompt wealthier households to move away, while attracting less affluent households to these zones, complicating the determination of which mechanism predominates.

Some studies highlight a "vote with their feet" mechanism, as demonstrated by Banzhaf and Walsh (2008) in California or Rüttenauer (2018) in West Germany, without, however, specifying whether it involves "fleeing from the nuisance" and/or "coming to the nuisance." Conversely, as Levasseur et al. (2021) observed in a study focusing on a sample of households in Southwest Europe, exposure is associated with a "fleeing from the nuisance" mechanism among wealthier households. The "disproportionate siting" and "post-siting demographic change" mechanisms do seem not to be independent. In a longitudinal study, Mohai and Saha (2015a) demonstrate that establishing waste treatment sites in the United States led to higher economic disparities, indicating a "post-siting demographic change." However, they also note that this demographic shift had begun before establishing these sites, revealing a "disproportionate siting" effect as well.

Empirically testing the presence of disparities in exposure to environmental nuisances amounts to testing one of the two mechanisms mentioned above. Specifically, are less affluent households

more exposed than the rest of the population because they have settled closer to the nuisance or because the nuisance has installed itself close to them? An endogeneity issue arises, induced by a simultaneity bias. Most empirical studies identify the disparities in exposure to environmental nuisances by assessing whether the level of economic disadvantage in a geographical area is a relevant determinant of exposure (e.g., Laurian and Pottratz, 2008; Levasseur et al., 2021; Neier, 2021; Zwickl, 2019). The primary strategies presented in the literature to address the reverse causality between income and exposure involve instrumenting or considering a past income. For instance, Levasseur et al. (2021), in assessing the likelihood of living in a polluted area, use individuals' height and parents' education level to instrument income. Conversely, Zwickl (2019), in evaluating the effect of income on residential distance from fracking activities, considers a past income level, explaining that disparities in exposure to environmental nuisances can be interpreted, in this case, as a phenomenon of "disproportionate siting" rather than a phenomenon of "post-siting demographic change." In fact, beyond correcting simultaneity bias, applying a temporal lag can also help understand the causal mechanism behind disparities in exposure to environmental nuisances. As highlighted by Banzhaf and Walsh (2008), who seek to identify a "vote with their feet" mechanism, considering past variability in environmental quality cannot be the result of future demographic changes; rather, it serves as a cause.

This paper makes a threefold contribution. First, we demonstrate that newly exposed urban and peri-urban units have a higher average poverty rate than those that have never been exposed, with no significant differences in poverty intensity between the two. In contrast, newly exposed rural areas exhibit both lower poverty rates and intensity. Second, we identify that newly exposed urban and peri-urban areas are associated with a sorting mechanism. Specifically, we observe that the growth rate of the proportion of poor households is significantly higher in newly exposed areas compared to those that have never been exposed. Third, we characterize this sorting mechanism. In newly exposed urban and peri-urban areas, sorting is linked to the "coming to the nuisance" phenomenon among poor households.

3 Empirical strategy

Effect of new exposure on poverty and its intensity

To assess the effect of environmental degradation on the poverty distribution across the territory, we adopted a statistical moment-based approach proposed by Antle (1983).³ This method of statistical moments enables us to assess the effect of environmental degradation (in newly exposed areas compared to never exposed ones) on the average, dispersion, and skewness of the proportion of poor households. To estimate the average effect, we use the following econometric specification:

$$\%Poverty_i = \beta_0 + \beta_1 Newly Exposed_i + \beta_2 X_i + u_i. \tag{1}$$

³See Appendix A for a detailed presentation of Antle (1983)'s method of moments.

The index i corresponds to the geographical unit considered. The variable $\%Poverty_i$ corresponds to the proportion of poor households in the geographical unit considered. The variable $NewlyExposed_i$ is a dummy variable that takes the value of 1 if the geographical unit has been newly exposed to environmental hazards, and 0 if it has never been exposed. The X_i is a vector representing a unit's socioeconomic and demographic characteristics, and u_i correspond to the error term.

We estimate the impact of environmental degradation on the variance and skewness of the proportion of poor households using the second and third moments of residuals from Eq.(1). We consider the following specifications:

$$(\hat{u}_i)^2 = \sigma_0 + \sigma_1 Newly Exposed_i + \sigma_2 X_i + \theta_i; \tag{2}$$

$$(\hat{u}_i)^3 = \lambda_0 + \lambda_1 Newly Exposed_i + \lambda_2 X_i + \rho_i;$$
(3)

where θ_i and ρ_i refer to error terms.⁴ A larger dispersion in the proportion of poor households in newly exposed units may indicate a higher intensity of poverty in these areas relative to never-exposed ones. Examining the third-order moment coefficient will help identify the source of this higher (or lower) dispersion and assess the intensity of poverty. Geographical units newly exposed to the hazard, with a positive (or negative) skewness coefficient, will experience accentuated (or reduced) skewness in their distribution compared to units that have never been exposed.

We define a higher intensity of poverty as a higher variance in the proportion of poor households, resulting from an accentuation of the skewed to the right in the distribution of the proportion of poor households. In other words, this indicates that we observe a greater number of geographical units recording a high level of poverty rate.

"Coming to the nuisance" phenomenon?

In this section, the objective is to assess the presence or absence of the "coming to the nuisance" phenomenon among poor households. To achieve this, we examine the impact of environmental degradation on the evolution of the poverty rate in exposed areas compared to those that have never been exposed. This involves analyzing the presence of a sorting mechanism within the studied population. To this end, we adopt the following specification:

$$\% \Delta Poverty_i = \beta_0 + \beta_1 Newly Exposed_i + \beta_2 X_i + u_i, \tag{4}$$

⁴The econometric approach considered induces the presence of heteroscedasticity in the error terms. Indeed, using the second (Eq.(2)) and third (Eq.(3)) moments implies that the variance of the error terms is not constant. While the estimators remain unbiased, they are no longer of minimum variance, potentially affecting the precision of the tests. To address the issue of heteroscedasticity, we employ Newey-West robust standard errors.

where $\%\Delta Poverty_i$ corresponds to the growth rate of the proportion of poor households between two periods for geographic unit i.⁵

As noted in the literature (Banzhaf and Walsh, 2008; Banzhaf et al., 2019a,b), a modification of the socioeconomic structure resulting from environmental degradation can be associated with a phenomenon of "coming to the nuisance" among poor households, and/or a phenomenon of "fleeing from the nuisance" among wealthier households. To characterize this sorting mechanism, if it exists, we measure the relative impact of environmental degradation on the growth rate of the number of poor households. The specification takes the following form:

$$\%\Delta NbPoor_i = \beta_0 + \beta_1 NewlyExposed_i + \beta_2 X_i + u_i, \tag{5}$$

where $\%\Delta NbPoor_i$ corresponds to the growth rate of the number of poor households in geographic unit i between two periods. For instance, if we observe that being newly exposed, in contrast to never having been exposed, is associated with a higher growth rate of the number of poor households, we infer the existence of a phenomenon of "coming to the nuisance" among these households. However, a pertinent question arises regarding non-poor households. To explore this, we estimate the relative effect of environmental degradation on the growth rate of non-poor households. The following specification is employed:

$$\% \Delta NbNonPoor_i = \beta_0 + \beta_1 NewlyExposed_i + \beta_2 X_i + u_i. \tag{6}$$

The variable $\%\Delta NbNonPoor_i$ corresponds to the growth rate of the number of non-poor households in unit i between two periods. We are thus able to characterize, if it exists, the sorting mechanism identified using Eq. (4). We suggest that if being newly exposed is associated with a higher growth rate of the number of poor households, while concurrently linked to a lower growth rate of non-poor households, this indicates a phenomenon of "coming to the nuisance" of poor households.

4 Data

4.1 Socioeconomic data

Derived from the Fichier Localisé Social et Fiscal (FiLoSoFi) and produced by Insee, the 200-meter gridded data are employed to estimate the models presented in Equations (1) to (6). We focus on geographical units that are observable in both periods. To this end, we combine gridded

⁵For percentage change, we use the average of the levels from 2015 and 2019 as the denominator.

⁶Given the data at our disposal, we are unable to identify the wealthiest households. Therefore, when we discuss the phenomenon of "fleeing from the nuisance" of wealthiest households, as suggested by the literature (Banzhaf and Walsh, 2008; Banzhaf et al., 2019a,b), we can only focus on the phenomenon of "fleeing from the nuisance" of non-poor households.

data from 2015 and 2019 for metropolitan France.⁷ The merging of these two datasets results in a sample comprising 1,677,895 geographical units. The gridded data indicate the proportion of poor households per geographical unit, representing a relative measure of poverty, with the threshold set at 60% of the median standard of living.

To account for socioeconomic factors that may influence the level of poverty in a geographical unit, we include the proportion of single-parent families and the proportion of households living in social housing in 2015 as control variables. Both family structure and housing type are relevant predictors of poverty (e.g., Gerardin, 2023; Di Fonzo et al., 2022).

To consider certain economic specificities at the municipal level, we include the proportion of households whose reference person holds a position as a farmer, artisan, merchant, or business owner in 2015. These two variables are derived from the Population Census, specifically Insee's "Couple - Families - Households" survey. Both correspond to a self-employed status, which is considered an economic disadvantage (Sicsic, 2018). We also include the proportion of employed individuals aged 15 or older working in their municipality of residence. This variable is derived from the Population Census conducted by Insee. Furthermore, to address housing market pressures within the municipality, which serve as a proxy for real estate prices, we incorporate a categorical variable known as ABC zoning. This variable classifies municipalities based on the imbalance between housing supply and demand. The ABC zoning system is defined by Article D304-1 of the Construction and Housing Code and is provided by the Ministry of Ecological Transition. Zones A, B, and C correspond to municipalities with very tight, tight, and relaxed housing markets, respectively.

Finally, to account for the heterogeneity introduced by population density in the relationship between poverty and exposure, as noted by Neier (2021) and Salesse (2022), we introduce a categorical variable representing municipal density in 2019. This variable, derived from the 7-level municipal grid published by Insee, considers both the total number of inhabitants and their spatial concentration within the municipality. The density variable takes a value of 2 if the municipality is classified as urban (including major urban centers, intermediate urban centers, and small towns), 1 if it is classified as peri-urban (including urban fringes), and 0 if it is classified as rural (including rural towns, municipalities with dispersed housing, and those with very dispersed housing).⁹

For all control variables, except for the density variable, the year 2015 was chosen to estimate equations (1) to (6) to address a potential endogeneity issue arising from simultaneity bias.

⁷For robustness, we also consider combined gridded data from 2017 and 2019. See Tables D.9 and D.10 in the Appendix D.

⁸To assign these municipal data to geographical units, we compute the intersection area between the geographical units and the municipalities, assigning municipal data to the geographical units with the highest intersection area with a municipality.

⁹For robustness, we also consider a binary classification of the density variable (urban vs. rural). See Table D.1, D.2, D.3, D.6 and D.7 in the Appendix D.

4.2 Variable of environmental degradation

For the variable of environmental degradation, we consider the location of polluting sites listed in the European Pollutant Release and Transfer Register (E-PRTR) in metropolitan France between 2010 and 2015. The location of these sites is taken from the Pollutant Release and Transfer Register, published by the French Ministry for Ecological Transition and Territorial Cohesion. This register of pollutant emissions is a national inventory of chemical substances released into the air, water, and soil. Also, it includes sites producing and processing hazardous and non-hazardous waste. This inventory meets the obligation of European Union member states (Regulation n°166/2006 of 18/01/06) to communicate to the European Commission data on pollutant emissions from sites carrying out at least one of the nine activities listed in Appendix I of the previous Regulation. Although the geographical coordinates of these polluting sites are provided, for the sake of homogeneity, we have redefined them using the geocoding service of the official national website Adresse.data.gouv.fr, as the reference geographical coordinate system had different projections in the initial database.

To identify the potential existence of a "coming to the nuisance" phenomenon of poor households, we focus on geographic units that have become exposed to E-PRTR sites (indicating environmental degradation) and those that have consistently been exempt from such exposure. To do so, using the location of E-PRTR sites from 2010 to 2015, we define a 3-kilometer buffer zone around each of these sites (see Figure 1).¹² Utilizing the merged gridded data (2015 and 2019), we establish an exposure profile for each geographic unit for each year between 2010 and 2015, categorizing units as either exposed or not exposed to E-PRTR sites. A geographic unit is considered exposed if at least 50% of its surface area falls within the buffer zone, according to the "50% areal containment" method by Mohai and Saha (2006). Given our research objective, we restricted our sample to geographic units that were not exposed in 2010 but became exposed between 2011 and 2015 (and remained exposed in 2015), as well as units that were never exposed to an E-PRTR site between 2010 and 2015 (and remained unexposed through 2019). We construct a binary variable representing environmental degradation. It takes the value 1 if the unit experienced a deterioration in environmental quality (newly exposed area), and 0 if it remained unaffected by such negative externalities (never exposed area) during the 2010-2019 period.

¹⁰We do not consider emissions induced by the sites nor the toxicity of the emissions when constructing our exposure variable. Indeed, as shown by Currie et al. (2015), the impact of the opening of a polluting site on the housing price is independent of the site's toxicity. They justify this phenomenon by the imperfect information available to households. Moreover, as Hausman and Stolper (2021) point out, the fact that some pollutants are invisible and odorless implies that households, in their choice of location, unwittingly do not take into account the types of pollutants in the air and their toxicity to health, but rather consider what is visible, such as distance from a source of environmental nuisance.

¹¹The energy sector, production and processing of metals, mineral industry, chemical industry, waste and wastewater management, manufacture and processing of paper and wood, products of animal or vegetable origin from the food and beverage industry, intensive livestock farming and aquaculture and others (Appendix 1 of Regulation n°166/2006 of 18/01/06).

¹²Studies in environmental justice generally consider a buffer zone with a radius between 1 km and 3 km (Glatter-Götz et al., 2019; Viel et al., 2011; Mohai and Saha, 2015a). For robustness, we also consider a 2 km buffer zone. See Tables D.4, D.5, D.6 and D.7 in Appendix D.

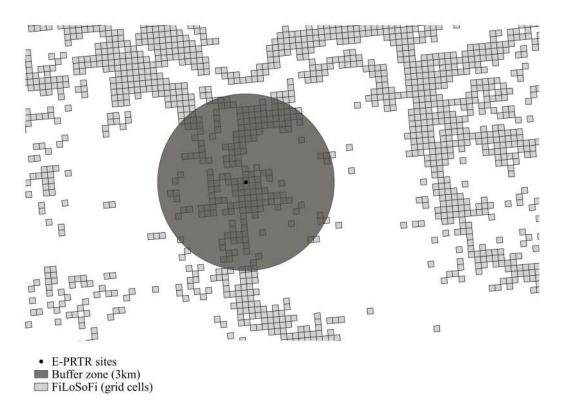


Figure 1: Construction of exposure profiles for each geographic unit

Notes: Data are from the FiLoSoFi database published by INSEE and the E-PRTR sites published by the French Ministry for Ecological Transition and Territorial Cohesion.

4.3 Descriptive statistics

Table 1 presents the descriptive statistics of the sample variables, distinguishing between newly exposed and never exposed geographical units. The sample consists of 1,677,895 geographical units, with 1,528,261 classified as never exposed and 149,634 as newly exposed. The descriptive statistics show that, on average, never exposed units exhibit a poverty rate of 12%, compared to 11% for newly exposed units. However, never exposed units, on average, have fewer poor households than newly exposed units. This suggests that newly exposed units have a relatively higher population density, which explains the lower average poverty rate but a higher average number of poor households. These results highlight the importance of considering population density when examining the link between poverty and environmental degradation.

Figure 2 illustrates the distribution of the proportion of poor households for newly exposed and never exposed units, differentiating across the three density categories. In rural areas, newly exposed units show a lower average and median proportion of poor households compared to never exposed units. Conversely, in urban areas, the trend is reversed, while peri-urban areas exhibit a smaller difference. The mean difference test confirms a statistically significant disparity in the average proportion of poor households relative to environmental degradation across urban, peri-urban, and rural units. We suggest, therefore, that population density generates spatial heterogeneity in the relationship between poverty and environmental degradation. This

Table 1: Descriptive statistics

| Vaniahla | Never E | xposed | Newly E | xposed | Ove | rall |
|--------------------------|-------------|---------|---------|---------------------|-------------|---------------------|
| Variable - | Mean | SD | Mean | SD | Mean | SD |
| % Poverty | 0.12 | 0.10 | 0.11 | 0.09 | 0.12 | 0.10 |
| # Poor households | 0.91 | 4.14 | 1.83 | 7.61 | 0.99 | 4.57 |
| % Social housing | 0.01 | 0.08 | 0.03 | 0.13 | 0.01 | 0.08 |
| % Single parents | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 | 0.07 |
| % Work resid. | 0.28 | 0.15 | 0.29 | 0.16 | 0.28 | 0.15 |
| % Farmers | 0.04 | 0.05 | 0.03 | 0.03 | 0.04 | 0.05 |
| % Artisans and others | 0.06 | 0.04 | 0.05 | 0.03 | 0.06 | 0.04 |
| ABC zoning : Obs. numb | er (%) | | | | | |
| C | 1,226,635 | 5 (80%) | 101,942 | (68%) | 1,328,57 | 7 (79%) |
| В | 256,741 | (17%) | 40,595 | (27%) | $297,\!336$ | (18%) |
| A | 44,885 | (3%) | 7,097 | (5%) | 51,982 | (3%) |
| Density : Obs. number (% | (0) | | | | | |
| Rural | 1,308,086 | 5 (85%) | 101,925 | (68%) | 1,410,011 | 1 (84%) |
| Peri-urban | 78,923 | (5%) | 15,883 | (11%) | $94,\!806$ | (6%) |
| Urban | 141,252 | (10%) | 31,826 | (21%) | 173,078 | (10%) |

Notes: The variable "Newly Exposed" refers to geographical units that became exposed between 2011 and 2015 and remained so in 2015. SD corresponds to the standard deviation. % Work resid. corresponds to the proportion of employed individuals aged 15 and over who work in their municipality of residence, calculated at the municipality level. % Farmers corresponds to the percentage of farmers at the municipality level. % Artisans and others corresponds to the percentage of artisans, merchants, and business owners at the municipality level. The variable "ABC zoning" reflects the degree of pressure in the housing market, with a value of "C" indicating an unstrained market, "B" indicating moderate strain, and "A" indicating high strain.

is evidenced by the disparities in new exposure to polluting sites in urban and peri-urban units, in contrast to the absence of such disparities disadvantaging the poorest households in rural areas.

Regardless of exposure status and density, the distribution of the proportion of poor households is characterized by a left-skewed distribution. This indicates a significant concentration of a low proportion of poor households. This observation aligns with the national poverty rate reported by Gerardin (2023), reaching 14.4% in 2020. However, we observe that the rightwards skeweness of the distribution of the proportion of poor households varies based on density and exposure status. Newly exposed rural units have lower first and third quartile values than never-exposed units, with fewer extreme values at the tail end of the distribution. Conversely, newly exposed urban units, and to a lesser extent newly exposed peri-urban units, show higher values for the first and third quartiles compared to never exposed units. Additionally, there is a greater presence of extreme values in the tail of the distribution of these newly exposed units. By the definition we provide for the intensity of poverty, we suggest that density also induces heterogeneity in the relationship between the intensity of poverty and exposure status. This

heterogeneity is characterized by a higher proportion of poor households in newly exposed urban and peri-urban units than their never exposed counterparts. Conversely, the opposite trend is observed for newly exposed rural units.

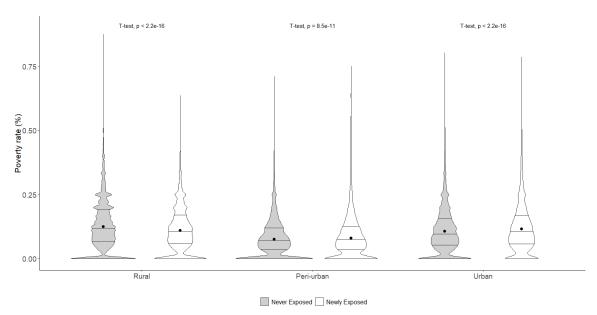


Figure 2: % Poverty distribution by density and exposure variable

Notes: % Poverty corresponds to the percentage of poverty by geographical unit in 2019. The variable "Newly Exposed" refers to geographical units that became exposed between 2011 and 2015 and remained so in 2015. The t-test corresponds to a test of mean difference. The circle in the violin plot represents the mean proportion of poor households.

5 Results

Effects of new exposure on poverty and its intensity

To explore the correlation between environmental degradation and both the proportion and intensity of poor households, we adopt the statistical moments approach proposed by Antle (1983). Table 2 presents the estimation results for Eq. (1), (2), and (3), with columns 1 to 3 reporting the results of the first-order moment (Eq. 1).¹³

 $^{^{13}}$ The detailed results, including the control variables, are displayed in Appendix B for all the benchmark results.

Table 2: Moments-based approach estimates for the proportion of poverty (2019)

| | | % Poverty | | Varian ce | Skewness |
|---|------------------------------------|--------------|----------------|--------------|------------|
| | (1) | (2) | (3) | (4) | (5) |
| Newly Exposed | -0.013*** | -0.015*** | -0.013*** | -0.001*** | -0.0002*** |
| | (0.001) | (0.001) | (0.001) | (0.0001) | (0.00002) |
| Newly Exposed*Peri-urban | | 0.019*** | 0.014*** | 0.001*** | 0.0002*** |
| | | (0.001) | (0.001) | (0.0001) | (0.00005) |
| Newly Exposed*Urban | | 0.025*** | 0.019*** | 0.001*** | 0.0003*** |
| | | (0.001) | (0.002) | (0.0002) | (0.0001) |
| Exposure Effects | | | | | |
| Rural $ H_0 : \beta_{[NE=1]-[l]}^R$ | NE=0 = 0 | | -0.012^{***} | -0.001*** | -0.0002*** |
| | , | | (-22.537) | (-16.928) | (-8.816) |
| Peri-urban $H_0: \beta_{[NE=1]-[1]}^{PU}$ | $NE=0] + \beta_{[NE=1]-[NE]}^{R}$ | =0 = 0 | 0.002* | -0.0001 | -0.00003 |
| | | | (2.1829) | (0.558) | (0.681) |
| Urban $ H_0: \beta_{[NE=1]-[}^U$ | $NE=0$ + $\beta_{[NE=1]-[NE]}^{R}$ | =0 = 0 | 0.006*** | 0.0003 | 0.0007 |
| | , , , , | , | (21.683) | (2.138) | (0.798) |
| Observations | 1,677,895 | 1,677,895 | 1,677,895 | 1,677,895 | 1,677,895 |
| \mathbb{R}^2 | 0.001 | 0.016 | 0.128 | 0.027 | 0.001 |
| ${ m Adjusted}~{ m R}^2$ | 0.001 | 0.016 | 0.128 | 0.027 | 0.001 |
| F Statistic | 2,275.434*** | 5,347.351*** | 20,542.720*** | 3,853.038*** | 128.911*** |

The results in column 1 show a significantly negative effect of environmental degradation on the poverty rate. Specifically, compared to units never exposed, newly exposed units are, on average, associated with a lower proportion of poor households. This finding may seem counterintuitive, as the negative externalities typically linked to exposure to polluting sites would suggest the opposite. Moreover, this result diverges from the existing literature, particularly from French studies. For example, researches by Salesse (2022) and Fosse et al. (2022) highlight a positive relationship between economic disadvantage and exposure to environmental nuisances. However, as these authors point out, population density creates heterogeneity in the relationship between poverty and exposure to environmental nuisances.

The results, incorporating the density variable into the relationship between poverty and environmental degradation, are presented in columns 2 and 3 of Table 2. As anticipated, the relationship between the proportion of poor households and new exposure to polluting sites varies depending on the population density of the municipalities where the units under study are located. Indeed, in rural areas, new exposure is associated with a lower proportion of poor households. In contrast, newly exposed urban and peri-urban areas, compared to those never exposed, exhibit a higher proportion of poor households. These findings are consistent with the

work of Salesse (2022) for France and Neier (2021) for Austria, both of which identified a positive relationship between exposure to environmental nuisances and socioeconomic deprivation, particularly in urban areas. We can understand the heterogeneity in the relationship between environmental quality (newly exposed versus never exposed areas) and poverty through the lens of housing prices.

Regarding socio-demographic factors, column 3 of Table 2 highlights that the proportion of single-parent families and proportion of households living in social housing is positively associated with the poverty rate, consistent with the existing literature (Gerardin, 2023; Di Fonzo et al., 2022). The percentage of self-employed individuals is also positively correlated with the poverty rate, confirming that this occupational status indicates economic disadvantage (Sicsic, 2021). Moreover, the proportion of employed individuals working in their municipality of residence is positively associated with the proportion of poor households. Finally, areas characterized by a lack of pressure on the housing market exhibit a higher proportion of poor households compared to those with very high pressure, suggesting that the majority of low-pressure areas are primarily located in rural regions. Conversely, areas with moderate housing market pressure show a relatively lower proportion of poor households than highly pressured areas.

To address the question of poverty intensity, we focus on the second and third moments of Antle (1983)'s statistical moments approach. Insee defines poverty intensity as a relative gap between poor households' median standard of living and the poverty threshold. In this study, we examine the association between environmental degradation and the entire distribution of the proportion of poor households. To do this, we compare the dispersion (column 4) and skewness (column 5) of the distribution of the proportion of poor households in newly exposed units to those in never exposed units.

From column 4, we observe that newly exposed urban and peri-urban areas do not exhibit a difference in the dispersion of the proportion of poor households compared to their counterparts that have never been exposed. Similarly, in these newly exposed areas, there is no difference in skewness relative to areas that have never been exposed (column 5). In contrast, newly exposed rural areas show lower dispersion in the proportion of poor households compared to those that have never been exposed. This relatively lower dispersion is associated with a less pronounced right skew in the distribution of the proportion of poor households. Consequently, newly exposed rural units are characterized by a relatively lower intensity of poverty than never exposed ones. These results align with the analysis of the first-order moment.

Is there a "Coming to nuisance" phenomenon?

To understand the mechanisms behind the over-representation of poor households around polluting sites, particularly in urban and peri-urban areas, we estimate the model presented in Eq.(4). The results of these estimations are reported in Table 3. As previously discussed, this equation assesses the effect of new exposure on the growth rate of the proportion of poor households between 2015 and 2019, allowing us to explore patterns of demographic sorting.

Table 3: Estimation results of the growth rate of poverty proportion (2015–2019)

| | Growth rate | of Poverty |
|---|-------------|------------|
| | (1) | (2) |
| Newly Exposed | 0.008** | 0.001 |
| | (0.003) | (0.004) |
| Newly Exposed*Peri-urban | | 0.026** |
| | | (0.012) |
| Newly Exposed*Urban | | 0.021** |
| | | (0.008) |
| Exposure Effects | | |
| | Coef. | Test-st at |
| Rural H_0 : $\beta^R_{[NE=1]-[NE=0]}=0$ | 0.001 | 0.254 |
| Peri-urban H_0 : $\beta_{[NE=1]-[NE=0]}^{PU} + \beta_{[NE=1]-[NE=0]}^{R} = 0$ | 0.027** | 6.063 |
| Urban $H_0:\beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.022*** | 10.062 |
| Observations | 1,677,895 | 1,677,895 |
| \mathbb{R}^2 | 0.002 | 0.002 |
| $Adjusted R^2$ | 0.002 | 0.002 |
| F Statistic | 370.278*** | 309.815*** |

We find that in newly exposed urban and peri-urban units, the growth rate of the proportion of poor households is higher than in those that have never been exposed. This suggests that a demographic shift has occurred in these areas following the establishment of new polluting sites. These results indicate a greater stratification of poor households around sources of pollution. However, this shift, or sorting, does not reveal whether it results from the arrival of poor households, the departure of non-poor households, or both. In contrast, no significant difference in the growth rate of the proportion of poor households is observed between newly exposed and non-exposed rural areas.

To further investigate this demographic sorting, we estimate Equations (5) and (6), with the results presented in columns 2 and 4 of Table 4. The results in column 2 illustrate the relative effect of new exposure on the growth rate of the number of poor households, while those in column 4 focus on the effect of environmental degradation on the growth rate of the number of non-poor households.

Table 4: Estimation results of the growth rate of the number of poor and non-poor households (2015–2019)

| _ | Growth of #poo | r households | Growth of #non- | poor households |
|---|----------------|----------------------------|-----------------|-----------------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.008** | 0.003 | -0.002* | 0.0004 |
| | (0.004) | (0.004) | (0.001) | (0.001) |
| Newly Exposed*Peri-urban | | 0.020* | | -0.008** |
| | | (0.012) | | (0.003) |
| Newly Exposed*Urban | | 0.017** | | -0.007*** |
| | | (0.008) | | (0.003) |
| Exposure Effects | | | | |
| | Coef. | $\operatorname{Test-stat}$ | Coef. | Test-stat |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.003 | 0.629 | 0.0004 | 0.348 |
| Peri-urban H_0 : $\beta^{PU}_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.022** | 4.095 | -0.008*** | 6.821 |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.0199*** | 8.186 | -0.007*** | 6.821 |
| Observations | 1,677,895 | 1,677,895 | 1,677,895 | 1,677,895 |
| \mathbb{R}^2 | 0.002 | 0.002 | 0.001 | 0.001 |
| Adjusted R^2 | 0.002 | 0.002 | 0.001 | 0.001 |
| F Statistic | 329.778*** | 329.778*** | 158.429*** | 158.429*** |

For newly exposed urban and peri-urban areas, we observe a higher growth rate in the number of poor households, alongside a lower growth rate in the number of non-poor households. Thus, the increase in the growth rate of the proportion of poor households observed in these urban and peri-urban units seems to be the result of an influx of poor households alongside a departure of non-poor households. Consequently, we propose the existence of a "coming to the nuisance" phenomenon among poor households, alongside a "fleeing from the nuisance" by non-poor households in these areas. Furthermore, the outmigration of non-poor households appears to be more important than the inflow of poor households. This is evidenced by a lower growth rate in the number of households in these newly exposed areas compared to those that are not exposed (see Table D.8 in Appendix D).

Urban areas, and to a lesser extent peri-urban areas, characterized by relatively high population density (Beck et al., 2022), generally experience higher real estate prices compared to rural areas. The literature highlights a positive relationship between population density and property values (e.g., Combes et al., 2019; Le Hir and Bono, 2023). The presence of amenities such as public services, transportation, shops, and employment opportunities enhances a geographical area's attractiveness, contributing to upward pressure on housing prices. Conversely, the introduction of a new environmental nuisance, such as pollution, noise, or unpleasant odors, can generate negative externalities, reducing the desirability of the newly exposed area. This reduced desirability can lead to decreased attractiveness and a decline in housing prices. For

example, Currie et al. (2015) and Hanna (2007) show that polluting sites have adverse effects on nearby real estate prices. Consequently, these newly exposed areas may become more attractive to lower-income households, particularly poor households. This observation may help explain the "coming to the nuisance" phenomenon associated with poor households in newly exposed urban and peri-urban areas.

In newly exposed rural areas, compared to those that have never been exposed, there is no significant difference in the growth rates of poor households. The same applies to the growth rate of non-poor households. Rural areas are, by definition, characterized by dispersed populations and relatively longer access times to amenities (Beck et al., 2022). We suggest that the presence of new polluting sites, due to the employment opportunities they create, increases the attractiveness of these areas for poor and non-poor households alike. Although the overall growth of households in newly exposed rural areas appears to be higher, indicating a sorting dynamic in these areas.¹⁴ However, the inflows and outflows of both poor and non-poor households do not impact the social composition (between poor and non-poor households), explaining the absence of difference in the growth rate of poverty proportion.

6 Sensitivity analysis

In this section, we employ the same empirical strategy as before, now focusing on the median standard of living. The median standard of living is derived from the FiLoSoFi database. Initially presented as a sum of winsorized living standards per geographical unit, we divided this sum by the number of households in each geographical unit to derive an average standard of living per household.¹⁵

Aiming to explore whether there is a phenomenon of "coming to the nuisance" of poor households, we explore the dynamics of standard of living to support our previous findings. To this end, we first examine the effect of being in a newly exposed area compared to an area that has never been exposed on the distribution of the logarithm of the median standard of living in 2019, using Antle's (1983) moments method. Secondly, we assess the impact of being newly exposed, as opposed to never having been exposed, on the growth of the median standard of living between 2015 and 2019.

¹⁴see Table D.8 in Appendix D.

¹⁵See Table C.1 in Appendix C for descriptive statistics.

Table 5: Estimation results of standard of living

| | $\operatorname{AverStandLiv}$ | Variance | ${\rm Skewness}$ | Growth rate |
|---|-------------------------------|--------------|------------------|-------------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.018*** | -0.004*** | 0.0003 | 0.003*** |
| | (0.002) | (0.0003) | (0.0002) | (0.001) |
| Newly Exposed*Peri-urban | -0.055*** | 0.003** | -0.001 | -0.006*** |
| | (0.005) | (0.001) | (0.001) | (0.002) |
| Newly Exposed*Urban | -0.043*** | 0.003** | 0.002** | -0.004*** |
| | (0.004) | (0.001) | (0.001) | (0.001) |
| Exposure Effects | | | | |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.018*** | -0.003*** | 0.0003 | 0.003*** |
| [142-1]-[142-0] | (11.178) | (-10.722) | (1.134) | (4.174) |
| Peri-urban H_0 : $\beta_{[NE=1]-[NE=0]}^{PU} + \beta_{[NE=1]-[NE=0]}^{R} = 0$ | -0.037*** | -0.0005 | -0.0005 | -0.003** |
| [1.2] [1.2] [1.2] | (58.156) | (0.201) | (0.307) | (5.848) |
| Urban $H_0: \beta_{[NE=1]-[NE=0]}^U + \beta_{[NE=1]-[NE=0]}^R = 0$ | -0.024*** | -0.001 | 0.002** | -0.001 |
| [| (45.203) | (0.831) | (6.186) | (1.848) |
| Observations | 1,677,895 | 1,677,895 | 1,677,895 | 1,677,895 |
| \mathbb{R}^2 | 0.248 | 0.013 | 0.001 | 0.001 |
| Adjusted R^2 | 0.248 | 0.013 | 0.001 | 0.001 |
| F Statistic | 46,214.470*** | 1,861.810*** | 72.165*** | 150.555*** |

The first column of Table 5 presents the effects of new exposure, relative to never having been exposed, on the logarithm of the standard of living in 2019. In newly exposed urban and peri-urban areas, the logarithm of the standard of living is lower compared to areas that have never been exposed. These findings align with previous literature (e.g., Salesse, 2022; Neier, 2021), which explores the relationship between environmental nuisances and socioeconomic deprivation. In contrast, newly exposed rural areas exhibit a higher standard of living than rural areas that have never been exposed. These results for the first-order moment are consistent with previous findings regarding the poverty rate. Regarding the second-order moment results, we observe that only the relative effect of environmental degradation in rural areas is significant and negative. This result suggests a relatively lower disparity in terms of standards of living in these newly exposed areas.

The findings related to the effects of new exposure, compared to never having been exposed, on the growth of standard of living between 2015 and 2019 are presented in column 4. We observe that newly exposed rural areas are associated with a higher growth rate of the standard of living compared to rural areas that have never been exposed. Considering the previous results, these findings confirm that the establishment of polluting sites enhances economic activity in these

areas, while the population structure (between poor and non-poor households) evolves similarly to that of areas that have never been exposed. However, although the socioeconomic structure does not seem to change between newly exposed areas and those that have never been exposed, the relatively higher growth rate in the standard of living suggests that the establishment of these sites creates employment opportunities and stimulates economic activity in the area.

Additionally, newly exposed peri-urban areas experience a relatively lower growth rate in the standard of living compared to areas that have never been exposed. In light of the previous section's findings on the growth rate of the proportion of poor households, we suggest that the slower growth in the standard of living in newly exposed areas supports the existence of a "coming to the nuisance" trend among poor households in these peri-urban areas. In contrast, for newly exposed urban units, compared to those that have never been exposed, we do not observe any difference in the growth rate of the standard of living. This result can be explained by the relatively higher density in urban areas and strong heterogeneity in the socioeconomic profiles.

7 Discussion and concluding remarks

Our study is the first national study in France to examine whether environmental degradation—specifically, the distinction between new exposure and no exposure—leads to a "coming to the nuisance" phenomenon among poor households, particularly at this fine level of analysis. To address this, we first analyze the correlation between environmental degradation and poverty and its intensity. Secondly, to identify a sorting mechanism, we evaluate the impact of new exposure, relative to never having been exposed, on the growth rate of the proportion of poor households between 2015 and 2019. Third, we aim to characterize, if it exists, this sorting mechanism, analyzing the effect of new exposure, relative to never having been exposed, on the growth rates of both poor and non-poor households.

Our initial findings are consistent with existing literature. Similar to the studies conducted by Salesse (2022) and Neier (2021), our results indicate that exposure in urban and peri-urban areas is associated with a higher proportion of poor households. These areas are characterized by high population density and substantial service availability, which exert pressure on housing prices (Combes et al., 2019; Le Hir and Bono, 2023). However, the emergence of new polluting sites that generate negative externalities can lead to a decline in housing prices, as demonstrated by Currie et al. (2015) and Hanna (2007). Consequently, newly exposed areas become more attractive to lower-income households.

Moreover, we find that new exposure in urban and peri-urban areas, when compared to areas that have never been exposed, is not associated with a higher intensity of poverty. In contrast, newly exposed rural areas exhibit a higher poverty rate than never exposed rural areas, suggesting that the introduction of polluting sites has stimulated surrounding economic activities. This finding diverges from Fosse et al. (2022), who identify disparities in exposure detrimental to more deprived households in rural areas, particularly related to agricultural pollution—an aspect not

fully considered in the present study (see footnote 11 in sub-section 4.2).

We also observe a relatively higher growth rate in the proportion of poor households in newly exposed urban and peri-urban areas compared to those that have never been exposed. These findings suggest a shift in the socioeconomic structure around newly established polluting sites. Furthermore, we note a relatively higher growth rate in the number of poor households around these new installations, accompanied by a relatively lower growth rate in the number of non-poor households. This indicates the presence of both a "coming to the nuisance" phenomenon among poor households and a "fleeing from the nuisance" behavior among non-poor households.

The fact that poor French households are more exposed to environmental nuisances, partially due to their "coming to the nuisance," raises concerns regarding health and equality of opportunities. As highlighted in the introduction, Hajat et al. (2015) shed light on the Triple Jeopardy for low-income households. Their overexposure increases the risk of poor health, even though they already face a heightened risk compared to the rest of the population. Additionally, Banzhaf et al. (2019b) emphasize the risk of perpetuating the poverty trap for future generations. Finally, Gerardin (2023) shows that many poor French households live in social housing (17.2%). Given that the construction of social housing is a responsibility delegated to municipalities, questions arise regarding the location of social housing, which, since the late 1990s, tends to accommodate more low-income households (Beaubrun-Diant and Maury, 2022). These elements underscore the necessity of incorporating environmental factors into public health, poverty alleviation, and urbanization policies to ensure equal opportunities among individuals.

Conflict of interest: The authors declare no conflict of interest.

Acknowledgements: We would like to thank the Editor and two anonymous referees for their valuable comments and suggestions. We are also grateful to Beal Sylvain and Peterle Emmanuel for their useful comments. The usual caveat applies.

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A Moment-based approach

To assess the effect of environmental degradation on the poverty distribution across the territory, we adopted a statistical-moment-based approach inspired by Antle (1983). We consider the proportion of poor households as a function, which has an exposure status (newly exposed versus never exposed geographical units), a component linked to socioeconomic and demographic characteristics, and a component related to what we will define as the intensity of poverty. It can be represented as follows:

$$\%Poverty_i = g(NewlyExposed_i, X_i, \epsilon_i), \tag{7}$$

where the index i corresponds to the geographical unit considered. The variable $\%Poverty_i$ corresponds to the proportion of poor households in the geographical unit considered. The variable $NewlyExposed_i$ is a dummy variable that takes the value of 1 if the geographical unit has been newly exposed to environmental hazards, and 0 if it has never been exposed. The X_i is a vector representing a unit's socioeconomic and demographic characteristics, and ϵ_i is a vector of unobservable and/ or omitted variables that can influence the proportion of poor households.

We employ a statistical-moment-based approach to assess the probability distribution of the stochastic poverty function $g(NewlyExposed_i, X_i, \epsilon_i)$. To do that, we proceed to estimate an Ordinary Least Squares (OLS) model, whose econometric specification takes the following form:

$$g(NewlyExposed_i, X_i, \epsilon_i) = f_1(NewlyExposed_i, X_i, \beta_1) + u_i, \tag{8}$$

where β_1 represents the various vectors of model parameters indexed by 1 to characterize the moment of order 1, and the error term u is a random variable of zero mean and constant variance in the case of our specification. Thus, $f_1(NewlyExposed_i, X_i, \beta_1)$ corresponds to the expectation of the poverty function, that is, the first statistical moment. The vector of estimated parameters, β_1 , captures the effects of environmental degradation, along with socioeconomic and demographic characteristics, on the average proportion of poor households per unit.

Higher-order statistical moments of Eq. (2) are expressed as follows:

$$E[(g(NewlyExposed_i, X_i, \epsilon_i) - f_1(NewlyExposed_i, X_i, \beta_1))^k | X] = f_k(NewlyExposed_i, X_i, \beta_k).$$
(9)

When k = 2, $f_2(NewlyExposed_i, X_i, \beta_2)$ refers to the moment of order 2, where β_2 describes the effect of environmental degradation and socioeconomic and demographic characteristics on the variance of the proportion of poor households. When k = 3, $f_3(NewlyExposed_i, X_i, \beta_3)$ refers to the moment of order 3, where β_3 describes the effect of environmental degradation and socioeconomic and demographic characteristics on the skewness of the proportion of poor households.

This statistical moment-based approach enables us to distinguish the effect of new exposure, relative to never exposure, on the average, the variance, and the skewness of the proportion of poor households. To estimate the average effect, we use the following econometric specification based on Eq. (8):

$$\%Poverty_i = \beta_0 + \beta_1 Newly Exposed_i + \beta_2 X_i + u_i. \tag{10}$$

We deduce the estimated residuals from the estimated coefficients, corresponding to the difference between observed value and estimated value. Thus, to estimate the effect of new exposure, relative to never exposure, on the variance of the proportion of poor households, we take the variance of the residuals obtained from Eq. (4) as the dependent variable. This estimate is derived from Eq. (9) when k=2 and takes the following form:

$$(\hat{u}_i)^2 = \sigma_0 + \sigma_1 Newly Exposed_i + \sigma_2 X_i + \theta_i, \tag{11}$$

where θ_i refers to the error term. The variance of the proportion of poor households quantifies the dispersion of its distribution around the mean. A positive (respectively, negative) dispersion coefficient indicates that newly exposed units are associated with a larger (respectively, smaller) dispersion of the proportion of poor households than never exposed units. A relatively larger dispersion of the proportion of poor households in newly exposed units can indicate a more pronounced poverty intensity in these areas. Analyzing the third-order moment coefficient will help identify the origin of a relatively higher (respectively, smaller) dispersion on the one hand and assess the question of poverty intensity on the other.

To estimate the effect of new exposure, relative to never exposure, on the skewness of the proportion of poor households, we use Eq. (9) when k=3, which takes the following form:

$$(\hat{u}_i)^3 = \lambda_0 + \lambda_1 Newly Exposed_i + \lambda_2 X_i + \rho_i, \tag{12}$$

where ρ_i refers to error term. To interpret the sign of the skewness coefficient, a statistical analysis of the distribution's skewness in the proportion of poor households helps identify the type of skewness. A right-skewed or left-skewed distribution corresponds to positive or negative skewness. Geographical units newly exposed to the hazard, with a positive (or negative) skewness coefficient, will experience accentuation (or reduction) skewness in their distribution compared to units that have never been exposed.

A higher intensity of poverty in newly exposed units is associated with greater variance in the proportion of poor households compared to never exposed units, driven by an accentuation of the skeweness to the right in the distribution. In other words, newly exposed units are likely to exhibit more extreme values in the right tail of the distribution relative to never exposed units.

B Benchmark results

Table B.1: Moments-based approach estimates for the proportion of poverty (2019)

| | | % Poverty | | Variance | Skewness |
|---|---|--------------------------|----------------------------|---------------------------|-----------------------------|
| | (1) | (2) | (3) | (4) | (5) |
| Newly Exposed | -0.013^{***} (0.001) | -0.015*** (0.001) | -0.013^{***} (0.001) | -0.001*** (0.0001) | -0.0002^{***} (0.00002) |
| Newly Exposed*Peri-urba | n | 0.019*** (0.001) | 0.014*** (0.001) | 0.001*** (0.0001) | 0.0002*** (0.00005) |
| Newly Exposed*Urban | | 0.025*** (0.001) | 0.019*** (0.002) | 0.001*** (0.0002) | 0.0003*** (0.0001) |
| Peri-urban | | -0.050^{***} (0.001) | -0.019^{***} (0.001) | -0.001^{***} (0.0001) | -0.0002^{***} (0.00004) |
| Urban | | -0.018^{***} (0.001) | -0.027^{***} (0.001) | -0.002^{***} (0.0001) | -0.0002^{***} (0.00004) |
| % Work resid. | | | 0.148*** (0.001) | 0.012*** (0.0002) | 0.001*** (0.0001) |
| Zoning B | | | -0.004^{***} (0.001) | 0.001*** (0.0001) | 0.0001 (0.0001) |
| Zoning C | | | 0.012*** (0.001) | 0.002*** (0.0001) | 0.0001 (0.0001) |
| % Social housing | | | 0.134*** (0.002) | 0.008*** (0.0003) | 0.0003** (0.0001) |
| % Single parents | | | 0.138*** (0.002) | 0.004*** (0.0003) | 0.0001 (0.0001) |
| % Farmers | | | 0.274*** (0.004) | 0.019*** (0.001) | -0.001** (0.0004) |
| % Artisans and others | | | 0.098*** (0.004) | 0.004*** (0.001) | 0.0002 (0.0002) |
| Constant | 0.120*** (0.0004) | 0.125*** (0.0004) | 0.045*** (0.001) | 0.002*** (0.0001) | 0.0004*** (0.0001) |
| Exposure Effects | | | | | |
| Rural $ H_0: \beta_{[NE]}^R$ | $_{[-1]-[NE=0]} = 0$ | | -0.012^{***} (-22.537) | -0.001^{***} (-16.928) | -0.0002^{***} (-8.816) |
| Peri-urban $H_0: \beta_{[NE]}^{PU}$ | $_{[-1]-[NE=0]}^{+}\beta_{[NE=1]-[NE=0]}^{R}$ | $_{[0]} = 0$ | 0.002* (2.1829) | -0.0001 (0.558) | -0.00003 (0.681) |
| Urban $\mid H_0: \beta_{[NE]}^U$ | $E=1]-[NE=0]+eta_{[NE=1]-[NE=1]}^{R}$ | $_{=0]} = 0$ | 0.006*** (21.683) | 0.0003 (2.138) | 0.0007 (0.798) |
| Observations $ m R^2$ Adjusted $ m R^2$ | 1,677,895 0.001 | 1,677,895 0.016 | 1,677,895 0.128 | 1,677,895 0.027 | 1,677,895 0.001 |
| Adjusted R ² F Statistic | 0.001 $2,275.434***$ | 0.016 $5,347.351***$ | 0.128 $20,542.720***$ | 0.027 $3,853.038****$ | 0.001 128.911***) |

Table B.2: Estimation results of the growth rate of poverty proportion (2015–2019)

| | Growth rate | e of Poverty |
|--|-----------------------------|-----------------------------|
| | (1) | (2) |
| Newly Exposed | 0.008** (0.003) | 0.001 (0.004) |
| Newly Exposed*Peri-urban | | 0.026** (0.012) |
| Newly Exposed*Urban | | 0.021** (0.008) |
| Peri-urban | -0.003 (0.005) | -0.007 (0.005) |
| Urban | 0.013*** (0.004) | 0.010** (0.004) |
| % Work resid. | 0.098*** (0.007) | 0.098*** (0.007) |
| Zoning B | -0.003 (0.006) | -0.003 (0.006) |
| Zoning C | -0.013** (0.006) | -0.013** (0.006) |
| % Social housing | 0.174*** (0.007) | 0.172*** (0.007) |
| % Single parents | -0.632^{***} (0.015) | -0.632^{***} (0.015) |
| % Farmers | -0.130^{***} (0.020) | -0.131*** (0.020) |
| % Artisans and others | -0.015 (0.024) | -0.015 (0.024) |
| Constant | -0.029^{***} (0.007) | -0.028^{***} (0.007) |
| Exposure Effects | | |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | Coef. 0.001 | Test-st at 0.254 |
| Peri-urban $H_0: \beta_{[NE=1]-[NE=0]}^{PU} + \beta_{[NE=1]-[NE=0]}^{R} = 0$ | 0.027** | 6.063 |
| Urban $H_0: \beta_{[NE=1]-[NE=0]}^U + \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.022*** | 10.062 |
| Observations $ m R^2$ Adjust ed $ m R^2$ | 1,677,895 0.002 0.002 | 1,677,895 0.002 0.002 |
| F Statistic | 370.278*** | 309.815*** |

Table B.3: Estimation results of the growth rate of the number of poor and non-poor households (2015–2019)

| _ | Growth of #poo | or households | Growth of #non- | poor households |
|---|-----------------------------|-----------------------------|-----------------------------|-----------------------------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.008** (0.004) | 0.003 (0.004) | -0.002^* (0.001) | 0.0004 (0.001) |
| Newly Exposed*Peri-urban | | 0.020* (0.012) | | -0.008** (0.003) |
| Newly Exposed*Urban | | 0.017** (0.008) | | -0.007*** (0.003) |
| Peri-urb an | 0.0004 (0.005) | -0.002 (0.005) | 0.007*** (0.001) | 0.008*** (0.002) |
| Jrb an | 0.020*** (0.004) | 0.018*** (0.004) | 0.008*** (0.001) | 0.009*** (0.001) |
| % Work resid. | 0.076*** (0.007) | 0.076*** (0.007) | -0.035*** (0.002) | -0.035*** (0.002) |
| Zoning B | 0.004 (0.006) | 0.003 (0.006) | 0.013*** (0.002) | 0.013*** (0.002) |
| Zoning C | -0.015** (0.006) | -0.016^{***} (0.006) | -0.001 (0.002) | -0.001 (0.002) |
| % Social housing | 0.146*** (0.008) | 0.145*** (0.008) | -0.065*** (0.003) | -0.065*** (0.003) |
| % Single parents | -0.678*** (0.015) | -0.678^{***} (0.015) | -0.091*** (0.005) | -0.091*** (0.005) |
| % Farmers | -0.183*** (0.020) | -0.183^{***} (0.020) | -0.040*** (0.007) | -0.040*** (0.007) |
| % Artisans and others | 0.015 (0.024) | 0.015 (0.024) | 0.046*** (0.008) | 0.046*** (0.008) |
| Const ant | -0.011^* (0.007) | -0.011 (0.007) | 0.032*** (0.002) | 0.032*** (0.002) |
| Exposure Effects | | | | |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | Coef. 0.003 | Test-stat 0.629 | Co ef. 0.0004 | Test-stat 0.348 |
| Peri-urban $H_0:\beta_{[NE=1]-[NE=0]}^{PU}+\beta_{[NE=1]-[NE=0]}^{R}=0$ | 0.022** | 4.095 | -0.008*** | 6.821 |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.0199*** | 8.186 | -0.007*** | 6.821 |
| Observations \mathfrak{A}^2 Adjusted \mathbb{R}^2 | 1,677,895 0.002 0.002 | 1,677,895 0.002 0.002 | 1,677,895 0.001 0.001 | 1,677,895 0.001 0.001 |
| F Statistic | 329.778*** | 329.778*** | 158.429*** | 158.429*** |

C Standard of living

C.1 Descriptive statistics

Table C.1: Statistics of the standard of living

| | | | | ${\bf AverStandLiv}$ | | | | |
|------------------|---------------|--------------------|---------------|----------------------|---------------|---------------|---------------|---------------|
| | Whole | Whole sample Urban | | Peri-ı | ırban | Rural | | |
| | Newly Exposed | Never Exposed | Newly Exposed | Never Exposed | Newly Exposed | Never Exposed | Newly Exposed | Never Exposed |
| N | 149,634 | 1,528,261 | 31,826 | 141,252 | 15,883 | 78,923 | 101,925 | 1,308,086 |
| % | 0,09 | 0.91 | 0,18 | 0,82 | 0,17 | 0,83 | 0.07 | 0,93 |
| Mean | 10.93 | 10.90 | 10.96 | 10.99 | 11.07 | 11.13 | 10.90 | 10.88 |
| $^{\mathrm{SD}}$ | 0, 25 | $0,\!25$ | 0,29 | 0.28 | 0,26 | 0,26 | 0,22 | 0,24 |
| Median | 10.93 | 10.91 | 10.97 | 11.00 | 11.08 | 11.13 | 10.91 | 10.89 |
| Mean - Median | -0.003 | -0.009 | -0.013 | -0.010 | -0.011 | -0.001 | -0.007 | -0.007 |

Notes: AverStandLiv corresponds to the average standard of living in logarithm by geographical unit in 2019. The variable Newly Exposed takes the value of 1 if the geographical unit became exposed between 2011 and 2015, and 0 if it was not exposed at any time between 2010 and 2019. SD corresponds to the standard deviation. N corresponds to the number of squares for each considered sample set, and the percentage distinguishes the proportion of exposed and non-exposed squares within the considered sample.

C.2 Standard of living results

Table C.1: Estimation results of standard of living

| | Av er St and Liv | Variance | ${\rm Skewness}$ | Growth rate |
|---|--|----------------------------|-------------------------------|----------------------------------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.018*** (0.002) | -0.004*** (0.0003) | 0.0003 (0.0002) | 0.003*** (0.001) |
| Newly Exposed*Peri-urban | -0.055*** (0.005) | 0.003** (0.001) | -0.001 (0.001) | -0.006*** (0.002) |
| Newly Exposed*Urban | -0.043^{***} (0.004) | 0.003** (0.001) | 0.002** (0.001) | -0.004*** (0.001) |
| Peri-urban | 0.089*** (0.003) | 0.002* (0.001) | 0.0004 (0.001) | -0.001 (0.001) |
| Urban | 0.097*** (0.003) | 0.004*** (0.001) | -0.002^{***} (0.001) | -0.003^{***} (0.001) |
| % Work resid. | -0.522^{***} (0.004) | 0.026*** (0.001) | -0.001 (0.001) | -0.004*** (0.001) |
| Zoning B | -0.134*** (0.006) | -0.014*** (0.001) | -0.001 (0.001) | 0.001 (0.001) |
| Zoning C | -0.255*** (0.006) | -0.026*** (0.001) | -0.001 (0.001) | 0.001 (0.001) |
| % Social housing | -0.417^{***} (0.004) | 0.020*** (0.001) | 0.004*** (0.001) | 0.019*** (0.002) |
| % Single parents | -0.326*** (0.004) | 0.001 (0.001) | 0.002** (0.001) | 0.020*** (0.002) |
| % Farmers | -0.439^{***} (0.011) | 0.015*** (0.005) | 0.017*** (0.006) | 0.080*** (0.004) |
| % Artisans and others | 0.092*** (0.010) | 0.010*** (0.003) | 0.003 (0.002) | -0.002 (0.004) |
| Constant | 11.304*** (0.006) | 0.061*** (0.001) | -0.001 (0.001) | 0.044*** (0.001) |
| Exposure Effects | | | | |
| Rural $ H_0: \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.018*** (11.178) | -0.003*** (-10.722) | 0.0003 (1.134) | 0.003*** (4.174) |
| $ \begin{aligned} & \text{Peri-urban} \ \ H_0: \ \beta^{PU}_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0 \\ \\ & \text{Urban} \qquad \ H_0: \ \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0 \\ \end{aligned} $ | -0.037^{***} (58.156) -0.024^{***} | -0.0005 (0.201) -0.001 | -0.0005 (0.307) 0.002** | -0.003^{**} (5.848) -0.001 |
| Observations $ M_0 \cdot P[NE=1] - [NE=0] \cdot P[NE=1] - [NE=0] $ | (45.203) 1,677,895 | (0.831) 1,677,895 | (6.186) 1,677,895 | (1.848) 1,677,895 |
| R^2 Adjusted R^2 | 0.248 0.248 | 0.013 0.013 | 0.001 0.001 | 0.001 0.001 |
| F Statistic | 46,214.470*** | 1,861.810*** | 72.165*** | 150.555*** |

D Robustness

Table D.1: Robustness estimates of the proportion of poverty (Urban vs Rural)

| | | % Poverty | | Variance | Skewness |
|-------------------------|---|---------------|----------------|----------------|------------|
| | (1) | (2) | (3) | (4) | (5) |
| Newly Exposed | -0.013*** | -0.015*** | -0.013*** | -0.001^{***} | -0.0002*** |
| | (0.001) | (0.001) | (0.001) | (0.0001) | (0.00002) |
| Newly Exposed*Urba | n | 0.024*** | 0.018*** | 0.001*** | 0.0002*** |
| | | (0.001) | (0.001) | (0.0002) | (0.0001) |
| Urban | | -0.030*** | -0.024*** | -0.002*** | -0.0002*** |
| | | (0.001) | (0.001) | (0.0001) | (0.00004) |
| % Work resid. | | | 0.146*** | 0.012*** | 0.001*** |
| | | | (0.001) | (0.0002) | (0.0001) |
| Zoning B | | | -0.003*** | 0.001*** | 0.0001 |
| | | | (0.001) | (0.0001) | (0.0001) |
| Zoning C | | | 0.012*** | 0.002*** | 0.0001 |
| | | | (0.001) | (0.0001) | (0.0001) |
| % Social housing | | | 0.133*** | 0.007*** | 0.0003** |
| | | | (0.002) | (0.0003) | (0.0001) |
| % Single parents | | | 0.138*** | 0.004*** | 0.0001 |
| | | | (0.002) | (0.0003) | (0.0001) |
| % Farmers | | | 0.276*** | 0.020*** | -0.001** |
| | | | (0.004) | (0.001) | (0.0004) |
| % Artisans and others | S | | 0.100*** | 0.004*** | 0.0002 |
| | | | (0.004) | (0.001) | (0.0002) |
| Constant | 0.120*** | 0.125*** | 0.045*** | 0.002*** | 0.0004*** |
| | (0.0004) | (0.0004) | (0.001) | (0.0001) | (0.0001) |
| Exposure Effects | | | | | |
| Rural $ H_0: \mu$ | $\beta_{[NE=1]-[NE=0]}^{R} = 0$ | | -0.012^{***} | -0.001*** | -0.0002*** |
| | | | (-22.509) | (-16.983) | (-8.854) |
| Urban $ H_0: $ | $\beta_{[NE=1]-[NE=0]}^{U} + \beta_{[NE=1]-}^{R}$ | $_{[NE=0]}=0$ | 0.005*** | 0.0001 | 0.00004 |
| | | | (21.076) | (1.050) | (0.640) |
| Observations | 1,677,895 | 1,677,895 | 1,677,895 | 1,677,895 | 1,677,895 |
| \mathbb{R}^2 | 0.001 | 0.012 | 0.128 | 0.027 | 0.001 |
| Adjusted R ² | 0.001 | 0.012 | 0.128 | 0.027 | 0.001 |
| F Statistic | 2,275.434*** | 6,620.710*** | 24,614.660*** | 4,621.870*** | 160.607*** |

Table D.2: Robustness estimates of the growth rate of poverty proportion (Urban vs Rural)

| | Growth rate | of Poverty |
|--|------------------|--|
| | (1) | (2) |
| Newly Exposed | 0.008** | 0.001 |
| | (0.003) | (0.004) |
| Newly Exposed*Urban | | 0.023*** |
| | | (0.007) |
| Urban | 0.007** | 0.004 |
| | (0.004) | (0.004) |
| % Work resid. | 0.104*** | 0.104*** |
| | (0.006) | (0.006) |
| Zoning B | -0.004 | -0.005 |
| 0 | (0.006) | (0.006) |
| Zoning C | -0.014** | -0.014** |
| Loning C | (0.006) | (0.006) |
| % Social housing | 0.175*** | 0.173*** |
| notonig | (0.007) | (0.007) |
| % Single parents | -0.631*** | -0.632*** |
| 70 Single parents | (0.015) | (0.015) |
| % Farmers | -0.134*** | -0.135*** |
| 70 Faintis | (0.020) | (0.020) |
| % Artisans and others | -0.020 | -0.020 |
| 70 Artisalis and others | (0.024) | -0.020 (0.024) |
| Constant | -0.030*** | -0.029*** |
| Constant | -0.030 (0.007) | -0.029 (0.007) |
| | (0.001) | (0.001) |
| Exposure Effects | | |
| | Coef. | $Test\text{-}\operatorname{st}\operatorname{at}$ |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.001 | 0.242 |
| Urban $H_0: \beta_{[NE=1]-[NE=0]}^U + \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.024*** | 16.382 |
| Observations | 1,677,895 | 1,677,895 |
| \mathbb{R}^2 | 0.002 | 0.002 |
| $ m Adjusted~R^2$ | 0.002 | 0.002 |
| F Statistic | 409.658*** | 370.222*** |

Table D.3: Robustness estimates of the growth rate of the number of poor and non-poor households (Urban vs Rural)

| | Growth of #poor households | | Growth of $\#$ non-poor households | |
|--|----------------------------|---|------------------------------------|------------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.008** | 0.003 | -0.002* | 0.0004 |
| | (0.004) | (0.004) | (0.001) | (0.001) |
| Newly Exposed*Urban | | 0.019** | | -0.007*** |
| | | (0.007) | | (0.002) |
| Urban | 0.013*** | 0.010*** | 0.008*** | 0.009*** |
| | (0.004) | (0.004) | (0.001) | (0.001) |
| % Work resid. | 0.083*** | 0.083*** | -0.035*** | -0.035*** |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| Zoning B | 0.002 | 0.001 | 0.013*** | 0.013*** |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| Zoning C | -0.016*** | -0.017*** | -0.001 | -0.001 |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| % Social housing | 0.148*** | 0.147*** | -0.065*** | -0.065*** |
| | (0.008) | (0.008) | (0.003) | (0.003) |
| % Single parents | -0.677*** | -0.678*** | -0.091*** | -0.091*** |
| | (0.015) | (0.015) | (0.005) | (0.005) |
| % Farmers | -0.188*** | -0.189*** | -0.040*** | -0.040*** |
| | (0.020) | (0.020) | (0.007) | (0.007) |
| % Artisans and others | 0.009 | 0.009 | 0.046*** | 0.046*** |
| | (0.024) | (0.024) | (0.008) | (0.008) |
| Constant | -0.012* | -0.011* | 0.032*** | 0.032*** |
| | (0.007) | (0.007) | (0.002) | (0.002) |
| Exposure Effects | | | | |
| | Coef. | $\operatorname{Test-st}\operatorname{at}$ | Coef. | Test-stat |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.003 | 0.614 | 0.0004 | 0.347 |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.021*** | 12.622 | -0.007*** | 15.262 |
| Observations | 1,677,895 | 1,677,895 | 1,677,895 | 1,677,895 |
| \mathbb{R}^2 | 0.002 | 0.002 | 0.001 | 0.001 |
| Adjusted R ² | 0.002 | 0.002 | 0.001 | 0.001 |
| F Statistic | 436.316*** | 393.638*** | 210.062*** | 190.092*** |

Table D.4: Robustness estimates of the growth rate of poverty proportion (2km buffer area)

| | Growth rate of Poverty | | |
|--|------------------------|----------------|--|
| | (1) | (2) | |
| Newly Exposed | 0.014** | 0.009 | |
| | (0.006) | (0.008) | |
| Newly Exposed*Peri-urban | | 0.023 | |
| | | (0.018) | |
| Newly Exposed*Urban | | 0.011 | |
| | | (0.012) | |
| Peri-urban | -0.003 | -0.006 | |
| | (0.008) | (0.008) | |
| Urban | 0.013** | 0.012* | |
| | (0.006) | (0.007) | |
| % Work resid. | 0.101*** | 0.102*** | |
| | (0.011) | (0.011) | |
| Zoning B | -0.002 | -0.003 | |
| | (0.008) | (0.008) | |
| Zoning C | -0.013 | -0.013 | |
| | (0.009) | (0.008) | |
| % Social housing | 0.170*** | 0.169*** | |
| | (0.009) | (0.009) | |
| % Single parents | -0.632^{***} | -0.632^{***} | |
| | (0.022) | (0.022) | |
| % Farmers | -0.126*** | -0.127^{***} | |
| | (0.033) | (0.033) | |
| % Artisans and others | -0.019 | -0.019 | |
| | (0.040) | (0.040) | |
| Constant | -0.031*** | -0.030*** | |
| | (0.010) | (0.010) | |
| Exposure Effects | | | |
| | Coef. | Test-st at | |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.009 | 1.112 | |
| Peri-urban $H_0: \beta_{[NE=1]-[NE=0]}^{PU} + \beta_{[NE=1]-[NE=0]}^{R} = 0$ | 0.032* | 3.799 | |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.019** | 4.421 | |
| Observations | 1,659,062 | 1,659,062 | |
| \mathbb{R}^2 | 0.002 | 0.002 | |
| Adjusted R^2 | 0.002 | 0.002 | |
| F Statistic | 373.110*** | 311.415*** | |

Table D.5: Robustness estimates of the growth rate of the number of poor and non-poor households (2km buffer area)

| | Growth of #poor households | | Growth of $\#$ non-poor households | |
|---|----------------------------|------------|------------------------------------|------------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.015** | 0.011 | -0.002 | 0.0004 |
| | (0.006) | (0.008) | (0.001) | (0.002) |
| Newly Exposed*Peri-urban | | 0.017 | | -0.008** |
| | | (0.018) | | (0.004) |
| Newly Exposed*Urban | | 0.007 | | -0.006** |
| | | (0.012) | | (0.003) |
| Peri-urb an | 0.001 | -0.001 | 0.008*** | 0.009*** |
| | (0.007) | (0.008) | (0.002) | (0.002) |
| Urban | 0.020*** | 0.019*** | 0.008*** | 0.009*** |
| | (0.006) | (0.006) | (0.001) | (0.002) |
| % Work resid. | 0.080*** | 0.080*** | -0.036*** | -0.036*** |
| | (0.011) | (0.011) | (0.002) | (0.002) |
| Zoning B | 0.004 | 0.004 | 0.012*** | 0.012*** |
| | (0.008) | (0.008) | (0.002) | (0.002) |
| Zoning C | -0.015* | -0.016* | -0.002 | -0.002 |
| | (0.008) | (0.008) | (0.002) | (0.002) |
| % Social housing | 0.142*** | 0.141*** | -0.067*** | -0.067*** |
| | (0.009) | (0.009) | (0.004) | (0.004) |
| % Single parents | -0.677*** | -0.677*** | -0.090*** | -0.090*** |
| | (0.022) | (0.022) | (0.005) | (0.005) |
| % Farmers | -0.177*** | -0.177*** | -0.038*** | -0.038*** |
| | (0.033) | (0.033) | (0.008) | (0.008) |
| % Artisans and others | 0.010 | 0.010 | 0.046*** | 0.046*** |
| | (0.039) | (0.039) | (0.009) | (0.009) |
| Constant | -0.012 | -0.012 | 0.032*** | 0.032*** |
| | (0.009) | (0.009) | (0.002) | (0.002) |
| Exposure Effects | | | | |
| | Coef. | Test-stat | Coef. | Test-stat |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.011 | 1.413 | 0.0004 | 0.247 |
| Peri-urban $H_0: \beta^{PU}_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.028^{*} | 2.825 | -0.008** | 4.239 |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.018* | 3.838 | -0.006** | 5.583 |
| Observations | 1,659,062 | 1,659,062 | 1,659,062 | 1,659,062 |
| \mathbb{R}^2 | 0.002 | 0.002 | 0.001 | 0.001 |
| ${ m Adjust}$ ed ${ m R}^2$ | 0.002 | 0.002 | 0.001 | 0.001 |
| F Statistic | 395.207*** | 329.564*** | 191.058*** | 159.797*** |

Table D.6: Robustness estimates of the growth rate of poverty proportion (2km buffer area | Urban vs Rural)

| | Growth rate of Poverty | | |
|--|------------------------|----------------------------|--|
| | (1) | (2) | |
| Newly Exposed | 0.014** | 0.009 | |
| | (0.006) | (0.008) | |
| Newly Exposed*Urban | | 0.016 | |
| | | (0.011) | |
| Urban | 0.007 | 0.005 | |
| | (0.005) | (0.006) | |
| % Work resid. | 0.107*** | 0.107*** | |
| | (0.010) | (0.010) | |
| Zoning B | -0.004 | -0.004 | |
| | (0.008) | (0.008) | |
| Zoning C | -0.013 | -0.014 | |
| | (0.009) | (0.009) | |
| % Social housing | 0.171*** | 0.170*** | |
| | (0.009) | (0.009) | |
| % Single parents | -0.632*** | -0.632*** | |
| | (0.022) | (0.022) | |
| % Farmers | -0.130*** | -0.131*** | |
| | (0.033) | (0.033) | |
| % Artisans and others | -0.024 | -0.024 | |
| | (0.040) | (0.040) | |
| Constant | -0.031*** | -0.030*** | |
| | (0.010) | (0.010) | |
| Exposure Effects | | | |
| | Coef. | $\operatorname{Test-stat}$ | |
| Rural $H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.009 | 1.098 | |
| Urban $H_0: \beta_{[NE=1]-[NE=0]}^U + \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.024*** | 8.925 | |
| Observations | 1,659,062 | 1,659,062 | |
| \mathbb{R}^2 | 0.002 | 0.002 | |
| Adjusted R^2 | 0.002 | 0.002 | |
| F Statistic | 412.880*** | 372.129*** | |

Table D.7: Robustness estimates of the growth rate of the number of poor and non-poor households (2km buffer area | Urban vs Rural)

| | Growth of #poor households | | Growth of #non-poor households | |
|--|----------------------------|------------|--------------------------------|------------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.015*** | 0.011 | -0.002 | 0.0004 |
| | (0.006) | (0.008) | (0.001) | (0.002) |
| Newly Exposed*Urban | | 0.011 | | -0.007** |
| | | (0.011) | | (0.003) |
| Urban | 0.013** | 0.012** | 0.008*** | 0.009*** |
| | (0.005) | (0.006) | (0.001) | (0.001) |
| % Work resid. | 0.087*** | 0.087*** | -0.036*** | -0.036*** |
| | (0.010) | (0.010) | (0.002) | (0.002) |
| Zoning B | 0.002 | 0.002 | 0.012*** | 0.012*** |
| | (0.008) | (0.008) | (0.002) | (0.002) |
| Zoning C | -0.016* | -0.016** | -0.002 | -0.002 |
| | (0.008) | (0.008) | (0.002) | (0.002) |
| % Social housing | 0.143*** | 0.142*** | -0.067*** | -0.066*** |
| | (0.009) | (0.009) | (0.004) | (0.004) |
| % Single parents | -0.676*** | -0.676*** | -0.090*** | -0.090*** |
| | (0.022) | (0.022) | (0.005) | (0.005) |
| % Farmers | -0.182*** | -0.183*** | -0.039*** | -0.038*** |
| | (0.033) | (0.033) | (0.008) | (0.008) |
| % Artisans and others | 0.004 | 0.004 | 0.046*** | 0.046*** |
| | (0.039) | (0.039) | (0.009) | (0.009) |
| Constant | -0.013 | -0.012 | 0.032*** | 0.032*** |
| | (0.010) | (0.010) | (0.002) | (0.002) |
| Exposure Effects | | | | |
| | Coef. | Test-stat | Coef. | Test-stat |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.011 | 1.395 | 0.0004 | 0.244 |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.022*** | 7.47 | -0.006*** | 9.524 |
| Observations | 1,659,062 | 1,659,062 | 1,659,062 | 1,659,062 |
| \mathbb{R}^2 | 0.002 | 0.002 | 0.001 | 0.001 |
| Adjusted R ² | 0.002 | 0.002 | 0.001 | 0.001 |
| F Statistic | 436.799*** | 393.376*** | 212.278*** | 191.724*** |

Table D.8: Estimates of the evolution of households number

| | Growth rate | | |
|--|--------------------------|-----------------------------|--|
| | (1) | (2) | |
| wly Exposed | 0.0003 (0.001) | 0.002* (0.001) | |
| wly Exposed*Peri-urban | | -0.007** (0.003) | |
| wły Exposed*Urban | | -0.006** (0.002) | |
| ri-urban | 0.009*** (0.001) | 0.010*** (0.001) | |
| ban | 0.011*** (0.001) | 0.012*** (0.001) | |
| Work resid. | -0.032^{***} (0.002) | -0.032^{***} (0.002) | |
| ning B | 0.012*** (0.002) | 0.012*** (0.002) | |
| ning C | -0.003^* (0.002) | -0.003 (0.002) | |
| Social housing | -0.036^{***} (0.003) | -0.035^{***} (0.003) | |
| Single parents | -0.169^{***} (0.005) | -0.169^{***} (0.005) | |
| Farmers | -0.085^{***} (0.006) | -0.085*** (0.006) | |
| Artisans and others | 0.037*** (0.008) | 0.037*** (0.008) | |
| onstant | 0.032*** (0.002) | 0.032*** (0.002) | |
| posure Effects | | | |
| ral $\mid H_0: eta^R_{[NE=1]-[NE=0]} = 0$ | Co ef. 0.002* | Test-st at 1.898 | |
| ri-urban $H_0: \beta_{[NE=1]-[NE=0]}^{PU} + \beta_{[NE=1]-[NE=0]}^{R} = 0$ | -0.005* | 3.165 | |
| ban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | -0.004* | 3.310 | |
| oservations : Sucted B ² | 1,677,895 0.002 | 1,677,895 0.002 0.002 | |
| ijustea K. Statistic | 319.705*** | 267.154*** | |
| $ m grad grad R^2$ | 0.002 0.002 | 0 | |

Table D.9: Robustness estimates of the growth rate of poverty proportion (Exposure 2010-2017)

| | Growth rate of Poverty | | |
|--|------------------------------------|------------------------------------|--|
| | (1) | (2) | |
| Newly Exposed | 0.008*** (0.003) | 0.002 (0.003) | |
| Newly Exposed*Peri-urban | | 0.018* (0.010) | |
| Newly Exposed*Urban | | 0.026*** (0.007) | |
| Peri-urban | 0.005 (0.005) | 0.002 (0.005) | |
| Urban | 0.020*** (0.004) | 0.015*** (0.004) | |
| % Work resid. | 0.083*** (0.006) | 0.083*** (0.006) | |
| Zoning B | -0.008 (0.005) | -0.009^* (0.005) | |
| Zoning C | -0.015*** (0.006) | -0.016*** (0.006) | |
| % Social housing | 0.117*** (0.006) | 0.115*** (0.006) | |
| % Single parents | -0.419*** (0.014) | -0.420*** (0.014) | |
| % Farmers | -0.125*** (0.018) | -0.126*** (0.018) | |
| % Artisans and others | 0.082*** (0.023) | 0.081*** (0.023) | |
| Constant | -0.044*** (0.006) | -0.043*** (0.006) | |
| Exposure Effects | | | |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | Coef. 0.001 | Test-stat 0.492 | |
| Peri-urban $H_0: \beta_{[NE=1]-[NE=0]}^{PU} + \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.019** | 4.540 | |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.028*** | 22.846 | |
| Observations $ m R^2$ Adjust ed $ m R^2$ | $1,706,597 \\ 0.001 \\ 0.001$ | $1,706,597 \\ 0.001 \\ 0.001$ | |
| Residual Std. Error F Statistic | 0.919 (df = 1706586) 227.759*** | 0.919 (df = 1706584) 191.749*** | |

Table D.10: Robustness estimates of the growth rate of the number of poor and non-poor households (Exposure 2010–2017)

| | Growth of #poor households | | Growth of $\#$ non-poor households | |
|---|----------------------------|------------|------------------------------------|-----------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.008*** | 0.002 | -0.002** | -0.001 |
| | (0.003) | (0.004) | (0.001) | (0.001) |
| Newly Exposed*Peri-urban | | 0.016 | | -0.004* |
| | | (0.010) | | (0.002) |
| Newly Exposed*Urban | | 0.025*** | | -0.003 |
| | | (0.007) | | (0.002) |
| Peri-urban | 0.006 | 0.004 | 0.003** | 0.003*** |
| | (0.005) | (0.005) | (0.001) | (0.001) |
| Urban | 0.022*** | 0.017*** | 0.002** | 0.003** |
| | (0.004) | (0.004) | (0.001) | (0.001) |
| % Work resid. | 0.075*** | 0.075*** | -0.017*** | -0.017*** |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| Zoning B | -0.005 | -0.005 | 0.008*** | 0.008*** |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| Zoning C | -0.016*** | -0.017*** | 0.002 | 0.002 |
| - | (0.006) | (0.006) | (0.002) | (0.002) |
| % Social housing | 0.094*** | 0.093*** | -0.052*** | -0.052*** |
| | (0.007) | (0.007) | (0.003) | (0.003) |
| % Single parents | -0.449*** | -0.449*** | -0.047*** | -0.047*** |
| | (0.014) | (0.014) | (0.004) | (0.004) |
| % Farmers | -0.165*** | -0.166*** | -0.022*** | -0.022*** |
| | (0.019) | (0.019) | (0.006) | (0.006) |
| % Artisans and others | 0.083*** | 0.083*** | -0.002 | -0.002 |
| | (0.023) | (0.023) | (0.007) | (0.007) |
| Constant | -0.036*** | -0.035*** | 0.016*** | 0.016*** |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| Exposure Effects | | | | |
| | Coef. | Test-stat | Coef. | Test-stat |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.002 | 0.651 | -0.0007 | -0.762 |
| Peri-urban H_0 : $\beta^{PU}_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.018* | 3.811 | -0.005** | 5.019 |
| Urban $ \mid H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0 $ | 0.027*** | 21.511 | -0.004** | 4.735 |
| Observations | 1,706,597 | 1,706,597 | 1,706,597 | 1,706,597 |
| \mathbb{R}^2 | 0.001 | 0.001 | 0.0005 | 0.0005 |
| $ m Adjusted~R^2$ | 0.001 | 0.001 | 0.0005 | 0.0005 |
| F Statistic | 240.747*** | 202.286*** | 84.211*** | 70.499*** |

Table D.11: Robustness estimates of the growth rate of poverty proportion (Exposure 10-17 | Urban vs Rural)

| | Growth rate of Poverty | | |
|--|------------------------|--|--|
| | (1) | (2) | |
| Newly Exposed | 0.008*** | 0.002 | |
| | (0.003) | (0.003) | |
| Newly Exposed*Urban | | 0.024*** | |
| | | (0.006) | |
| Urban | 0.014*** | 0.010*** | |
| | (0.003) | (0.004) | |
| % Work resid. | 0.089*** | 0.089*** | |
| | (0.006) | (0.006) | |
| Zoning B | -0.010^* | -0.011** | |
| - | (0.005) | (0.005) | |
| Zoning C | -0.016*** | -0.017*** | |
| | (0.006) | (0.006) | |
| % Social housing | 0.118*** | 0.116*** | |
| | (0.006) | (0.006) | |
| % Single parents | -0.419*** | -0.419*** | |
| | (0.014) | (0.014) | |
| % Farmers | -0.129*** | -0.130*** | |
| | (0.018) | (0.018) | |
| % Artisans and others | 0.077*** | 0.077*** | |
| | (0.023) | (0.023) | |
| Constant | -0.045*** | -0.043*** | |
| | (0.006) | (0.006) | |
| Exposure Effects | | | |
| | Coef. | $Test\text{-}\operatorname{st}\operatorname{at}$ | |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.002 | 0.486 | |
| Urban $H_0: \beta_{[NE=1]-[NE=0]}^U + \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.026*** | 26.413 | |
| Observations | 1,706,597 | 1,706,597 | |
| \mathbb{R}^2 | 0.001 | 0.001 | |
| $ m Adjusted~R^2$ | 0.001 | 0.001 | |
| F Statistic | 251.348*** | 228.556*** | |

Table D.12: Robustness estimates of the growth rate of the number of poor and non-poor households (Exposure 10-17 | Urban vs Rural)

| | Growth of #poor households | | Growth of $\#$ non-poor households | |
|--|----------------------------|------------|------------------------------------|-----------|
| | (1) | (2) | (3) | (4) |
| Newly Exposed | 0.009*** | 0.002 | -0.002** | -0.001 |
| | (0.003) | (0.004) | (0.001) | (0.001) |
| Newly Exposed*Urban | | 0.023*** | | -0.003** |
| | | (0.006) | | (0.002) |
| Urban | 0.016*** | 0.012*** | 0.002*** | 0.003*** |
| | (0.003) | (0.004) | (0.001) | (0.001) |
| % Work resid. | 0.081*** | 0.081*** | -0.017*** | -0.017*** |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| Zoning B | -0.006 | -0.007 | 0.008*** | 0.008*** |
| | (0.005) | (0.005) | (0.002) | (0.002) |
| Zoning C | -0.017*** | -0.018*** | 0.002 | 0.002 |
| - | (0.006) | (0.006) | (0.002) | (0.002) |
| % Social housing | 0.095*** | 0.094*** | -0.052*** | -0.052*** |
| | (0.007) | (0.007) | (0.003) | (0.003) |
| % Single parents | -0.448*** | -0.449*** | -0.047*** | -0.047*** |
| _ | (0.014) | (0.014) | (0.004) | (0.004) |
| % Farmers | -0.169*** | -0.170*** | -0.022*** | -0.022*** |
| | (0.019) | (0.019) | (0.006) | (0.006) |
| % Artisans and others | 0.078*** | 0.078*** | -0.002 | -0.002 |
| | (0.023) | (0.023) | (0.007) | (0.007) |
| Constant | -0.036*** | -0.035*** | 0.016*** | 0.016*** |
| | (0.006) | (0.006) | (0.002) | (0.002) |
| Exposure Effects | | | | |
| | Coef. | Test-stat | Coef. | Test-stat |
| Rural $ H_0: \beta_{[NE=1]-[NE=0]}^R = 0$ | 0.002 | 0.644 | -0.0007 | -0.762 |
| Urban $H_0: \beta^U_{[NE=1]-[NE=0]} + \beta^R_{[NE=1]-[NE=0]} = 0$ | 0.025*** | 24.332 | -0.004*** | 9.345 |
| Observations | 1,706,597 | 1,706,597 | 1,706,597 | 1,706,597 |
| \mathbb{R}^2 | 0.001 | 0.001 | 0.0005 | 0.0005 |
| ${ m Adjusted}{ m R}^2$ | 0.001 | 0.001 | 0.0005 | 0.0005 |
| F Statistic | 265.694*** | 241.101*** | 93.555*** | 84.575*** |