Who Is Most at Risk? Uncovering the Determinants of Population Vulnerability to Heat Waves in France *

Hamza Bennani
University of Nantes

Marc Pourroy†
University of Poitiers

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Abstract

Heat waves are becoming more frequent in France, raising concerns about their public health impacts. Existing studies highlight the role of temperature and individual risk factors in heat-related morbidity that generally focus on large cities such as Paris, but overlook nonfatal consequences and other areas. Using healthcare service areas (*Territoire de Vie Santé*, TVS) as a spatial unit, we examine how exposure, sensitivity, and adaptive capacity shape vulnerability to extreme heat. Our results show that high temperatures and social isolation significantly increase hospital admissions and emergency visits, while wealth and vegetation mitigate health risks. In contrast, age, deprivation, and education do not significantly influence vulnerability, suggesting that economic resources are more critical for adaptation than traditional social risk factors. These findings challenge assumptions about the primary drivers of heat vulnerability and highlight the importance of targeted policies—such as strengthening support networks for isolated individuals—to reduce heat-related health risks in a warming climate.

Keywords: Heat vulnerability ; Public health ; Risk ; Climate adaptation

JEL classification: I12 ;I18 ;Q54 ;R23

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†Corresponding author: LéP, Université de Poitiers, 2 rue Jean Carbonnier, TSA 81100, 86073 Poitiers Cedex 9; Phone 0033549454208; E-mail: marc.pourroy@univ-poitiers.fr

1 Introduction

A recent report published by the National Institute of Statistics and Economic Administration (INSEE) revealed that France had already crossed alarming temperature thresholds, with peaks reaching up to 40 degrees Celsius (INSEE, 2020). This implies more frequent, persistent, and intense heat waves, which in turn have substantial public health burdens, including additional hospital admissions and emergency room visits (ERVs). An illustrative case is provided by Campbell et al. (2018), who estimate the health impacts of heatwaves in 854 locations and highlight the major toll on health systems through ambulance and hospital workloads.

However, there still exists a significant research gap on the effect of extreme heat on hospitalizations and ERVs given that most studies explore fatal health outcomes, such as mortality, and do not consider the multifaceted nature of the nonfatal healthcare costs related to climate change. As a matter of fact, very few studies report the temperature-related nonfatal consequences through hospitalizations and ERVs, although the latter can articulate the intensity through which temperature is triggering and exacerbating the load on the healthcare system. Moreover, the scarce studies looking at the impact of heat waves on hospitalizations focus on specific cities, such as Paris (Sabri et al., 2024). This is all the more surprising given that a public policy designed to address the consequences of heat waves can only be successful if implemented at a national scale. Indeed, the latter is essential to avoid the overcrowding of hospital beds in areas heavily affected by high temperatures and where the local community is particularly sensitive to such conditions.[1]

Building on this context, this article examines the determinants of population vulnerability to heat waves through the lens of environmental, demographic, and socioeconomic characteristics, across different regions of France. For that purpose, we first collect the number of hospitalizations and ERVs for each area corresponding to a *Territoire de vie santé* (TVS), which is a geographic unit created by the French Directorate for Research,

[1] During the COVID-19 crisis, a similar situation arose, with patients being transferred between areas due to the limited availability of hospital beds.

Studies, Evaluation, and Statistics (DREES). Second, we rely on the literature to identify the various dimensions affecting the population's vulnerability to heat waves. These dimensions predominantly pertain to the environmental, socioeconomic and the demographic status of the population. For instance, age is a crucial factor of vulnerability since heat alters thermoregulation, which older adults and young children have difficulty managing. In addition, people with higher income levels are less vulnerable to heat waves than those with lower income, particularly in France (Vandentorren et al., 2004; Rey et al., 2009).[2] Hence, ethnic minority groups with lower socioeconomic status are more likely to be exposed to heat stress (Harlan et al., 2006).[3] The level of education also shapes how people respond and adapt to heat waves, with higher levels of education associated with greater awareness of heat-related vulnerabilities and with a healthier lifestyle (Johnson et al., 2009). Finally, population density, particularly in urban areas, exacerbates the phenomenon of heat island effect, which plays a crucial role in intensifying extreme heat events. (Robine et al., 2008).[4] Consequently, we identify three sets of variables that may help explain population vulnerability to heat waves. First, for the *environmental* set, we use: (i) the average summer temperature, (ii) the vegetalization rate, and (iii) air quality. For the *demographic* set, we include: (i) population density and density of urban development, (ii) age distribution, (iii) gender, and for the *socioeconomic* set, we consider: (i) access to healthcare, (ii) deprivation, (iii) social isolation, (iv) wealth, (v) capital, (vi) income, (vii) education, (viii) building characteristics (including air conditioning and number of rooms), (ix) the share of foreigners, and (x) the proportion of outdoor workers, reflected by the share of employment in agriculture. As a final step, we relate the metrics of nonfatal health outcomes, hospitalizations and ERVs, to our set of variables describing the characteristics of the cities within each TVS using

[2]This is due to the fact that wealthier people live in better homes equipped with air conditioning, have more access to healthcare and social services, and a higher adaptive capacity to changing conditions.

[3]Although most of the research highlighting the different impacts of heat waves on different ethnic groups was conducted in the United States (O'Neill et al., 2003), similar findings might be expected in France given the presence of disadvantaged minorities.

[4]Urban areas, for instance, were the most affected by the 2003 European heat wave. However, although the impact of heat waves on cities is often emphasized due to the heat island effect, non-urban areas—characterized by high sensitivity and low adaptive capacity—are also highly vulnerable.

Ordinary Least Squares method.

Our results indicate that areas with a higher concentration of individuals vulnerable to extreme heat are, unsurprisingly, those most exposed to high temperatures during the summer months. Beyond this natural factor, we find that social isolation significantly increases vulnerability. In contrast, wealthier areas and areas with greater vegetation coverage tend to have populations that are less vulnerable. Additional findings show that, on the one hand, age (whether young or old) and social factors (such as foreign status, education level, or social deprivation) do not appear to have a significant impact, which suggests that these social characteristics do not act as barriers to accessing healthcare. On the other hand, economic factors such as income and wealth play a crucial role in reducing vulnerability. We interpret this as evidence that these factors enhance individuals' ability to adapt during extreme heat events.

This article relates to research examining the association between temperature variability and morbidity, analyzed through climatic, socioeconomic, and demographic lenses. The study most similar to ours is that of Sabri et al. (2024), who consider the effects of heatwaves, environmental factors, and demographic variables on healthcare needs in Paris, proxied by information about hospital stays spanning from June to September over the years 2009 to 2019.[5] They consider various variables based on their implications for the population's vulnerability to heat effects, such as the index of social disadvantage values, building ages, the percentage of residents above 75 years old, prevalence of air conditioning, and availability of elevators. They find that the age group over 75 was identified as the most significant factor influencing hospitalization rates. Expanding the scope of the analysis to 1814 Brazilian cities, Xu et al. (2020) found significant associations between temperature variability and hospitalisation associations across sex, age groups, specific causes, and geographical regions during the period 2000–2015. Specifically, the hospitalisation risk due to every 1°C increase in the temperature variability in the current and previous day increased by 0.52%, and the vulnerability was especially

[5] These detailed information are the purpose of hospitalization, the residential location, and hospitalization dates.

relevant for people aged 0–19 year, 60 years or older, and for lower-middle incomes. Our contribution in the existing literature is thus threefold. First, we create a set of socioeconomic, demographic and environmental variables at the TVS scale. Second, we estimate the determinants of nonfatal health outcomes due to heat waves in France through these multifaceted dimensions. Third, we are the first to provide evidence of population's vulnerability to extreme temperatures at a national scale.

This paper is organized as follows. Section 2 presents the data and stylized facts about the nonfatal health outcomes. Section 4 introduces the empirical setup and section **??** describe the blocks of variables used to investigate the determinants of population's vulnerability to heat waves. Section 5 reports the main results.Section 6 concludes.

2 The "Territoire de vie santé"

To conduct our study, we aggregate municipal data at the level of healthcare service territories, proxied by the *Territoire de Vie Santé* (TVS), which is a territorial unit defined as an aggregation of municipalities organized around a central hub providing essential services and infrastructure.[6] Each TVS consists of a cluster of municipalities, which are grouped around a service hub or urban center. The grouping criteria prioritize the proximity and accessibility of services for the residents within the territory. Notably, each municipality belongs to a single TVS, with the exception of the three largest French cities : Paris, Marseille and Lyon. In these cities, municipal districts (*arrondissements*) work as independent TVSs due to their distinct administrative and service structures.[7] Furthermore, the boundaries of a TVS may transcend regional or departmental borders, as the territorial grouping is determined by the functional relationship of municipalities to a central hub, rather than strictly adhering to administrative limits.[8]

[6] This delineation closely mirrors the concept of "living areas" which used by the INSEE to identify the smallest geographic areas within which residents have access to the most common and essential services and facilities. TVSs are the adaptation of these areas to health related issues, done by the DREES.

[7] In our study, we exclude these municipal districts as they differ from other cities in many dimensions, and therefore could be seen as outliers in our econometric analysis.

[8] In cases where new municipalities are created through mergers involving multiple TVSs, the newly formed municipality is assigned to the TVS corresponding to the municipality whose INSEE code it inherits. Similarly, if the merging municipalities serve as service hubs within their respective TVSs, the

The TVS framework is specifically designed to address challenges related to geographic access to healthcare. By structuring territories around service hubs, the TVS serves as a practical basis for identifying and mitigating disparities in healthcare provision across different areas. As an illustration, Legendre (2015) examines the distribution of general practitioners and finds that nearly 6% of the population resides in territories undeserved by general practitioners. Gautier and Josseran (2024) examine the organization of primary care in France, while Davin-Casalena et al. (2023) explore the acceptance of new patients by general practitioners. Finally, Chevillard and Mousquès (2020) analyze the ability of health centers to attract young doctors.

Against this backdrop, we consider that the TVS represents an appropriate scale for analyzing the effects of heat waves on the number of hospitalizations and ERVs in France for multiple reasons. First, the TVSare specifically designed to group populations based on access to healthcare infrastructure, rather than relying on administrative boundaries. This distinction is particularly useful for analyzing hospitalizations during heat waves, as healthcare utilization is driven by accessibility and proximity to services. Since the TVS encapsulate real-world healthcare access patterns, they allow for a more nuanced understanding of hospital admissions triggered by heat-related illnesses, especially in vulnerable populations such as the elderly or those with chronic health conditions. By studying data at this scale, we can capture the localized effects of heat waves on healthcare demand without any distortion caused by aggregating data over larger, less homogeneous administrative regions. Second, heat wave impacts are inherently localized due to spatial variations in temperature and humidity. In this context, the TVS scale provides a valuable framework for integrating environmental and health data since its boundaries align closely with geographical and climatic variation. In a nutshell, the TVS scale ensures that environmental and health data are analyzed within territories that share similar exposure to heat-related risks. Finally, TVS are the operational units used by French healthcare authorities to design and implement policies aimed at reducing geographic disparities in healthcare access (Legendre, 2015).

latter are merged into a single unified territory.

Against this backdrop, conducting research at the TVS level ensures that our findings are directly relevant to policymakers and healthcare planners. For example, understanding how heat waves impact hospitalizations within specific TVS can inform resource allocation decisions, such as increasing hospital capacity, deploying mobile medical units, or establishing cooling centers in the most affected areas. Actionable insights derived from TVS-level research can contribute to more effective public health interventions and preparedness strategies.

To account for the nonfatal-health outcomes at the TVS scale, two variables are considered, *erv*, which represents the number of ERVs due to heat-related issues, and *hospits*, the number of ERVs followed by hospitalization due to heat. These two variables are produced by *Santé Publique France* and measured at the establishment level (hospital or other forms of emergency facility) for each municipality, which we can then link to a TVS.[9] Figures 1 and 2 show the number of hospitalisations and ERVs due to heat waves. Both figures show that these two metrics are not uniformly distributed at the country level, with areas more heavily impacted than others, such as the North and the East of France. These figures also show that these data are not available in many municipalities located in the West and the South West and South East of France.

[9]Hospital centers are typically located in the municipality that serves as the hub of the TVS, though this is not always the case. If two establishments are located within the same TVS, we consider the sum of both.

Figure 1: Number of hospitalisations by TVS (2022)

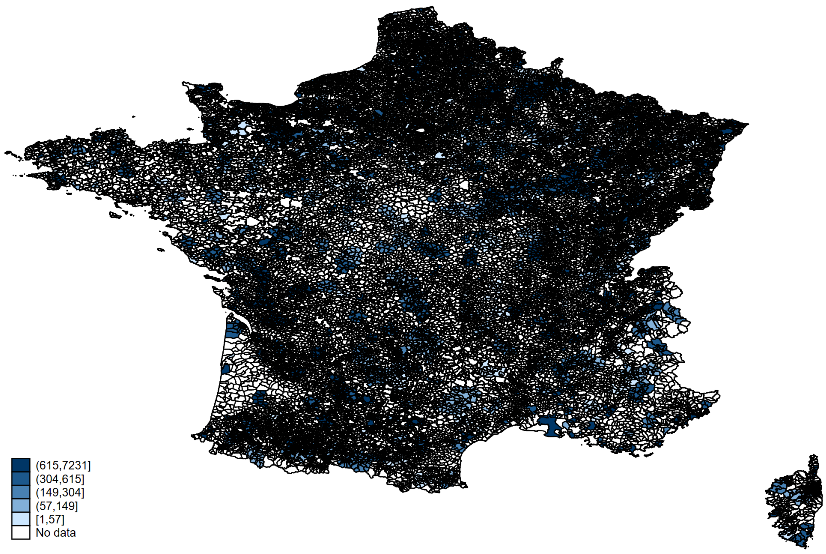
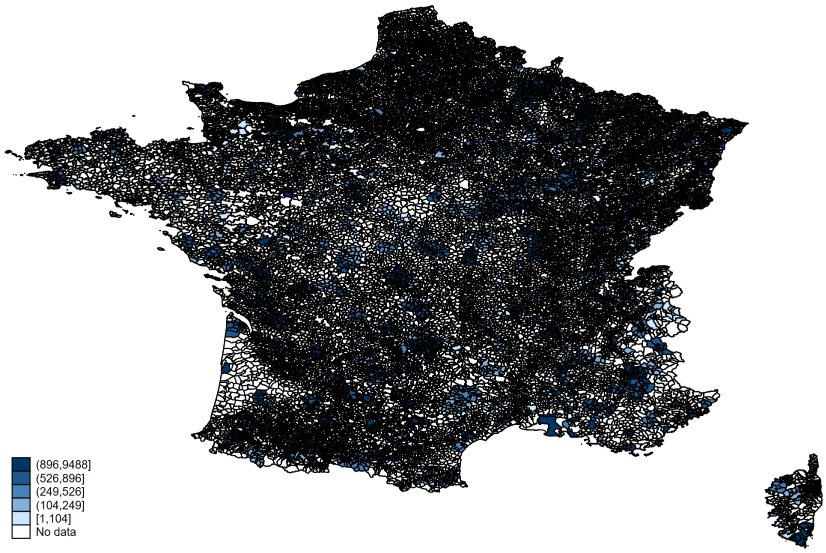


Figure 2: Number of emergency room visits by TVS (2022)



3 Theoretical framework

Our approach relies on a broad literature about *vulnerability*, which is defined in the context of climate change as "*the degree to which a system is susceptible to, or unable to* *cope with, adverse effects of climate change, including climate variability and extremes. Vulnerability is a function of the character, magnitude, and rate of climate change and variation to which a system is exposed, its sensitivity, and its adaptive capacity*" (Watson et al., 2001). Following McCarthy (2001), the literature generally assume that vulnerability relies on three main factors : (i) exposure, which refers to "the nature and degree to which a system is exposed to significant climatic variations". (ii) sensitivity, which is "to the degree to which a system is affected, either adversely or beneficially, by climate-related stimuli", and (iii) adaptive capacity, that can be seen as "the ability of a system to adjust climate change". Therefore, following Szagri et al. (2023), vulnerability can be represented as: $Vulnerability = Exposure + Sensitivity - Adaptive\ capacity$

For the purposes of our study, we refine these definitions as follows. First, we define *vulnerability* as the degree to which extreme temperatures affect health. At the individual level, vulnerability can be measured by the severity of symptoms caused by extreme heat. At the territorial level, it can be understood as the scope of the phenomenon within the population or the number of people affected. As described in section **??**, we consider two metrics to capture vulnerability: hospital admissions and emergency room visits (ERVs), both explained by heat-related symptoms. Second, from an empirical perspective, *exposure* can be understood as the intensity of a shock or the severity of the hazard. Our objective is to identify factors that account for why, in specific climate contexts, one region might face greater consequences from extreme temperatures compared to another. In other words, we seek to identify the territorial characteristics that amplify the impact of the event or hazard. Factors such as air quality, population density, and the proportion of vegetated surfaces are key considerations in this context. Third, we consider *sensitivity* as a dimension of vulnerability that reflects individual characteristics that can explain the extent of health deterioration following a shock. This includes factors such as advanced age and socioeconomic variables like social isolation or being a foreigner. Finally, *adaptive capacity* can be defined as the ability of individuals to access tools or resources that help them mitigate the effects of a heatwave. This includes access to air conditioning, medical infrastructure, or the flexibility to adjust work schedules based on temperature conditions.

This theoretical framework, though broadly endorsed, presents difficulties when attempting to convert it into an explicit empirical methodology. Many variables appear to simultaneously influence sensitivity, exposure, and adaptive capacity. Consider, for example, an individual's income: it is an inherent characteristic, categorized under sensitivity by Szagri et al. (2023). However, one could also argue that a wealthy person is more likely to live in a less densely populated area, such as a villa surrounded by a shaded garden, which mitigates the hazard and reduces exposure to extreme temperatures. Moreover, wealthier households are more likely to have air conditioning, thus enhancing their capacity to adapt. The same complexity applies to social isolation: a person living alone (a characteristic linked to sensitivity) is more likely to reside in a smaller apartment, which can increase exposure. Furthermore, in the event of health issues, social isolation reduces the likelihood of receiving immediate first aid from nearby friends or family members when mild symptoms appear, thereby limiting adaptive capacity.

Therefore, while the theoretical framework of vulnerability proves useful for guiding our analysis and interpreting our results, it appears essential to complement it with a more pragmatic framework that aligns with our empirical approach. Specifically, the variables representing exposure, sensitivity, and adaptive capacity can be categorized into three groups based on what they reveal about the studied territories: socio-economic, environmental, and demographic variables.

4 Data and Empirical setup

4.1 Data and Stylized facts

As mentioned in Section XX, we use three sets of data to highlight the determinants of the vulnerability of the population to heat waves.

- **The environmental data.** We first use temperature as a measure of exposure to extreme heat, measured at the land surface during the summer period (average temperature for the summer of 2022, June, July, and August, in °C). We use data from Carbonnel et al. (2023), extracted from Copernicus via the Historical Weather API, which allows us to query daily average temperatures for specific geographic coordinates at a given date range. We use the average temperature of the land surface over the entire TVS zone. Second, vegetalization measures the percentage of vegetative cover in a territory, and is used to capture the potential for urban heat islands and their mitigation. We use data from Carbonnel et al. (2023), extracted from the Corine Land Cover (CLC) database, which is available in the French government's website.[10]

- **The demographic data.** Based on the literature, we consider three demographic dimensions in which TVS may vary from one another: (i) population density, measured as the number of inhabitants per square kilometer, (ii) age distribution and (iii) gender. Regarding age, we consider three metrics: the average age of the population, the proportion of children (under 14 years of age) and the proportion of elderly individuals (over 60 years of age).[11]

- **The socioeconomic data.** To assess socioeconomic conditions, we first examine wealth and income levels within the territory. Wealth is measured by the proportion of homeowners, as real estate represents the primary form of wealth in France. Capital is defined as real estate capital per capita relative to the national average, while income is assessed through municipal GDP as a percentage of the national average. Next, we consider household characteristics, including the proportion of single-person households, the percentage of individuals aged 25 and older with a higher education qualification, and the share of the foreign population within the territory. In addition, we analyze two variables related to housing:

[10]The following types of areas are classified as vegetated: urban green spaces, orchards and small fruit plantations, olive groves, grasslands and other permanent agricultural grass surfaces, agroforestry areas, broad-leaved forests, coniferous forests, mixed forests, natural grasslands and pastures, heathlands and scrubs, sclerophyllous vegetation, transitional woodland and shrub vegetation, and sparse vegetation.

[11]All demographic data are obtained from the INSEE database. In particular, we use the base "Population municipale des communes - France entière" that contains the data of the municipal population census in the French communes, and the database "Couples - Familles- Ménages" that provides data on the characteristics of households (age, marital status, socio-professional category, etc).

the percentage of air-conditioned buildings and the average number of rooms per residence. Finally, we include a composite indicator of social disadvantage, the Deprivation Index, where higher scores indicate higher levels of deprivation.[12]

4.2 Empirical setup

The aim of our empirical approach is to identify the factors across socio-economic, environmental, and demographic dimensions that influence the impact of extreme temperatures on morbidity. The two metrics considered to capture the nonfatal health outcomes of heat waves will alternatively figure at the left-hand side of the following equation:

$$y_i = \alpha + \gamma E_i + \beta S_i + \mu D_i + \epsilon_i; \tag{1}$$

where y_i is the vector of outcome variables (hospital admissions or ERV), with subscript i representing the TVS area. On the right-hand side, three matrices are considered. E_i represents the set of variables related to the *environment*, the matrix S_i represents our set of *socioeconomic* variables, while matrix D_i is related to the *demographic* characteristics of the TVS territory i. Matrix size $(m.n)$ is given by the number of TVSs covered (m) and the number of variables considered in the matrix (n) times. Finally, ϵ_i is the error term (size m), which captures the individual specificities of TVS. The vectors γ, β, μ (size n) are estimated with an OLS approach. To avoid issues of collinearity, we do not estimate all the variables simultaneously but test them individually, typically when their characteristics are similar (such as wealth and capital).

It is worth noting that there is no temporal dimension in our empirical specification given that all observations are made at a specific point in time. For the outcome variables, we have data on hospital admissions and ERV for each location from 2012 to 2022. However, the set of explanatory variables, which capture the socioeconomic, environmental and demographic characteristics of the TVS territories, are measured at

[12] This index is derived from the first principal component of a weighted principal component analysis based on four key variables: the unemployment rate, the proportion of manual laborers, the proportion of high school graduates, and the median income.

a fixed point in time, typically 2022.

5 Results

5.1 Baseline results

Table 1 depicts the coefficients estimated from eq. (1). We observe that variables related to the environmental and the socieconomic sets are significantly associated to nonfatal health outcomes related to heat waves. Specifically, we find these outcomes to be positively associated to temperature and social isolation, while the relationship with capital, vegetalization and the number of rooms is negative. Interestingly, these relationships are similar, is terms of sign and significance, regardless of the metric used to assess morbidity, except for capital which is not significantly associated with the number of hospitalisations. Hence, these results provide first evidence of the importance of considering socioeconomic and environmental factors when gauging the effect of heat waves on non fatal health outcomes.

Table 1: Baseline estimations

	(1)	(2)
	erv	*hospits*
temperature	94.20***	54.20***
	(24.57)	(18.93)
isolation	3952.93***	2487.74***
	(826.25)	(645.18)
capital	-200.48**	-127.85
	(100.98)	(82.13)
vegetalization	-3.81***	-2.43**
	(1.44)	(1.13)
rooms	-384.07**	-222.30*
	(157.57)	(121.46)
constant	-1014.89	-561.38
	(986.31)	(759.30)
N	492	485

5.2 Demography

Tables 2 and 3 show the estimated results when including variables related to the demographic set. Beyond the sociological variables (age and gender), we also incorporate urban density by categorizing municipalities based on their population density.[13] On the one hand, we find that temperature and social isolation are still relevant to explain the relationship between heat waves and nonfatal health outcomes. On the other hand, socioeconomic and environmental variables, proxied by capital, the number of rooms and vegetalization, are no longer significant when including the demographic variables, in particular age. However, while age doesn't seem to be an explanatory factor, female population are more likely to be hospitalized and to visit emergencies following a heat wave. Finally, urban density, in particular for highly dense municipalities, exacerbate the health impact of heat waves.

[13]density val = 4 if "Densely populated municipalities"; density val = 3 if ""municipalities with intermediate density"; density val = 2 if "Sparsely populated municipalities"; density val = 1 if "Very sparsely populated municipalities".

Table 2: Demography and the ERVs

	(1)	(2)	(3)	(4)	(5)	(6)
	erv	erv	erv	erv	erv	erv
temperature	83.17***	94.40***	106.58***	104.28***	97.54***	87.48***
	(24.56)	(24.63)	(24.65)	(24.36)	(24.96)	(24.50)
isolation	3792.35***	4231.90***	4704.17***	4601.78***	4380.23***	3412.74***
	(814.03)	(831.84)	(1162.73)	(1149.50)	(1432.17)	(888.76)
capital	-126.84	-247.75**	-162.00	-180.41*	-181.90	-236.53**
	(109.39)	(100.88)	(112.18)	(106.94)	(115.35)	(101.65)
vegetalization	-4.81***	-1.60	-2.67*	-3.03**	-3.49**	-3.73***
	(1.41)	(1.60)	(1.61)	(1.52)	(1.53)	(1.42)
rooms	-518.73***	-270.27	-228.87	-252.64	-338.89	-408.85***
	(164.36)	(170.52)	(239.40)	(233.50)	(222.92)	(156.25)
2.density_val_m		105.57				
		(86.77)				
3.density_val_m		250.36***				
		(90.31)				
4.density_val_m		437.50***				
		(108.82)				
mean age			-23.81			
			(18.04)			
old age				-1154.75		
				(980.52)		
youg age					1067.31	
					(2439.07)	
female pop						6253.67*
						(3383.10)
constant	-138.27	-1961.11*	-1260.89	-1724.47	-1650.60	-3768.11**
	(995.78)	(1054.52)	(1067.44)	(1320.17)	(1999.24)	(1785.87)
N	492	492	492	492	492	492

Table 3: Demography and the number of hospitalisations

	(1) hospits	(2) hospits	(3) hospits	(4) hospits	(5) hospits	(6) hospits
temperature	45.93**	54.29***	61.76***	60.93***	54.09***	48.14**
	(18.88)	(18.98)	(19.79)	(19.45)	(19.93)	(18.84)
isolation	2392.23***	2711.83***	2937.33***	2906.45***	2473.55**	1999.28***
	(640.43)	(648.90)	(930.36)	(915.81)	(1151.79)	(694.19)
capital	-69.56	-161.84**	-104.67	-114.48	-128.47	-159.68*
	(87.54)	(81.82)	(91.61)	(87.14)	(94.07)	(82.02)
vegetalization	-3.20***	-0.73	-1.75	-1.93	-2.44**	-2.36**
	(1.14)	(1.28)	(1.28)	(1.20)	(1.22)	(1.11)
rooms	-321.85**	-131.77	-128.57	-135.98	-223.80	-243.69**
	(128.46)	(132.94)	(190.08)	(185.57)	(175.93)	(120.14)
2.density_val_m		0.57				
		(66.48)				
3.density_val_m		197.35**				
		(76.43)				
4.density_val_m		313.85***				
		(87.87)				
mean age			-14.15			
			(14.17)			
old age				-745.50		
				(771.84)		
youg age					-35.13	
					(1898.91)	
female pop						5678.53**
						(2690.95)
constant	79.58	-1284.23	-719.43	-1030.15	-540.30	-3068.27**
	(779.99)	(811.48)	(846.98)	(1069.75)	(1625.89)	(1399.20)
N	485	485	485	485	485	485

5.3 Economic variables

When adding extra variables related to the economic dimension of the territories within the TVS (see tables 4 and 5), we first observe that all variables included in the baseline estimation are still significant and with a similar sign, except for the number of rooms. Second, we find that all economic variables included, i.e. wealth and income, are significantly and negatively associated with ERV and the number of hospitalisation.

Table 4: Economic variables and ERVs

	(1)	(2)	(3)
	erv	erv	erv
temperature	94.20***	108.01***	90.68***
	(24.57)	(23.67)	(24.49)
isolation	3952.93***	4280.79***	4267.30***
	(826.25)	(778.35)	(796.03)
vegetalization	-3.81***	-2.79**	-3.72***
	(1.44)	(1.36)	(1.42)
rooms	-384.07**	89.23	-321.88**
	(157.57)	(239.43)	(135.96)
capital	-200.48**		
	(100.98)		
wealth		-1808.89**	
		(776.08)	
income			-153.02**
			(69.16)
constant	-1014.89	-2512.26***	-1348.43
	(986.31)	(914.39)	(898.69)
N	492	492	492

Table 5: Economic variables and the number of hospitalisations

	(1) hospits	(2) hospits	(3) hospits
temperature	54.20***	64.77***	52.48***
	(18.93)	(18.50)	(18.93)
isolation	2487.74***	2672.92***	2728.24***
	(645.18)	(608.57)	(616.49)
vegetalization	-2.43**	-1.71	-2.34**
	(1.13)	(1.06)	(1.11)
rooms	-222.30*	117.98	-171.86*
	(121.46)	(185.49)	(103.80)
capital	-127.85		
	(82.13)		
wealth		-1347.19**	
		(596.56)	
income			-72.33
			(48.97)
constant	-561.38	-1590.20**	-867.75
	(759.30)	(712.18)	(682.16)
N	485	485	485

5.4 Social variables

While the literature indicates that foreign status and greater deprivation increase vulnerability to heat waves (O'Neill et al., 2003), education is generally associated to lower exposure to nonfatal health outcomes (Johnson et al., 2009). To test these hypotheses, we introduce the corresponding variables in eq. (1). The results show that the larger the share of the foreign population in the TVS, the higher the ERVn (column (2) in table 6). However, the coefficients associated to education and deprivation are not significant to explain ERVs and the number of hospitalisations.

Table 6: Social variables and the ERVs

	(1)	(2)	(3)	(4)	(5)	(6)
	erv	erv	erv	erv	erv	erv
temperature	92.29***	103.45***	94.19***	107.46***	94.53***	109.73***
	(24.49)	(26.30)	(24.71)	(26.77)	(24.46)	(26.72)
isolation	3549.58***	5480.31***	3958.25***	5551.55***	4276.93***	5619.96***
	(1074.05)	(743.64)	(910.42)	(799.16)	(889.36)	(759.53)
capital	-224.50**		-199.05		-64.56	
	(111.00)		(143.48)		(150.39)	
vegetalization	-3.94***	-4.08***	-3.82**	-4.97***	-3.55**	-5.04***
	(1.44)	(1.38)	(1.48)	(1.53)	(1.40)	(1.41)
rooms	-494.15**		-384.12**		-352.03**	
	(248.20)		(158.25)		(161.51)	
foreigner	-881.04	1164.40*				
	(1173.21)	(683.28)				
education			-9.11	-82.19		
			(739.59)	(441.27)		
deprivation					55.69	44.94
					(51.67)	(30.58)
constant	-282.68	-3608.52***	-1014.87	-3583.00***	-1428.32	-3702.06***
	(1538.67)	(702.17)	(987.58)	(698.16)	(1023.63)	(693.56)
N	491	491	492	492	492	492

Table 7: Social variables and the number of hospitalisations

	(1) hospits	(2) hospits	(3) hospits	(4) hospits	(5) hospits	(6) hospits
temperature	53.36***	59.21***	54.52***	61.41***	54.31***	62.89***
	(19.21)	(19.94)	(19.10)	(20.43)	(18.90)	(20.51)
isolation	2307.58***	3370.64***	2354.16***	3375.86***	2605.60***	3445.85***
	(849.88)	(583.72)	(717.88)	(630.62)	(702.48)	(596.89)
capital	-138.68		-163.69		-78.24	
	(88.51)		(115.33)		(123.72)	
vegetalization	-2.48**	-2.53**	-2.35**	-2.98**	-2.33**	-3.08***
	(1.13)	(1.07)	(1.16)	(1.19)	(1.11)	(1.09)
rooms	-271.52		-220.70*		-210.85*	
	(189.93)		(121.94)		(124.97)	
foreigner	-396.67	689.86				
	(842.66)	(480.93)				
education			228.38	15.48		
			(585.10)	(357.59)		
deprivation					20.31	23.71
					(40.90)	(24.67)
constant	-234.13	-2067.29***	-563.00	-2055.65***	-710.84	-2118.11***
	(1223.47)	(540.17)	(760.08)	(536.86)	(807.42)	(535.79)
N	484	484	485	485	485	485

6 Conclusion

Heat waves are expected to become increasingly frequent in France. In this context, understanding their impact on public health is essential. This paper aims to assess which populations are most vulnerable to extreme heat. To do so, we identify the environmental, demographic, and socioeconomic factors that explain heat-related hospital admissions and emergency room visits.

Our study aggregates municipal data at the level of healthcare service areas, using *Territoire de Vie Santé* (TVS) as a proxy. These units group municipalities based on functional ties to a central hub offering essential services, rather than administrative boundaries. Since TVSs are designed around healthcare access, they provide a relevant scale for analyzing hospitalizations and emergency visits during heat waves, where service proximity plays a key role.

Our findings reveal that the most heat-vulnerable populations are concentrated in areas experiencing the highest summer temperatures. Beyond this environmental factor, social isolation emerges as a major contributor to vulnerability. In contrast, regions with higher income levels and greater vegetation coverage tend to have more resilient populations. Further analysis indicates that age (whether young or elderly) and social characteristics (such as immigrant status, education, or deprivation) do not significantly influence vulnerability, suggesting that these factors do not hinder healthcare access. Instead, economic variables like income and wealth appear to be key in reducing heat-related risks, likely by enhancing individuals' capacity to adapt to extreme temperatures.

To mitigate the impact of heat waves on public health, policymakers should focus on strategies that address both climate change adaptation and socio-economic resilience. Urban planning policies should prioritize increasing green spaces and vegetation coverage, as these have proven to reduce heat vulnerability and provide cooling benefits in densely populated areas. Given the role of social isolation in exacerbating heat-related health risks, strengthening support networks for isolated individuals is crucial. This could include community outreach programs, better access to health services, and targeted interventions for vulnerable groups. Moreover, urban density planning should ensure adequate space and air circulation, which would prevent overheating, especially in high-density areas. These measures will help build resilience, reduce health risks, and improve outcomes as heat events become more frequent due to climate change.

As a next step, we aim to extend this study by using projected temperatures for France in 2050 to estimate future healthcare demand under extreme heat conditions, assuming alternative socioeconomic scenarios.

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