Preventive Medicine 173 (2023) 107587

Contents lists available at ScienceDirect

Preventive Medicine

journal homepage: www.elsevier.com/locate/ypmed

Functional forms of socio-territorial inequities in breast cancer screening – A French cross-sectional study using hierarchical generalised additive models

Quentin Rollet [a,b,*], Aimilia Exarchakou [a], Guy Launoy [b], Ophélie Merville [b], Francisco J. Rubio [c], Aurélien Belot [a]

[a] Inequalities in Cancer Outcomes Network (ICON), Department of Non-Communicable Disease Epidemiology, Faculty of Epidemiology and Population Health, London School of Hygiene and Tropical Medicine, Keppel Street, London WC1E 7HT, UK
[b] U1086 "ANTICIPE" INSERM, University of Caen Normandie, Centre François Baclesse, 3, Avenue du Général Harris, Caen 14000, France
[c] Department of Statistical Science, University College London, Gower St, London WC1E 6BT, UK

ARTICLE INFO

Keywords:
Hierarchical generalised additive model
Early detection of cancer
Breast neoplasms
Social inequities
Territorial inequities
Socio-economic environment

ABSTRACT

To reduce the breast cancer burden, the French National Organised Breast Cancer Screening Programme (FNOBCSP) was implemented in 2004. The recommended participation rate has never been achieved and socio-territorial inequities in participation have been reported on several occasions. We investigated the functional forms and consistency of the relationships between neighbourhood deprivation, travel time to the nearest accredited radiology centre and screening uptake. We used two-level hierarchical generalised additive models in 8 types of territories classified by socio-demographic and economic factors. The first level was 368,201 women aged 50–72 invited to the 2013–2014 screening campaign in metropolitan France. They were nested in 41 *départements*, the level of organisation of the FNOBCSP. The effect of travel time showed two main patterns: it was either linear (with participation decreasing as travel time increased) or participation first increased with increasing travel time to a peak around 5–15 min and decreased afterward. In nearly all types and *départements*, the probability of participation decreased linearly with increasing deprivation. Territorial inequities in participation were more context-dependent and complex than social inequities. Inequities in participation represent a loss of opportunity for individuals who already have the worst cancer outcomes. Evidence-based public health policies are needed to increase the effectiveness and equity of breast cancer screening.

1. Background

Breast cancer is the most common cancer localisation and the leading cause of cancer deaths in women worldwide (Sung et al., 2021), in Europe (European Cancer Information System, 2023) and in France (Defossez et al., 2021). To reduce this burden (Lauby-Secretan et al., 2015), the European Union recommended the implementation of population-based organised cancer screening programmes in 2003 (European Union, 2003).

The French National Organised Breast Cancer Screening Programme (FNOBCSP) was implemented nationally in 2004 (Santé publique France, 2023). Women aged 50–74 at average risk for breast cancer are invited by screening management structures to perform, every two years, a free of charge mammography and a clinical breast exam in an accredited radiology centre. Alongside this practice, France has maintained opportunistic screening (Quintin et al., 2022).

Despite 18 years of implementation, overall participation has always been lower than the European recommendation of 70%. It peaked at 52% in 2011–2012 and has declined ever since (Santé publique France, 2022). Significant inequities in participation have been reported. Social inequities refer to the differences in participation that are observed between social groups. In previous studies, except one that showed an inverse U-shaped relationship between participation and area-based deprivation (Deborde et al., 2018), screening uptake was consistently lower among individuals with lower social status (income, number of adverse economic conditions, education, occupation) or in less favourable environments (area-based deprivation) (Rollet et al., 2021a; Kelly et al., 2017; Menvielle et al., 2014; Guillaume et al., 2017; Ouédraogo

* Corresponding author at: London School of Hygiene and Tropical Medicine, Keppel Street, London WC1E 7HT, UK.
E-mail address: Quentin.rollet@inserm.fr (Q. Rollet).

https://doi.org/10.1016/j.ypmed.2023.107587
Received 23 January 2023; Received in revised form 15 June 2023; Accepted 21 June 2023
Available online 23 June 2023

et al., 2014; Poiseuil et al., 2019; Ouanhnon et al., 2022; Duport, 2012). Territorial inequities refer to the differences in participation that are related to the geographical location of individuals and services. In France, participation in breast cancer screening varies with individuals' physical proximity to accredited radiology centres but also more general measure of accessibility such as potential localised accessibility to the general practitioner or urbanicity of the area of residence (Rollet et al., 2021a; Guillaume et al., 2017; Ouédraogo et al., 2014; Ouanhnon et al., 2022).

We led a first study, using the hierarchical generalised linear framework (Lee and Nelder, 1996), showing that the strength of inequities in participation based on area-based deprivation and travel time to the nearest accredited radiology centre varied according to the *départements* level, the level of operational organisation of the FNOBCSP during the years covered by our data (Rollet et al., 2021a). We assumed log-linear relationship between the predictors and the outcome. This allowed us to identify overall trends, but not to describe the functional forms of the relationships. This might have led to some residual confounding because of an oversimplification (Benedetti and Abrahamowicz, 2004). This study was designed to identify differences between *départements*, geographical units resulting from an administrative division of the territory. They have high heterogeneity in terms of population size, density, socio-demographic characteristics, and lifestyle. This left an open question about whether inequities in participation are modulated by the socio-demographic and economic characteristics of the context (called types of territory hereafter).

The aim of this study was to evaluate whether the functional forms of social and territorial inequities in breast cancer screening participation were consistent across types of territory beyond and accounting for the differences existing across the levels of organisation using hierarchical generalised additive models (HGAM) (Wood, 2006). This question is important as it can help elucidate whether a uniform policy would be enough to reduce such inequities, or if more territory-specific policies are needed.

2. Methods

Preparation of this article followed the Strengthening the Reporting of Observational Studies in Epidemiology guidelines (von Elm et al., 2014). The study protocol was approved by the *Commission Nationale de l'Informatique et des Libertés* (authorization no. 917208).

2.1. Population and sample

Data selection process is described in Appendix 1. We received data from 41 voluntary screening management structures in metropolitan France. The process has already been described in our previous study (Rollet et al., 2021a). After data management (duplicates, ineligible dates or places: $n = 234{,}841$) we identified 4,001,225 women aged 50–74 (42% of the eligible population in France) invited between 2013 and 2014 to undergo a screening mammography within two years. We randomly drew 10% of the population in each *département* to allow geolocation (*i.e.*, identifying the geographical location) of individuals' places of residence ($n = 400{,}125$). After further data management (ungeocodable addresses and ineligible locations: $n = 2527$) and the exclusion of women invited after 72 years ($n = 29{,}397$) because not all of them were followed up after the eligible age, the analytic sample included 368,201 women.

2.2. Variables

Data included individuals' age at invitation, whether a mammography was performed through the FNOBCSP in the two years following the invitation, and their home address. The geolocation of individuals enabled us to assign the 2011 French version of the European Deprivation index (Pornet et al., 2012) and the typology. After geolocation of the accredited radiology centres, we computed the travel time to the nearest for all individuals.

2.2.1. French version of the European Deprivation index (F-EDI)

The F-EDI is an area-based ecological index based on census data defined at the IRIS level ("*Îlots Regroupés pour l'Information Statistique*"). These IRIS are proxies for neighbourhoods in nearly all municipalities with more than 5000 inhabitants or the municipalities themselves otherwise (Insee, 2023). A higher F-EDI score reflects higher deprivation (*i.e.*, a greater lack of access to fundamental needs associated with objective and subjective poverty for individuals in the IRIS).

2.2.2. Typology

We used Reynard's classification (INSEE, 2014), based on the "*territoires de vie*". It was constructed using 27 indicators covering 14 dimensions of quality of life, resulting in 8 levels. We will refer to "type x" when talking about all individuals in the *territoires de vie* contained in the type x, and "type x *départements*" when talking about the effect between *départements' territoires de vie* contained in type x. These different types were: **Type 1**: Highly urbanised and rather favourable areas, but with socio-economic difficulties and jobs that are often far away. **Type 2**: Rather favourable areas with rapid access to facilities, but with socio-economic difficulties. **Type 3:** Dense and rich territories, but with significant gender disparities. **Type 4:** Rather well-off areas, but far from employment, mainly located in the suburbs. **Type 5:** Rather dense areas in an unfavourable situation. **Type 6:** Small towns in an intermediate situation. **Type 7:** Remote and sparsely urbanised areas outside the influence of major centres. **Type 8:** Areas around medium-sized towns, offering jobs and rather favourable living conditions.

3. Statistical analysis

Descriptive analyses were performed by comparing the characteristics of the population of each type with those of the rest of the sample.

We performed the following modelling strategy separately for each type. The terminology used is based on Pedersen's paper (Pedersen et al., 2019). Model selection was performed using Akaike Information Criteria (AIC) (Akaike, 1998) converted to a relative likelihood scale (Burnham and Anderson, 2004). We set an alpha level of 0.05 (corresponding to a delta AIC of 6) below which the competing models were dismissed. Among the remaining candidates, we retained the simpler model (*i.e.*, the model with the lowest number of degrees of freedom). Details of the regression models are provided in Appendix 2.

We fitted an empty multilevel model (M0) with a fixed and random intercept defined at the *départements* level. We tested a common smoother (model G) successively for age, travel time, F-EDI and a tensor between the two latter. Applying our model selection, we retained one model (M1) among the candidates. For each predictor variable retained in M1, we investigated 5 different possibilities of random effects: random slopes (a linear effect added to the global smoother, model RS), random smooths (a non-linear effect added to the global smoothers) with or without shared wiggliness (models GS and GI), or models without global smoothers with or without shared wiggliness (models S and I). For predictors without common smoother in M1, only the last two models were tested. We used the same order of variables and applied our model selection at each step between the candidate models and the model selected in the preceding step, leading to M2.

Data management, analysis (mgcv package) and illustrations (ggplot2 package) were performed using R Version 4.1.1.

4. Results

4.1. Populations and types

4.1.1. Distribution of the population by types

Distribution of *départements* and individuals by type is available in

Appendix 3.

4.1.2. Description and comparisons of the variables by types

The population characteristics by type are showed in Fig. 1 and Appendix 4. Differences in age at invitation were minor. There were higher differences for mean travel time, ranging from 1.8 min (Type 1) to 12 min (Type 7), mean deprivation, ranging from −4.0 (Type 3) to 6.5 (Type 1), and screening uptake, ranging from 42% (Type 1) to 62% (Type 8).

4.2. Models' results

The results of the model selections are available in Appendixs 5 and 6. Results concerning age at invitation are available in Appendix 7.

4.2.1. Results from M0

The random and fixed intercepts by type are illustrated in Fig. 2 after back transforming these intercepts on the probability scale. For an average *département*, the estimated probability of screening uptake was the lowest in Type 1 (41% [35–47]), followed by Type 3 (42% [35–49]), Type 7 (56% [53–58]), Type 5 (57% [54–59]), Type 6 (57% [55–59]), Type 2 (58% [56–61]), Type 4 (61% [57–64]) and Type 8 (62% [60–63]). The estimated variance of the random intercepts (the inter-*départements* variability) was the lowest in Type 6 ($\sigma^2 = 0.05$ [0.03–0.08]), followed by Type 8 ($\sigma^2 = 0.06$ [0.04–0.10]), Type 3 ($\sigma^2 = 0.07$ [0.01–0.41]), Type 7 ($\sigma^2 = 0.07$ [0.04–0.10]), Type 1 ($\sigma^2 = 0.08$ [0.02–0.31]), Type 5 ($\sigma^2 = 0.08$ [0.04–0.14]), Type 2 ($\sigma^2 = 0.10$ [0.06–0.16]) and Type 4 ($\sigma^2 = 0.14$ [0.08–0.24]).

4.2.2. Results from M1

Travel time to the nearest accredited radiology centre (Fig. 3a). Travel time had no global effect in Types 1 and 3. In the other types, it followed two distinct patterns: participation decreased almost linearly as travel time increased in Types 6 and 7 or participation first increased with travel time, reaching a peak around 5–15 min and decreased afterward in the other types.

Deprivation (Fig. 3b). Except for Types 1 and 3, with no global effect, the link between participation and deprivation followed a simple pattern across different types: participation decreased almost linearly as deprivation increased.

Tensor (Fig. 3c). There was a non-linear interaction between travel time and deprivation for Type 2. Regarding the effect of travel time, the initial increase was stronger as deprivation decreased. After reaching a plateau around 10 min, the decrease was stronger as deprivation increased. Regarding deprivation, participation decreased as deprivation increased, but the slope became steeper as travel time increased.

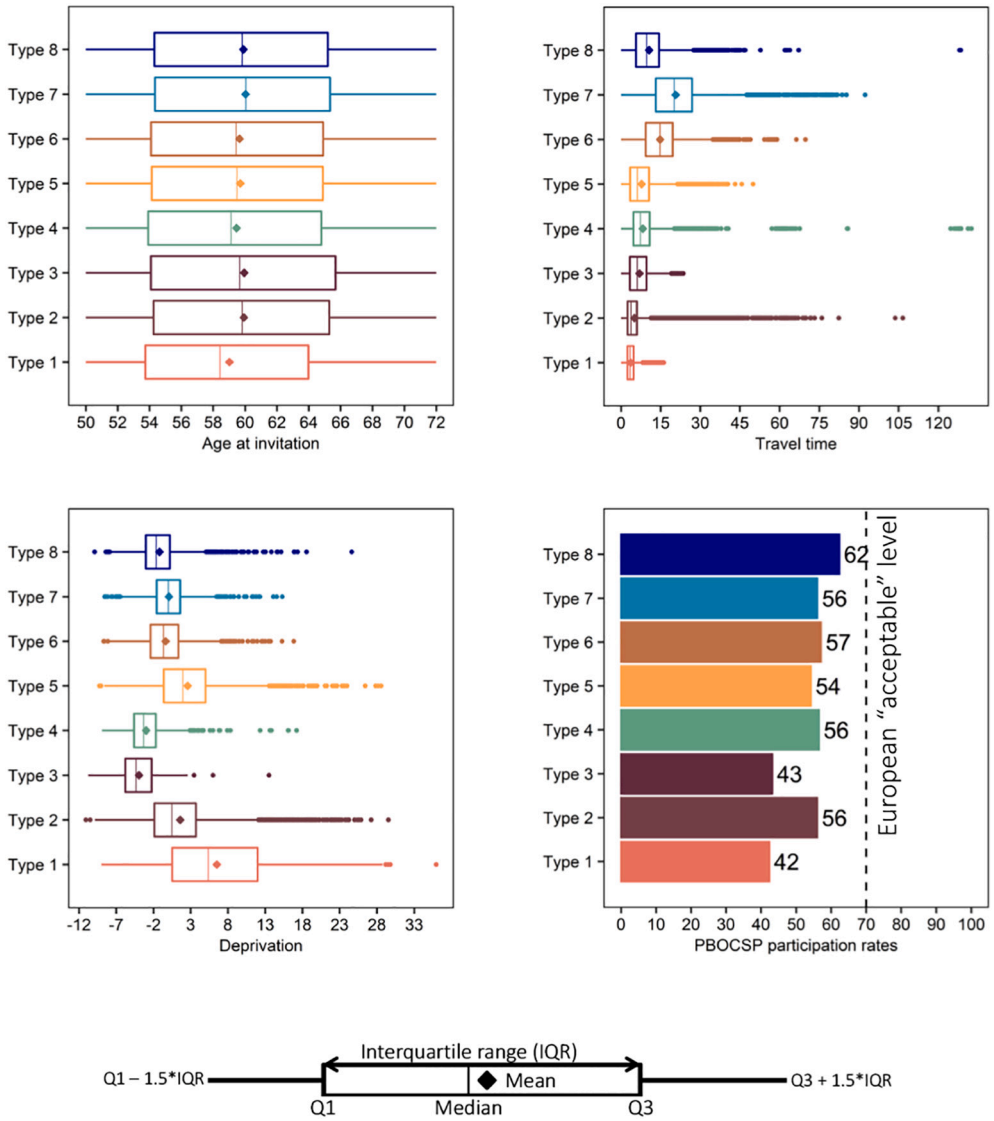


Fig. 1. Distribution of the predictors and outcome by types.

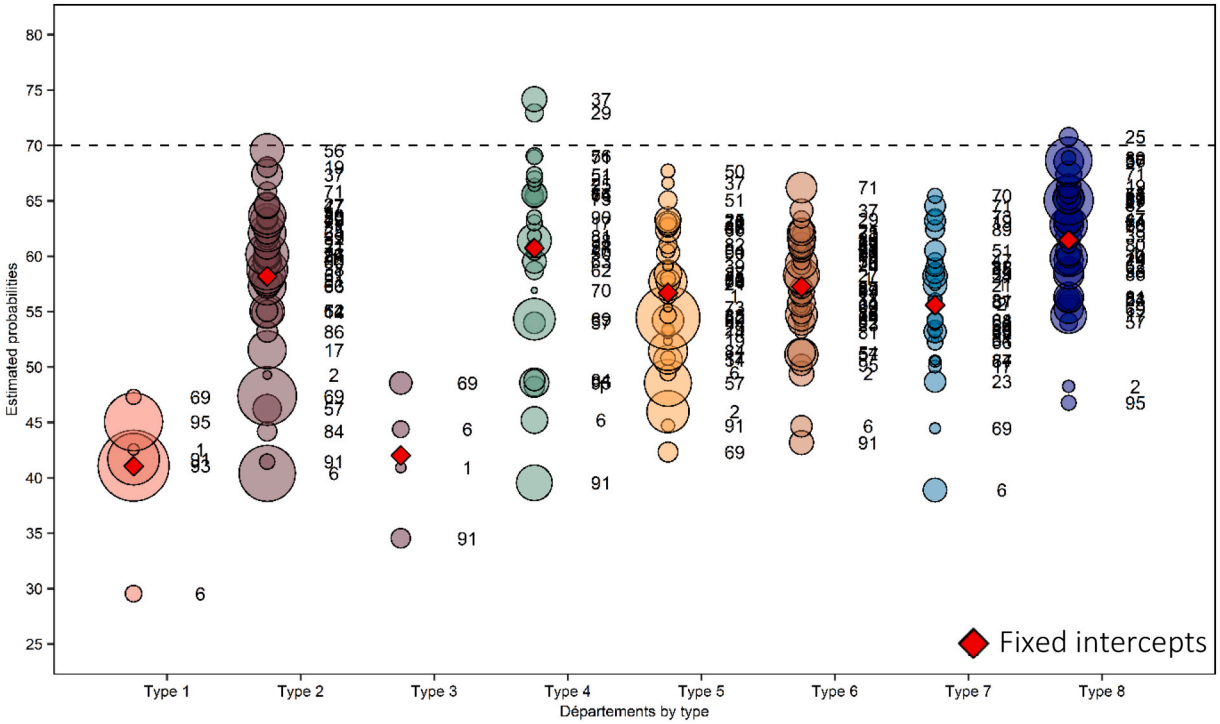


Fig. 2. *Départements'* random and fixed intercepts by types in M0.

4.2.3. Results from M2

Travel time to the nearest accredited radiology centre (Fig. 4). Travel time had no effect for Type 1 *départements*. The effect was the same across *départements* in four types (Types 4,6–8) of which two (Types 6 and 7) were linear. In Type 4, participation decreased almost linearly after a slight increase for the closest individuals. In Type 8, there was a net initial increase in participation as travel time increased until approximately 10 min in all *départements*, followed by a linear decrease before increasing again from a certain point onwards (~30 min). Random slopes were retained in Type 5: some *départements* had low/no effects of travel time, others had a more or less strong linear effect, and the rest had a slight initial increase and a decrease from a certain point onward. For Type 3, *départements*-specific relationships with shared wiggliness were retained. There was an inverse relationship between *départements* 1 and 69 where participation decreased as travel time increased and *départements* 6 and 91 where participation increased with increasing travel time.

Deprivation (Fig. 5). Deprivation had no effect in Type 1 and Type 3 *départements*. In Types 5–7, participation decreased linearly as deprivation increased without differences between *départements*. Random slopes were retained in Type 4, however, the direction of the effect (participation decreasing linearly as deprivation increased) was similar in most of the *départements*. Type 8 had the most complex relationship, with *département*-specific effects and individual wiggliness. However, in most *départements*, the relationship followed the same pattern as for the other types except few exceptions.

Tensor (Fig. 6). In Type 2, a random smooth with shared wiggliness was retained for the interaction between deprivation and travel time. There was an initial increase in participation as travel time increased, to a larger degree as deprivation decreased. From a certain point onward, participation then decreased with increasing travel time. Uptake decreased linearly with increasing deprivation; however, the slope became steeper as travel time increased.

5. Discussion

We examined the functional forms of social and territorial inequities in participation to the FNOBCSP in 41 *départements*, simultaneously combined with 8 types of territories. Uptake varied according to the Type, with a 20% difference between the two extremes, and between *départements* within Types to varying degrees, suggesting that the impact of the organizational level could be sensitive to the characteristics of the territories. Type 8 ensured both the best FNOBCSP participation (8% below the European recommendation (Perry et al., 2008)) and the lowest between-*départements* heterogeneity.

Travel time is generally used as a proxy to evaluate the accessibility of individuals to the systems required for their examination, and territorial inequities are often defined as a deterioration of the outcome as accessibility decreases. Despite higher travel time in Type 6 and 7, uptake was comparable with Types 2, 4, and 5, however participation decreased linearly with increasing travel time, without any differences between *départements*. Type 8 ranked third in travel time, followed by Types 4 and 5, and Type 2, with the second-lowest mean travel time. All these types shared the same tendency: participation decreased with increasing travel time, but from a certain point onwards (~5–15 min). Before this point, participation was stable or decreased as individuals were closer to the accredited radiology centre. Few studies in France have evaluated the effect of travel time on breast cancer screening, all of which found a small negative effect of increasing travel time (Rollet et al., 2021a; Guillaume et al., 2017; Ouédraogo et al., 2014).

Using a non-linear framework allowed the identification of two populations at risk of non-participation, those with the lowest and, in some places, those with the highest accessibility. In those with the lowest accessibility, improving/helping with transportation or available time could help to reduce disparities. An alternative approach is to reduce the distance between individuals and the centres. The results of the ongoing French randomized cluster trial for the evaluation of mobile mammography units will be particularly interesting in this direction

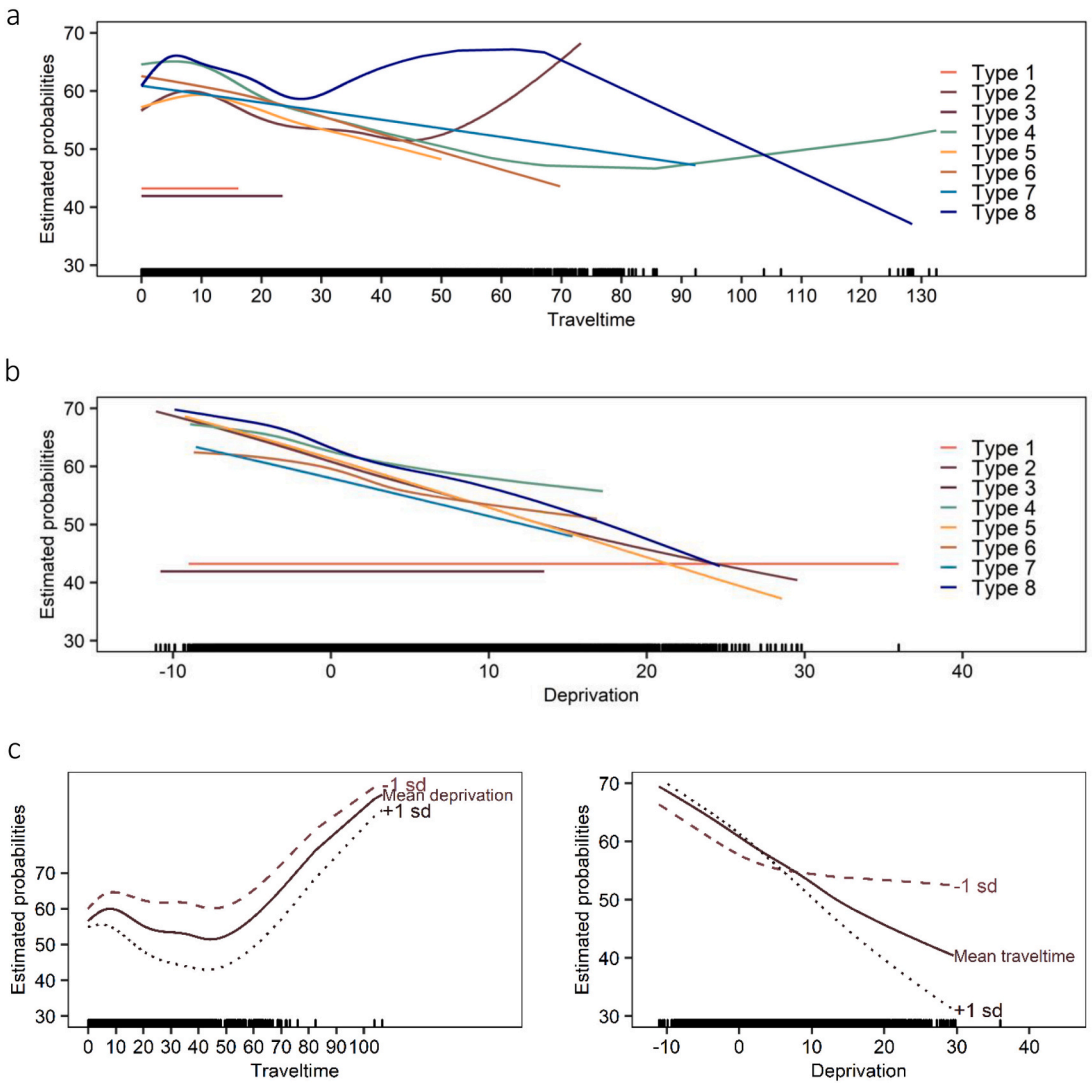


Fig. 3. Overall functional forms of the effect of travel time and deprivation on FNOBCSP participation by types in M1. a. Functional forms of the overall effect of travel time by type. b. Functional forms of the overall effect of deprivation by type. c. Tensor between deprivation and travel time in Type 2.

(Guillaume et al., 2022). More studies are needed to understand the underlying causes of the effect of accessibility in order to improve the balance between the supply and the needs. In those with the highest accessibility, opportunistic screening could explain these lower rates (discussed below), but they might also have lower participation. This relationship deserves further study to be confirmed and understood.

Neighbourhood deprivation is a combination of two effects: a direct measure of the social environment and a proxy for the individuals' socioeconomic levels. Social inequities are defined as a worsening of outcomes as deprivation increases. Types 2, 4, 5, 6, 7, and 8 have very different social profiles; however, the effect was very consistent: participation decreased linearly as deprivation increased, with no or few differences between *départements*. Our results are consistent with other studies in France, regardless of the method (Rollet et al., 2021a; Kelly et al., 2017; Menvielle et al., 2014; Guillaume et al., 2017; Ouédraogo et al., 2014; Deborde et al., 2018; Poiseuil et al., 2019; Ouanhnon et al., 2022; Duport, 2012; Devaux, 2015; Carrieri and Wuebker, 2013; Sicsic and Franc, 2014; Pornet et al., 2010; Challier et al., 2000; Duport et al., 2008; Rigal et al., 2011; Grillo et al., 2012; Vallée et al., 2010; Herbert et al., 1997). Interestingly, we did not observe lower participation among the least deprived, as reported by Deborde et al. (Duport, 2012). Addressing social inequities is complex due to the numerous factors that might contribute to them, and more research is required to disentangle the different determinants. Without considering the specific solutions to each problem, addressing the root causes of these inequities (*i.e.*, social inequalities) could drastically reduce the scale of the problem.

Types 1 and 3 are the types with the lowest uptake despite having among the lowest travel times. They are the two ends of the deprivation scale, with Type 1 concentrated in the most deprived areas (showing, however, the largest social heterogeneity), and Type 3 concentrated in the wealthiest areas (but, as defined by the authors of the typology, significant gender disparities). In these areas, deprivation showed no effect and travel time had no effect in Type 1. Compared to the other Types, participation was comparable for the most deprived, but much lower for the least deprived. Regarding travel time in Type 3, each *département* had a specific relationship with two *départements* with the "classical" territorial inequities, while an inverse relationship was observed in the two others, illustrating the paradox previously described. It should be noted that the number of *départements* composing these types is low.

The results described above are limited to organised screening. It is known that opportunistic screening is more common in *départements* including large cities, and specifically high in the *départements* composing Types 1 and 3 (Quintin et al., 2022). This practice is much

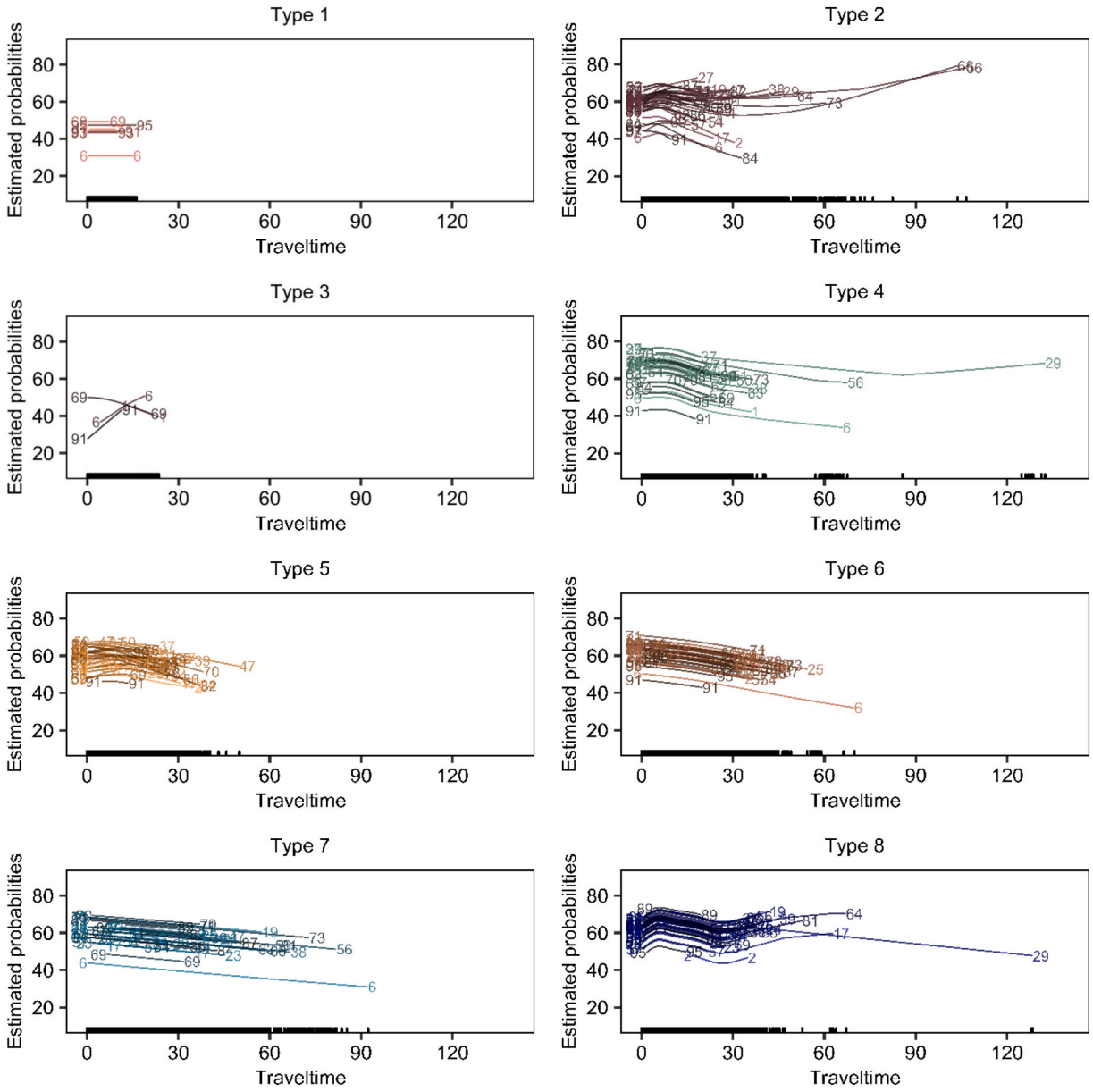


Fig. 4. Random effects of the relationship between travel time and FNOBCSP participation by type in M2.

more frequent among the wealthiest and more unfair than organised screening (Ouédraogo et al., 2015; Kalecinski et al., 2015; Palència et al., 2010; Walsh et al., 2011). It could explain the differences in the FNOBCSP uptake and the absence of measurable social inequities in Type 1 and 3. In the other types, these *départements* generally followed the functional forms of the others. That might be explained by a differential distribution of opportunistic screening in these *départements* between types, but also by the modelling, since the small number of départements and individuals involved may be overshadowed by the effect of other départements. Opportunistic screening could also explain the heterogeneity in social inequities we observed between the other Types and between départements within Types, as well as why uptake is lower for individuals with the lowest travel time, as most of them are from large cities. However, we found no study showing that the closer you live to an accredited radiology centre, the more you participate in opportunistic screening. Opportunistic screening has lower quality requirements, is not free of charges, and there is no system to properly evaluate it (Institut National du Cancer, 2022). It raises questions about the benefit-risk balance for individuals who make this choice. The lack of information on opportunistic screening data makes the overall picture of screening coverage and inequities partial, and efforts should be made in collecting these data at the individual level for a more complete evaluation.

Our study has some limitations. Our sample was randomly drawn from 42% of the estimated eligible population, that might not be representative of all the eligible population in France. In addition, random sampling error may have influenced unmeasured characteristics.

We measured travel time to the nearest accredited radiology centre as the shortest time by car between the home address and the closest practice. It does not account for individuals and areas traveling capacity, nor for the freedom of choice of the individuals on the practice they go to. We worked with the screening management structures to create the database of the centres, and those from bordering non-participant *départements* were excluded. No other database exists at the national level. It should be created and updated by competent authorities.

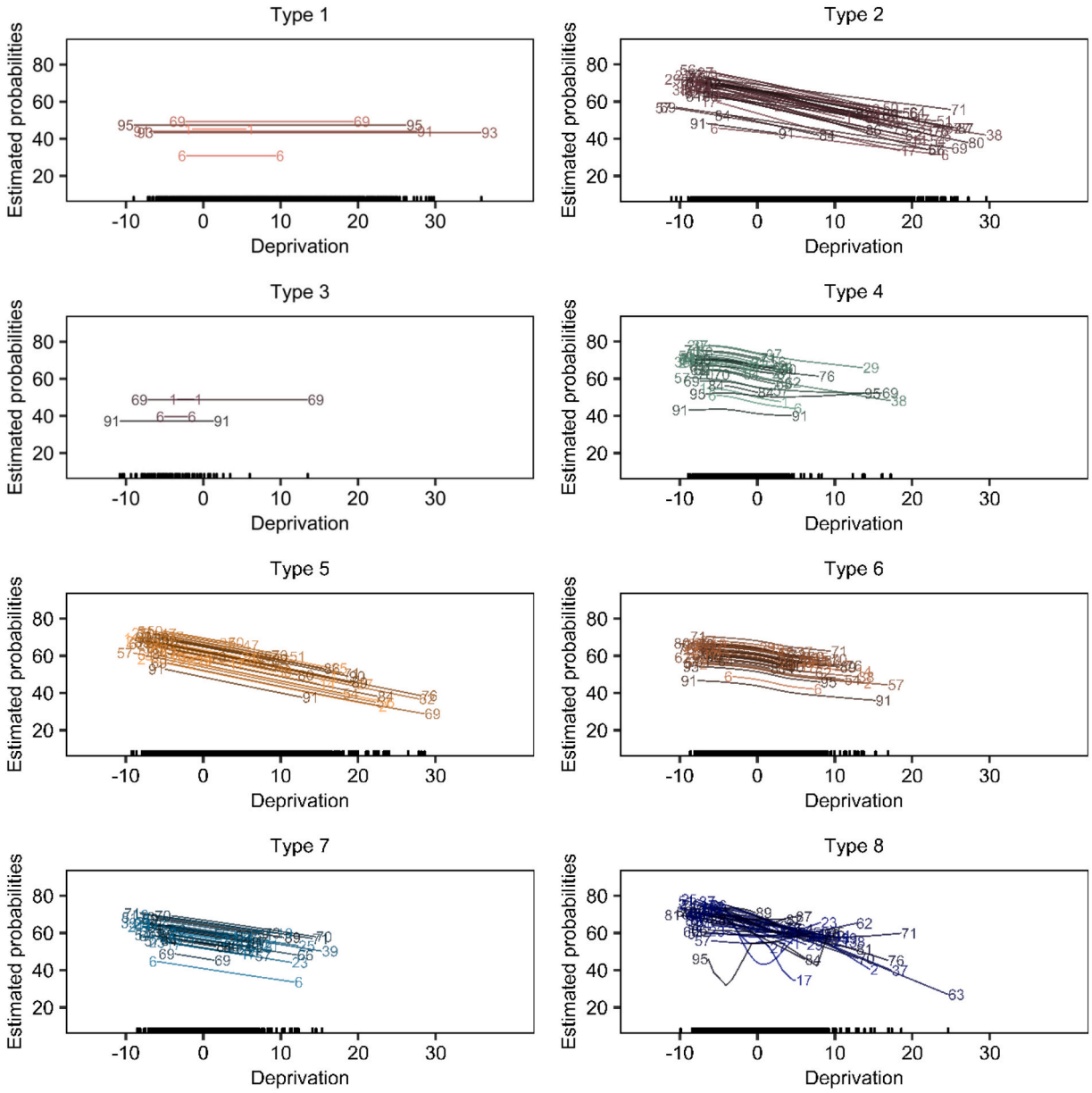


Fig. 5. Random effects of the relationship between deprivation and FNOBCSP participation by type in M2.

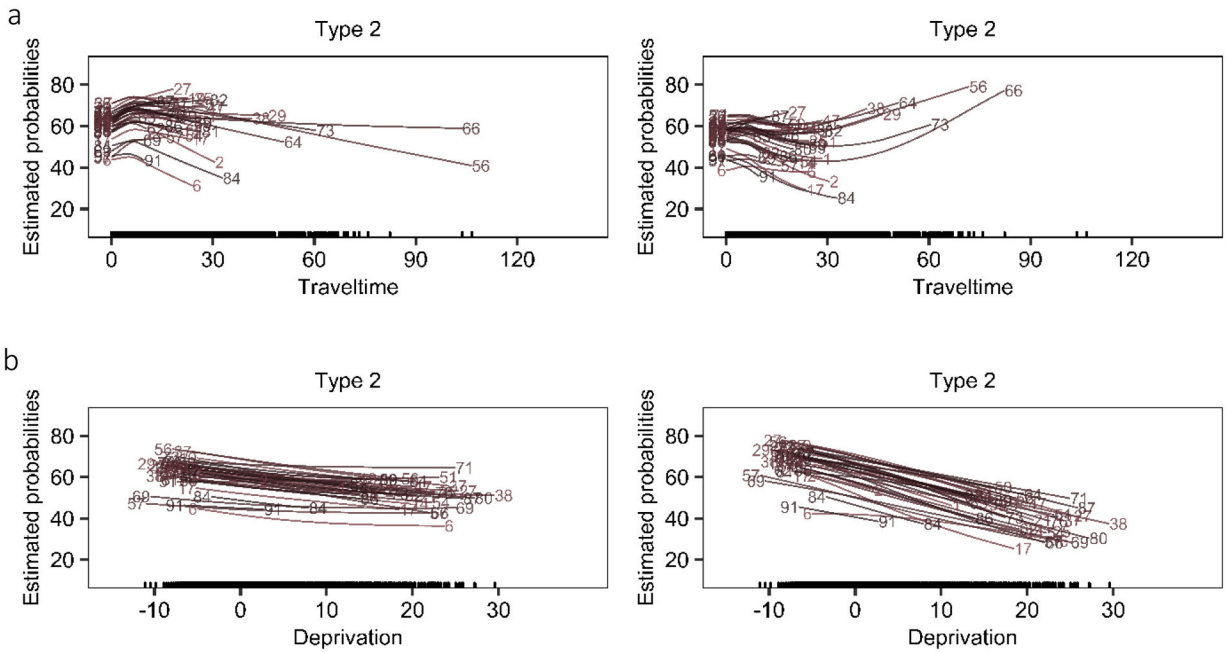


Fig. 6. Random effects of the tensor between deprivation and travel time on FNOBCSP participation in Type 2 in M2. a. Functional forms of the effect of travel time on FNOBCSP participation with low (-1σ, left) or high (+1σ, right) deprivation. b. Functional forms of the effect of deprivation on FNOBCSP participation with low (-1σ, left) or high (+1σ, right) travel time.

The F-EDI is an ecological deprivation index and its associated limitations have been described in the literature (Diez Roux, 2015; Blakely and Woodward, 2000). One of them is that we captured both a contextual and an individual effect. Accounting for individual characteristics could help disentangling these effects; however, none were available. The indicator used is defined at an administrative level for which data are available, used as a proxy for neighbourhoods. We would gain in accuracy by having more grounded definitions of what neighbourhoods are.

Only a few studies have used the HGAM framework. Many theoretical discussions about model building, selection, and interpretability should take place to better identify the limitations and strengths of these models. Variance analysis is an essential component of multilevel modelling, however, estimating variance parameters for Models 2 is a complex task as in many cases, the retained Models 2 do not independently model the random intercept from the random smooth. Further methodological development in this direction would be interesting. This is also a limitation for the comparability of our results, since to our knowledge, this is one of the few studies to have used these models in social epidemiology, and the sole in the context of cancer screening.

We chose only one typology for territories, whereas others exist. This quality-of-life based typology has been used to try to get out of the urbanicity dimensions, which often returns inconsistent definitions and results (Rollet et al., 2021b), and because the deprivation index we used has shown consistency in the different types (Merville et al., 2022). Although these tools are very powerful, multiplying the typologies *ad infinitum* without seeking to describe, compare and understand them risks leading to an increasing confusion.

This study reports the results of only one invitation campaign. We cannot conclude that all campaigns generated or will generate the same amount of inequities; however, they have been found every time we have looked for them. In the meantime, very little has been done in France to target their reduction, and it would be surprising if they were to disappear on their own.

Although this study focused solely on the social and territorial factors that affect breast cancer screening participation, there are several other factors reported that could mediate or add to their effects. Studies have indicated that participants in breast cancer screening programmes tend to have better health insurances, more frequent contact with general practitioners or gynaecologists, and better overall health (Menvielle et al., 2014; Ouanhnon et al., 2022; Duport, 2012). On the other hand, non-participants have been found to face several obstacles, including limited available time, negative past experiences with mammography, differing perceptions and fear of mammography and cancer, and fatalistic attitudes towards health (Ferrat et al., 2013; Tomietto et al., 2014). Following a positive screening exam, individuals must undergo a diagnosis pathway, and after diagnosis, patients must receive treatment. While the French healthcare system covers most of the costs associated with diagnosis and treatment there may still be some out-of-pocket costs that patients are responsible for. Other socioeconomic factors such as limited access to healthcare services, competing priorities, lack of time, language barriers, and cultural beliefs may also discourage some women from participating in breast cancer screening programmes. More studies are needed in these directions.

Inequities in cancer screening are not a French-specific issue, as they have been found in most countries proposing an organised cancer screening program (Rollet et al., 2021b; Smith et al., 2019; Pruitt et al., 2009). Direct comparisons between countries are difficult because of different methodological cultures and data availability. Organised cancer screening is a European policy, and the settings should be comparable. In addition, the deprivation index we used is theoretically possible to construct at this scale (Guillaume et al., 2016). Comparing the extent of participation inequities across European countries would allow the identification of organizational levers ensuring the best adherence of the population and/or the minimization of these inequities. There is every reason to believe that inequities in participation have consequences, in a context where the most deprived already have the worst cancer outcomes (Woods et al., 2006; Tron et al., 2019). This is difficult to measure as it would require linking screening data with clinical cancer data. Existing cancer registries are the major sources of such information, yet this possibility seems to be overlooked (Forsea, 2016). It would make it possible to assess and quantify the benefits of breast cancer screening in

the eligible population and the opportunity losses caused by inequities in participation. This would help, based on evidence, to modify existing programmes and develop new ones towards higher effectiveness and equity.

Funding information

The authors received no specific funding for this work.

Ethics approval and consent to participate

Not applicable.

CRediT authorship contribution statement

Quentin Rollet: Conceptualization, Data curation, Formal analysis, Investigation, Methodology, Project administration, Resources, Software, Validation, Visualization, Writing – original draft, Writing – review & editing. **Aimilia Exarchakou:** Conceptualization, Investigation, Methodology, Validation, Writing – review & editing. **Guy Launoy:** Investigation, Resources, Validation, Writing – review & editing. **Ophélie Merville:** Investigation, Resources, Validation, Writing – review & editing. **Francisco J. Rubio:** Conceptualization, Investigation, Methodology, Resources, Validation, Writing – review & editing. **Aurélien Belot:** Conceptualization, Investigation, Methodology, Supervision, Validation, Writing – review & editing.

Declaration of Competing Interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

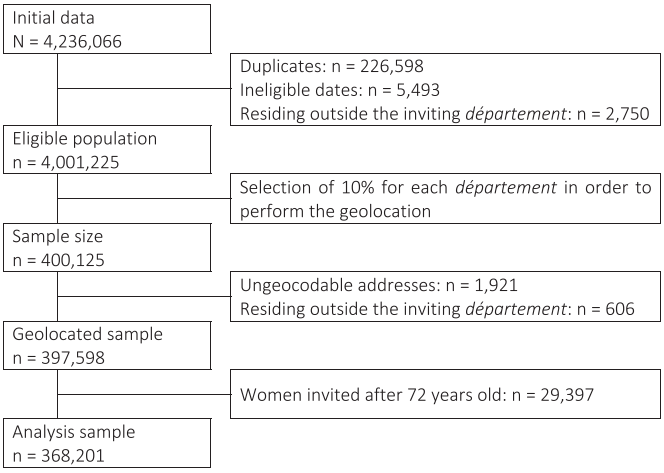
Data availability

Access to data that support the findings of this study is restricted. These data are not publicly available.

Acknowledgments

We would like to thank the staff of the screening management structures of the départements of *Ain, Aisne, Alpes-Maritimes, Calvados, Charente-Maritime, Corrèze, Côte-d'Or, Creuse, Dordogne, Doubs, Eure, Finistère, Indre-et-Loire, Isère, Jura, Lot-et-Garonne, Manche, Marne, Meurthe-et-Moselle, Morbihan, Moselle, Pas-de-Calais, Puy-de-Dôme, Pyrénées-Atlantiques, Pyrénées-Orientales, Rhône, Haute-Saône, Saône-et-Loire, Savoie, Seine-Maritime, Somme, Tarn, Tarn-et-Garonne, Vaucluse, Vienne, Haute-Vienne, Yonne, Territoire de Belfort, Essonne, Seine-Saint-Denis, Val-d'Oise, Guadeloupe, Martinique* and *Guyane* who participated in this study by providing data, Élodie Guillaume who helped to set up this project, and the MapInMed platform staff (Ludivine Launay, Catherine Grin, Charlene Daix and Fanny Deshayes Pinçon) who ensured geolocalisation.

Appendix A. Appendix



Appendix 1. Flowchart of the population.

Appendix B. Statistical details of the regression models

In the following, Y_{ij} is a binary variable equal to 1 if a person i in *département* j attended the screening, and 0 otherwise.

Empty hierarchical logistic model (M0)

$$\text{logit}\{Pr(Y_{ij}=1|u_j)\} = \beta_0 + u_j$$

where u_j is the random intercept associated with *département* j and is assumed to follow a normal distribution, $u_j \sim N(0, \sigma_1^2)$ where σ_1^2 is the variance of the random intercept.

Candidates for model M1: Global smoother model (Model G).

Depending on the variables retained after model selection (see Appendix 5), the candidate models for M1 could be one of the following:

$$\text{logit}\{Pr(Y_{ij}=1; age_{ij}, tra_{ij}, dep_{ij}|u_j)\} = \beta_0 + u_j = M0$$

$$\text{logit}\{Pr(Y_{ij}=1; age_{ij}, tra_{ij}, dep_{ij}|u_j)\} = \beta_0 + u_j + f(age_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+g(\text{tra}_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+h(\text{dep}_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+f(\text{age}_{ij})+g(\text{tra}_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+f(\text{age}_{ij})+h(\text{dep}_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+g(\text{tra}_{ij})+h(\text{dep}_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+f(\text{age}_{ij})+g(\text{tra}_{ij})+h(\text{dep}_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+te(\text{tra}_{ij},\text{dep}_{ij})$$

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+f(\text{age}_{ij})+te(\text{tra}_{ij},\text{dep}_{ij})$$

where $\text{age}_{ij}, \text{tra}_{ij}, \text{dep}_{ij}$ represent age, travel time and deprivation of person i in *département* j respectively, the functions f, g and h are univariate smoothers, te is a tensor product, and $u_j \sim N(0,\sigma_1^2)$

Candidates for model M2: adding random effects

We then evaluated the random effects for each variable retained in M1 in turn, looking first at age (Step 1 in Appendix 6), then travel time (Step 2a in Appendix 6) and finally at deprivation (Step 3a in Appendix 6) (or the tensor between the two latter, Step 2b in Appendix 6).

We illustrate below our strategy for investigating random effects, taking the example of model M1 that includes age and deprivation:

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+f(\text{age}_{ij})+h(\text{dep}_{ij})$$

Age – Step 1:

1. Global smoother plus random slope model (Model RS)

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+v_j\,\text{age}_{ij}+f(\text{age}_{ij})+h(\text{dep}_{ij})$$

where $u_j \sim N(0,\sigma_1^2)$ and $v_j \sim N(0,\sigma_2^2)$

2. Global smoother plus random smooth with shared wiggliness model (Model GS)

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+f(\text{age}_{ij})+f_j(\text{age}_{ij};\text{smooth}=k)+h(\text{dep}_{ij})$$

where $f_j(\text{age}_{ij},\text{smooth}=k)$ are *département*-specific smoothers with shared wiggliness k across *départements*. These *département*-specific smoothers $f_j(\text{age}_{ij};\text{smooth}=k)$ allow inter-*département* variations from the global effect $f(\text{age}_{ij})$, but only one smoothing parameter is estimated across all *départements*.

3. Global smoother plus random smooth with individual wiggliness model (Model GI)

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_{ij},\text{tra}_{ij},\text{dep}_{ij}|u_j)\}=\beta_0+u_j+f(\text{age}_{ij})+f_j(\text{age}_{ij};\text{smooth}=k_j)+h(\text{dep}_{ij})$$

where $f_j(\text{age}_{ij},\text{smooth}=k_j)$ are *département*-specific smoothers with individual wiggliness k_j across *départements*. These *département*-specific smoothers $f_j(\text{age}_{ij};\text{smooth}=k_j)$ allow inter-*département* variations from the global effect $f(\text{age}_{ij})$ with different levels of smoothness.

4. Random smooth with shared wiggliness model (Model S)

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_i,\text{tra}_i,\text{dep}_i|u_j)\}=\beta_0+f_j(\text{age}_{ij};\text{smooth}=k)+h(\text{dep}_{ij})$$

In this model, no global smoothers are shared between *départements*. This means that the age effect on each *département* may be modelled with completely independent and different functional forms (but with the same level of smoothness).

5. Random smooth with individual wiggliness model (Model I)

$$\text{logit}\{Pr(Y_{ij}=1;\text{age}_i,\text{tra}_i,\text{dep}_i|u_j)\}=\beta_0+f_j(\text{age}_{ij};\text{smooth}=k_j)+h(\text{dep}_{ij})$$

In this model, no global smoothers are shared between *départements*. This means that the age effect on each *département* may be modelled with completely independent and different functional forms and with different levels of smoothness.

We would then apply our model selection for these 5 candidates for the random effect of age and M1 using AIC and degrees of freedom. In this example, we would re-start the process for travel time fitting only models S and I as there was no global smoother retained in M1 and apply our model selection between these models and the model retained in Step 1 (Step 2a), and then fit the 5 candidate models for the random effect of deprivation and apply our model selection between these models and the model retained in Step 2a (Step 3a).

Appendix 3
Distribution of *départements* and individuals by type.

	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8	Total
Département ID									
1	125	768	87	853	498	3054	141	1741	7267
2	0	30	0	0	5592	1501	34	162	7319
6	479	10,767	488	1828	428	1022	1335	0	16,347
14	0	2634	0	642	231	1987	0	4137	9631
17	0	4388	0	413	319	1003	188	3771	10,082
19	0	906	0	0	33	72	957	1425	3393
21	0	1797	0	445	0	1389	1312	1404	6347
23	0	0	0	0	0	284	1006	631	1921
24	0	1517	0	0	352	774	1454	2286	6383
25	0	1766	0	214	1698	1980	192	651	6501
27	0	1629	0	413	1943	3793	0	130	7908
29	0	4130	0	610	168	538	110	7929	13,485
37	0	2602	0	1524	169	1238	0	2363	7896
38	0	5170	0	3309	463	2821	402	2309	14,474
39	0	627	0	0	79	447	749	1613	3515
47	0	1567	0	0	539	248	387	2277	5018
50	0	970	0	322	251	1137	0	4188	6868
51	0	3974	0	420	660	630	934	765	7383
54	0	3434	0	220	2178	2067	9	1884	9792
56	0	3242	0	490	0	227	80	6997	11,036
57	0	2139	0	1050	7170	3116	148	596	14,219
62	0	1023	0	643	14,236	1889	0	855	18,646
63	0	1594	0	1346	349	1725	1123	2722	8859
64	0	4218	0	1556	253	660	444	2155	9286
66	0	4221	0	0	1561	0	375	795	6952
69	342	11,832	1158	5378	821	789	106	2260	22,686
70	0	0	0	2	565	1182	335	1260	3344
71	0	713	0	340	1379	2574	914	1681	7601
73	0	3360	0	630	41	588	438	756	5813
76	0	5793	0	1562	4360	2820	0	2392	16,927
80	0	2128	0	0	2754	2009	0	479	7370
81	0	2508	0	268	0	189	294	2402	5661
82	0	1155	0	0	612	456	671	507	3401
84	0	776	0	972	4634	517	43	1093	8035
86	0	946	0	0	838	890	323	2552	5549
87	0	1935	0	0	0	1069	252	2514	5770
89	0	986	0	0	1394	1644	710	307	5041
90	0	0	0	323	1260	156	0	0	1739
91	8876	367	777	3743	213	1396	0	0	15,372
93	18,129	0	0	0	0	0	0	0	18,129
95	11,613	0	0	2288	0	1000	0	334	15,235
Total	39,564	97,612	2510	31,804	58,041	50,881	15,466	72,323	368,201

Appendix 4
Description of the population by types.

	n (%)	Age (years) Mean (sd)	Travel time (minutes) Mean (sd)	F-EDI (dimensionless) Mean (sd)	FNOBCSP uptake (%)
Type 1	39,564 (11%)	59.0 (6.2)	3.6 (1.8)	6.5 (7.5)	42%
Type 2	97,612 (27%)	59.9 (6.4)	5.0 (4.9)	1.6 (5.1)	56%
Type 3	2510 (1%)	59.9 (6.5) *	7.0 (4.6)	−4.0 (3.0)	43%
Type 4	31,804 (9%)	59.5 (6.4)	8.2 (5.8)	−3.0 (2.5)	56%
Type 5	58,041 (16%)	59.7 (6.3)	7.8 (5.8) *	2.6 (4.6)	54%
Type 6	50,881 (14%)	59.7 (6.3)	14.8 (7.5)	−0.4 (2.9)	57%
Type 7	15,466 (4%)	60.0 (6.4)	20.7 (12.0)	0.1 (2.7)	56% *
Type 8	72,323 (20%)	59.9 (6.4)	10.6 (6.5)	−1.2 (2.8)	62%

* No statistical differences between the type and the rest of the population.

Appendix 5
Models' selection for M0 and M1.

	Type 1	Type 2	Type 3	Type 4	Type 5	Type 6	Type 7	Type 8
LMR0								
AIC model	53,909	133,939	3434	43,556	80,062	69,518	21,220	95,856
Degrees of freedom	1	1	1	1	1	1	1	1
Delta AIC with M0	/	/	/	/	/	/	/	/
Empty model								
AIC model	**53,824 = M0**	**131,299 = M0**	**3396 = M0**	**42,321 = M0**	**79,387 = M0**	**68,970 = M0**	**20,921 = M0**	**95,224 = M0**
Degrees of freedom	5.8	34.6	3.6	25.8	30.0	34.9	24.4	34.6
*Delta AIC with **LMR0***	−85	−2640	−38	−1235	−675	−548	−299	−632
Age at invitation								
AIC model G1	**53,644 = M1**	**130,731 = VR**	**3380 = M1**	**42,152 = VR**	**79,082 = VR**	**68,690 = VR**	**20,855 = VR**	**94,845 = VR**
Degrees of freedom	9.9	45.2	4.7	31.6	34.8	40.5	28.3	40.2
*Delta AIC with **M0***	−180	−568	−16	−169	−305	−280	−66	−379
Travel time								
AIC model G2	53,644	**130,630 = VR**	3380	**42,120 = VR**	**78,980 = VR**	**68,639 = VR**	**20,846 = VR**	**94,709 = VR**
Degrees of freedom	12.8	51.1	5.8	36.9	40.7	44.4	29.3	47.3
*Delta AIC with **BM***	0	−101	0	−32	−102	−51	−9	−136
Deprivation								
AIC model G3	53,648	**130,207 = VR**	3380	**42,102 = M1**	**78,713 = M1**	**68,590 = M1**	**20,830 = M1**	**94,570 = M1**
Degrees of freedom	12.3	53.5	5.6	41.4	38.8	48	30.2	51.9
*Delta AIC with **BM***	4	−423	0	−18	−267	−49	−16	−139
Deprivation*Traveltime								
AIC model G4	53,643	**130,183 = M1**	3380	42,100	78,712	68,586	20,833	94,577
Degrees of freedom	21.3	57.9	8.4	43.9	42	52	33.1	56.4
*Delta AIC with **BM***	−1	−24	0	−2	−1	−4	3	7

M0 = Selected empty model; **BM** = Best model in the preceding step; **M1** = Selected model 1; **VR** = Variable retained

Appendix 6
Models' selection for M2 (1/2).

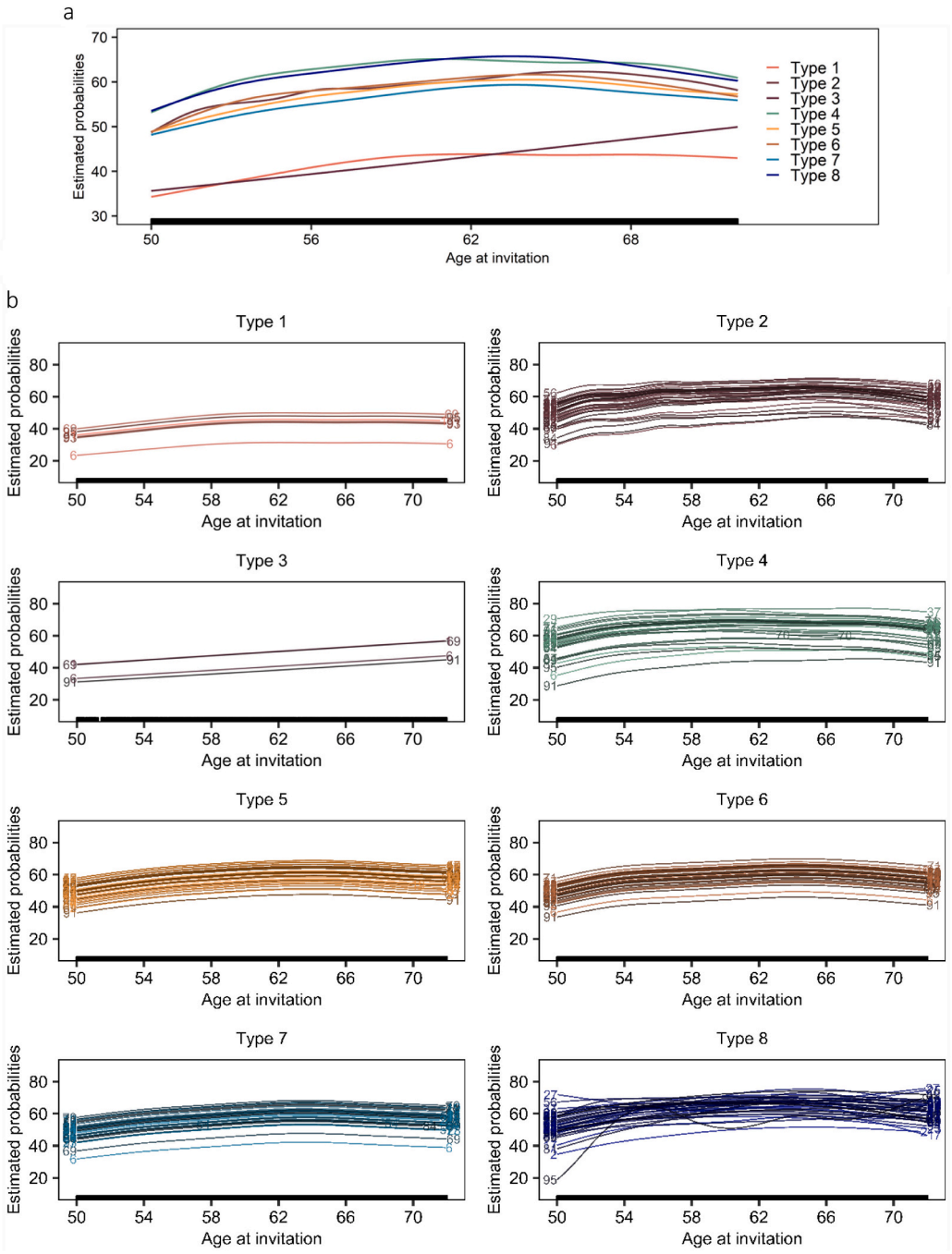
	Step 1 Age			Step 2a Traveltime			Step 3a Deprivation			Step 2b Deprivation * Traveltime		
	AIC	*Df*	*Δ*	AIC	*Df*	*Δ*	AIC	*Df*	*Δ*	AIC	*Df*	*Δ*
Type 1												
M1 BM*	**53,644**	9.9	4	**53,644 = M2**	9.9	/	53,644	9.9	/	X	X	X
Model RS	53,640	12.1	/	X	X	X	X	X	X	X	X	X
Model GS	53,645	14.3	5	X	X	X	X	X	X	X	X	X
Model GI	53,642	20.9	2	X	X	X	X	X	X	X	X	X
Model S	53,644	19.6	4	53,647	18.2	3	53,653	14.8	9	X	X	X
Model I	53,647	24.0	7	53,649	19.3	5	53,653	18.8	9	X	X	X
Type 2												
M1 BM*	130,183	57.9	69	X	X	X	X	X	X	130,116	112.2	10
Model RS	130,124	78.8	10	X	X	X	X	X	X	X	X	X
Model GS	**130,116**	112.2	2	X	X	X	X	X	X	**130,107 = M2**	162.3	1
Model GI	130,114	132.5	/	X	X	X	X	X	X	130,106	221.8	/
Model S	130,148	133.4	34	X	X	X	X	X	X	130,133	178.7	27
Model I	130,154	156.3	40	X	X	X	X	X	X	130,137	231.9	31
Type 3												
M1 BM*	**3380**	4.7	/	3380	4.7	7	3374	7.0	2	X	X	X
Model RS	3380	4.7	0	X	X	X	/	/	X	X	X	X
Model GS	3383	9.6	3	X	X	X	/	/	X	X	X	X
Model GI	3382	9.5	2	X	X	X	/	/	X	X	X	X
Model S	3383	9.7	3	**3374 = M2**	7.0	1	3372	11.2	/	X	X	X
Model I	3382	9.5	2	3373	10.4	/	3374	14.2	2	X	X	X
Type 4												
M1 BM*	42,102	41.4	28	**42,078**	55.1	4	42,078	55.1	7	X	X	X
Model RS	**42,078**	55.1	4	42,079	62.4	5	**42,071 = M2**	60.5	/	X	X	X
Model GS	42,088	70.6	14	42,079	64.1	5	42,083	74.3	12	X	X	X
Model GI	42,074	92.7	/	42,074	77.1	/	42,100	93.3	29	X	X	X
Model S	42,106	88.7	32	42,090	68.6	6	42,083	72.2	12	X	X	X
Model I	42,105	99.2	31	42,078	79.7	4	42,097	90.9	26	X	X	X

* BM = best model in the preceding step.

Appendix 6
Models' selection for M2 (2/2).

	Step 1 Age			Step 2a Traveltime			Step 3a Deprivation			Step 2b Deprivation * Traveltime		
	AIC	*Df*	Δ	AIC	*Df*	Δ	AIC	*Df*	Δ	AIC	*Df*	Δ
Type 5												
M1 BM*	**78,713**	38.8	1	78,713	38.8	24	**78,691 = M2**	51.1	/	X	X	X
Model RS	78,712	45.5	/	**78,691**	51.1	2	78,691	54.8	0	X	X	X
Model GS	78,733	63.4	21	78,689	51.2	/	78,703	67.2	12	X	X	X
Model GI	78,746	88.0	34	78,690	74.6	1	78,718	97.9	27	X	X	X
Model S	78,758	88.2	46	78,695	53.2	6	78,706	70.2	15	X	X	X
Model I	78,779	109.6	67	78,697	78.2	8	78,718	97.9	27	X	X	X
Type 6												
M1 BM*	**68,590**	48	3	**68,590**	48	/	**68,590 = M2**	48	5	X	X	X
Model RS	68,587	58.3	/	68,590	54.8	0	68,586	58.1	1	X	X	X
Model GS	68,604	86.7	17	68,603	69.7	13	68,589	69.4	4	X	X	X
Model GI	68,618	116.5	31	68,614	93.5	24	68,599	10.4	14	X	X	X
Model S	68,627	117.0	40	68,606	70.7	16	68,585	67.4	/	X	X	X
Model I	68,651	134.6	64	68,614	93.2	24	68,599	104.3	14	X	X	X
Type 7												
M1 BM*	**20,830**	30.2	/	**20,830**	30.2	/	**20,830 = M2**	30.2	/			
Model RS	20,830	38.6	0	20,830	30.2	0	20,832	34.5	2	X	X	X
Model GS	20,835	52.7	5	20,831	38.8	0	20,840	44.9	10	X	X	X
Model GI	20,846	77.7	16	20,851	61.2	21	20,862	71.3	32	X	X	X
Model S	20,840	62.2	10	20,833	39.6	3	20,842	46.5	12	X	X	X
Model I	20,850	82.7	20	20,850	61.1	20	20,862	71.3	32	X	X	X
Type 8												
M1 BM*	94,570	51.9	52	**94,518**	136.0	/	94,518	136.0	9	X	X	X
Model RS	94,537	69.7	19	94,525	148.2	7	94,514	156.7	5	X	X	X
Model GS	94,543	89.5	25	94,532	156.3	14	94,513	162.5	4	X	X	X
Model GI	**94,518**	136.0	/	94,521	163.2	3	**94,509 = M2**	190.4	/	X	X	X
Model S	94,553	132.2	35	94,578	153.0	60	94,520	166.8	11	X	X	X
Model I	94,550	162.1	32	94,539	169.3	21	94,509	190.4	0	X	X	X

* BM = best model in the preceding step.



Appendix 7. Overall functional forms and random effects of the relationships between age and FNOBCSP participation by type. a. Overall functional forms of the effect of age on FNOBCSP participation by types in M1. b. Random effects of the relationship between FNOBCSP participation and age by type in M2.

References

Akaike, H., 1998. Information theory and an extension of the maximum likelihood principle. In: Parzen, E., Tanabe, K., Kitagawa, G. (Eds.), Selected Papers of Hirotugu Akaike [Internet]. Springer, New York, NY, pp. 199–213 [cited 2022 Jul 12]. (Springer Series in Statistics). Available from: https://doi.org/10.1007/978-1-4612-1694-0_15 [cited 2022 Jul 12]. (Springer Series in Statistics). Available from:

Benedetti, A., Abrahamowicz, M., 2004. Using generalized additive models to reduce residual confounding. Stat. Med. 23 (24), 3781–3801. https://doi.org/10.1002/sim.2073. Dec 30.

Blakely, T.A., Woodward, A.J., 2000. Ecological effects in multi-level studies. J. Epidemiol. Community Health 54 (5), 367–374. https://doi.org/10.1136/jech.54.5.367. May.

Burnham, K.P., Anderson, D.R. (Eds.), 2004. Model Selection and Multimodel Inference [Internet]. Springer, New York, NY [cited 2022 Nov 22]. Available from: http://link.springer.com/10.1007/b97636 [cited 2022 Nov 22]. Available from:

Carrieri, V., Wuebker, A., 2013. Assessing inequalities in preventive care use in Europe. Health Policy Amst Neth. 113 (3), 247–257. https://doi.org/10.1016/j.healthpol.2013.09.014. Dec.

Challier, B., Meslans, Y., Viel, J.F., 2000. Deprived areas and attendance to screening of cervix uteri cancer in a French region. Cancer Causes Control CCC. 11 (2), 157–162. https://doi.org/10.1023/a:1008998322628. Feb.

Deborde, T., Chatignoux, E., Quintin, C., Beltzer, N., Hamers, F.F., Rogel, A., 2018. Breast cancer screening programme participation and socioeconomic deprivation in France. Prev. Med. 115, 53–60. https://doi.org/10.1016/j.ypmed.2018.08.006. Oct.

Insee, 2023. Définition - IRIS. [Internet - cited 2022 Nov 22]. Available from: https://www.insee.fr/fr/metadonnees/definition/c1523.

Defossez, G., Uhry, Z., Delafosse, P., Dantony, E., d'Almeida, T., Plouvier, S., et al., 2021. Cancer incidence and mortality trends in France over 1990-2018 for solid tumors:

the sex gap is narrowing. BMC Cancer 21 (1), 726. https://doi.org/10.1186/s12885-021-08261-1. Jun 24.
Santé publique France, 2022. Dépistage du cancer du sein : quelle participation des femmes en 2021 ? [Internet. cited 2022 Nov 22]. Available from: https://www.santepubliquefrance.fr/les-actualites/2022/depistage-du-cancer-du-sein-quelle-participation-des-femmes-en-2021.
Devaux, M., 2015. Income-related inequalities and inequities in health care services utilisation in 18 selected OECD countries. Eur. J. Health Econ. HEPAC Health Econ. Prev. Care. 16 (1), 21–33. https://doi.org/10.1007/s10198-013-0546-4. Jan.
Diez Roux, A.V., 2015. Ecological variables, ecological studies, and multilevel studies in public health research. In: Detels, R., Gulliford, M., Karim, Q.A., Tan, C.C. (Eds.), Oxford Textbook of Global Public Health [Internet]. Oxford University Press, p. 0. https://doi.org/10.1093/med/9780199661756.003.0104 [cited 2022 Nov 23].
Duport, N., 2012. Characteristics of women using organized or opportunistic breast cancer screening in France. Analysis of the 2006 French health, health care and insurance survey. Rev. Epidemiol. Sante Publique 60 (6), 421–430. https://doi.org/10.1016/j.respe.2012.05.006. Dec.
Duport, N., Serra, D., Goulard, H., Bloch, J., 2008. Which factors influence screening practices for female cancer in France? Rev. Epidemiol. Sante Publique 56 (5), 303–313. https://doi.org/10.1016/j.respe.2008.07.086. Oct.
European Union, 2003. Council Recommendation of 2 December 2003 on cancer screening. EUR-Lex - 32003H0878 - EN - EUR-Lex [Internet], 2023. [cited 2022 Nov 22]. Available from: https://eur-lex.europa.eu/eli/reco/2003/878/oj/eng.
European Cancer Information System [Internet - cited 2022 Nov 22]. Available from: https://ecis.jrc.ec.europa.eu/.
Santé publique France, 2023. Evaluation du programme de dépistage du cancer du sein [Internet - cited 2022 Nov 22]. Available from: https://www.santepubliquefrance.fr/maladies-et-traumatismes/cancers/evaluation-du-programme-de-depistage-du-cancer-du-sein.
Ferrat, E., Le Breton, J., Djassibel, M., Veerabudun, K., Brixi, Z., Attali, C., Renard, V., 2013. Understanding barriers to organized breast cancer screening in France: women's perceptions, attitudes, and knowledge. Fam. Pract. 30 (4), 445–451. https://doi.org/10.1093/fampra/cmt004. Aug. (Epub 2013 Mar 11).
Forsea, A.M., 2016. Cancer registries in Europe-going forward is the only option. Ecancermedicalscience. 10, 641. https://doi.org/10.3332/ecancer.2016.641.
Grillo, F., Vallée, J., Chauvin, P., 2012. Inequalities in cervical cancer screening for women with or without a regular consulting in primary care for gynaecological health, in Paris. France. Prev Med. 54 (3–4), 259–265. https://doi.org/10.1016/j.ypmed.2012.01.013.
Guillaume, E., Pornet, C., Dejardin, O., Launay, L., Lillini, R., Vercelli, M., et al., 2016. Development of a cross-cultural deprivation index in five European countries. J. Epidemiol. Community Health 70 (5), 493–499. https://doi.org/10.1136/jech-2015-205729. May.
Guillaume, E., Launay, L., Dejardin, O., Bouvier, V., Guittet, L., Déan, P., et al., 2017. Could mobile mammography reduce social and geographic inequalities in breast cancer screening participation? Prev. Med. 100, 84–88. https://doi.org/10.1016/j.ypmed.2017.04.006. Jul.
Guillaume, E., Rollet, Q., Launay, L., Beuriot, S., Dejardin, O., Notari, A., et al., 2022. Evaluation of a mobile mammography unit: concepts and randomized cluster trial protocol of a population health intervention research to reduce breast cancer screening inequalities. Trials. 23 (1), 562. https://doi.org/10.1186/s13063-022-06480-w. Jul 8.
Herbert, C., Launoy, G., Gignoux, M., 1997. Factors affecting compliance with colorectal cancer screening in France: differences between intention to participate and actual participation. Eur. J. Cancer Prev. Off. J. Eur. Cancer Prev. Organ. ECP. 6 (1), 44–52. https://doi.org/10.1097/00008469-199702000-00008. Feb.
Kalecinski, J., Régnier-Denois, V., Ouédraogo, S., Dabakuyo-Yonli, T.S., Dumas, A., Arveux, P., et al., 2015. Organized or individual breast cancer screening: what motivates women? Sante Publique Vandoeuvre–Nancy Fr 27 (2), 213–220.
Kelly, D.M., Estaquio, C., Léon, C., Arwidson, P., Nabi, H., 2017. Temporal trend in socioeconomic inequalities in the uptake of cancer screening programmes in France between 2005 and 2010: results from the Cancer barometer surveys. BMJ Open 7 (12), e016941. https://doi.org/10.1136/bmjopen-2017-016941. Dec 14.
Lauby-Secretan, B., Scoccianti, C., Loomis, D., Benbrahim-Tallaa, L., Bouvard, V., Bianchini, F., et al., 2015. Breast-cancer screening–viewpoint of the IARC Working Group. N. Engl. J. Med. 372 (24), 2353–2358. https://doi.org/10.1056/NEJMsr1504363. Jun 11.
Institut National du Cancer, 2022. Le programme de dépistage organisé des cancers du sein - Dépistage du cancer du sein [Internet - cited 2022 Nov 23]. Available from: https://www.e-cancer.fr/Professionnels-de-sante/Depistage-et-detection-precoce/Depistage-du-cancer-du-sein/Le-programme-de-depistage-organise.
Lee, Y., Nelder, J.A., 1996. Hierarchical generalized linear models. J. R. Stat. Soc. Ser. B Methodol. 58 (4), 619–656. https://doi.org/10.1111/j.2517-6161.1996.tb02105.x.
Menvielle, G., Richard, J.B., Ringa, V., Dray-Spira, R., Beck, F., 2014. To what extent is women's economic situation associated with cancer screening uptake when nationwide screening exists? A study of breast and cervical cancer screening in France in 2010. Cancer Causes Control CCC. 25 (8), 977–983. https://doi.org/10.1007/s10552-014-0397-z. Aug.
Merville, O., Launay, L., Dejardin, O., Rollet, Q., Bryère, J., Guillaume, É., et al., 2022. Can an ecological index of deprivation be used at the country level? The case of the French version of the European deprivation index (F-EDI). Int. J. Environ. Res. Public Health 19 (4), 2311. https://doi.org/10.3390/ijerph19042311. Feb 17.
Ouanhnon, L., Rougé Bugat, M.E., Lamy, S., Druel, V., Delpierre, C., Grosclaude, P., 2022. Social and territorial inequalities in breast and cervical cancers screening uptake: a cross-sectional study in France. BMJ Open 12 (2), e055363. https://doi.org/10.1136/bmjopen-2021-055363. Feb 22.
Ouédraogo, S., Dabakuyo-Yonli, T.S., Roussot, A., Pornet, C., Sarlin, N., Lunaud, P., et al., 2014. European transnational ecological deprivation index and participation in population-based breast cancer screening programmes in France. Prev. Med. 63, 103–108. https://doi.org/10.1016/j.ypmed.2013.12.007. Jun.
Ouédraogo, S., Dabakuyo-Yonli, T.S., Roussot, A., Dialla, P.O., Pornet, C., Poillot, M.L., et al., 2015. Breast cancer screening in thirteen French departments. Bull. Cancer (Paris). 102 (2), 126–138. https://doi.org/10.1016/j.bulcan.2014.07.002. Feb.
Palència, L., Espelt, A., Rodríguez-Sanz, M., Puigpinós, R., Pons-Vigués, M., Pasarín, M.I., et al., 2010. Socio-economic inequalities in breast and cervical cancer screening practices in Europe: influence of the type of screening program. Int. J. Epidemiol. 39 (3), 757–765. https://doi.org/10.1093/ije/dyq003. Jun.
Pedersen, E.J., Miller, D.L., Simpson, G.L., Ross, N., 2019. Hierarchical generalized additive models in ecology: an introduction with mgcv. PeerJ. 7, e6876 https://doi.org/10.7717/peerj.6876.
Perry, N., Broeders, M., de Wolf, C., Törnberg, S., Holland, R., von Karsa, L., 2008. European guidelines for quality assurance in breast cancer screening and diagnosis. Fourth edition–summary document. Ann. Oncol. Off. J. Eur. Soc. Med. Oncol. 19 (4), 614–622. https://doi.org/10.1093/annonc/mdm481. Apr.
Poiseuil, M., Coureau, G., Payet, C., Savès, M., Debled, M., Mathoulin-Pelissier, S., et al., 2019. Deprivation and mass screening: survival of women diagnosed with breast cancer in France from 2008 to 2010. Cancer Epidemiol. 60, 149–155. https://doi.org/10.1016/j.canep.2019.03.016. Jun.
Pornet, C., Dejardin, O., Morlais, F., Bouvier, V., Launoy, G., 2010. Socioeconomic and healthcare supply statistical determinants of compliance to mammography screening programs: a multilevel analysis in Calvados, France. Cancer Epidemiol. 34 (3), 309–315. https://doi.org/10.1016/j.canep.2010.03.010. Jun.
Pornet, C., Delpierre, C., Dejardin, O., Grosclaude, P., Launay, L., Guittet, L., et al., 2012. Construction of an adaptable European transnational ecological deprivation index: the French version. J. Epidemiol. Community Health 66 (11), 982–989. https://doi.org/10.1136/jech-2011-200311. Nov.
Pruitt, S.L., Shim, M.J., Mullen, P.D., Vernon, S.W., Amick, B.C., 2009. Association of area socioeconomic status and breast, cervical, and colorectal cancer screening: a systematic review. Cancer Epidemiol. Biomark Prev. Publ. Am. Assoc. Cancer Res. Cosponsored. Am. Soc. Prev. Oncol. 18 (10), 2579–2599. https://doi.org/10.1158/1055-9965.EPI-09-0135. Oct.
Quintin, C., Chatignoux, E., Plaine, J., Hamers, F.F., Rogel, A., 2022. Coverage rate of opportunistic and organised breast cancer screening in France: department-level estimation. Cancer Epidemiol. 7 (81), 102270. https://doi.org/10.1016/j.canep.2022.102270. Oct.
Rigal, L., Saurel-Cubizolles, M.J., Falcoff, H., Bouyer, J., Ringa, V., 2011. Do social inequalities in cervical cancer screening persist among patients who use primary care? The Paris prevention in general practice survey. Prev. Med. 53 (3), 199–202. https://doi.org/10.1016/j.ypmed.2011.06.016. Sep.
Rollet, Q., Guillaume, É., Launay, L., Launoy, G., 2021a. Socio-territorial inequities in the French National Breast Cancer Screening Programme-a Cross-Sectional Multilevel Study. Cancers. 13 (17), 4374. https://doi.org/10.3390/cancers13174374. Aug 30.
Rollet, Q., Tron, L., De Mil, R., Launoy, G., Guillaume, É., 2021b. Contextual factors associated with cancer screening uptake: a systematic review of observational studies. Prev. Med. 150, 106692. https://doi.org/10.1016/j.ypmed.2021.106692. Sep.
Sicsic, J., Franc, C., 2014. Obstacles to the uptake of breast, cervical, and colorectal cancer screenings: what remains to be achieved by French national programmes? BMC Health Serv. Res. 4 (14), 465. https://doi.org/10.1186/1472-6963-14-465. Oct.
Smith, D., Thomson, K., Bambra, C., Todd, A., 2019. The breast cancer paradox: a systematic review of the association between area-level deprivation and breast cancer screening uptake in Europe. Cancer Epidemiol. 60, 77–85. https://doi.org/10.1016/j.canep.2019.03.008. Jun.
Sung, H., Ferlay, J., Siegel, R.L., Laversanne, M., Soerjomataram, I., Jemal, A., et al., 2021. Global Cancer statistics 2020: GLOBOCAN estimates of incidence and mortality worldwide for 36 cancers in 185 countries. CA Cancer J. Clin. 71 (3), 209–249. https://doi.org/10.3322/caac.21660. May.
Tomietto, M., Soyer, P., Heitz, D., Fauconnier, A., Huchon, C., 2014. Réticences au dépistage organisé du cancer du sein dans les Yvelines [Reluctances in organized breast cancer screenig in Yvelines]. Gynecol. Obstet. Fertil. 42 (11), 761–765. Nov. French. https://doi.org/10.1016/j.gyobfe.2014.09.002. Nov. French.
Tron, L., Belot, A., Fauvernier, M., Remontet, L., Bossard, N., Launay, L., et al., 2019. Socioeconomic environment and disparities in cancer survival for 19 solid tumor sites: an analysis of the French network of Cancer registries (FRANCIM) data. Int. J. Cancer 144 (6), 1262–1274. https://doi.org/10.1002/ijc.31951. Mar 15.
Institut national de la statistique et des études économiques, 2014. Une approche de la qualité de vie dans les territoires - Insee Première - 1519 [Internet - cited 2022 Nov 22]. Available from: https://www.insee.fr/fr/statistiques/1281328.
Vallée, J., Cadot, E., Grillo, F., Parizot, I., Chauvin, P., 2010. The combined effects of activity space and neighbourhood of residence on participation in preventive health-care activities: the case of cervical screening in the Paris metropolitan area (France). Health Place 16 (5), 838–852. https://doi.org/10.1016/j.healthplace.2010.04.009. Sep.

von Elm, E., Altman, D.G., Egger, M., Pocock, S.J., Gøtzsche, P.C., Vandenbroucke, J.P., et al., 2014. The strengthening the reporting of observational studies in epidemiology (STROBE) statement: guidelines for reporting observational studies. Int. J. Surg. Lond Engl. 12 (12), 1495–1499. https://doi.org/10.1136/bmj.39335.541782.AD. Dec.

Walsh, B., Silles, M., O'Neill, C., 2011. The importance of socio-economic variables in cancer screening participation: a comparison between population-based and opportunistic screening in the EU-15. Health Policy Amst Neth. 101 (3), 269–276. https://doi.org/10.1016/j.healthpol.2011.02.001. Aug.

Wood, S.N., 2006. Generalized Additive Models: An Introduction with R. Chapman and Hall/CRC, New York, p. 416.

Woods, L.M., Rachet, B., Coleman, M.P., 2006. Origins of socio-economic inequalities in cancer survival: a review. Ann. Oncol. 17 (1), 5–19. https://doi.org/10.1093/annonc/mdj007. Jan 1.