Abstract

Background: International comparisons of social inequalities in health outcomes and behaviours are challenging. Due to the level of disaggregation often required, data can be sparse and methods to make adequately powered comparisons are lacking. We aimed to illustrate the value of a hierarchical Bayesian approach that partially pools country-level estimates, reducing the influence of sampling variation and increasing the stability of estimates. We also illustrate a new way of simultaneously displaying the uncertainty of both relative and absolute inequality estimates.

Methods: We used the 2014 European Social Survey to estimate smoking prevalence, absolute and relative inequalities for men and women with and without disabilities in 21 European countries. We simultaneously display smoking prevalence for people without disabilities (x-axis), absolute (y-axis) and relative inequalities (contour lines), capturing the uncertainty of these estimates by plotting a 2-D normal approximation of the posterior distribution from the full probability (Bayesian) analysis.

Results: Our study confirms, at a European-level for men and women, smoking prevalence is higher for people with disabilities than for those without. Our model shifts more extreme prevalence estimates that are based on fewer observations, toward the European mean.

Conclusions: We demonstrate the utility of partial pooling to make adequately powered estimates of inequality, allowing estimates from countries with smaller

sample sizes to benefit from the increased precision of the European average. Including uncertainty on our inequality plot provides a useful tool for evaluating both the geographical patterns of variation in, and strength of evidence for, differences in social inequalities in health.

Key words: international comparisons, inequalities, Bayesian, uncertainty, smoking, disability, health behaviours

1 Introduction

There is extensive literature on the international variation in social inequalities in health and health behaviours (e.g. [1,2]). Measuring and monitoring these social inequalities points to injustice and unfairness in society [3], can help identify where the largest gains in health could be made [4], and aids the assessment of policy decisions and their impact on different groups in society [5]. Furthermore, international comparisons of social inequalities in health and health behaviours can facilitate understanding of the social and political context in which inequalities arise [2].

International comparisons, however, are challenging. With a focus on comparing disadvantaged minority groups (e.g. people with disabilities [6] or minority ethnic groups [7]) to a benchmark group; and a need to disaggregate social inequalities in health by basic demographic information (e.g. gender and/or age), researchers often run into the familiar statistical problems associated with small sample sizes. To overcome this, countries (or groups) can be *pooled* until random variation no longer dominates inference [8]. For example, previous pan-European research has grouped countries into regions [9]. There is a risk, however, that these studies have missed important trends or patterns and/or model estimates have a poor fit to observed data [10]. Even if some data pooling is used, researchers often choose to conduct an *unpooled* analysis either by calculating inequalities in each country or region separately (e.g. [1]) or by fitting a statistical model with a large number of interactions (i.e. country dummy variables interacted with the socio-demographic variable(s) of interest (e.g. [9])). If there are small cell sizes at a country-level, this unpooled approach risks overfitting the model(s) to the data, with sampling variation overly influencing country-level inferences [10,11].

The first aim of this paper is show how researchers can compromise between the pooled and unpooled approaches outlined above, and use hierarchical Bayesian methods that *partially pool* inequality estimates. Hierarchical Bayesian modelling is long established [12] has been applied in the analysis of data which both does have a natural hierarchical structure (e.g. small area estimation [13]) and where it does not (e.g. multiple exposure modelling [14] and social group variation in health [15]). Partial pooling [10] preserves country-level variation in social inequalities in health and health behaviours. It also mitigates the risk of sample noise dominating country-level inference by being robust where it needs to be through shifting (or shrinking) estimates from countries with smaller sample sizes toward the overall average [8]. Consequently, estimates where data are sparse benefit from the increased precision of the pooled estimate that combines data from all sources. While there are a number of examples of partial pooling in, for example, education (e.g. [16]) and health research (e.g. [15]), to our knowledge this approach has not been used in the large number of studies making international comparisons of health inequalities.

Having estimated social inequalities in a health behaviour or outcome, a further challenge faced by researchers is how to analyse simultaneously and then present both the level of inequality *and* the precision of these estimates on both relative and absolute scales. Given that presentation of results on either the absolute or relative scale can have a dramatic effect on the interpretation of whether inequalities are bigger or smaller in one region or another [17], there is a growing consensus that researchers and policy makers should consider inequality on both absolute and relative scales [5,18–21], alongside the overall prevalence of the outcome of interest. Nevertheless, most studies on health inequalities have focused on relative inequalities, often neglecting absolute inequalities [17], or if both are estimated they are displayed on separate plots [22]. Recent examples have shown how all three quantities – prevalence and absolute and relative inequalities - can be displayed together on the same plot [20,23]. The precision of inequality estimates according to both scales, though, is often ignored and when uncertainty is considered, it is often only considered on either the relative or absolute scale separately (e.g. [1,24,25]).

The second aim of the paper, therefore, is to illustrate how the inequality plots outlined by Blakely et al [20] and Kjellsson and Petrie [23] can be extended to simultaneously display estimates of prevalence and relative and absolute inequalities of a health behaviour or outcome, and the uncertainty of these three estimates, on one plot. We achieve this by displaying a 2-dimensional summary of the posterior distribution of each country's inequality estimates. Most previous research has assessed strength of evidence for international variation in inequalities using p-values from statistical models or ad hoc statistical tests [24,26,27]. Given that the use of p-values has been widely criticised [28,29], visualising the uncertainty of inequalities in this way provides researchers with a tool to assess the strength of their evidence that avoids relying on them.

We address the two aims of the paper using a case study of disability-related smoking prevalence inequalities in 21 European countries (see EAppendix 1 for background). For aim 1, to illustrate the impact of partial pooling, we compare the unpooled results from a single level Bayesian model to the partially pooled results from a hierarchical Bayesian model. To address aim 2 we demonstrate how our inequality plots with uncertainty can be used to evaluate both the geographical patterns of variation in, and strength of evidence for, differences in prevalence and absolute and relative inequalities in smoking.

2 Methods

Aim 1: Partial pooling of country-level inequality estimates

For our case study – disability related smoking prevalence inequalities in 21 European countries – an unpooled model takes the form:

$$y_i \sim \text{Bernoulli}(\varphi_{j[i]}) \qquad (1)$$

$$\varphi_{j[i]} = \text{logit}^{-1}(p_{j[i]}) \qquad (2)$$

where we assume y_i, a binary indicator of smoking status for each individual i is generated from a Bernoulli distribution, where $\varphi_{j[i]}$ is the probability of smoking for each individual i in country j. This is, in effect, a country-specific intercept-only model for prevalence of the outcome, where log-odds of smoking $p_{j[i]}$ is transformed onto the probability scale using an inverse-logit function (see equation 2). Our analysis is stratified by both gender (male/female) and disability (with/without disability), and we fit the model specified by equations 1 and 2 to these four separate sub-populations. The inferences from an unpooled model, effectively, use only the information in each country to obtain the country level smoking prevalence estimate and associated uncertainty [16]. As such, there is a risk of overfitting where the data are sparse.

An alternative approach is to *partially pool* smoking prevalence estimates. To do this we extend the model specified by equations 1 and 2 to assume that the country-specific intercepts (representing prevalences on the logit scale), $p_{j[i]}$, in each of the four stratification groups are drawn from a population distribution, with mean α and standard deviation σ (equation 3).

$$p_{j[i]} \sim \text{Normal}(\alpha, \sigma) \tag{3}$$

$$\alpha \sim \text{Normal}(0, 10) \tag{4}$$

$$\sigma \sim \text{Half Cauchy}(0, 5)\,. \tag{5}$$

Equation 3 is effectively a prior for the likelihood (equations 1 and 2) and is estimated from the data. Weakly informative hyper-priors for α and σ (equations 4 and 5) are specified by us, to keep the resulting estimates within reasonable bounds but do not attempt to introduce any extra information (e.g. expert judgement or findings from a previous study). The half-Cauchy distribution is chosen for the standard deviation prior because of its long tail, which allows for the possibility of occasional large or small country-specific prevalences. Both priors are commonly used in models of this kind [10].

The main advantage of using this model is that it “borrows strength” [10] from countries with larger sample sizes to help inform estimates where there are smaller numbers. Unlike the unpooled model, it allows for information to be shared between countries. A consequence of this is that the estimates of smoking prevalence from the model represent a compromise between the overall European average smoking prevalence and the variation in this between countries. Partial pooling also allows for improved estimates when there is imbalance in sampling, as it prevents countries with much larger sample sizes from unfairly dominating inference [10,11].

Hierarchical models of this kind are set up with the likelihood (i.e. the data model, equation 1) and priors (equation 3) pulling in opposite directions [8]. The likelihood pulls the country-specific smoking prevalence estimate towards the observed value, whereas the priors pull the estimate towards the prediction from the model for the intercepts (equation 2), a phenomenon known as shrinkage [10]. The level of shrinkage is proportionate to the amount of data for a given country and distance from the overall average. For countries where there are lots of observations, the estimate of φ_i will be largely driven by the data and there is less shrinkage towards the overall European-wide mean, α. For countries where data are sparse (and the unpooled estimate is further away from the overall average), the smoking prevalence estimates will shrink further towards α.

All models are estimated using Stan, a probabilistic programming language for Bayesian inference [30]. Stan code is included in the EMaterial. We report the median of the posterior distribution as a point estimate of prevalence and 95% credible intervals (CrI), the 2.5th and 97.5th percentiles of the posterior distribution, respectively. Prevalence differences and prevalence ratios for each country are calculated by comparing estimates of smoking prevalence for men and women, with and without disabilities, in the standard way, based on the posterior values of φ_i.

Aim 2: Methods for displaying inequalities, inequality plots including uncertainty

The prevalence of smoking among people without (or with) disabilities is mathematically related to both the prevalence ratio and prevalence difference. Consequently, all three quantities of interest can be displayed simultaneously on the same plot (Blakely et al [20]). Prevalence of smoking for people without disabilities is plotted on the x-axis, we plot the prevalence difference (absolute inequality) on the y-axis and the combinations of prevalence and absolute inequality where the prevalence ratio (relative inequality) is the same are represented by a series of contour lines. From a public health perspective, focusing on both improving overall health and reducing health disparities, low smoking prevalence and low inequalities are desirable, which would generally appear toward the bottom left-hand quadrant. Conversely, a country with both high smoking prevalence and high inequality would appear toward the top right-hand quadrant. Any points plotted above a given relative inequality contour line implies a higher level of relative inequality than is indicated by that contour.

A key feature of Bayesian data analysis is explicitly modelling uncertainty. To illustrate the extent of uncertainty in our estimates on the inequality plot, we have used the posterior distributions from smoking prevalence for people without disabilities and relative inequality estimates (i.e. the x and y coordinates of the inequality plot). These posterior distributions are then plotted via a series of equally probable contours, out to the 95% CrI ellipse, based on a 2-D normal approximation.

Case study data

We use the 2014 wave of the European Social Survey (ESS), which includes a special module on health and health-related behaviours from twenty one countries [31]. For information on ESS data collection refer to EAppendix 2. The question - “Are you hampered in your daily activities in any way by any longstanding illness, or disability, infirmity or mental health problem?” – identified people with disabilities. Individuals who respond that they are hampered ‘a lot’ or ‘to some extent’ were deemed to have a disability. Smokers are deemed to be people who smoke currently, with ex and never smokers defined as non-smokers. Cases with missing values were removed (see ETable 3 for percentage missing values). We focus on smoking prevalences for working aged people - those aged 15-64 years old. At older ages ill health resulting from smoking could in fact contribute to individual’s response to the disability question. To reduce the risk of this reverse causation we restrict the analysis to those aged 15-64 years old.

Survey weights and direct age standardisation

To ensure estimates are representative of smoking prevalence in each country we make use of the census post-stratified survey weights of the ESS (see EAppendix 2 for more details) for each individual in the whole sample. Furthermore, to ensure the sub-populations of people with disabilities and without disabilities within each country are comparable with respect to age, we directly age-standardise rates of smoking in each country to the cross-country population age distribution of people with disabilities. To do this, we first created a reference age distribution, based on 5-year age groups, for the population with a disability, using the whole ESS cross-country sample with a disability. We then used this structure to re-weight individuals in each country's population for two groups – people with and without a disability. The census post-stratified weights and the age-standardisation weights are multiplied together to produce a combined weight. This is then used to weight each individuals predicted probability of smoking, estimated by equation 2 above.

3 Results

Comparison of unpooled and partially pooled prevalence estimates

ETables 1a and 1b detail a comparison of unpooled (i.e. from the single level model) and partially pooled (i.e. from the hierarchical model) estimates of smoking prevalence. The level of shrinkage (or the extent to which the model 'borrows strength' for countries with smaller samples sizes) is largest in circumstances where both data are sparse and the unpooled smoking prevalence estimate is further from the overall mean (see ETables 2a and 2b). In general the more substantial examples of shrinkage occur for people with disabilities, as sample sizes are smaller (see ETable 3 for sample sizes). For example, for males in Portugal, with 23 smokers with disabilities in the sample and the unpooled estimate of smoking prevalence being one of the highest, the hierarchical model shrinks the unpooled prevalence estimate of 53% (CrI 42% - 63%) by 5% toward the overall mean for people with disabilities to give a partially pooled estimate of 48% (CrI 38% - 58%). For females, shrinkage is clearly evident for Spain (number of smokers with disability: 36) the unpooled estimate of shrinks by 4% from 43% to 39%.

In contrast, there is less shrinkage for countries with a larger sample size that are a similar distance from the mean as the examples given above. For males with a disability in Estonia (number of smokers: 58), the unpooled estimate of 46% (CrI 39% - 53%) only shrinks 2% toward the mean for people with disabilities, giving a partially pooled estimate of 44% (CrI 38% - 51%).

The partially pooled estimates also exhibit a modest reduction in uncertainty in comparison to the unpooled estimates. Again, this is mainly evident where there is less data and for countries further from the overall mean for people with and without disabilities respectively. However, there are also modest reductions in uncertainty for estimates close to the European mean for people with disabilities (e.g. Israel for males and females).

Effect of partial pooling on smoking inequality estimates

Figure 1 uses an inequality plot to provide an illustration of the effect of shrinkage, from the hierarchical model, on smoking prevalence among people without a disability (x-axis) and relative (contours) and absolute (y-axis) inequalities for a selection of countries. The country initials are placed next to the unpooled estimate (blue dot) with the red dot representing that country's partially pooled estimate from the hierarchical model. The black dots show the European average, by gender, for smoking prevalence for people without a disability, relative and absolute inequalities.

[Place figure 1 about here]

Again, there is greater shrinkage for combinations of prevalence, relative and absolute inequalities that are further from the overall European mean for each disability-gender average. For example Switzerland for males and Norway for females. For countries in similar parts of the inequality plot there is greater shrinkage where there is less data: e.g. for males, the sub-sample of Swiss people with a disability is smaller than for Finland.

Smoking inequality results, including assessment of uncertainty

Figure 2 shows the inequality plot for males and females, providing a summary of the prevalence among people without a disability (x-axis), standardised prevalence differences (SPDs, on y-axis) and standardised prevalence ratios (SPRs, dotted contours) simultaneously. Given that it is impractical to plot uncertainty for each country on the typology plot, figure 3 illustrates typical uncertainty levels for a selection of countries (EFigures 1 and 2 illustrate uncertainty for all countries). To aid interpretation there are two dashed lines on each panel, bisecting the European average smoking prevalence for people without disability (vertical line) and the SPD (horizontal line). The resulting quadrants represent the four combinations of low and high smoking prevalence and absolute inequalities.

[Place figure 2 about here]

Males

Portugal has the most extreme combination of high absolute inequality (plotted towards the top, in respect of the y-axis) and high relative inequality (plotted on the 1.5 SPR contour line). However, smoking prevalence for people without disabilities in Portugal is not the worst (plotted in the middle of the x-axis range). Conversely the country with the lowest smoking prevalence *and* low levels of inequality, and hence plotted in the bottom-left quadrant of the graph, is Sweden.

In general, one can identify three groups of countries that have similar levels of smoking prevalence for men without disabilities, absolute and relative inequalities.

First, countries with high relative and absolute inequalities, but with lower smoking prevalence for men without disabilities. For example, Ireland, Finland and Switzerland have high absolute inequalities (an SPD of around 12.5, and towards the top of the plot in respect of the y-axis) and high relative inequalities (plotted around the 1.5 SPR contour lines). With no probability density attached to values less than zero for SPDs and one for SPRs (e.g. Switzerland on figure 3), these modelled inequalities provide strong evidence of inequalities in their corresponding populations.

The second group (e.g. Austria, Poland, Czech Republic, Germany, Lithuania and Hungary) have high smoking prevalences for men without disabilities and low absolute and relative inequalities. These countries, therefore, are plotted on the bottom right-hand quadrant of figure 2. For these countries, while just over half of the probability density of the posterior inequality distribution are greater than zero for SPDs and one for SPRs (e.g. Germany on figure 3), the model shows that smoking prevalences for men with disabilities are broadly similar to those without disabilities.

The third group (e.g. Belgium, Netherlands, Great Britain, Norway and Spain) has slightly lower smoking prevalences for men without disabilities but slightly higher absolute and relative inequalities than the second group identified above. Most of the posterior distribution for these measures of inequality are greater than zero for SPDs and one for SPRs, meaning we can be fairly certain they reflect genuine inequalities at the population level (e.g. Britain on figure 3).

[Place figure 3 about here]

Females

For women there is clear evidence of inequalities. Most countries (e.g. Belgium, Switzerland and Denmark) are clustered in the central area of figure 2 – absolute inequalities between 7.5% and 10% SPD in respect of the y-axis, relative inequalities between the 1.25 and 1.5 SPR contours, and smoking prevalence for people without disabilities between 20% and 25% in respect of the x-axis.

Examples of countries with the worst combination of high absolute and relative inequalities are Britain, Hungary, France and Spain. Each are plotted towards the top of figure 2 in respect of the y-axis (high absolute inequalities) and around the 1.5 SPR contour. For these countries there is no probability density overlapping the x-axis or attached to values less than one for the posterior SPR estimates (e.g. Spain on figure 3).

At the bottom of the plot, in respect of the y-axis, Poland has an estimated smoking prevalence for people with disabilities that is lower than for people without disabilities. Sweden, Lithuania Portugal and Slovenia, for example, also have low relative and absolute inequalities (toward the bottom of the plot, in respect of the y-axis). For each of these countries a large portion of the inequality posterior distribution is below one for SPR and zero for SPD, reflecting weak evidence for inequalities in their corresponding populations.

4 Discussion

This article demonstrates how to use Bayesian hierarchical models and partial pooling to improve estimates of the international variation in health outcome and behaviour inequalities when data are sparse. We show how partial pooling shifts estimates from countries where data are sparse toward the overall European average, guarding against sampling variation dominating inference. Furthermore, our inequality plots with uncertainty also present a useful graphical tool for evaluating both the geographical patterns of variation in, and strength of evidence for, differences in social inequalities in health, which avoids reliance on p-values or statistical tests to make multiple comparisons. The probability of finding significant differences between estimates (regardless of these differences being true) increases with the number of comparisons being made [16,29]. Partial pooling has been suggested as a way to safeguard against false discoveries. Variation in estimates is preserved and intervals for comparisons are more likely to include zero as estimates are shifted toward the overall mean [16].

Pooling or averaging data prior to carrying out analysis risks missing important trends and patterns in health outcomes and behaviours. Adopting a hierarchical approach, which instead partially pools data, could help identify important trends or patterns, which could otherwise be missed. This approach, while having been suggested previously [e.g.[15]], is, to our knowledge, rarely applied. This paper is the first study of this kind – an international comparison of inequalities – that explicitly adopts a hierarchical modelling approach. Our results demonstrate how estimates from countries with a smaller sample size are shifted toward the overall mean. Inferences are therefore not dominated by sampling noise and benefit from the greater precision of the smoking prevalence estimate from all countries.

Recently, papers on tracking [17,19] and displaying inequality [20,23] have emphasised how simultaneously analysing and displaying relative and absolute inequalities, alongside prevalence, can be useful for inequality monitoring and assisting target setting. However, none of these previous papers have displayed the uncertainty associated with estimates of prevalence, relative and absolute inequality. We argue that coherently modelling and displaying inequality has the potential to improve the presentation of data used to monitor inequalities. We encourage researchers to build on this, extending these plots to situations when trends over time are being considered. One could then potentially use them to attach a probability value to whether absolute and/or relative inequalities are remaining stable or changing over time.

In some circumstances, using partially pooled estimates could lead to different public health decisions. Using the case study, consider Sweden and Norway for males and Portugal for females. The unpooled estimates indicate that there is little to no inequality between those with and without disability, in this circumstance a whole-of-population approach to smoking cessation would be an appropriate policy response. The partially pooled estimates do not unequivocally support that conclusion and it might, therefore, be necessary to have a dual focus on the whole population (e.g. tobacco tax) and a concerted effort to close inequalities (e.g. cessation programmes specifically designed for people with disabilities). Here partial pooling and the extent to which estimates are sensitive to shrinkage, can also be used to indicate whether a decision maker could benefit from more data to make an informed decision. For example, if partially pooled estimates do not shrink away from the unpooled estimate (e.g. Belgium for males) then, assuming the estimate is unbiased, a policy maker in that country could be relatively confident in their evidence/data. Conversely, in a country (e.g. Spain for females or Portugal for males) where there is a large amount of shrinkage, it could indicate that decision making could benefit from the collection of more data. Considering both the unpooled and partially pooled estimates together, provides a full picture for policy makers about the strength of evidence for inequalities. In the absence of collecting more data and in the presence of considerable uncertainty, we would argue that a prudent decision would be to use the partially pooled estimate to inform policy, as this guards against inference being overly influenced by sampling noise.

Previous research using partial pooling, in the presence of sparse data, has made use of group-level predictors at the level of the model hierarchy equivalent to the country-level in this paper (e.g. [32]). We did not include country-level predictors because the relevant data at the country-level is not available for all countries. As mentioned previously, through our use of partial pooling, we are assuming that the underlying effects of all 21 countries in our study come from a population distribution, that captures between-country variation in prevalences that could be driven, for example, by different tobacco control regimes or social support between countries.. Future studies could include predictors (e.g. extent of tobacco control) at the second level of hierarchy in the model (i.e. equation 3). This could reduce the variance of the conditional “population distribution” and potentially increase the precision of estimates.

Our case-study results show that, at a European level, smoking prevalence is higher for people with disabilities than for those without disabilities. This inequality holds when disaggregated by gender, with both absolute and relative inequalities higher for females than males, supporting previous studies that have documented gender differences in smoking prevalence [24]. These findings are consistent with previous research in Europe which has found similar country-specific patterns to inequality [24] and that smoking prevalence is high among males and disadvantaged females [33].

A potential limitation of only having self-reported smoking is the possibility of misclassification. It is possible, due to social desirability bias, that people may underreport their smoking status. <u>To take this into account we conducted a sensitivity analysis, extending the hierarchical model specified above (equations 1-5) to model the impact of potential misclassification of smoking on inequality estimates (see EAppendix 3 for full model and results). This adds to the literature by showing how accounting for misclassification and partial pooling can be combined within the one model. Modelling the presence of misclassification, which by itself increases the uncertainty around the point prevalence estimate for each country, increases the usefulness of the shrinkage resulting from partial pooling. Given that verifying smoking status is expensive and that large prevalence surveys are unlikely to include verified smoking status, our extended model illustrates how future research</u>

can use partial pooling and include misclassification parameters elicited from smaller sub-studies that verify smoking status.

Additionally, the smoking question in the survey only gathers information on cigarette smoking. Here we only examine a binary measure of smoking but knowing inequalities in the number of cigarettes smoked or pack years would also be useful. We also lack information on other harmful tobacco use such as chewing tobacco and smoking cigars.

To conclude, this paper has demonstrated how partial pooling can be used to estimate international variations in inequality where data are sparse, and how one can use inequality plots to simultaneously assess the magnitude and strength of evidence of relative and absolute inequalities and prevalence of health or health behaviours.

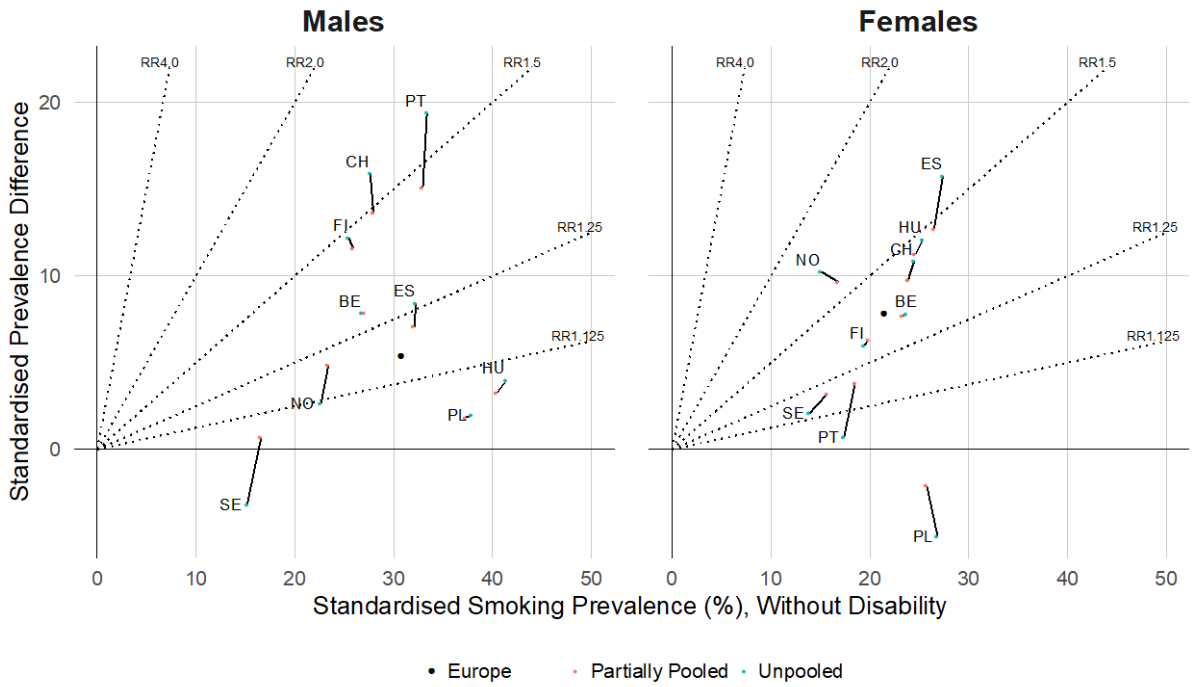
Figure captions

Fig 1: Inequality typology plot to illustrate the effect of shrinkage on prevalence estimates for people without disabilities (x-axis), absolute inequalities (prevalence differences, y-axis) and relative inequalities (prevalence ratios, denoted by contour lines. All x-y coordinates on a given contour line will have the same prevalence ratio). Partially pooled estimates are represented by blue dots, unpooled estimates are represented by red dots and completely pooled estimates by a black dot (effectively the overall European average). (Abbreviations for countries on plot: CH – Switzerland, ES – Spain, FI – Finland, HU – Hungary, NO – Norway, PL – Poland, PT – Portugal, SE – Sweden)

Fig 2: Inequality typology plot, comparing age-standardised smoking prevalence and inequalities for people with disabilities, aged 20-64 years old, in 21 European countries. Dashed quadrant lines bisect the European average values for smoking prevalence for people without disabilities and absolute inequalities (standardised prevalence differences). (Abbreviations, all countries: AT – Austria, BE – Belgium, CH – Switzerland, CZ – Czech Republic, DE – Germany, DK – Denmark, EE – Estonia, ES – Spain, FI – Finland, FR – France, GB – United Kingdom, HU – Hungary, IE – Ireland, IL – Israel, LT – Lithuania, NL – Netherlands, NO – Norway, PL – Poland, PT – Portugal, SE – Sweden, SI – Slovenia).

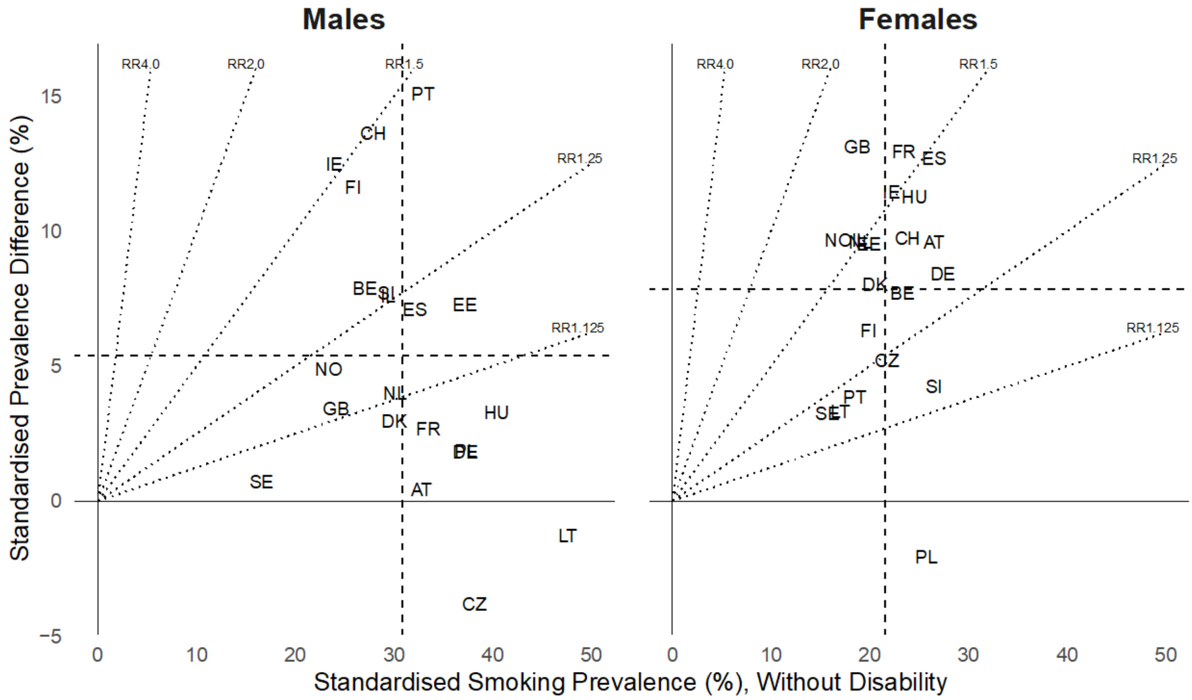
Fig 3: Selected countries displayed on an inequality typology plot, including posterior density contours - a series of equally probable contours (25%, 50% 75%) out to the 95% ellipse, based on a 2-D normal approximation.

Figure 1



Males
Females
RR4.0
RR2.0
RR1.5
RR1.25
RR1.125
PT
CH
FI
BE
ES
HU
NO
PL
SE
Standardised Prevalence Difference
Standardised Smoking Prevalence (%), Without Disability
Europe
Partially Pooled
Unpooled

Figure 2


Males
Females
Standardised Prevalence Difference (%)
Standardised Smoking Prevalence (%), Without Disability
RR4.0
RR2.0
RR1.5
RR1.25
RR1.125
PT
CH
IE
FI
BE
SI
ES
EE
NO
NL
GB
DK
FR
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SE
AT
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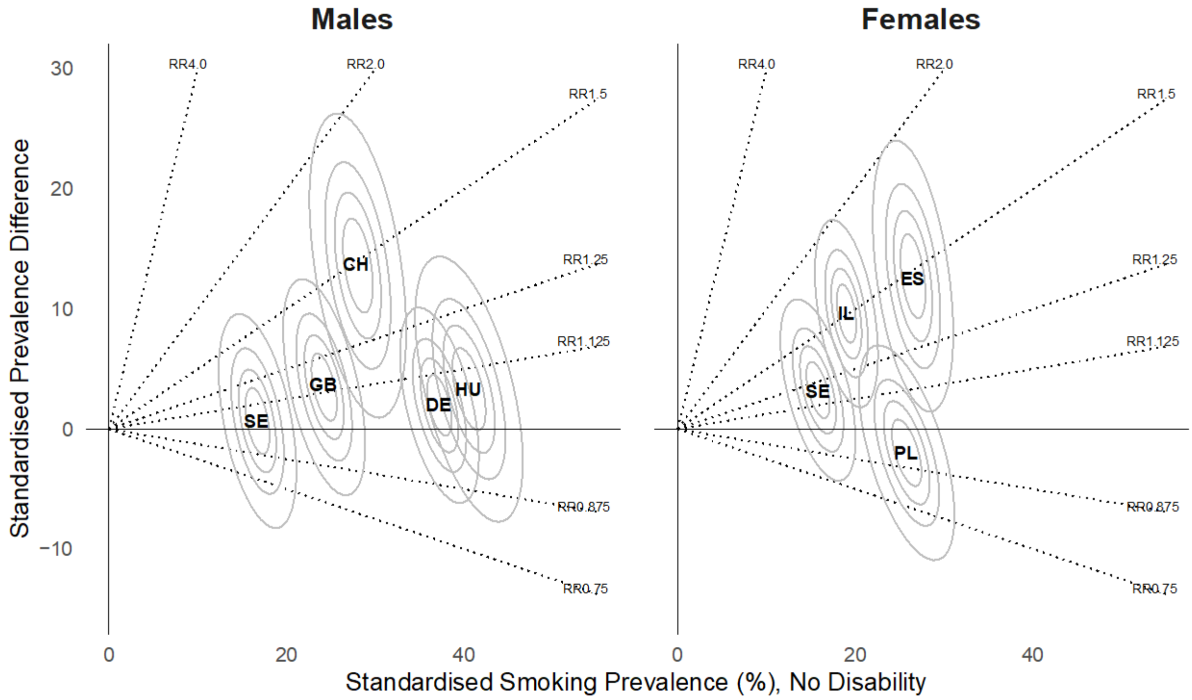
Figure 3


Males
Females
Standardised Prevalence Difference
Standardised Smoking Prevalence (%), No Disability
30
20
10
0
−10
0
20
40
RR4.0
RR2.0
RR1.5
RR1.25
RR1.125
RR0.875
RR0.75
CH
GB
SE
DE
HU
ES
IL
SE
PL

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