# Partial Identification of the Effect of Retirement on Mental Health with Panel Data.

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# Partial Identification of the Effect of Retirement on Mental Health with Panel Data.

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**Abstract**

We study how retirement affects mental health using a partial identification framework for panel data. With this framework, we estimate identification regions that are transformed into quantitative policy recommendations by adopting a minimax-regret decision rule. Under relatively weak assumptions, we find that retirement can have a moderate, positive effect on individuals whose pre-retirement mental health is below average of the corresponding age cohort. Our minimax-regret analysis further suggests that while retirement can be delayed without affecting the mental health of most of the population, it is advisable to facilitate the retirement of people with poor mental health.

**Key Words**: *Partial Identification, Panel Data, Retirement, Mental Health, Average Treatment Effect on the Treated, Minimax Regret.*

**JEL Classification**: *C22, C33, C54, J26, I1.*

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# 1 Introduction.

Across the OECD, the population is ageing, people are living longer and staying healthy for longer (Crimmins, 2015, 2021), spending longer periods in formal education (Barro and Lee, 2013; OECD, 2021a), and having fewer children (OECD, 2019). These trends increase the old age dependency ratio and cause problems for defined-benefit and pay-as-you-go public pension systems (prevalent in the OECD -where average public spending on old-age pensions has steadily increased from 6.6% in 2000 to 7.9% in 2019; OECD, 2021b). Governments are implementing policies to address this issue[1], but to evaluate these policies, we need to understand how retirement affects people and if any such effect is amplified or mitigated by the new policies.

In this paper, we study the effect of retirement on mental health using the UK Household Longitudinal Study (HLS), a representative panel tracking over 40,000 households since 2009. The analysis period is 2010-2019, post-Great Recession and pre-Covid-19. Like most OECD countries, the UK has a public pension system with state pension age and replacement rates aligning with the OECD average. The UK has a universal tax-funded health system, eliminating healthcare as a variable in retirement decisions. These factors make the UK a representative and compelling case study.

Mental health is an important and consequential dimension of health that could be impacted by retirement. Medical research shows that depression accounts for around 14.2% of all years lived with disability worldwide (Anderson et al., 2002, Prince et al., 2007), and it is associated with all-cause excess mortality risk (Saz and Dewey, 2001), heart disease (Lawrence et al., 2003, Hemingway and Marmot, 1999, Kuper et al., 2002, Larson et al., 2001, Ohira et al., 2001), poor glycemic control (Lustman et al., 2000, Anderson et al., 2002) and lower adherence to recommendations for diet, exercise or medication (including vital oral hypoglycemic medication; Ciechanowski et al., 2000, Lin et al., 2004, Jones et al.,

[1] Because of the desirability of educational attainment, longevity, and improved health, these measures primarily affect pension and early retirement rules. In the OECD, for instance, countries such as Finland, the Netherlands, the UK, or the Czech Republic have increased the 'normal' retirement age by an average of 2 years; countries such as Australia, Greece, or Hungary have introduced changes to the rules defining individual contributions to public and private pensions; and two-thirds of OECD countries have strengthened or introduced Automatic Adjustment Mechanisms to take demographic trends into consideration when computing pension benefits (OECD, 2021b).

2004, Desai et al., 2002). Other mental health problems such as anxiety are also correlated with poor physical health, adherence to guidance, loneliness and boredom, to mention but a few issues (e.g. Losada et al., 2015 and references therein). Economists have further detected that poor mental health can lead to substantive decreases in academic performance (Ding et al., 2009) and differential response levels to financial incentives (Kung et al., 2018). Economic models of fear-related avoidance behaviour (e.g. Koszegi, 2003) have also found empirical ratification in the medical literature (Delbaere et al., 2004).

This paper makes two principal contributions. We first add to the empirical literature studying the consequences of retirement on mental health. This literature has grown considerably since the seminal paper by Charles (2004), although retirement has been found to improve mental health (Charles, 2004; Eibich, 2015; Johnston and Lee, 2009; Rose, 2020), hinder it (Butterworth et al., 2006; Dave et al., 2008; Grip et al., 2012), be innocuous (Fé and Hollingsworth, 2016), and to only have negative long-term effects (Heller-Sahlgren, 2017), to mention but a small selection of studies (comprehensive surveys can be found in Nishimura et al., 2018, Garrouste and Perdrix, 2022). We contribute to the literature by studying how the levels of mental health before retirement determine people's response to retirement and how these levels interact with job satisfaction. This allows to understand whether retirement is beneficial when mental health is poor but job satisfaction is high (so that employment is a contributor to people's well-being). To the best of our knowledge, this question has not been studied to date.

Our second contribution is to the literature on partial identification methods for panel data. Specifically, we propose partial identification regions that bind the effect of retirement on those observed to retire in the sample (the Average Treatment Effect on the Treated, ATT). The bounds are obtained by adapting monotonicity and bounded variation assumptions of the type discussed in Manski (1990, 1997) and Manski and Pepper (2013, 2017). As a result, the bounds are easy to implement and interpret. Confidence intervals for the bounds can be obtained using established methods (e.g., Imbens and Manski, 2004 or Chernozhukov et al., 2013)[2].

[2] At the time of writing, we are aware of only two other partial identification frameworks for panel data: Torgovitsky (2019) and Callaway (2021). More precisely, Torgovitsky (2019) presented a nonparametric

The paper fills a substantive methodological gap in the literature. Earlier empirical research has relied on the quasi-experimental variation in retirement caused by early retirement and pension eligibility rules. That approach is compelling because it makes plausible instrumental variables available, facilitating point estimation. The partial identification framework we employ, however, has two advantages. The instrumental variable literature reports an effect that refers to a small subpopulation whose retirement decision is solely influenced by exogenous early retirement/pension eligibility rules (the compliers), estimated to be between 7% and 20% of retirees. Since only the proportion of compliers is identifiable, it's unclear how representative they are of the whole population. In contrast our framework binds the ATT, which refers to all those observed to retire in a sample (and is typically a larger proportion of individuals -not all seen to retire are compliers).

The second methodological advantage of our approach is that it relies on assumptions that are weaker and more credible than those for standard panel data models and, arguably, those underpinning instrumental variable methods, yet still provides informative causal estimates. Specifically, we do not require an exclusion restriction, (which forces researchers' models to isolate the direct effect of age on outcomes like cognition and health, which is challenging -see, e.g., Fé, 2021, Eibich, 2015).

The final question this article explores is policy recommendations. Partial Identification frameworks can be turned into informative policy recommendations using a minimax-regret decision rule (Manski, 2000, 2004, 2007). This rule helps determine what proportion of a population a policy should target to minimize the maximum possible loss of utility, and it will help us to inform how much the retirement age can be delayed based on findings about retirement's effect on mental health[3].

dynamic potential outcomes model to explore state dependence in unemployment for working-age, high-school-educated men. Callaway (2021) is concerned with general parameters that depend on the joint distribution of potential outcomes, for which he exploits panel data together with a restriction on the temporal variation of the dependence of untreated potential outcomes over time (the outcomes outside retirement, in our context), and under the assumption of identifiable marginal distributions. In this paper we focus on a static parameter (unlike Torgovitsky, 2019, who is interested in dynamic effects), but the former has the advantage of not requiring assumptions about the joint distribution of potential outcomes. Despite of focusing on a static parameter, we can still enable treatment status in the past to affect potential outcomes in the present (therefore allowing long-term effects). Our focus is also narrower than that in Callaway (2021), as we focus on an average effect of retirement.

[3]These methods fit within a much broader agenda of research developed by Charles Manski. They have been successfully applied to a range of areas, including search profiling in policing settings clinical

Overall, the contribution of the paper is both empirical and methodological. From an empirical perspective, we provide new data on the influence of retirement on mental health. To the best of our knowledge, this is the first paper to explicitly consider how the interaction of pre-retirement mental health and job-satisfaction shapes the causal effect of retirement. We are also the first to provide a minimax regret analysis to elicit policy recommendations. From a methodological perspective, we provide a partial identification framework for panel data which is simple to implement in practice and which relies on well-understood identification assumptions. Within the literature on retirement, only one previous paper (Fé, 2021) has considered partial identification approaches to study retirement. There are some significant differences between both papers, however. Our earlier work focused on the effect of retirement on American men whose retirement decision was determined by a pension eligibility rule only. That work used cross-sectional data. In contrast we bind the effect of retirement on those seen to retire in the U.K. HLS by exploiting the longitudinal nature of those data.

The rest of the paper is organised as follows. We first describe the partial identification framework and present the main identification assumptions. To keep the technical detail to a minimum, the bounds are derived in the Appendix accompanying this paper. Section 3 presents the empirical analysis. After presenting the data and some descriptive statistics, we provide a justification of the identification assumptions in the context of our application. The main set of results then follows. Section 4 describes the minimax-regret method and presents the results, describing how these findings can translate into recommendations regarding the delay of the retirement age. Section 5 concludes with some remarks.

## 2 Identification.

In this section, we outline our identification strategy. The Appendix contains a detailed technical discussion with derivations of the bounds. We assume access to a panel dataset,

practice, vaccination, climate policy, and the size of government; see Manski (2000, 2004, 2007) and references therein) which need not be balanced. Throughout, $Z_{it}$ denotes person $i$'s retirement status at time $t$, where $Z_{it} = 1$ if retired and $Z_{it} = 0$ otherwise. We focus on permanent retirements: if $Z_{it-1} = 1$, then $Z_{it} = 1$.

A person's mental health at time $t$ depends on their retirement status. Panel data allows us to consider two significant effects of retirement on mental health. First, as in Mazzonna and Peracchi (2012, 2016), we incorporate the impact of retirement spell duration on yearly health variations. Second, we allow prior work histories to influence current potential outcomes. This motivates the definition of potential outcomes $Y_{it}(Z_{it}, Z_{it-1})$, explicitly linking today's mental health status to both today's and the previous period's retirement status[4]. For any given pair $Z_{it} = z_{it}$ and $Z_{it-1} = z_{it-1}$, we denote $Y_{it}(z_{it}, z_{it-1})$ as $Y^{z_{it}z_{it-1}}$.

We are interested in the effect of retirement on mental health at time $t$, defined as:

$$\tau_t = E\Big(Y_{it}(1,0) - Y_{it}(0,0) \mid Z_{it} = 1\Big) = E(Y_{it}^{10} - Y_{it}^{00} \mid 1) \tag{2.1}$$

This is the Average Treatment Effect on the Treated at time $t$ (ATT$_t$) studied in the panel data literature. It measures the change in mental health when a person transitions from not being retired to being retired. For simplicity, we have omitted dependence on additional exogenous variables. However, $\tau_t$ can also be interpreted conditional on a set of regressors (e.g. age group). Conditioning on regressors imposes stronger requirements on the assumptions, which must hold for every combination of values of the regressors.

Let $P(Z_{it-1} = z', Z_{it-2} = z''|Z_{it} = z) = \Pi_{z'z''|z}$. Then $\tau_t$ decomposes into the effect of retirement on two sub-populations: those newly retired and those retired for at least two

[4] Extending potential outcomes to $Y_{it}(Z_{it}, Z_{it-1}, Z_{it-2}, \ldots)$ would require extensive data on entire work histories for each respondent, imposing stronger demands on data availability and identification assumptions, with minimal additional benefit in terms of narrower identification regions. As shown next, allowing potential outcomes to vary up to time $t-1$ provides substantial flexibility.

years:

$$\begin{aligned}\tau_t = &\Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,0,0) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,0,0)\Big]\Pi_{00|1} \\ &+ \Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,0) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,0)\Big]\Pi_{10|1} \\ &+ \Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,1) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,1)\Big]\Pi_{11|1} \end{aligned} \tag{2.2}$$

This expansion shows that by generalising the potential outcomes to depend on $Z_{t-1}$, $\tau_t$ now accounts for the duration of retirement (through the conditioning set, up to three consecutive periods). Equation (2.2) also emphasises that nonparametric point identification of $\text{ATT}_t$ is not feasible due to unknown pre-retirement mental health states. Only the proportions of each sub-population $\Pi$ and the first term are identifiable. To progress forward, we need to consider assumptions about the non-identifiable terms.

## 2.1 No Assumption Bounds

Our baseline identification regions rely on the existence of upper and lower bounds for the outcome variable, so that $\alpha \leq Y_{it}^{\bullet} - Y_{it-1}^{\bullet} \leq \beta$ and $a \leq Y_{it}^{\bullet} \leq b$. Under this assumption, one can show that $\tau_t \in [\underline{\tau}, \overline{\tau}]$, where

$$\underline{\tau} = \Big[E(Y_{it} - Y_{it-1}|1,0,0) - \min(\beta, b - E(Y_{t-1}|1,0,0))\Big]\Pi_{00|1} + \Big[(\alpha - \beta)(1 - \Pi_{00|1})\Big]$$

and

$$\overline{\tau} = \Big[E(Y_{it} - Y_{it-1}|1,0,0) - \max(\alpha, a - E(Y_{t-1}|1,0,0))\Big]\Pi_{00|1} + \Big[(\beta - \alpha)(1 - \Pi_{00|1})\Big] \tag{2.3}$$

These are commonly referred to as the No-Assumption Bounds (NAB). As noted already in Manski (1990), these bounds include 0 and thus do not identify the sign of the ATT. Further, they can be too general in practice, limiting the amount of information the contribute. Next we explore assumptions that can help to build narrower identification regions[5].

## 2.2 Assumptions characterising agents' behaviour.

The NAB can be improved upon by incorporating additional assumptions. Our first such assumption is the following version of the Optimal Treatment Selection (OTS) assumption in Manski (1990):

**Assumption 1.** *Contemporary Optimal Treatment Selection (COTS).* $Z_{it} - Z_{it-1} = 1 \rightarrow Y_{it}^{10} \geq Y_{it}^{00}$

Under permanent retirement, COTS implies that people choose to retire at a moment when it is not detrimental to do so. In this sense, the decision is 'optimal'. It is a contemporary assumption because it does not characterise the potential outcomes after retirement, thus allowing for scenarios where a retired person might have been better off working in the second or later periods of retirement. Further, COTS leaves the sign of $\tau_t$ unrestricted and is agnostic about retirees having superior or inferior potential outcomes than non-retirees. The identification region under COTS and NAB are in the Appendix. These are narrower than the baseline regions under NAB alone, due to additional information on the evolution of $Y_{it}^{00}$ among just-retired individuals.

We can achieve narrower bounds by further restricting the long-term impact of retirement among those retired for at least two time periods. Specifically, we might consider the idea that retirement maintains mental health levels, as follows:

**Assumption 2.** *Dynamic Optimal Treatment Selection (DOTS).* For all $i, t$, if $Z_{it} = 1, Z_{it-1} = z$ then $Y_{it}^{1z} \geq Y_{it}^{uw}$ for every $u \neq 1 \cup w \neq z$

This assumption implies that the observed mental health of retirees is no worse than the average mental health they would have exhibited if they had retired at a different

[5] We deliberately avoid assumptions ranking potential outcomes, specifically Monotone Treatment Response (MTR) in Manski (1997) and Monotone Treatment Selection (MTS) in Manski and Pepper (2000). While MTR identifies the treatment effect's direction, MTS elucidates the selection process. Both are useful in contexts such as schooling (e.g., Manski and Pepper, 2000), food stamps (Kreider et al., 2012), or parental inputs (de Haan, 2011). However, attributing a specific effect to retirement or assuming mental health's positive or negative role in retirement decisions lacks sufficient basis.

point in time. Therefore, DOTS suggests that people do not choose to retire in a manner that is sub-optimal in the long run. The ensuing identification region under NAB and DOTS is at least as narrow as that obtained under COTS and NAB. It will be narrower if $\beta > E(Y_{it}|1, 1, \bullet) - a$ or $\alpha < a - E(Y_{it}|1, 1, \bullet)$.

## 2.3 Assumptions about inter-temporal outcome variability.

COTS and DOTS assume a motivation behind retirement which some researchers might find contentious. In such cases, we can use bounded variation assumptions like those introduced by Manski and Pepper (2013, 2017). These assumptions limit the variation of counterfactual moments, assuming that counterfactual and equivalent observable moments cannot differ significantly. This approach is advantageous in panel data, as it restricts variation in first differences rather than levels. We consider two types of assumptions:

**Assumption 3.** *Bounded Variation Within Units (BW).*

$$\left|E(Y_{it}^{10} - Y_{it-1}^{00}|1, 1, z) - E(Y_{it}^{11} - Y_{it-1}^{1z}|1, 1, z)\right| \leq \theta^{(1)} \tag{2.4}$$

$$\left|E(Y_{it}^{00} - Y_{it-1}^{00}|1, z, z') - E(Y_{it}^{1z} - Y_{it-1}^{zz'}|1, z, z')\right| \leq \theta^{(2)} \tag{2.5}$$

BW assumes that within a sub-population defined by $Z$, counterfactual and observable moments cannot differ by more than an unspecified amount $\theta > 0$. Researchers choose $\theta$ differently for $Y_{it}^{10} - Y_{it-1}^{00}$ and $Y_{it}^{00} - Y_{it-1}^{00}$, reflecting varying beliefs about the information provided by observable moments.

**Assumption 4.** *Bounded Variation Between Sub-populations (BB)*

$$\left|E(Y_{it}^{10} - Y_{it-1}^{00}|1, 0, 0) - E(Y_{it}^{10} - Y_{it-1}^{00}|1, 1, z)\right| \leq \theta^{(1)} \tag{2.6}$$

$$\left|E(Y_{it}^{00} - Y_{it-1}^{00}|0, 0, 0) - E(Y_{it}^{00} - Y_{it-1}^{00}|1, z, z')\right| \leq \theta^{(2)} \tag{2.7}$$

The BB assumption states that observed moments in one sub-population provide information about equivalent counterfactual moments in other sub-populations. Under BB, identification regions are centered around the fixed effects estimator in first differences. In contrast to BW, where regions are centered at zero and do not indicate the treatment effect's direction, BB allows the fixed effect estimator to provide information about ATT based on subjective beliefs about the information carried by observed moments and their counterfactual equivalents in other sub-populations.

## 2.4 Assumptions about the average variation of non-retirees' outcomes.

One primary source of uncertainty regarding $\tau_t$ stems from the lack of data on the mental health of retirees if they had remained at work. The difference-in-differences literature addresses this uncertainty by assuming that treated and untreated sub-populations exhibit identical trends under the control treatment (alongside an additional structural assumption, $E(Y_{it}^{00}|\Omega_{it} = \omega_{it}) = \phi t + f(\omega_{it})$, where $f(.)$ is assumed to be known or approximated by a flexible model, and $\Omega_{it}$ comprises covariates, lagged treatment indicators, fixed effects, and other variables). A similar, albeit weaker, assumption that requires no structural constraints and only needs to hold at each time point $t$ is as follows:

**Assumption 5.** *Homogeneous Average Variation of Outcomes (HV).*

$$E(Y_{it}^{00} - Y_{it-1}^{00}|z, z', z'') = E(Y_{it}^{00} - Y_{it-1}^{00}|0, 0, 0) \tag{2.8}$$

This assumption asserts that, within periods $t$ and $t-1$, workers' mental health follows a trend observed among non-retirees in the sample. Specifically, HV implies that $E(Y_{it}^{00} - Y_{it-1}^{00}|z, z', z'') = E(Y_{it} - Y_{it-1}|0, 0, 0)$, meaning retirees and non-retirees are comparable on average while working.

The Appendix demonstrates that the partial identification region obtained under HV reduces, though does not completely resolve, the uncertainty surrounding $\tau_t$, as the impact of retirement on those already retired for two periods or more remains unknown. Given the similarity between the HV assumption and the typical common trend / fixed-effect assumption in panel data literature, the identification region under HV assesses the role of structural models (especially linear models) in producing point estimates.

### 2.5 Identification without Long Term Effects and Combination of Assumptions.

By considering potential outcomes that depend on current and past retirement indicators, we acknowledge the possibility of long-term effects. This includes scenarios where retirement leads to sustained improvements or declines in mental health due to ongoing trends. However, if retirement only has a single discrete or temporary effect, the broader definition of potential outcomes introduces unnecessary uncertainty. To address this, we redefine potential outcomes as $Y_{it}(Z_{it})$ where $Z_{it} \in \{0, 1\}$.

**Assumption 6: No inter-temporal interference (NI)** $Y_{it}(Z_{it}, Z_{it-1}) = Y_{it}(Z_{it})$

Under NI, we can simplify $\tau_t$ as follows:

$$\begin{aligned}\tau_t =& \Big[E(Y^1_{it} - Y^0_{it-1}|1,0) - E(Y^0_{it} - Y^0_{it-1}|1,0)\Big]\Pi_{0|1} \\ &+ \Big[E(Y^1_{it} - Y^0_{it-1}|1,1) - E(Y^0_{it} - Y^0_{it-1}|1,1)\Big]\Pi_{1|1} \end{aligned} \tag{2.9}$$

By eliminating the influence of treatment status on future potential outcomes (referred to as inter-temporal interference), we essentially restore Rubin's Stable Unit Treatment Value Assumption (SUTVA; Rubin, 1974). SUTVA assumes that each unit's treatment status does not affect other units' outcomes. When inter-temporal interference is absent, we reduce ambiguity caused by long-term retirement effects (from the sub-population where $Z_t = Z_{t-1} = 1$) and enhance the identification of $E(Y^1_{it}|1, 1)$.

The NI assumption, when combined with Assumptions 1 to 5, provides narrower bounds compared to the broader setting. These bounds are in the Appendix, which also discusses the estimation of identification regions and the construction of confidence intervals following Imbens and Manski (2004).

# 3 Empirical analysis.

We analyzed data from male respondents in the UK Household Longitudinal Study (HLS), a dataset tracking over 40,000 households since 2009. Our study focused on the period 2010-2019, spanning from the 2008 Financial Crisis to the Covid-19 pandemic[6]. We excluded respondents with missing job status, age, interview date, or responses needed to construct our dependent variable (described below). We specifically focused on permanent retirements and excluded individuals who returned to full or part-time employment after retirement. Moreover, we excluded those reporting long-term illness, disability, or unemployment, resulting in 20,633 observations from 3,300 individuals born between 1945 and 1959, interviewed in at least one of the nine waves conducted between 2010 and 2019.

## 3.1 Dependent, treatment and pre-treatment variables.

To measure mental health, we used the General Health Questionnaire (GHQ), a 12-item questionnaire designed to assess various aspects of mental health. Each item in the GHQ is scored from 1 to 4, with 1 indicating the best mental health status. Factor analysis revealed two or three factors that, while suggesting different mental health domains, were highly correlated and conveyed similar information in practice, consistent with findings by other researchers (e.g., Gao et al., 2004). Therefore, for our analysis, we aggregated the scores of all 12 items of the GHQ. Prior to aggregation, we re-coded the items so that higher scores indicate better mental health, maintaining consistency with previous sections. Thus, the GHQ aggregate score ranges from 12 (indicating very poor mental health) to 48 points. We further transformed the GHQ aggregate score by taking the natural logarithm and re-scaling it by 100:

$$100 * \Big[\log(Y_{it}) - \log(Y_{i,t-1})\Big]. \tag{3.10}$$

[6]Our focus on men is substantively and practically motivated. Women in our dataset are more likely to provide care for elderly or disabled individuals and are twice as likely to work part-time compared to men. This could introduce confounding factors. Additionally, stepped changes in women's state pension age since 2010 have led to increasing employment rates among women, adding complexity to the causal analyses (see Goodman-Bacon, 2021; de Chaisemartin, 2017).

| | Age category | | | |
|---|---|---|---|---|
| | [ 58, 61] | [62, 65] | [66, 69] | All |
| % Inter-temporal Variation in GHQ | 0.20 | 0.18 | 0.03 | 0.14 |
| Age | 57.04 | 62.19 | 67.46 | 62.11 |
| Satisfied with job | 0.51 | 0.52 | 0.59 | 0.53 |
| High M. H. pre-retirement | 0.59 | 0.59 | 0.58 | 0.59 |
| Duration of spell | 6.86 | 6.84 | 6.88 | 6.86 |
| $P(Z_t = 0, Z_{t-1} = 0, Z_{t-2} = 0)$ | 0.89 | 0.67 | 0.31 | 0.63 |
| $P(Z_t = 1, Z_{t-1} = 0, Z_{t-2} = 0)$ | 0.03 | 0.06 | 0.06 | 0.05 |
| $P(Z_t = 1, Z_{t-1} = 1, Z_{t-2} = 0)$ | 0.02 | 0.04 | 0.05 | 0.04 |
| $P(Z_t = 1, Z_{t-1} = 1, Z_{t-2} = 1)$ | 0.06 | 0.23 | 0.57 | 0.28 |
| $E(Y_t - Y_{t-1}\|0,0,0)$ | 0.16 | 0.14 | 0.27 | 0.17 |
| $E(Y_t - Y_{t-1}\|1,0,0)$ | 2.68 | 2.57 | 0.41 | 1.69 |
| $E(Y_t - Y_{t-1}\|1,1,0)$ | −0.30 | −1.02 | −0.64 | −0.71 |
| $E(Y_t - Y_{t-1}\|1,1,1)$ | −0.40 | −0.13 | −0.08 | −0.12 |
| $NT$ | 7326.00 | 6445.00 | 6862.00 | 20 633.00 |

Table 1: Descriptive statistics. † working-life average is above the cohort (pre/post-1951) median. We report estimates of $P(Z_t = ., Z_{t-1} = ., Z_{t-2} = .,$ which refers to the probability of individuals who are currently retired ($Z_t = 1$) or not ($Z_t = 0$), and their retirement status during the last two periods ($Z_{t-1} = ., Z_{t-2} = ..$ We report estimates of $E(Y_t - Y_{t-1}|Z_t = z_t, Z_{t-1} = z_{t-1}, Z_{t-2} = z_{t-2}) = E(Y_t - Y_{t-1}|z_t, z_{t-1}, z_{t-2})$ that is the average difference in observed outcomes for individuals with retirement histories $Z_t = z_t, Z_{t-1} = z_{t-1}, Z_{t-2} = z_{t-2}$.

This allowed us to interpret first differences in the outcome (our dependent variable) as percentage changes.

Our treatment variable relies on individuals' self-reported job market status. If someone reports retirement at time $t$ then $Z_{it} = 1$. We focus solely on permanent retirements and transitions from employment to retirement. Consequently, the control group consists of individuals whose job status (working or retired) remains unchanged from $t-1$ to $t$. Thus, $Z_{it} - Z_{it-1}$ equals 1 if a person retires at time $t$ and 0 otherwise.

We calculate unconditional and conditional bounds using pre-treatment covariates. We differentiate between *categories*, based on pre-treatment characteristics, and *sub-populations*, defined by $(Z_{it}, Z_{it-1}, Z_{it-2})$. Three age groups are created: [58-61], [62-65], [66-69], each with approximately equal sample sizes. This aggregation ensures $0 < P(Z_{it} - Z_{it-1} = 1) < 1$ across all age groups, enabling comparisons among units at similar life stages.

In addition to age, we examine how job satisfaction categories influence the impact of retirement. Workers in the HLS rate their overall job satisfaction on a 7-point scale (1 =

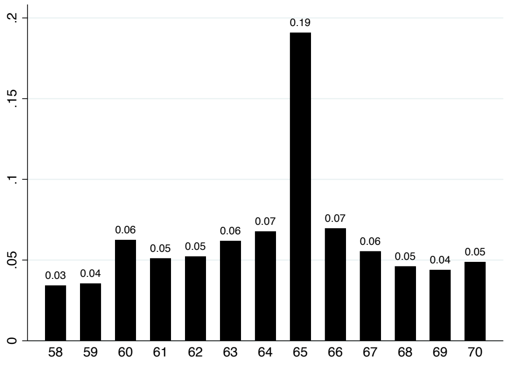


Figure 1: Distribution of retirements, by age

completely dissatisfied). We calculate the average job satisfaction over their working lives for each panel member. To account for cohort effects, respondents are grouped based on whether their satisfaction score exceeds the median of their birth cohort. We also investigate how retirement interacts with mental health over the working life, categorizing respondents based on whether their average GHQ score is above or below their birth cohort's median..

Descriptive statistics in Table 1 reveal stable average inter-temporal variation in the GHQ index across age groups, ranging from 0.3% to 0.20%, with an overall sample average of 0.14%. The proportion of individuals with high pre-retirement mental health remains consistent at 50%, independent of age. However, there is an increasing proportion of individuals reporting high job satisfaction with age, suggesting greater job satisfaction among those who work longer. As age increases, the percentage of workers decreases while the proportion retiring at each age rises.

Figure 1 details the distribution of retirement episodes in the sample, highlighting a notable peak at age 65. In the UK, men within our sample's birth years qualify for a state pension at this age[7]. The current basic state pension stands at GBP 137, equivalent to 23% of the average UK weekly salary of GBP 581. This substantial pension may incentivize individuals to prolong their working lives, even if facing challenges like low mental health or job satisfaction, especially for those expecting minimal retirement income from other sources. This explains the observed spike[8].

[7]This qualifying age has remained unchanged historically, although younger cohorts have seen progressive increases to 66-67.

[8]This observation often forms the basis for instrumental variable strategies in UK studies. These

## 3.2 Justification of the identifying assumptions.

The NAB assumption establishes natural upper and lower bounds on the conditional moments of the potential outcomes and is therefore uncontroversial. The COTS assumption suggests that individuals choose to retire at a time that is advantageous for them to do so. In the UK, where there is no mandatory retirement age, Figure 1 reveals significant variability in retirement ages, with many retirements occurring before individuals qualify for the state pension. Waves 11 and 16 of the British Household Panel Survey (which preceded the UK HLS used in this study) explored the reasons for early and late retirements. Early retirements were commonly motivated by financial incentives, lifestyle enjoyment, and spending time with partners, whereas late retirements often stemmed from enjoyment of work itself. This variability indicates considerable discretion in retirement timing, providing some support for the COTS assumption, although it does not fully validate it.

DOTS further attributes a mental health-preserving quality to retirement (on average). This assumption is somewhat more controversial, as one might expect declining mental health among individuals who feel socially isolated or lack purpose after leaving the workplace. DOTS does not rule out these effects, as it needs to hold only on average. However, as noted above, we only need the weaker restrictions (3.7)-(3.12), which only need to hold on average. Thus, it seems reasonable to argue that while retirement might be detrimental to the mental health of some individuals, most people will retain their social ties, hobbies, and other activities that contribute to at least preserving (if not improving) their mental health.

The validity of the bounded variation assumptions depends on the values of $\theta^{(\cdot)}$, which are not identified from the data. In the application below, we will consider a range of

strategies divide an Intention-to-Treat (ITT) estimate by the model-adjusted proportion of excess retirements at age 65. The premise is that excess retirements accurately reflect individuals whose retirement decisions are solely driven by pension eligibility. If age has no direct effect on the outcome of interest (mental health in this study), this approach estimates the Local Average Treatment Effect (LATE) of retirement at age 65. However, whether age truly does not affect mental health levels is uncertain. Given the small magnitude of excess retirements (under 0.2, possibly close to 0.12), the estimated LATE can be highly sensitive to variations in modeling the spike at age 65. For example, an ITT of 1% with excess retirement proportions of 0.08, 0.1, 0.12, and 0.14 would yield LATE estimates of approximately 12.5, 10, 8.34, and 7.14, respectively.

values between 2% and 10%, the latter upper bound being generous, given our focus on short-term effects.

The no-inter temporal interference assumption implies that retirement status in the previous year has no bearing on potential mental health levels today. This assumption does not rule out the usual "trend" assumption made in regression analyses, where the effect of retirement may vary with the number of years away from the workforce. In this sense, the number of years retired serves as a proxy for age, and therefore, mental health outcomes may differ conditional on age, as well as the average treatment effect on the treated (ATT). However, the assumption rules out a direct effect of the duration of retirement on health levels. It implies that, while retiring at age 62 and 65 may have different outcomes, the duration of retirement does not affect mental health levels. This assumption is strong, but it would be nonrestrictive if retirement only had a one-off effect (which may or may not be permanent). Therefore, we cannot rule it out a priori.

The final assumption, HV, posits a common trend in mental health across all individuals. This trend must hold on average. In our analysis, we will segment individuals by age group and restrict the cohorts under consideration to a relatively narrow range. Thus, conditional on age groups, the HV assumption seems plausible.

### 3.3 Results for the full sample.

Table 2 presents the partial identification regions for the full sample across age categories. Several key findings emerge and recur in subsequent analyses. First, COTS and DOTS provide additional information beyond the data alone, with DOTS yielding identification regions that are typically as narrow or narrower than those under COTS. Second, HV demonstrates significant information power, often halving the size of identification regions. Eliminating inter-temporal interference within individuals consistently results in substantially narrower identification regions, sometimes reducing their width by a third.

Data alone indicate that uncertainty about the Average Treatment Effect on the Treated (ATT) is similar across age groups. The ATT could range from a decrease of 27% to an increase of 27%. Combining the COTS and DOTS assumptions with NAB slightly

Partial Identification Regions, ATT.

| | Age categories. | | |
|---|---|---|---|
| | [ 58, 61] | [62, 65] | [66, 69] |
| NAB | [−24.87 27.52] | [−24.74 26.18] | [−27.09 27.44] |
| | [−26.72 29.47] | [−26.13 27.70] | [−28.39 28.77] |
| COTS | [−21.93 27.52] | [−21.86 26.18] | [−26.70 27.44] |
| | [−23.86 29.47] | [−23.27 27.70] | [−28.00 28.77] |
| DOTS | [−21.93 27.52] | [−21.77 26.09] | [−26.70 27.44] |
| | [−23.85 29.47] | [−23.16 27.59] | [−28.00 28.77] |
| NAB+HV | [−11.13 11.93] | [ −9.76 11.72] | [−13.78 12.83] |
| | [−12.23 13.11] | [−10.66 12.57] | [−14.55 13.73] |
| COTS+HV | [−11.13 11.93] | [ −9.76 11.72] | [−13.78 12.83] |
| | [−12.23 13.11] | [−10.66 12.57] | [−14.55 13.73] |
| DOTS+HV | [−11.13 11.93] | [ −9.76 11.63] | [−13.78 12.83] |
| | [−12.23 13.09] | [−10.66 12.45] | [−14.56 13.73] |
| NAB+NI | [−22.09 27.52] | [−22.91 26.18] | [−20.27 27.44] |
| | [−24.10 29.46] | [−24.22 27.67] | [−21.62 28.77] |
| COTS+NI | [−20.28 27.52] | [−19.65 26.18] | [−19.80 27.44] |
| | [−22.16 29.46] | [−20.89 27.67] | [−21.11 28.77] |
| DOTS+NI | [−12.00 27.52] | [−12.25 26.18] | [−12.25 27.44] |
| | [−13.17 29.46] | [−13.05 27.67] | [−13.08 28.77] |
| NAB+NI+HV | [ −8.35 11.93] | [ −7.93 11.72] | [ −6.97 12.83] |
| | [ −9.67 13.08] | [ −8.78 12.55] | [ −7.85 13.73] |
| COTS+NI+HV | [ −8.35 11.93] | [ −7.93 11.72] | [ −6.97 12.83] |
| | [ −9.67 13.08] | [ −8.78 12.55] | [ −7.85 13.73] |
| DOTS+NI+HV | [ −0.07 11.93] | [ −0.53 11.72] | [ 0.58 12.83] |
| | [ −0.72 13.08] | [ −0.93 12.55] | [ 0.21 13.73] |

Table 2: Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ). The outcome is the % variation in the GHQ. Imbens-Manski 95% confidence intervals are provided under each estimate. Standard errors for the Confidence Intervals were obtained with 100 replications of bootstrap with re-sampling at cluster level (individual).

reduces this ambiguity, as does incorporating the no-interference assumption. Incorporating HV, which posits similar mental health trends for all sub-populations while working, narrows the ATT range considerably, by more than halving the width of the bounds. For instance, in the 58-61 age group to HV reduces the NAB to $[-11.13\%, 11.93\%]$. Under the most stringent assumptions (combining DOTS, HV, and no interference), we can actually infer that the ATT of retirement on mental health is positive for the older population (66-69 year olds). Indeed, in the other age groups retirement is likely to be innocuous or improve mental health, up to 12% points.

We next turn to the BW and BB assumptions. The results are presented in Table 3. The table confirms previous findings but still shows uncertainty in the sign and magnitude of the ATT, which depends on the level of heterogeneity within and across sub-populations. This uncertainty persists whether or not HV is assumed, although HV generally narrows the identification regions. As the proportion of individuals retired for more than two years increases with age, the width of the identification intervals also increases accordingly.

How do our results relate to the preceding literature? Answering this question is complicated because of two principal reasons. First, units of measurement are different across papers, and the interpretation of the coefficients differs. Only the results in Grip et al. (2012) can be directly interpreted as a percentage change. This can be overcome somehow, by focusing on the ratio of the estimated coefficient to the average of the outcome (when that average is available, which is not always the case). Further, note that the correct comparison would be against the average outcome in the group of non-retired people, but this is rarely reported (note that we cannot use the intercept of regression models as the intercept captures additional noise or bias). A more substantive complication is that most papers report a Local Average Treatment Effect (or, in the case of Grip et al., 2012, an Intention to Treat Effect), whereas we report an Average Treatment Effect on the Treated. These parameters refer to different groups of people so they are not directly comparable.

Partial Identification Regions, ATT.

| $\theta^{(1)}$ | $\theta^{(2)}$ | BW | BW+HV | BB | BB+HV |
|---|---|---|---|---|---|
| | | Age 58 to 61 | | | |
| 0 | 0 | [ 0.00 0.00] | [ 0.89 0.89] | [ 3.03 3.03] | [ 3.03 3.03] |
| 0 | 5 | [ −3.38 3.38] | [ 0.89 0.89] | [ −1.97 8.03] | [ 3.03 3.03] |
| 0 | 10 | [ −6.77 6.77] | [ 0.89 0.89] | [ −6.97 13.03] | [ 3.03 3.03] |
| 5 | 0 | [ −5.00 5.00] | [ −2.50 4.27] | [ −0.36 6.41] | [ −0.36 6.41] |
| 5 | 5 | [ −8.38 8.38] | [ −2.50 4.27] | [ −5.36 11.41] | [ −0.36 6.41] |
| 5 | 10 | [−11.77 11.77] | [ −2.50 4.27] | [−10.36 16.41] | [ −0.36 6.41] |
| 10 | 0 | [−10.00 10.00] | [ −5.88 7.66] | [ −3.74 9.79] | [ −3.74 9.79] |
| 10 | 5 | [−13.38 13.38] | [ −5.88 7.66] | [ −8.74 14.79] | [ −3.74 9.79] |
| 10 | 10 | [−16.77 16.77] | [ −5.88 7.66] | [−13.74 19.79] | [ −3.74 9.79] |
| | | Age 62 to 65 | | | |
| 0 | 0 | [ 0.00 0.00] | [ −0.04 −0.04] | [ 1.74 1.74] | [ 1.74 1.74] |
| 0 | 5 | [ −3.86 3.86] | [ −0.04 −0.04] | [ −3.26 6.74] | [ 1.74 1.74] |
| 0 | 10 | [ −7.72 7.72] | [ −0.04 −0.04] | [ −8.26 11.74] | [ 1.74 1.74] |
| 5 | 0 | [ −5.00 5.00] | [ −3.90 3.82] | [ −2.12 5.60] | [ −2.12 5.60] |
| 5 | 5 | [ −8.86 8.86] | [ −3.90 3.82] | [ −7.12 10.60] | [ −2.12 5.60] |
| 5 | 10 | [−12.72 12.72] | [ −3.90 3.82] | [−12.12 15.60] | [ −2.12 5.60] |
| 10 | 0 | [−10.00 10.00] | [ −7.76 7.68] | [ −5.98 9.47] | [ −5.98 9.47] |
| 10 | 5 | [−13.86 13.86] | [ −7.76 7.68] | [−10.98 14.47] | [ −5.98 9.47] |
| 10 | 10 | [−17.72 17.72] | [ −7.76 7.68] | [−15.98 19.47] | [ −5.98 9.47] |
| | | Age 66 to 69 | | | |
| 0 | 0 | [ 0.00 0.00] | [ −0.09 −0.09] | [ 0.27 0.27] | [ 0.27 0.27] |
| 0 | 5 | [ −4.63 4.63] | [ −0.09 −0.09] | [ −4.73 5.27] | [ 0.27 0.27] |
| 0 | 10 | [ −9.27 9.27] | [ −0.09 −0.09] | [ −9.73 10.27] | [ 0.27 0.27] |
| 5 | 0 | [ −5.00 5.00] | [ −4.72 4.55] | [ −4.37 4.90] | [ −4.37 4.90] |
| 5 | 5 | [ −9.63 9.63] | [ −4.72 4.55] | [ −9.37 9.90] | [ −4.37 4.90] |
| 5 | 10 | [−14.27 14.27] | [ −4.72 4.55] | [−14.37 14.90] | [ −4.37 4.90] |
| 10 | 0 | [−10.00 10.00] | [ −9.35 9.18] | [ −9.00 9.54] | [ −9.00 9.54] |
| 10 | 5 | [−14.63 14.63] | [ −9.35 9.18] | [−14.00 14.54] | [ −9.00 9.54] |
| 10 | 10 | [−19.27 19.27] | [ −9.35 9.18] | [−19.00 19.54] | [ −9.00 9.54] |

Table 3: Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ) under the Bounded Variation Within Units (BW) and Bounded Variation Between Sub-Populations (BB). The outcome is the % variation in the GHQ. $\theta^{(\cdot)}$ determine the maximal variation allowed within units (BW assumption) and across sub-populations (BB assumption).

Partial Identification Regions, ATT.

| | Age category. [ 63, 67] | |
|---|---|---|
| NAB | [−24.54 | 25.10] |
| | [−25.77 | 26.43] |
| COTS | [−24.01 | 25.10] |
| | [−25.24 | 26.43] |
| DOTS | [−24.01 | 25.10] |
| | [−25.27 | 26.45] |
| NAB+HV | [−12.26 | 11.86] |
| | [−13.02 | 12.63] |
| COTS+HV | [−12.26 | 11.86] |
| | [−13.02 | 12.63] |
| DOTS+HV | [−12.26 | 11.86] |
| | [−13.02 | 12.67] |
| NAB+NI | [−20.01 | 25.10] |
| | [−21.23 | 26.45] |
| COTS+NI | [−19.59 | 25.10] |
| | [−20.76 | 26.45] |
| DOTS+NI | [−12.05 | 25.10] |
| | [−12.77 | 26.45] |
| NAB+NI+HV | [ −7.73 | 11.86] |
| | [ −8.53 | 12.68] |
| COTS+NI+HV | [ −7.73 | 11.86] |
| | [ −8.53 | 12.68] |
| DOTS+NI+HV | [ −0.19 | 11.86] |
| | [ −0.52 | 12.68] |

Table 4: Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ). The outcome is the % variation in the GHQ. Imbens-Manski 95% confidence intervals are provided under each estimate. Standard errors for the Confidence Intervals were obtained with 100 replications of bootstrap with resampling at cluster level (individual).

There is a final complication: the age groups considered across papers vary. We have tried to address this to some extent by re-estimating the bounds for the group of 63- to 67-year-old men (where most retirement decisions occur; see Table 4). We will base the comparison on those results.

| | | | | | Effect (% Mean outcome) | |
|---|---|---|---|---|---|---|
| Article | Country | Identification | Outcome | Mean (Std. Dev.) | Min. Effect | Max |
| Charles (2004)* | U.S. | FE-TSLS | Depressed | 0.15 (0.36) | 0.09 (60%) | 0.19 (126%) |
| Johnston and Lee (2009)* | U.K. | FRDD | GHQ-12 | 10.11 . | 1.445(14%) | 1.857 (18.3%) |
| Eibich (2015) | Germany | FE-FRDD | SF-12 | 51.683 (9.999) | 2.573 (5.03%) | 2.573 (5.03%) |
| Rose (2020) | U.K. | FRDD | Depression Score | -0.058 | -0.058 | |
| Dave et al. (2008) | U.S. | FE | Psychological Problems | 0.091 (0.288) | -0.082 (90%) | 0 (0) |
| Grip et al. (2012)* | Netherlands | SRD | Self-reported depressed | N/A (N/A) | -0.024 (2.4%) | -0.088 (8.8%) |
| Heller-Sahlgren (2017) | Europe | FE-FRDD | Clincal Depression | 0.23(0.42) | -0.09 (0.21) | -0.04 (0.09) |

Table 5: Results from the literature. Minimum and Maximum effects reported (in brackets, proportion of one standard deviation -when available). FE = Fixed Effects; TSLS = Two Stage Least Squares; FRDD = Fuzzy Regression Discontinuity Design; SRD = Sharp Regression Discontinuity Design. (*) Sign of coefficient has been changed to positive/negative to denote improvement/drop in mental health. Sources: Charles (2004), Tables 5 and 7; Johnston and Lee (2009), Table 1; Eibich (2015), Table 3; Rose (2020), Table 4;Dave et al. (2008), Table 3; Grip et al. (2012), Tables 2 and 3; Heller-Sahlgren (2017), Table 4.

With these caveats in mind, Table 5 presents a summary of a small selection of leading papers where statistically significant effects have been reported. In the table we report the country of the study, the model used for identification (without mentioning the identification assumptions), outcome, mean outcome, standard error, and the smallest and largest effect found in the paper, alongside the ratio of these effects to the standard error of the outcome, when reported in the paper. In absolute value, the coefficients reported in the literature range between 5% and 126%. Our partial identification regions in Table 4 exclude effects greater than 26% in absolute value and the most stringent bouds essentially rule out negative effects or effects above 11.8%. This would mean that only the effects in the papers by Eibich (2015), Heller-Sahlgren (2017), and Grip et al. (2012) would conform to our identification regions.

## 3.4 Pre-retirement Mental Health and Job Satisfaction.

We next explore how results vary across pre-retirement mental health and job satisfaction categories. The results are presented in Tables E.1 - E.4 in the Appendix. The main qualitative difference across the Tables is driven by pre-retirement mental health: in the high pre-retirement mental health groups, the bound are narrower, denoting less uncertainty or potentially smaller effect. On the contrary, job satisfaction does not seem to have much effect. As before, however, the sharper conclusions come from the combination of DOTS, NI and HV. Under this combination of assumptions the conclusion that follows is stark. Retirement significantly and positively aids individuals with low pre-retirement mental health and low job satisfaction. The effect can range from 1.7% to 19% and the confidence intervals suggest that this effect is statistically significant. Low mental health and high job satisfaction does not seem to have a clear effect, however, with the only exception being in the 66+ age group, if the strongest combination of assumptions is considered. In the latter case, ATT is suggested to be contained in the 1.83-5.5% interval, indicating a moderate positive effect of retirement on mental health.

In the high mental health group, we find considerably less ambiguity about ATT, reflected in narrower identification regions across age groups and assumptions. These regions are generally centered around zero and the upper and lower bounds are smaller than those found in the low mental health group. Variation across job satisfaction sub-categories is small. None of the identification regions identify the sign of the ATT. Unlike in the low mental health group, accumulation of assumptions leads to regions of vanishing width, and this suggests either a small or negligible ATT. This is particularly true in the high mental health, high job satisfaction group, where the strongest assumptions rule out drops in the GHQ beyond 2.77% (in the 62-65 age category) or improvements beyond 8%. When pre-retirement mental health is high, the role that job satisfaction might play in our identification regions is weak.

We now turn to the bounds obtained under BW and BB. These are presented in Tables E.5 to E.8 in the Appendix. In the low pre-retirement mental health/low satisfaction group, results are highly suggestive of a positive ATT even with high levels of heterogeneity. BW does not have an ability to identify the sign of ATT, but when combined with HV, results suggest that younger individuals in this sub-category benefit from retirement, a conclusion that we can sustain even when $\theta^{(1)} = 10\%$ and $\theta^{(2)} = 5\%$. This finding is not as clear among the older sub-categories. The finding replicates under BB alone, provided that combined heterogeneity is at most moderate (typically, $\theta^{(1)} + \theta^{(2)}$ does not exceed 10%). Under BB, this positive ATT is suggested for all age groups (being largest in the youngest age group and smallest in the oldest age group). If the HV assumption is added, then the identification regions identify a positive ATT in all combinations of $\theta^{(1)}, \theta^{(2)}$ except in the old age group and only if $\theta^{(1)} \geq 10\%$. What the BB and BW results indicate is that the variation in the outcome among those seen to retire in the low-mental health, low-satisfaction group is unlikely to be explained by heterogeneity alone, particularly if the levels of heterogeneity across or within sub-populations are moderate. Only if the inter-temporal variation in outcomes across or within sub-populations in the study is high, could the observed differences be explained.

The remaining tables in the Appendix essentially replicate the findings we obtained before. When job satisfaction is high, retirement has an ambiguous effect. Under BW and BB, results suggest a positive ATT in the younger age group, provided that heterogeneity is moderate. However the suggested effects would be considerably smaller than those seen when satisfaction is also low. When mental health is good, none of the results identify the sign of the ATT and, when they do (under BB + HV), the suggested effects are very small.

As with the full sample, the latest set of results still suggest that uncertainty about ATT is overall substantive. However, there is variation of results across pre-retirement mental health groups. This variation invites us think that people in poor mental health who also have lower levels of job satisfaction might experience an improvement in mental health following retirement. The youngest individuals might be particularly benefited. People whose mental health is poor but who show high levels of job satisfaction, however, would not see such a benefit. Conversely, under our strongest assumptions, we cannot attribute any substantive effect of retirement for people whose mental health is good prior to retirement.

# 4 Minimax-Regret analysis.

The findings highlight significant uncertainty in the effect of retirement on mental health, particularly when strong parametric assumptions and linear additive models are avoided. The ATT appears to be only partially identified across the various scenarios considered, with the sign often remaining uncertain. This poses a challenge for policymakers and officials tasked with implementing retirement policies, as they must make decisions under ambiguity.

Drawing on Manski's insights (e.g., Manski, 2000, 2004, 2007), decision-making under ambiguity in econometrics offers a framework to translate our results into informed policy recommendations. In this framework, a utilitarian social planner must allocate treatments for a heterogeneous population based on observed mental health outcomes from work and retirement decisions in the HLS dataset, alongside relevant covariates such as pre-retirement mental health status. Despite variations in treatment response functions among individuals, those with identical covariates are treated similarly in the decision-making process.

In line with Manski (2000, 2004, 2007), we adopt a minimax-regret rule to guide decision-making under ambiguity. This rule minimizes the maximum regret a planner might face across all possible outcome distributions. It achieves this by assigning individuals with identical covariates to the same treatment (either retirement or continued work) if one treatment clearly dominates. When no treatment is dominated, as indicated by the non-trivial identification regions reported earlier, the rule allocates a proportion of individuals to each treatment based on the width and boundaries of the identification regions and their associated assumptions.

Specifically, in the Appendix, we demonstrate that the optimal minimax-regret rule is:

$$\delta^* = \frac{R_U - W_L}{(W_U - W_L) + (R_U - R_L)} \in [0, 1] \tag{4.11}$$

where $E(Y_{it}^{10}|Z_{it} = 1) \in [R_L, R_U]$ and $E(Y_{it}^{00}|Z_{it} = 1) \in [W_L, W_U]$ denote the partial identification regions obtained under any of the previously discussed assumptions. The numerator $R_U - W_L$ corresponds to the upper bound on $\text{ATT}_t$. The rule assigns a significant proportion of individuals to retirement only if the evidence supports a non-negative $\text{ATT}_t$. The proportion allocated to retirement increases with a larger upper bound on $\text{ATT}_t$ (indicating a potentially positive effect of retirement) and with narrower identification regions for $E(Y_{it}^{10}|Z_{it} = 1), E(Y_{it}^{00}|Z_{it} = 1)$.

We can compute $\delta^*$ using any of the assumptions introduced earlier, substituting unknown conditional moments with their sample counterparts. Figures 2 to 4 depict $\delta^*$, under various identifying assumptions (NAB, NAB+COTS, NAB+DOTS with HV and/or NI), segmented by age group and pre-retirement mental health. These figures reveal several key insights:

Regarding decision conservatism, NAB provides the most conservative estimates, while DOTS yields the least conservative. COTS aligns more closely with NAB. Across all scenarios, the minimax decision rule tends to favor retirement more for individuals with poorer pre-retirement mental health, even amid substantial uncertainty. For instance, under NAB alone, the rule suggests allocating 53-61% of individuals with poor mental health to retirement, compared to 38-41% for those with good mental health.

The inclusion of inter-temporal interference assumptions (HV) consistently reduces $\delta^*$ by 6-10 percentage points across mental health groups, particularly discouraging retirement among those with good mental health. Conversely, under the assumption of no inter-temporal interference, $\delta^*$ moderately increases for individuals with poor mental health. Assuming HV increases $\delta^*$, but particularly for individuals with poor pre-retirement mental health. These findings underscore the nuanced impact of identifying assumptions on retirement policy recommendations, reflecting the heterogeneous nature of pre-retirement mental health across different age cohorts.

Next, we examine the BH assumption. The Appendix provides explicit expressions for $\delta^*$ under both BW and BB, with and without HV. $\delta^*$ varies based on the assumed level of variation or heterogeneity $\theta$, approaching $\delta^* = 1/2$ under BW alone. This implies that BW is generally not very informative for policy decisions. When combined with HV, informative $\delta^*$ values are derived under both BW and BB assumptions, depending on the assumed average variation $\theta^{(1)}$. Therefore, we focus on $\delta^*$ derived under BB alone as it represents a more constrained variation assumption.

Figures 5 and 6 depict $\delta^*$ values across $\theta^{(1)}$ and $\theta^{(2)}$ combinations for low and high pre-retirement mental health groups, respectively. In Figure 5, darker colors indicate higher proximity to $\delta^* = 1$. The figures show that the minimax regret rule suggests retirement rates ranging from 60% to 100% in the low mental health group, with rates declining as ambiguity increases. For example, when $\theta^{(1)} = \theta^{(2)} = 10\%$ retirement rates are suggested to be between 60% and 70%. For moderate ambiguity ($\theta^{(1)} = \theta^{(2)} = 5\%$), retirement rates range from 75% to 96%, with higher rates observed among younger age groups.

Conversely, in the high mental health group, the minimax rule approaches 50% or below. Under BB, for moderate ambiguity ($\theta^{(1)} = \theta^{(2)} = 5\%$), retirement rates are recommended at 54%, 43%, and 36% for the ages 58-61, 62-65, and 66-69. For higher ambiguity ($\theta^{(1)} = \theta^{(2)} = 10\%$), these rates adjust to 52%, 46%, and 43% for the same age groups.

The minimax-regret rule used in our study focuses solely on mental health outcomes, while broader considerations such as public finances, which are crucial in retirement policy debates, are overlooked. Our findings are contingent on this narrow focus. Additionally, Figure 1 highlights the discretionary nature of retirement age decisions, which are often influenced by arbitrary pension eligibility thresholds. Therefore, our results should be interpreted within the broader context of effective governmental decision-making.

Moreover, the fractional allocation under the minimax rule, which involves randomly assigning individuals with similar characteristics to either retirement or work, is unconventional (as discussed in Manski (2005)). We consider values $\delta^* \gg 0.5$ as promoting retirement, $\delta^* \ll 0.5$ as suggesting caution in emphasizing retirement, and $\delta^* = 0.5$ as signifying uncertainty about the role of retirement. Considering these points, our results suggest that policies facilitating early retirement for individuals with mental health concerns could be beneficial. Alternatively, extending the working lives of remaining workers may present minimal risk of mental health disruptions.

The minimax analysis above suggests different policies based on pre-retirement mental health levels. Implementing such policies across all industrial sectors might be challenging. Additionally, a policy targeting mental health around retirement might be prone to manipulation, potentially undermining the primary goal of extending the retirement age. An alternative option would be to exempt specific job categories from legislation that extends the retirement age. This would require a thorough understanding of the causal effects of different occupations on mental health, which is beyond the scope of this paper. However, we can identify sectors with a higher proportion of cases of poor mental health using official statistics. Indeed, Stansfeld et al. (2011) study the prevalence of common mental health disorders in the UK, finding they concentrate in a sub-group of occupations. The data from the Office for National Statistics they analyse reveals higher prevalence of common mental health disorders among clerical, secretarial, teaching, sales, and personal and protective services. In light of the minimax estimates above, a planner might consider setting different pension or retirement ages for these more exposed categories.

# 5 Conclusion.

In this paper, we conduct a partial identification analysis of retirement's effect on a mental health index. Our focus is on the Average Treatment Effect on the Treated (ATT) in the population of British men aged 58-69 who participated in the UK Household Longitudinal Study (Understanding Society). Building on earlier literature, we present identification regions that are applicable when panel data are available. We then combine these regions with a minimax-regret decision rule to guide policy making.

Regarding the identification of the ATT in the overall population, we conclude that retirement will have at most a moderate effect on mental health, although the sign of this effect is generally not identifiable. However, when we split the sample based on pre-retirement mental health and job satisfaction, we find that individuals with poor pre-retirement mental health may benefit from retirement. Similarly, we find evidence suggesting that people with poor pre-retirement mental health but high job satisfaction do not benefit significantly from retirement.

Using a minimax-regret rule, we find that policies facilitating early retirement for those with mental health concerns may be beneficial. Alternatively, extending the working lives of remaining workers might pose minimal risk of mental health disruptions. The minimax analysis suggests different policies based on pre-retirement mental health, but implementing these universally might be challenging and susceptible to manipulation. A better option might be to exempt specific job categories from retirement age extensions, which would require an understanding of the effect of occupations on mental health. Official statistics reveal a higher prevalence of mental health issues in certain occupations, such as clerical, secretarial, teaching, sales, and personal services. Planners could consider setting different retirement or pension ages for individuals in these categories.

Our results align with the general conclusion from the descriptive survey by Garrouste and Perdrix (2022), which suggests that retirement either improves mental health or has no effect. However, our findings emphasize that pre-existing mental health plays a crucial role in this debate: while retirement can be beneficial for vulnerable individuals, it is not a lever for improving mental health across the entire population.

An important consideration is that during our sample period, the U.K.'s state pension age for women (initially 60 years) was gradually increased starting in 2010 at a rate of one month every two months. Cribb et al. (2013) found that these changes led to a 7% increase in women's labor supply when the pension age reached 61 in 2012. Although our paper focuses on men's mental health, Cribb et al. (2013) also reported a 4% increase in the labor supply of the male partners of affected women. If increases in the pension age affect women's mental health, this could confound the data and complicate the estimation of retirement effects on men. However, Cribb et al. (2013) explain that the 7% increase in female labor supply corresponds to a rise in the average retirement age by about one month, making it unclear how severely mental health might be affected by such a change.

Our analysis indicates that a minimax-regret decision rule offers clear policy guidance, even in highly ambiguous scenarios where identifying assumptions are very weak. Policymakers looking to increase the retirement age to alleviate financial pressures could do so confidently by restricting the proportion of people allowed to retire, thus avoiding major mental health crises. Although a top-down approach to retirement allocation is neither feasible nor desirable, tools such as pension and early retirement rules can help achieve this goal (e.g., by discouraging early retirement or tightening pension eligibility conditions). Nevertheless, it is crucial to provide provisions that facilitate early retirement for younger individuals experiencing poor mental health at work.

From a methodological perspective, our findings on the identification of the Average Treatment on the Treated (ATT) of retirement suggest that the effect of retirement on mental health is subject to high levels of ambiguity, with empirical findings largely dependent on identifying assumptions. Importantly, the sign of the retirement effect is elusive and assumption-dependent. To contextualize our results within previous literature, we note that assumptions characterizing the selection process (e.g., assuming a 'best-response' approach) are informative but not definitive. While assuming that the length of retirement spells does not matter helps to reduce uncertainty, this assumption (which differs from a state dependence assumption, a fixed-effect assumption, and a time trend assumption) can be controversial in practice. This assumption is implicit in any analysis that does not consider past retirement status as part of the conditional mean of the main outcome. Additionally, common-trend assumptions are highly informative and significantly reduce any remaining ambiguity in an econometric analysis. Although the crucial role of common-trend assumptions is recognized in the literature, this paper quantifies their impact. Finally, we observe that assumptions limiting the variation in potential outcomes can be both informative and relatively unobtrusive. Overall, combining partial identification methods with a minimax-regret rule proves to be a powerful tool for advancing policy design.

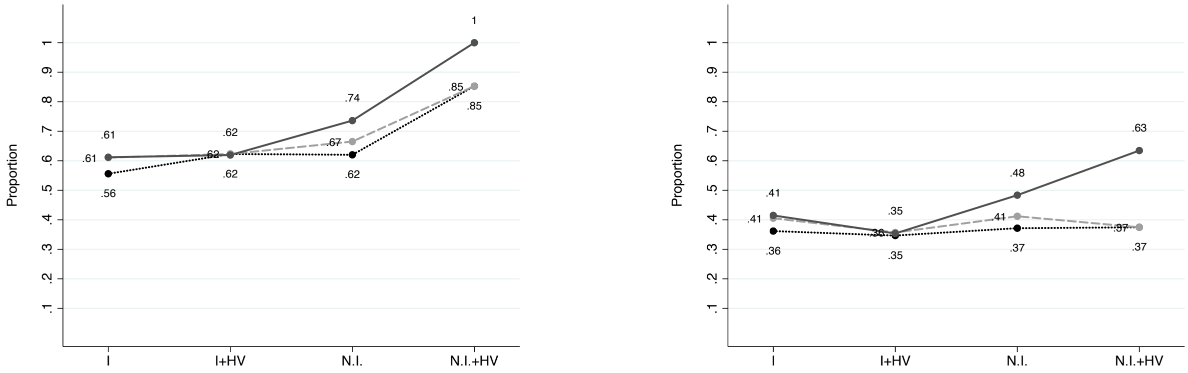


Figure 2: Delta for 58 to 61; dotted is NAB, dashed is COTS and Solid is DOTS. Low pre-retirement mental health (left), high pre-retirement mental health (right)

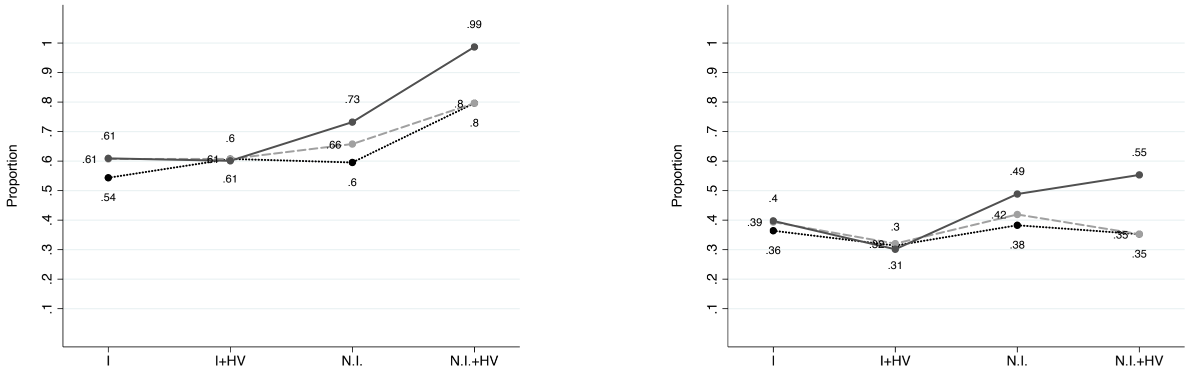


Figure 3: Delta for 62 to 65; dotted is NAB, dashed is COTS and Solid is DOTS. Low pre-retirement mental health (left), high pre-retirement mental health (right)

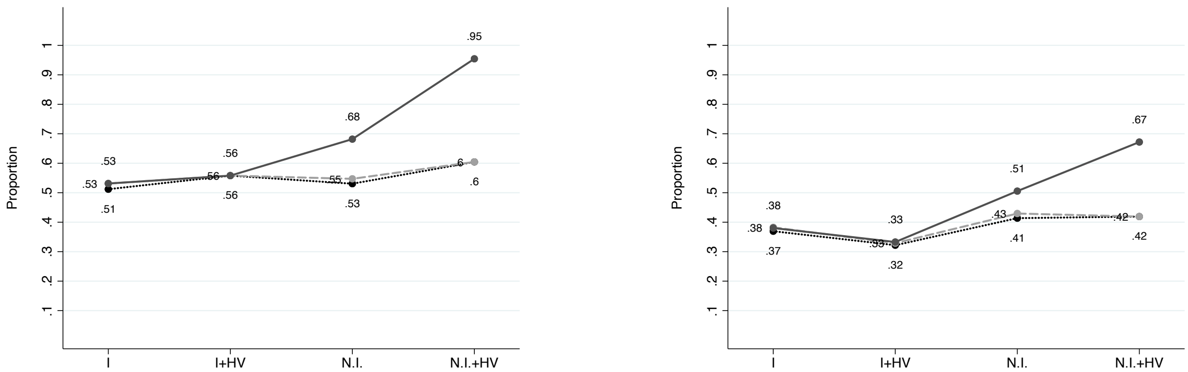


Figure 4: Delta for 66 to 69; dotted is NAB, dashed is COTS and Solid is DOTS. Low pre-retirement mental health (left), high pre-retirement mental health (right)

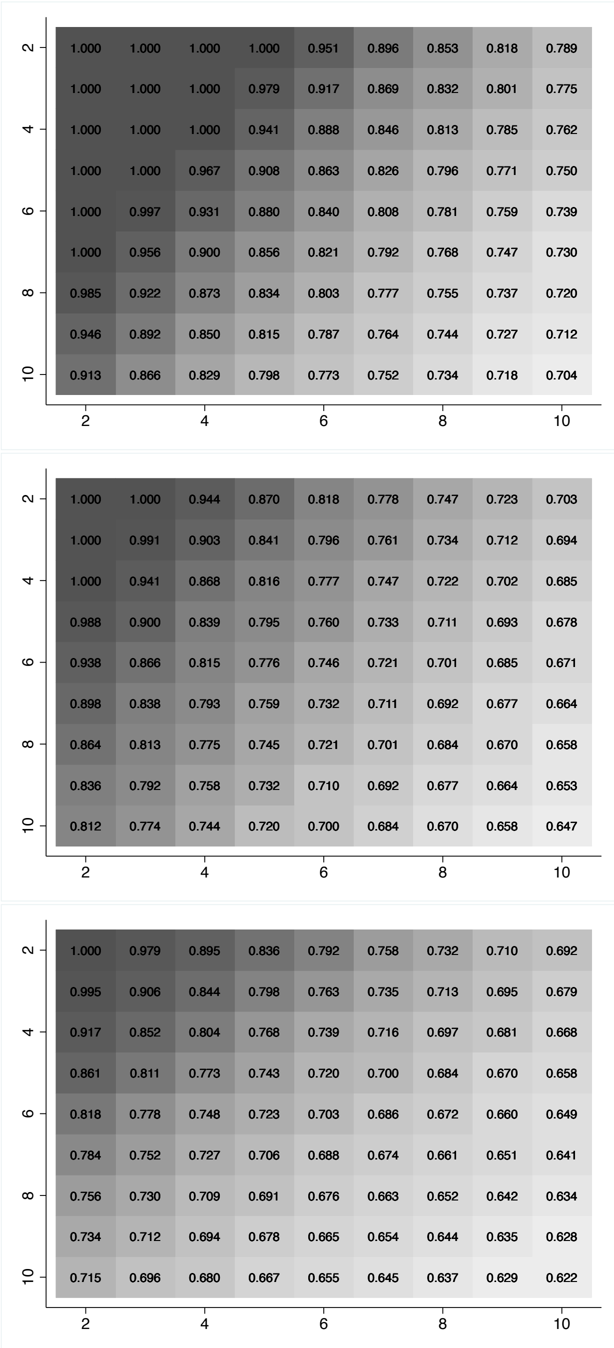


Figure 5: Low pre-retirement mental health. Value of the minimax regret rule, $\delta^*$, under Bounded Heterogeneity for the age groups 58-61 (top figure), 62-65 (middle) and 66-69 (bottom). In each figure, the horizontal axis corresponds to $\theta^{(2)}$ and the vertical axis corresponds to $\theta^{(1)}$. The value of $\delta^*$ for each combination of $\theta^{(1)}$, $\theta^{(2)}$ is presented in the cells

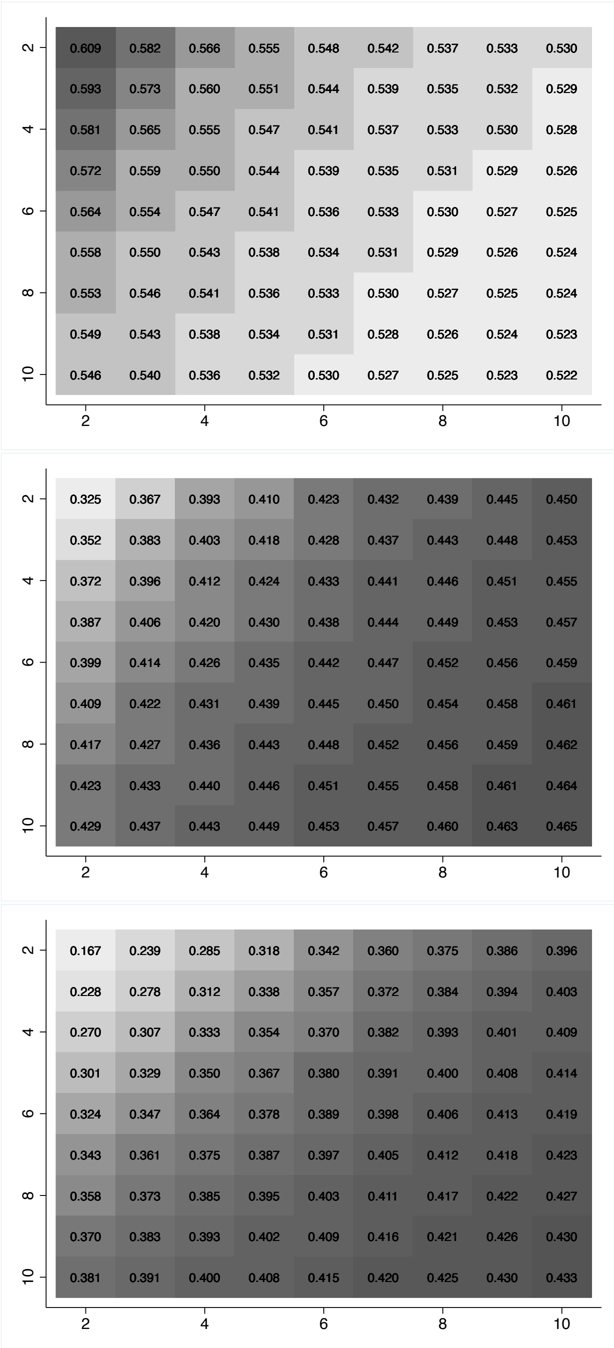


Figure 6: High pre-retirement mental health. Value of the minimax regret rule, $\delta^*$, under Bounded Heterogeneity for the age groups 58-61 (top figure), 62-65 (middle) and 66-69 (bottom). In each figure, the horizontal axis corresponds to $\theta^{(2)}$ and the vertical axis corresponds to $\theta^{(1)}$. The value of $\delta^*$ for each combination of $\theta^{(1)}$, $\theta^{(2)}$ is presented in the cells

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# Supplementary Materials for '*Partial Identification With Panel Data: Identifying the Effect of Retirement on Mental Health*'. (**For On-Line Publication**).

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## A. Bounds with temporal interference.

In this paper, interference between units occurs along the longitudinal dimension, with the potential outcomes defined as $Y_{it}(Z_{it}, Z_{it-1}) = Y_{it}^{Z_{it}Z_{it-1}}$. In our empirical application, this means that retirement status at time $t-1$ could determine mental health at time $t$. With this definition of the potential outcomes, the parameter of interest, the Average Treatment on the Treated (ATT), is defined as follows[1]:

$$\text{ATT}_t \coloneqq E\big(Y_{it}(1,0) - Y_{it}(0,0)|Z_{it}=1\big) = E(Y_{it}^{10} - Y_{it}^{00}|1) \tag{A.1}$$

We have defined the ATT unconditionally, however the results and definition apply conditionally on a set of pre-treatment variables. In the latter case, however, the identifying assumptions have to hold at each sub-category defined by the pre-treatment convariates (therefoer conditional identification rests on stronger requirements than unconditional identification). In our main application, bounds are obtained conditional on age.

Let us adopt the following shorthand notation:

$$E\big(Y_{it}^{Z_{it}Z_{it-1}}|z,z',z''\big) \coloneqq E\big(Y_{it}(Z_{it}, Z_{it-1})|Z_{it}=z, Z_{it-1}=z', Z_{it-2}=z''\big) \tag{A.2}$$

$$\Pi_{z'z''|z} \coloneqq P(Z_{it-1}=z', Z_{it-2}=z''|Z_{it}=z). \tag{A.3}$$

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[1] An alternative definition of this parameter is also possible, namely $\text{ATT}_t = E\Big(Y_{it}^{11} - Y_{it}^{10}|1\Big)$. Bounds for this parameter can be obtained in a similar fashion.

The ATT can be decomposed as follows:

$$\begin{aligned}\text{ATT}_t =& \Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,0,0) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,0,0)\Big]\Pi_{00|1} \\ &+ \Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,0) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,0)\Big]\Pi_{10|1} \\ &+ \Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,1) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,1)\Big]\Pi_{11|1} \end{aligned} \tag{A.4}$$

The first term is identified from data alone, as is the second part of the second term,

$$\begin{aligned}\text{ATT}_t =& \Big[E(Y_{it} - Y_{it-1}|1,0,0) - E(Y_{it}^{00} - Y_{it-1}|1,0,0)\Big]\Pi_{00|1} \\ &+ \Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,0) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,0)\Big]\Pi_{10|1} \\ &+ \Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,1) - E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,1)\Big]\Pi_{11|1}. \end{aligned} \tag{A.5}$$

Let $a, b$ denote the lower and upper bounds of $Y$ (when these exist), and let $\alpha, \beta$ be defined similarly, but for the first differences of $Y$.

### No-Assumption Bounds, NAB.

Using only the bounds $a, b, \alpha, \beta$, and noting that

$$\max(\alpha, a - E(Y_{t-1}|1,0,0)) \leq E(Y_{it}^{00} - Y_{it-1}) \leq \min(\beta, b - E(Y_{t-1}|1,0,0)) \tag{A.6}$$

it follows that,

$$\begin{aligned}&\Big[E(Y_{it} - Y_{it-1}|1,0,0) - \min(\beta, b - E(Y_{t-1}|1,0,0))\Big]\Pi_{00|1} + (\alpha - \beta)(1 - \Pi_{00|1}) \\ \leq& ATT_t \\ \leq& \Big[E(Y_{it} - Y_{it-1}|1,0,0) - \max(\alpha, a - E(Y_{t-1}|1,0,0))\Big]\Pi_{00|1} + (\beta - \alpha)(1 - \Pi_{00|1})\end{aligned} \tag{A.7}$$

### Bounds with Contemporaneous Optimal Treatment Selection, COTS

Under this assumption, individuals select the job status that maximises mental health in the current period. However, since retirement is a permanent state, optimisation beyond the retirement decision cannot be guaranteed. Under this consideration, we can find the following inequalities. First,

$$E(Y_{it}^{00}|1,0,0) = E(Y_{it}^{00}|Y_{it}^{10} \geq Y_{it}^{00}, 0, 0) \leq E(Y_{it}^{00}|Y_{it}^{10} < Y_{it}^{00}, 0, 0) = E(Y_{it}|0,0,0)$$

$$E(Y_{it-1}^{00}|1,1,0) = E(Y_{it-1}^{00}|1, Y_{it-1}^{10} \geq Y_{it-1}^{00}, 0) \leq E(Y_{it-1}^{10}|1, Y_{it-1}^{10} < Y_{it-1}^{00}, 0) = E(Y_{it-1}|1,0,0)$$

From these it follows that,

$$\begin{aligned}\max\Big(\alpha, a - E(Y_{it-1}|1,0,0)\Big) \leq& E(Y_{it}^{00} - Y_{it-1}|1,0,0) \\ \leq& \min\Big(\beta, E(Y_{it}|0,0,0) - E(Y_{it-1}|1,0,0)\Big)\end{aligned} \tag{A.8}$$

$$\max\Big(\alpha, a - E(Y_{it-1}|1,0,0)\Big) \leq E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,0) \leq \beta \tag{A.9}$$

The remaining non-identifiable terms do not have a natural upper bound under the COTS assumption. For instance, under COTS $E(Y_{it}^{10}|1,1,0) \leq E(Y_{it}^{11}|1,1,0)$ and $E(Y_{it}^{10}|1,1,0) \geq E(Y_{it}^{11}|1,1,0)$ are both potentially valid because because the decision to retire was optimal at $t-1$, but we do not know if people would be optimising their outcome after retirement. The ensuing bounds are,

$$\begin{aligned}
&\Big[E(Y_{it} - Y_{it-1}|1,0,0) - \min\Big(\beta, E(Y_{it}|0,0,0) - E(Y_{it-1}|1,0,0)\Big)\Big]\Pi_{00|1} \\
&+\Big[\max\Big(\alpha, a - E(Y_{it-1}|1,0,0)\Big) - \beta\Big]\Pi_{10|1} + (\alpha-\beta)\Pi_{11|1} \\
&\leq ATT_t \\
&\leq\Big[E(Y_{it} - Y_{it-1}|1,0,0) - \max\Big(\alpha, a - E(Y_{it-1}|1,0,0)\Big)\Big]\Pi_{00|1} \\
&+\Big[\beta - \max(\alpha, a - E(Y_{t-1}|1,0,0))\Big]\Pi_{10|1} + (\beta-\alpha)\Pi_{11|1}
\end{aligned} \tag{A.10}$$

### Dynamic Optimal Treatment Selection, DOTS

Under this assumption, people retire at a point when it is optimal to do so (as with COTS), however retiring at that stage results in higher mental health thereafter (than working, even for one additional period). In other words, people retire when they anticipate that work stops contributing to their overall wellbeing. The implication of this assumption is that now we can be sure that

$$\begin{aligned}
&a \leq E(Y_{it}^{10}|1,1,0) \leq E(Y_{it}|1,1,0) \\
&a \leq E(Y_{it}^{00}|1,1,0) \leq E(Y_{it}|1,1,0) \\
&a \leq E(Y_{it-1}^{00}|1,1,0) \leq E(Y_{it-1}|1,1,0) \\
&a \leq E(Y_{it}^{10}|1,1,1) \leq E(Y_{it}|1,1,1) \\
&a \leq E(Y_{it}^{00}|1,1,1) \leq E(Y_{it}|1,1,1) \\
&a \leq E(Y_{it-1}^{00}|1,1,1) \leq E(Y_{it-1}|1,1,1)
\end{aligned}$$

From these inequalities, we have,

$$\begin{aligned}
&\max(\alpha, a - E(Y_{it-1}|1,1,0)) \leq E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,0) \leq \min(\beta, E(Y_{it}|1,1,0) - a) \\
&\max(\alpha, a - E(Y_{it-1}|1,1,0)) \leq E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,0) \leq \min(\beta, E(Y_{it}|1,1,0) - a) \\
&\max(\alpha, a - E(Y_{it-1}|1,1,1)) \leq E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,1) \leq \min(\beta, E(Y_{it}|1,1,1) - a) \\
&\max(\alpha, a - E(Y_{it-1}|1,1,1)) \leq E(Y_{it}^{00} - Y_{it-1}^{00}|1,1,1) \leq \min(\beta, E(Y_{it}|1,1,1) - a)
\end{aligned}$$

The ensuing bounds under the DOTS assumption are then,

$$\begin{aligned}
&\Big[E(Y_{it}-Y_{it-1}|1,0,0) - \min\Big(\beta, E(Y_{it}|0,0,0) - E(Y_{it-1}|1,0,0)\Big)\Big]\Pi_{00|1}\\
+&\Big[\max(\alpha, a - E(Y_{it-1}|1,1,0)) - \min(\beta, E(Y_{it}|1,1,0) - a)\Big]\Pi_{10|1}\\
+&\Big[\max(\alpha, a - E(Y_{it-1}|1,1,1)) - \min(\beta, E(Y_{it}|1,1,1) - a)\Big]\Pi_{11|1}\\
\leq& ATT_t\\
&\Big[E(Y_{it}-Y_{it-1}|1,0,0) - \max\Big(\alpha, a - E(Y_{it-1}|0,0,0)\Big)\Big]\Pi_{00|1}\\
+&\Big[\min(\beta, E(Y_{it}|1,1,0) - a) - \max(\alpha, a - E(Y_{it-1}|1,1,0))\Big]\Pi_{10|1}\\
+&\Big[\min(\beta, E(Y_{it}|1,1,1) - a) - \max(\alpha, a - E(Y_{it-1}|1,1,1))\Big]\Pi_{11|1}
\end{aligned} \tag{A.11}$$

# B. Bounds under Homogeneous Variation.

If we impose the HV assumption, by which $E(Y_{it}^{00} - Y_{it-1}^{00}|z,z',z'') = E(Y_{it}^{00} - Y_{it-1}^{00}|0,0,0) = E(Y_{it}-Y_{it-1}|0,0,0)$ the above simplifies to:

$$\begin{aligned}
ATT =& \Big[E(Y_{it}-Y_{it-1}|1,0,0) - E(Y_{it}-Y_{it-1}|0,0,0)\Big]\Pi_{00|1}\\
&+\Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,0) - E(Y_{it}-Y_{it-1}|0,0,0)\Big]\Pi_{10|1}\\
&+\Big[E(Y_{it}^{10} - Y_{it-1}^{00}|1,1,1) - E(Y_{it}-Y_{it-1}|0,0,0)\Big]\Pi_{11|1}.
\end{aligned} \tag{B.12}$$

HV on its own does not identify the ATT because we do not know how the treatment had affected today to those who retired one or two periods ago (even if we assume that all individuals share a common trend in mental health when working). Obtaining the bounds under HV and NAB/COTS/DOTS is straightforward. The NAB,

$$\begin{aligned}
&\Big[E(Y_{it}-Y_{it-1}|1,0,0) - E(Y_{it}-Y_{it-1}|0,0,0)\Big]\Pi_{00|1}\\
+&(\alpha - E(Y_{it}-Y_{it-1}|0,0,0))(1-\Pi_{00|1})\\
\leq& ATT_t\\
\leq&\Big[E(Y_{it}-Y_{it-1}|1,0,0) - E(Y_{it}-Y_{it-1}|0,0,0)\Big]\Pi_{00|1}\\
+&(\beta - E(Y_{it}-Y_{it-1}|0,0,0))(1-\Pi_{00|1})
\end{aligned} \tag{B.13}$$

The COTS assumption affects the second and third terms of the expansion. The second term is now replaced with $E(Y_{it} - Y_{it-1}|0,0,0)$.

$$\begin{aligned}
&\Big[E(Y_{it} - Y_{it-1}|1,0,0) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{00|1}\\
+&\Big[\max(\alpha, a - E(Y_{it-1}|1,1,0)) - E(Y_{it} - Y_{it-1}|0,0,0))\Big]\Pi_{10|1}\\
+&\Big[\alpha - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{11|1}\\
\leq& ATT_t\\
\leq&\Big[E(Y_{it} - Y_{it-1}|1,0,0) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{00|1}\\
+&\Big[\beta - E(Y_{it} - Y_{it-1}|0,0,0)\Big](1 - \Pi_{00|1})
\end{aligned} \tag{B.14}$$

The DOTS assumption affects also the leading terms. So

$$\begin{aligned}
&\Big[E(Y_{it} - Y_{it-1}|1,0,0) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{00|1}\\
+&\Big[\max(\alpha, a - E(Y_{it-1}|1,1,0)) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{10|1}\\
+&\Big[\max(\alpha, a - E(Y_{it-1}|1,1,1)) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{11|1}\\
\leq& ATT_t\\
&\Big[E(Y_{it} - Y_{it-1}|1,0,0) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{00|1}\\
+&\Big[\min(\beta, E(Y_{it}|1,1,0) - a) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{10|1}\\
+&\Big[\min(\beta, E(Y_{it}|1,1,1) - a) - E(Y_{it} - Y_{it-1}|0,0,0)\Big]\Pi_{11|1}
\end{aligned} \tag{B.15}$$

# C. No-interference

If we rule out the existence of interference within units over time, the potential outcomes become $Y_{it}(Z_{it}) = Y_{it}^{Z_{it}}$. The ATT becomes,

$$\begin{aligned}
ATT_t =& \Big[E(Y_{it}^1 - Y_{it-1}^0|1,0) - E(Y_{it}^0 - Y_{it-1}^0|1,0)\Big]\Pi_{0|1}\\
&+ \Big[E(Y_{it}^1 - Y_{it-1}^0|1,1) - E(Y_{it}^0 - Y_{it-1}^0|1,1)\Big]\Pi_{1|1}
\end{aligned} \tag{C.16}$$

On this occasion, $E(Y_{it}^1|1,1)$ is also identified, therefore,

$$\begin{aligned}
ATT =& \Big[E(Y_{it} - Y_{it-1}|1,0) - E(Y_{it}^0 - Y_{it-1}|1,0)\Big]\Pi_{0|1}\\
&+ \Big[E(Y_{it} - Y_{it-1}^0|1,1) - E(Y_{it}^0 - Y_{it-1}^0|1,1)\Big]\Pi_{1|1}
\end{aligned} \tag{C.17}$$

The NAB bounds follow, by noting that

$$\max\Big(\alpha, a - E(Y_{it-1}|1,0)\Big) \leq E(Y_{it}^0 - Y_{t-1}|1,0) \leq \min\Big(\beta, b - E(Y_{it-1}|1,0)\Big) \tag{C.18}$$

and

$$\max\Big(\alpha, E(Y_{it}|1,1) - b\Big) \leq E(Y_{it} - Y^0_{t-1}|1,1) \leq \min\Big(\beta, E(Y_{it}|1,1) - a\Big) \tag{C.19}$$

The bounds are,

$$\begin{aligned}
&\Big[E(Y_{it} - Y_{it-1}|1,0) - \min\Big(\beta, b - E(Y_{it-1}|1,0)\Big)\Big]\Pi_{0|1} \\
&\Big[\max\Big(\alpha, E(Y_{it}|1,1) - b\Big) - \beta\Big]\Pi_{1|1} \\
\leq& ATT_t \\
\leq& \Big[E(Y_{it} - Y_{it-1}|1,0) - \max\Big(\alpha, a - E(Y_{it-1}|1,0)\Big)\Big]\Pi_{0|1} \\
+& \Big[\min\Big(\beta, E(Y_{it}|1,1) - a\Big) - \alpha\Big]\Pi_{1|1}
\end{aligned}$$

Under COTS, $E(Y^0_{it}|1,0) \leq E(Y_{it}|1,0)$, implying that

$$E(Y^0_{it} - Y_{it-1}|1,0) \leq \min(\beta, E(Y_{it} - Y_{it-1})|1,0) \tag{C.20}$$

The bounds are thus,

$$\begin{aligned}
&\Big[E(Y_{it} - Y_{it-1}|1,0) - \min(\beta, E(Y_{it} - Y_{it-1}|1,0))\Big]\Pi_{0|1} \\
+&\Big[\max\Big(\alpha, E(Y_{it}|1,1) - b\Big) - \beta\Big]\Pi_{1|1} \\
\leq& ATT_t \\
\leq& \Big[E(Y_{it} - Y_{it-1}|1,0) - \max(\alpha, a - E(Y_{it-1}|1,0))\Big]\Pi_{0|1} \\
+& \Big[\min(\beta, E(Y_{it}|1,1) - a) - \alpha)\Big]\Pi_{1|1}
\end{aligned}$$

Next, we consider the effect of the DOTS assumption. Note that, under this assumption, $E(Y^0_{it-1}|1,1) \leq E(Y_{it-1}|1,1)$ and $E(Y^0_{it}|1,1) \leq E(Y_{it}|1,1)$, but $E(Y^1_{it} - Y^0_{it-1}|1,1) = E(Y_{it} - Y^0_{it-1}|1,1)$, so that this term is bounded by

$$\max(\alpha, E(Y_{it} - Y_{it-1}|1,1)) \leq E(Y_{it} - Y^0_{it-1}|1,1) \leq \min(\beta, E(Y_{it}|1,1) - a) \tag{C.21}$$

and so,

$$\begin{aligned}
&\Big[E(Y_{it} - Y_{it-1}|1,0) - \min(\beta, E(Y_{it} - Y_{it-1}|1,0))\Big]\Pi_{0|1} \\
+&\Big[\max(\alpha, E(Y_{it} - Y_{it-1}|1,1)) - \beta\Big]\Pi_{1|1} \\
\leq& ATT_t \\
\leq& \Big[E(Y_{it} - Y_{it-1}|1,0) - \max(\alpha, a - E(Y_{it-1}|1,0))\Big]\Pi_{0|1} \\
+& \Big[\min(\beta, E(Y_{it}|1,1) - a) - \alpha)\Big]\Pi_{1|1}
\end{aligned} \tag{C.22}$$

Finally, under HV, the above bounds reduce, as follows. The NAB,

$$
\begin{aligned}
&\Big[E(Y_{it}-Y_{it-1}|1,0)-E(Y_{it}-Y_{it-1}|0,0)\Big)\Big]\Pi_{0|1}\\
&\Big[\max\Big(\alpha,E(Y_{it}|1,1)-b\Big)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{1|1}\\
\leq& ATT_t\\
\leq&\Big[E(Y_{it}-Y_{it-1}|1,0)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{0|1}\\
+&\Big[\min\Big(\beta,E(Y_{it}|1,1)-a\Big)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{1|1}
\end{aligned}
$$

COTS,

$$
\begin{aligned}
&\Big[E(Y_{it}-Y_{it-1}|1,0)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{0|1}\\
+&\Big[\max\Big(\alpha,E(Y_{it}|1,1)-b\Big)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{1|1}\\
\leq& ATT_t\\
\leq&\Big[E(Y_{it}-Y_{it-1}|1,0)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{0|1}\\
+&\Big[\min(\beta,E(Y_{it}|1,1)-a)-E(Y_{it}-Y_{it-1}|0,0))\Big]\Pi_{1|1}
\end{aligned}
\tag{C.23}
$$

DOTS

$$
\begin{aligned}
&\Big[E(Y_{it}-Y_{it-1}|1,0)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{0|1}\\
+&\Big[\max(\alpha,E(Y_{it}-Y_{it-1}|1,1))-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{1|1}\\
\leq& ATT_t\\
\leq&\Big[E(Y_{it}-Y_{it-1}|1,0)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{0|1}\\
+&\Big[\min(\beta,E(Y_{it}|1,1)-a)-E(Y_{it}-Y_{it-1}|0,0)\Big]\Pi_{1|1}
\end{aligned}
\tag{C.24}
$$

### C..1 Estimation

Valid estimation of the bounds for $\text{ATT}_t$ is straightforward by replacing expectations with their sample equivalents. It will often be desirable to obtain bounds for more general treatment parameters that do not depend on $t$ or that represent specific periods of time. In our application, for example, we are interested in treatment effects at different age stages, so the temporal dimension of interest is, in fact, age. In situations such as these, we can define

$$
ATT_{[s,s+k]}=\sum_{j=0}^{k}P(T=s+j)\cdot ATT_{s+j} \tag{C.25}
$$

where $P(T)$ is the distribution of time in the data. Once a identification region $[LB_t, UB_t]$ is obtained for each $\text{ATT}_t$, then the upper and lower bounds for $ATT_{[s,s+k]}$ follow by averaging the individual bounds,

$$\sum_{j=0}^{k} P(T = s+j) \cdot LB_{s+j} \leq ATT_{[s,s+k]} \leq \sum_{j=0}^{k} P(T = s+j) \cdot UB_{s+j} \tag{C.26}$$

We emphasise here that the above bounds require that the identification assumptions hold at each time period. Therefore, the bounds are underpinned by assumptions that are at least as strong as those underlying the individual ATT$_t$.

Note also that the above bounds can be estimated conditionally on the values of some covariates. In our application, for instance, we obtain bounds for various ATTs across two dimensions: pre-retirement mental health and life-time average job satisfaction. The bounds can be computed within each cell defined by the covariates without modification. However, once again, we need the identifying assumptions to hold within each class defined by the covariates. The ensuing assumptions are thus not weaker than those required for each unconditional $ATT$.

Finally, to compute standard errors of the bounds we resort to a cluster bootstrap, with individuals $i$ acting as clusters and resampling with replacement at cluster level. This allows us to maintain the within-individual correlation structure. Our results were based on 100 bootstrap replications (larger number of replications of up to 1000 replications did not provide noticeable refinements). We further report 95% confidence intervals for partially identified parameters in Imbens and Manski (2004).

# D. Minimax Rule

As in in Manski (2004, 2005, 2009, 2010); Manski et al. (2021), here we adopt a minimax-regret rule. This rule minimises the maximum regret over all possible distributions of potential outcomes. The minimax rule allocates all people with the same covariates to the same treatment (retirement or work) if that treatment is dominant. Otherwise, it allocates a fraction of the people to each treatment. The starting point is to assume that a policymaker is interested in achieving the highest possible levels of mental health in society by articulating retirement policies. The policymaker will base decisions on data from observed retirees and partial knowledge about the sign and magnitude of the ATT. The question is, ultimately, what had been the most desirable allocation among the labour force. To answer the question the policymaker needs estimates of the moments $E(Y_{it}^{10}|Z_{it} = 1)$ and $E(Y_{it}^{00}|Z_{it} = 1)$. An optimal decision would be to allocate all the people in a given sub-category to retirement if $E(Y_{it}^{10}|Z_{it} = 1) > E(Y_{it}^{00}|Z_{it} = 1)$. Otherwise, the policymaker would maintain people at work. Optimisation is not feasible because the objective function (which maps retirement onto the GHQ score above) is not known, and is only partially identified because $E(Y_{it}^{10}|Z_{it} = 1), E(Y_{it}^{00}|Z_{it} = 1)$ are only partially identified.

To proceed further, let Social Welfare be

$$\mathcal{V}(\delta, P) = E(Y_{it}^{10}|Z_{it} = 1) \cdot \delta + E(Y_{it}^{00}|Z_{it} = 1) \cdot (1 - \delta). \tag{D.27}$$

Using data and the assumptions considered in the previous section, the planner can establish only that $E(Y_{it}^{10}|Z_{it} = 1) \in [R_L, R_U]$ and $E(Y_{it}^{00}|Z_{it} = 1) \in [W_L, W_U]$. For any $r \in [R_L, R_U]$,

$w \in [W_L, W_U]$ and $\delta$, the loss of welfare resulting from choosing $\delta$ (or regret) is

$$\begin{aligned}\text{Regret} =& \max(w, r) - [w + (r - w)] \cdot \delta \\ =& (w - r) \cdot \delta \cdot \mathbb{I}(w > r) + (r - w) \cdot (1 - \delta) \cdot \mathbb{I}(w < r)\end{aligned} \tag{D.28}$$

Then, the maximum regret is

$$\max_{r \in [R_L, R_U], w \in [W_L, W_U]} \text{Regret} = \max \Big[(W_U - R_L) \cdot \delta, (R_U - W_L)(1 - \delta)\Big] \tag{D.29}$$

Finally, a minimax-regret rule selects $\delta$ so that,

$$\min_{\delta \in [0,1]} \max \Big[(W_U - R_L) \cdot \delta, (R_U - W_L)(1 - \delta)\Big] \tag{D.30}$$

with solution given by

$$\delta^* = \frac{R_U - W_L}{(W_U - W_L) + (R_U - R_L)} \in [0, 1] \tag{D.31}$$

The numerator of the rule $\delta^*$ corresponds to the upper bound on the $\text{ATT}_t$. The rule allocates a nontrivial proportion of people to retirement only if evidence supports a non-negative $ATT_t$. The proportion of people allocated to retirement grows the larger is the upper bound on $\text{ATT}_t$ (the more positive $\text{ATT}_t$ could be), and the greater the knowledge of $E(Y_{it}^{10}|Z_{it} = 1), E(Y_{it}^{00}|Z_{it} = 1)$ is (the narrower the associated identification regions).

## D..1 Minimax Rule under BV and BH.

Applying the definition of BV and BH to the following decompositions

$$E(Y_{it}^{10}|1) = \sum_{z \geq z'} E(Y_{it}^{10}|1, z', z')\Pi_{zz'|1} \text{ and } E(Y_{it}^{00}|1) = \sum_{z \geq z'} E(Y_{it}^{00}|1, z', z')\Pi_{zz'|1} \tag{D.32}$$

we can show that

1. $\delta^*_{BV} = \dfrac{1}{2}$
2. $\delta^*_{BV+HV} = \dfrac{1}{2} \dfrac{\Big(E(Y_{it}^{10}|1, 0, ) - E(Y_{it}^{00}|0, 0)\Big)\Pi_{00|1} + \Big(E(Y_{it}^{11}|1, 1) + \theta^{(1)} - E(Y_{it}^{00}|0, 0)\Big)(1 - \Pi_{00|1})}{\theta^{(1)}\Big(1 - \Pi_{00|1}\Big)}$
3. $\delta^*_{BV} = \dfrac{1}{2} \dfrac{\Big(E(Y_{it}^{10}|1, 0, ) - E(Y_{it}^{00}|0, 0)\Big) + \theta^{(2)} + \theta^{(1)}\big(1 - \Pi_{00|1}\big)}{\theta^{(2)} + \theta^{(1)}\big(1 - \Pi_{00|1}\big)}$
4. $\delta^*_{BV+HV} = \dfrac{1}{2} \dfrac{\Big(E(Y_{it}^{10}|1, 0, ) - E(Y_{it}^{00}|0, 0)\Big) + \theta^{(1)}\big(1 - \Pi_{00|1}\big)}{\theta^{(1)}\big(1 - \Pi_{00|1}\big)}$

# E. Additional results.

Partial Identification Regions, ATT.
Low Pre-retirement Satisfaction
Low Pre-retirement Mental Health.

| | Age categories. | | |
|---|---|---|---|
| | [ 58, 61] | [62, 65] | [66, 69] |
| NAB | [−36.08 44.74] | [−26.38 32.46] | [−28.29 29.90] |
| . | [−40.78 49.07] | [−29.51 35.92] | [−33.15 34.98] |
| COTS | [−31.48 44.74] | [−18.60 32.46] | [−24.84 29.90] |
| . | [−36.66 49.26] | [−22.10 35.91] | [−29.55 34.85] |
| DOTS | [−31.48 44.74] | [−16.04 29.90] | [−24.84 29.90] |
| . | [−36.47 49.02] | [−19.56 33.39] | [−29.23 34.69] |
| NAB+HV | [−15.41 19.14] | [ −5.18 15.17] | [ −7.58 18.06] |
| . | [−18.73 21.96] | [ −7.60 17.26] | [−10.79 21.20] |
| COTS+HV | [−15.41 19.14] | [ −5.18 15.17] | [ −7.58 18.06] |
| . | [−18.71 21.96] | [ −7.59 17.26] | [−10.76 21.20] |
| DOTS+HV | [−15.41 19.14] | [ −5.18 12.61] | [ −7.58 18.06] |
| . | [−18.73 21.92] | [ −7.59 14.64] | [−10.65 20.83] |
| NAB+SUTVA | [−25.05 44.74] | [−26.00 29.90] | [−26.59 29.90] |
| . | [−29.37 48.99] | [−28.25 33.42] | [−30.36 34.76] |
| COTS+SUTVA | [−23.52 44.74] | [−19.97 29.90] | [−23.94 29.90] |
| . | [−27.17 48.99] | [−22.30 33.42] | [−27.57 34.76] |
| DOTS+SUTVA | [−15.09 44.74] | [−13.44 29.90] | [−12.90 29.90] |
| . | [−17.69 48.99] | [−15.29 33.42] | [−15.64 34.76] |
| NAB+SUTVA+HV | [ −4.38 19.14] | [ −4.80 12.61] | [ −5.88 18.06] |
| . | [ −7.25 21.92] | [ −6.58 14.69] | [ −7.87 20.84] |
| COTS+SUTVA+HV | [ −4.38 19.14] | [ −4.80 12.61] | [ −5.88 18.06] |
| . | [ −7.25 21.92] | [ −6.58 14.69] | [ −7.87 20.84] |
| DOTS+SUTVA+HV | [ 4.05 19.14] | [ 1.73 12.61] | [ 5.16 18.06] |
| . | [ 2.10 21.92] | [ 0.42 14.69] | [ 3.89 20.84] |

**Table E.1:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ). The outcome is the % variation in the GHQ. Imbens-Manski 95% confidence intervals are provided under each estimate. Standard errors for the Confidence Intervals were obtained with 100 replications of bootstrap with resampling at cluster level (individual).

Partial Identification Regions, ATT.
High Pre-retirement Satisfaction
Low Pre-retirement Mental Health.

| | Age categories. | | |
|---|---|---|---|
| | [ 58, 61] | [62, 65] | [66, 69] |
| NAB | [−36.37 38.46] | [−19.26 20.63] | [−30.67 31.21] |
| . | [−41.51 43.49] | [−22.52 24.01] | [−34.11 34.95] |
| COTS | [−33.18 38.46] | [−11.74 20.39] | [−28.75 30.35] |
| . | [−39.19 43.47] | [−15.20 23.80] | [−32.14 34.22] |
| DOTS | [−33.18 38.46] | [−11.74 21.16] | [−21.82 23.99] |
| . | [−39.91 44.47] | [−14.89 24.50] | [−25.17 27.66] |
| NAB+HV | [−16.10 17.95] | [ −6.13 4.99] | [−14.55 14.81] |
| . | [−19.67 21.20] | [ −7.91 7.41] | [−16.30 17.39] |
| COTS+HV | [−16.10 17.95] | [ −6.13 4.99] | [−14.24 14.81] |
| . | [−19.76 21.20] | [ −7.90 7.41] | [−15.98 17.39] |
| DOTS+HV | [−16.10 17.95] | [ −6.13 4.99] | [ −9.36 12.75] |
| . | [−20.06 21.58] | [ −8.03 6.94] | [−11.10 15.25] |
| NAB+SUTVA | [−31.32 38.46] | [−16.69 20.63] | [−22.82 29.16] |
| . | [−35.98 43.55] | [−19.56 23.68] | [−26.00 32.82] |
| COTS+SUTVA | [−29.01 38.46] | [ −8.55 20.63] | [−21.51 29.16] |
| . | [−33.96 43.55] | [−11.35 23.68] | [−24.74 32.82] |
| DOTS+SUTVA | [−18.80 38.46] | [ −5.61 20.63] | [−12.98 29.16] |
| . | [−22.35 43.55] | [ −7.98 23.68] | [−15.49 32.82] |
| NAB+SUTVA+HV | [−11.05 17.95] | [ −3.56 4.99] | [ −6.70 12.75] |
| . | [−14.15 21.60] | [ −5.03 6.95] | [ −8.19 15.24] |
| COTS+SUTVA+HV | [−11.05 17.95] | [ −3.56 4.99] | [ −6.70 12.75] |
| . | [−14.15 21.60] | [ −5.03 6.95] | [ −8.19 15.24] |
| DOTS+SUTVA+HV | [ −0.85 17.95] | [ −0.62 4.99] | [ 1.83 12.75] |
| . | [ −2.92 21.60] | [ −1.82 6.95] | [ 0.89 15.24] |

**Table E.2:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ). The outcome is the % variation in the GHQ. Imbens-Manski 95% confidence intervals are provided under each estimate. Standard errors for the Confidence Intervals were obtained with 100 replications of bootstrap with resampling at cluster level (individual).

Partial Identification Regions, ATT.
Low Pre-retirement Satisfaction
High Pre-retirement Mental Health.

| | Age categories. | | |
|---|---|---|---|
| | [ 58, 61] | [62, 65] | [66, 69] |
| NAB | [−15.27 16.69] | [−15.48 16.17] | [−16.82 17.02] |
| | [−17.63 18.80] | [−17.36 18.05] | [−19.93 20.23] |
| COTS | [−12.41 16.22] | [−11.68 15.98] | [−16.68 17.02] |
| | [−15.21 18.25] | [−13.60 17.78] | [−19.51 20.08] |
| DOTS | [−12.01 17.02] | [ −9.41 13.69] | [−16.51 16.85] |
| | [−14.63 19.31] | [−11.45 15.75] | [−18.94 19.40] |
| NAB+HV | [ −5.47 6.91] | [ −6.52 4.16] | [ −7.60 9.04] |
| | [ −7.18 8.11] | [ −7.82 5.37] | [ −9.80 10.70] |
| COTS+HV | [ −5.47 6.91] | [ −6.13 4.16] | [ −7.60 9.04] |
| | [ −7.12 8.11] | [ −7.32 5.37] | [ −9.58 10.70] |
| DOTS+HV | [ −5.47 6.51] | [ −4.78 3.24] | [ −7.60 8.87] |
| | [ −6.93 7.89] | [ −6.00 4.44] | [ −9.40 10.09] |
| NAB+SUTVA | [−13.22 16.69] | [−12.99 15.46] | [−14.86 16.91] |
| | [−15.61 18.68] | [−14.92 17.25] | [−16.93 19.76] |
| COTS+SUTVA | [−10.34 16.69] | [ −8.20 15.46] | [−14.69 16.91] |
| | [−12.82 18.68] | [−10.05 17.25] | [−16.72 19.76] |
| DOTS+SUTVA | [ −7.07 16.69] | [ −4.45 15.46] | [−10.95 16.91] |
| | [ −8.63 18.68] | [ −5.58 17.25] | [−12.48 19.76] |
| NAB+SUTVA+HV | [ −3.43 6.91] | [ −4.04 3.44] | [ −5.65 8.93] |
| | [ −5.21 8.32] | [ −5.35 4.63] | [ −6.74 10.15] |
| COTS+SUTVA+HV | [ −3.43 6.91] | [ −4.04 3.44] | [ −5.65 8.93] |
| | [ −5.21 8.32] | [ −5.35 4.63] | [ −6.74 10.15] |
| DOTS+SUTVA+HV | [ −0.16 6.91] | [ −0.29 3.44] | [ −1.91 8.93] |
| | [ −1.08 8.32] | [ −0.95 4.63] | [ −2.70 10.15] |

**Table E.3:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ). The outcome is the % variation in the GHQ. Imbens-Manski 95% confidence intervals are provided under each estimate. Standard errors for the Confidence Intervals were obtained with 100 replications of bootstrap with resampling at cluster level (individual).

Partial Identification Regions, ATT.
High Pre-retirement Satisfaction
High Pre-retirement Mental Health.

| | Age categories. | | |
|---|---|---|---|
| | [ 58, 61] | [62, 65] | [66, 69] |
| NAB | [−12.85 15.10] | [−11.82 13.53] | [−20.20 20.11] |
| . | [−14.33 16.41] | [−13.30 15.03] | [−22.40 22.32] |
| COTS | [−10.09 15.06] | [ −9.37 13.53] | [−19.10 20.11] |
| . | [−11.66 16.36] | [−10.89 14.98] | [−21.18 22.26] |
| DOTS | [ −9.41 14.07] | [ −8.75 12.52] | [−18.11 18.87] |
| . | [−10.91 15.53] | [−10.18 13.99] | [−20.22 21.05] |
| NAB+HV | [ −5.25 5.25] | [ −6.39 2.01] | [−10.64 8.28] |
| . | [ −6.31 6.20] | [ −7.40 2.92] | [−12.07 9.64] |
| COTS+HV | [ −5.25 5.25] | [ −6.39 2.01] | [−10.39 8.28] |
| . | [ −6.36 6.20] | [ −7.38 2.92] | [−11.73 9.64] |
| DOTS+HV | [ −5.25 4.57] | [ −6.28 1.50] | [ −9.40 8.28] |
| . | [ −6.27 5.69] | [ −7.25 2.25] | [−10.66 9.40] |
| NAB+SUTVA | [−11.10 14.42] | [−10.31 13.02] | [−15.11 20.11] |
| . | [−12.78 15.70] | [−11.66 14.42] | [−16.94 22.29] |
| COTS+SUTVA | [ −8.75 14.42] | [ −6.89 13.02] | [−13.81 20.11] |
| . | [−10.25 15.70] | [ −8.18 14.42] | [−15.49 22.29] |
| DOTS+SUTVA | [ −6.10 14.42] | [ −4.78 13.02] | [ −7.74 20.11] |
| . | [ −7.03 15.70] | [ −5.64 14.42] | [ −8.91 22.29] |
| NAB+SUTVA+HV | [ −3.50 4.57] | [ −4.88 1.50] | [ −5.54 8.28] |
| . | [ −4.72 5.71] | [ −5.77 2.27] | [ −6.61 9.40] |
| COTS+SUTVA+HV | [ −3.50 4.57] | [ −4.88 1.50] | [ −5.54 8.28] |
| . | [ −4.72 5.71] | [ −5.77 2.27] | [ −6.61 9.40] |
| DOTS+SUTVA+HV | [ −0.85 4.57] | [ −2.77 1.50] | [ 0.53 8.28] |
| . | [ −1.85 5.71] | [ −3.38 2.27] | [ −0.09 9.40] |

**Table E.4:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ). The outcome is the % variation in the GHQ. Imbens-Manski 95% confidence intervals are provided under each estimate. Standard errors for the Confidence Intervals were obtained with 100 replications of bootstrap with resampling at cluster level (individual).

Partial Identification Regions, ATT, low mh low sat

| | $\delta^{(1)}$ | $\delta^{(2)}$ | BV | BV+HV | BH | BV+HV |
|---|---|---|---|---|---|---|
| r1 | 0 | 0 | [ 0.00 0.00] | [ 4.19 4.19] | [ 9.04 9.04] | [ 9.04 9.04] |
| r2 | 0 | 5 | [ −2.71 2.71] | [ 4.19 4.19] | [ 4.04 14.04] | [ 9.04 9.04] |
| r3 | 0 | 10 | [ −5.42 5.42] | [ 4.19 4.19] | [ −0.96 19.04] | [ 9.04 9.04] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ 1.48 6.90] | [ 6.33 11.75] | [ 6.33 11.75] |
| r5 | 5 | 5 | [ −7.71 7.71] | [ 1.48 6.90] | [ 1.33 16.75] | [ 6.33 11.75] |
| r6 | 5 | 10 | [−10.42 10.42] | [ 1.48 6.90] | [ −3.67 21.75] | [ 6.33 11.75] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −1.24 9.61] | [ 3.62 14.47] | [ 3.62 14.47] |
| r8 | 10 | 5 | [−12.71 12.71] | [ −1.24 9.61] | [ −1.38 19.47] | [ 3.62 14.47] |
| r9 | 10 | 10 | [−15.42 15.42] | [ −1.24 9.61] | [ −6.38 24.47] | [ 3.62 14.47] |
| r1 | 0 | 0 | [ 0.00 0.00] | [ 2.50 2.50] | [ 6.16 6.16] | [ 6.16 6.16] |
| r2 | 0 | 5 | [ −2.69 2.69] | [ 2.50 2.50] | [ 1.16 11.16] | [ 6.16 6.16] |
| r3 | 0 | 10 | [ −5.37 5.37] | [ 2.50 2.50] | [ −3.84 16.16] | [ 6.16 6.16] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −0.19 5.18] | [ 3.48 8.85] | [ 3.48 8.85] |
| r5 | 5 | 5 | [ −7.69 7.69] | [ −0.19 5.18] | [ −1.52 13.85] | [ 3.48 8.85] |
| r6 | 5 | 10 | [−10.37 10.37] | [ −0.19 5.18] | [ −6.52 18.85] | [ 3.48 8.85] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −2.88 7.87] | [ 0.79 11.53] | [ 0.79 11.53] |
| r8 | 10 | 5 | [−12.69 12.69] | [ −2.88 7.87] | [ −4.21 16.53] | [ 0.79 11.53] |
| r9 | 10 | 10 | [−15.37 15.37] | [ −2.88 7.87] | [ −9.21 21.53] | [ 0.79 11.53] |
| r1 | 0 | 0 | [ 0.00 0.00] | [ 2.02 2.02] | [ 6.09 6.09] | [ 6.09 6.09] |
| r2 | 0 | 5 | [ −4.25 4.25] | [ 2.02 2.02] | [ 1.09 11.09] | [ 6.09 6.09] |
| r3 | 0 | 10 | [ −8.49 8.49] | [ 2.02 2.02] | [ −3.91 16.09] | [ 6.09 6.09] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −2.22 6.27] | [ 1.85 10.34] | [ 1.85 10.34] |
| r5 | 5 | 5 | [ −9.25 9.25] | [ −2.22 6.27] | [ −3.15 15.34] | [ 1.85 10.34] |
| r6 | 5 | 10 | [−13.49 13.49] | [ −2.22 6.27] | [ −8.15 20.34] | [ 1.85 10.34] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −6.47 10.52] | [ −2.40 14.59] | [ −2.40 14.59] |
| r8 | 10 | 5 | [−14.25 14.25] | [ −6.47 10.52] | [ −7.40 19.59] | [ −2.40 14.59] |
| r9 | 10 | 10 | [−18.49 18.49] | [ −6.47 10.52] | [−12.40 24.59] | [ −2.40 14.59] |

**Table E.5:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ) under the Bounded Variation Within Units (BW) and Bounded Variation Between Sub-Populations (BB). The outcome is the % variation in the GHQ. $\theta^{\cdot}$ determine the maximal variation allowed within units (BW assumption) and across sub-populations (BB assumption).

Partial Identification Regions, ATT, low mh high sat

| | $\delta^{(1)}$ | $\delta^{(2)}$ | BV | BV+HV | BH | BV+HV |
|---|---|---|---|---|---|---|
| r1 | 0 | 0 | [ 0.00 0.00] | [ 1.74 1.74] | [ 3.81 3.81] | [ 3.81 3.81] |
| r2 | 0 | 5 | [ −2.99 2.99] | [ 1.74 1.74] | [ −1.19 8.81] | [ 3.81 3.81] |
| r3 | 0 | 10 | [ −5.98 5.98] | [ 1.74 1.74] | [ −6.19 13.81] | [ 3.81 3.81] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −1.25 4.73] | [ 0.82 6.79] | [ 0.82 6.79] |
| r5 | 5 | 5 | [ −7.99 7.99] | [ −1.25 4.73] | [ −4.18 11.79] | [ 0.82 6.79] |
| r6 | 5 | 10 | [−10.98 10.98] | [ −1.25 4.73] | [ −9.18 16.79] | [ 0.82 6.79] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −4.24 7.72] | [ −2.17 9.78] | [ −2.17 9.78] |
| r8 | 10 | 5 | [−12.99 12.99] | [ −4.24 7.72] | [ −7.17 14.78] | [ −2.17 9.78] |
| r9 | 10 | 10 | [−15.98 15.98] | [ −4.24 7.72] | [−12.17 19.78] | [ −2.17 9.78] |
| r1 | 0 | 0 | [ 0.00 0.00] | [ 0.38 0.38] | [ 1.34 1.34] | [ 1.34 1.34] |
| r2 | 0 | 5 | [ −2.80 2.80] | [ 0.38 0.38] | [ −3.66 6.34] | [ 1.34 1.34] |
| r3 | 0 | 10 | [ −5.59 5.59] | [ 0.38 0.38] | [ −8.66 11.34] | [ 1.34 1.34] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −2.41 3.18] | [ −1.46 4.14] | [ −1.46 4.14] |
| r5 | 5 | 5 | [ −7.80 7.80] | [ −2.41 3.18] | [ −6.46 9.14] | [ −1.46 4.14] |
| r6 | 5 | 10 | [−10.59 10.59] | [ −2.41 3.18] | [−11.46 14.14] | [ −1.46 4.14] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −5.21 5.98] | [ −4.25 6.93] | [ −4.25 6.93] |
| r8 | 10 | 5 | [−12.80 12.80] | [ −5.21 5.98] | [ −9.25 11.93] | [ −4.25 6.93] |
| r9 | 10 | 10 | [−15.59 15.59] | [ −5.21 5.98] | [−14.25 16.93] | [ −4.25 6.93] |
| r1 | 0 | 0 | [ 0.00 0.00] | [ −0.36 −0.36] | [ 2.48 2.48] | [ 2.48 2.48] |
| r2 | 0 | 5 | [ −4.15 4.15] | [ −0.36 −0.36] | [ −2.52 7.48] | [ 2.48 2.48] |
| r3 | 0 | 10 | [ −8.29 8.29] | [ −0.36 −0.36] | [ −7.52 12.48] | [ 2.48 2.48] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −4.50 3.79] | [ −1.67 6.63] | [ −1.67 6.63] |
| r5 | 5 | 5 | [ −9.15 9.15] | [ −4.50 3.79] | [ −6.67 11.63] | [ −1.67 6.63] |
| r6 | 5 | 10 | [−13.29 13.29] | [ −4.50 3.79] | [−11.67 16.63] | [ −1.67 6.63] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −8.65 7.94] | [ −5.81 10.77] | [ −5.81 10.77] |
| r8 | 10 | 5 | [−14.15 14.15] | [ −8.65 7.94] | [−10.81 15.77] | [ −5.81 10.77] |
| r9 | 10 | 10 | [−18.29 18.29] | [ −8.65 7.94] | [−15.81 20.77] | [ −5.81 10.77] |

**Table E.6:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ) under the Bounded Variation Within Units (BW) and Bounded Variation Between Sub-Populations (BB). The outcome is the % variation in the GHQ. $\theta^{\cdot}$ determine the maximal variation allowed within units (BW assumption) and across sub-populations (BB assumption).

Partial Identification Regions, ATT, high mh low sat

| | $\delta^{(1)}$ | $\delta^{(2)}$ | BV | BV+HV | BH | BV+HV |
|---|---|---|---|---|---|---|
| r1 | 0 | 0 | [ 0.00 0.00] | [ 0.63 0.63] | [ 2.56 2.56] | [ 2.56 2.56] |
| r2 | 0 | 5 | [ −2.83 2.83] | [ 0.63 0.63] | [ −2.44 7.56] | [ 2.56 2.56] |
| r3 | 0 | 10 | [ −5.66 5.66] | [ 0.63 0.63] | [ −7.44 12.56] | [ 2.56 2.56] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −2.20 3.46] | [ −0.27 5.40] | [ −0.27 5.40] |
| r5 | 5 | 5 | [ −7.83 7.83] | [ −2.20 3.46] | [ −5.27 10.40] | [ −0.27 5.40] |
| r6 | 5 | 10 | [−10.66 10.66] | [ −2.20 3.46] | [−10.27 15.40] | [ −0.27 5.40] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −5.03 6.30] | [ −3.10 8.23] | [ −3.10 8.23] |
| r8 | 10 | 5 | [−12.83 12.83] | [ −5.03 6.30] | [ −8.10 13.23] | [ −3.10 8.23] |
| r9 | 10 | 10 | [−15.66 15.66] | [ −5.03 6.30] | [−13.10 18.23] | [ −3.10 8.23] |
| | | | | | | |
| r1 | 0 | 0 | [ 0.00 0.00] | [ −0.42 −0.42] | [ 0.20 0.20] | [ 0.20 0.20] |
| r2 | 0 | 5 | [ −3.20 3.20] | [ −0.42 −0.42] | [ −4.80 5.20] | [ 0.20 0.20] |
| r3 | 0 | 10 | [ −6.41 6.41] | [ −0.42 −0.42] | [ −9.80 10.20] | [ 0.20 0.20] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −3.63 2.78] | [ −3.01 3.40] | [ −3.01 3.40] |
| r5 | 5 | 5 | [ −8.20 8.20] | [ −3.63 2.78] | [ −8.01 8.40] | [ −3.01 3.40] |
| r6 | 5 | 10 | [−11.41 11.41] | [ −3.63 2.78] | [−13.01 13.40] | [ −3.01 3.40] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −6.83 5.99] | [ −6.21 6.61] | [ −6.21 6.61] |
| r8 | 10 | 5 | [−13.20 13.20] | [ −6.83 5.99] | [−11.21 11.61] | [ −6.21 6.61] |
| r9 | 10 | 10 | [−16.41 16.41] | [ −6.83 5.99] | [−16.21 16.61] | [ −6.21 6.61] |
| | | | | | | |
| r1 | 0 | 0 | [ 0.00 0.00] | [ −0.92 −0.92] | [ −1.45 −1.45] | [ −1.45 −1.45] |
| r2 | 0 | 5 | [ −4.15 4.15] | [ −0.92 −0.92] | [ −6.45 3.55] | [ −1.45 −1.45] |
| r3 | 0 | 10 | [ −8.30 8.30] | [ −0.92 −0.92] | [−11.45 8.55] | [ −1.45 −1.45] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −5.07 3.23] | [ −5.60 2.70] | [ −5.60 2.70] |
| r5 | 5 | 5 | [ −9.15 9.15] | [ −5.07 3.23] | [−10.60 7.70] | [ −5.60 2.70] |
| r6 | 5 | 10 | [−13.30 13.30] | [ −5.07 3.23] | [−15.60 12.70] | [ −5.60 2.70] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −9.22 7.38] | [ −9.75 6.86] | [ −9.75 6.86] |
| r8 | 10 | 5 | [−14.15 14.15] | [ −9.22 7.38] | [−14.75 11.86] | [ −9.75 6.86] |
| r9 | 10 | 10 | [−18.30 18.30] | [ −9.22 7.38] | [−19.75 16.86] | [ −9.75 6.86] |

**Table E.7:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ) under the Bounded Variation Within Units (BW) and Bounded Variation Between Sub-Populations (BB). The outcome is the % variation in the GHQ. $\theta^{\cdot}$ determine the maximal variation allowed within units (BW assumption) and across sub-populations (BB assumption).

Partial Identification Regions, ATT, high mh high sat

| | $\delta^{(1)}$ | $\delta^{(2)}$ | BV | BV+HV | BH | BV+HV |
|---|---|---|---|---|---|---|
| r1 | 0 | 0 | [ 0.00 0.00] | [ −0.32 −0.32] | [ −0.33 −0.33] | [ −0.33 −0.33] |
| r2 | 0 | 5 | [ −2.50 2.50] | [ −0.32 −0.32] | [ −5.33 4.67] | [ −0.33 −0.33] |
| r3 | 0 | 10 | [ −5.00 5.00] | [ −0.32 −0.32] | [−10.33 9.67] | [ −0.33 −0.33] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −2.82 2.17] | [ −2.83 2.17] | [ −2.83 2.17] |
| r5 | 5 | 5 | [ −7.50 7.50] | [ −2.82 2.17] | [ −7.83 7.17] | [ −2.83 2.17] |
| r6 | 5 | 10 | [−10.00 10.00] | [ −2.82 2.17] | [−12.83 12.17] | [ −2.83 2.17] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −5.32 4.67] | [ −5.32 4.67] | [ −5.32 4.67] |
| r8 | 10 | 5 | [−12.50 12.50] | [ −5.32 4.67] | [−10.32 9.67] | [ −5.32 4.67] |
| r9 | 10 | 10 | [−15.00 15.00] | [ −5.32 4.67] | [−15.32 14.67] | [ −5.32 4.67] |
| | | | | | | |
| r1 | 0 | 0 | [ 0.00 0.00] | [ −0.91 −0.91] | [ −1.08 −1.08] | [ −1.08 −1.08] |
| r2 | 0 | 5 | [ −3.07 3.07] | [ −0.91 −0.91] | [ −6.08 3.92] | [ −1.08 −1.08] |
| r3 | 0 | 10 | [ −6.14 6.14] | [ −0.91 −0.91] | [−11.08 8.92] | [ −1.08 −1.08] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −3.98 2.16] | [ −4.14 1.99] | [ −4.14 1.99] |
| r5 | 5 | 5 | [ −8.07 8.07] | [ −3.98 2.16] | [ −9.14 6.99] | [ −4.14 1.99] |
| r6 | 5 | 10 | [−11.14 11.14] | [ −3.98 2.16] | [−14.14 11.99] | [ −4.14 1.99] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −7.05 5.22] | [ −7.21 5.06] | [ −7.21 5.06] |
| r8 | 10 | 5 | [−13.07 13.07] | [ −7.05 5.22] | [−12.21 10.06] | [ −7.21 5.06] |
| r9 | 10 | 10 | [−16.14 16.14] | [ −7.05 5.22] | [−17.21 15.06] | [ −7.21 5.06] |
| | | | | | | |
| r1 | 0 | 0 | [ 0.00 0.00] | [ −0.57 −0.57] | [ −3.06 −3.06] | [ −3.06 −3.06] |
| r2 | 0 | 5 | [ −3.97 3.97] | [ −0.57 −0.57] | [ −8.06 1.94] | [ −3.06 −3.06] |
| r3 | 0 | 10 | [ −7.93 7.93] | [ −0.57 −0.57] | [−13.06 6.94] | [ −3.06 −3.06] |
| r4 | 5 | 0 | [ −5.00 5.00] | [ −4.53 3.40] | [ −7.03 0.91] | [ −7.03 0.91] |
| r5 | 5 | 5 | [ −8.97 8.97] | [ −4.53 3.40] | [−12.03 5.91] | [ −7.03 0.91] |
| r6 | 5 | 10 | [−12.93 12.93] | [ −4.53 3.40] | [−17.03 10.91] | [ −7.03 0.91] |
| r7 | 10 | 0 | [−10.00 10.00] | [ −8.50 7.37] | [−10.99 4.87] | [−10.99 4.87] |
| r8 | 10 | 5 | [−13.97 13.97] | [ −8.50 7.37] | [−15.99 9.87] | [−10.99 4.87] |
| r9 | 10 | 10 | [−17.93 17.93] | [ −8.50 7.37] | [−20.99 14.87] | [−10.99 4.87] |

**Table E.8:** Partial Identification regions for the ATT of retirement on the aggregated General Health Questionnaire (GHQ) under the Bounded Variation Within Units (BW) and Bounded Variation Between Sub-Populations (BB). The outcome is the % variation in the GHQ. $\theta^{\cdot}$ determine the maximal variation allowed within units (BW assumption) and across sub-populations (BB assumption).

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