Estimating the effect or retirement on health via panel discontinuity designs

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Abstract

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1 Introduction.

The causal effect that retirement might have on health and health care is a topic of considerable interest, not only for economists, but also for legislators, due to the potential consequences of that link on public finance and the welfare system. Before the proliferation of debates and policies affecting the delay of the default retirement age, there has been a trend towards early retirement, especially in OECD countries. Published literature has identified several of the drivers explaining such a trend, among which special prominence has been given to the implicit disincentives faced by workers about retirement age (Krueger and Pischke, 1992, Blundell et al. (2002), Gruber and Wise, 2002, 2004), the disadvantage of older workers during industrial restructuring and periods of technological change (Banks and Smith, 2006), as well as an ageing population. The trend has been exacerbated by a rise in the age at which people leave school (Banks and Smith, 2006) and its ultimate consequence has been a rise in the ratio of retirees per person of working age. The implications are well known: in pay-as-you-go systems it can compromise the solvency of pensions and welfare funds, while in the context of fully funded systems, a too high proportion of retirees would affect the amount of savings available for investment and, therefore, economic growth.

To counter balance the negative effects of retirement dynamics, policy makers in developed countries are now debating or implementing increases in the retirement age and the age at which people are eligible for pensions. Most policies that have been brought forward contemplate increases of one to two years in the default retirement age, what constitutes a 2.5 % - 5% increase in a working life of 40 years. However it has been argued that retirement might affect health, in which case the valuation of policies that prolong retirement should account for such an effect. In the presence of health effects, a longer retirement horizon, by postponing changes in health outcomes, should affect the utilization of health services by older adults (conditional on life expectancy), and this would impact on the projected variation in health care expenditures.

When it comes to unveiling any causal relations between retirement and health, economic theory can often be inconclusive as pointed out by Dhaval et al. (2008). These authors outline that, in accordance to "*...the Grossman model...*"(Grossman, 1972), if the marginal value of time increases after retirement, individuals will increase their expenditure in preventive health care because of the consumption value of health but, simultaneously, this effect might be mitigated by the fact that the cost of visiting a medical practice or health provider increases. Therefore, there is a need for empirical studies than can help to articulate the potential relationship between retirement and health.

In practice, selection bias complicates the identification of the effect of retirement on health and practitioners have addressed this problem using a variety of instrumental variable strategies. However existing results tend to be contradictory, even after taking into account the potential endogeneity of retirement. Seminal work by Charles (2004) concludes that the "... *direct effect of retirement on well-being is positive once the fact that retirement and well being are simultaneously determined is accounted for...*". Dhaval et al. (2008) find that retirement leads to 6-9% decrease in mental health, and 5-6% increase in illness conditions. Coe and Lindeboom (2008) conclude that there are no negative health effects of retirement. Neuman (2008) finds that there is strong evidence dismissing the idea that retirement harms health, while Johnston and Lee (2009) conclude that retirement improves individuals' sense of well-being and mental health, but not necessarily physical health. In this article we present further evidence regarding the average causal effect of retirement on health introducing a number of methodological novelties.

Among the many dimensions of health, mental well-being plays an important role in our analysis because, as it is implicit in most published work, this is likely to be the most vulnerable dimension of a person's health upon retirement. Yet the transmission mechanism between retirement and health has not been well explored. Medical and sociological research has put forward a set of theories trying to model this relationship, among which role theory has been specially favoured (Kim and Moen, 2002). In accordance with this theory, people who have retired from their career are vulnerable to feeling a role loss, which could lead to psychological distress (a counter argument could be made, namely that retirement from demanding roles might lead to an improvement of mental well-being). To the best of our knowledge, role theory remains untested and this paper sets out to evaluate this hypothesis. Understanding the drivers of any potential relationship between retirement and health is important, as it can inform policy making, but also because there might exist a lag between the time when strain or a sense of role loss develops and the moment when any impact on health manifests itself, and thus identifying these effects can help planning and increase the effect of interventions.

One of the pervasive problems faced by researchers modelling any dimension of health is that outcomes are typically based on self-reported information. In the best scenario such information constitutes an approximation to actual health status subject to arbitrary levels of subjectivity. Our data set, the British Household Panel Survey, is equally affected by this characteristic, but it gives us the opportunity to extend our analysis to other more objective dimensions of mental health. In particular, recent medical research suggests that high blood pressure and migraine are highly correlated with poor mental health (Ahn and Ashizawa, 2010, Stam et al., 2010). These are relatively objective measures -in particular, medical examination is normally required prior to knowing if one has high blood pressure- and can be affected relatively quickly by a change of job status. Therefore we use these outcomes to provide a broader image about psychological well being after retirement.

Unlike previous contributions we also explore ways retirement might affect utilisation of health care services. Ultimately, this is a key aspect for policy making and the result that is of interest in order to inform any intervention. Because utilisation will increase with poor health outcomes, this analysis will also allow us to check the consistency of our results about the link between retirement and mental health.

As pointed out in Blundell et al. (2002), Gruber and Wise (2002, 2004) or Banks and Smith (2006), there are very different experiences of retirement, and different groups of the population are likely to respond differently to it. To account for this potential heterogeneity, this article pays special attention to the roles played by education and occupation. As discussed in a number of references, (Fuchs, 1982, Cawley and Ruhm, 2011), utility maximising agents exhibit different discount rates that determine different levels of schooling. If, as suggested by Fuchs (1982) discounting is stable over time and is formed in early stages of life, it will affect equally any health care decisions. Similarly, a number of recent articles (see Autor et al., 2003, Acemoglu and Autor, 2011 and references therein) have noted that occupational mix can explain evolution of wage differentials via, for example, the introduction of new technologies and off-shoring. This channel can further induce different retirement patterns among occupations, an argument that is implicit in (Banks and Smith, 2006), when they mention the disadvantage of older workers during industrial restructuring and technological change as a potential determinant of retirement.

Finally, our identification strategy is also new. It is well know that, in the United Kingdom, the conditional distribution of retirement on age exhibits a discontinuity at the, recently disappeared, default retirement age (DRA) of 65 (for men). For instance, Blundell et al. (2002), Smith (2006), Banks and Smith (2006) report 20%-25% jumps in the proportion of retirees at that age. Johnston and Lee (2009) exploit this feature[1] *à la* regression discontinuity (Thistlethwaite and Campbell, 1960, van der Klaauw, 1996, Hahn et al., 1999), using an indicator of exceeding the default retirement age as an in-

[1]It is convenient to remark that Johnston and Lee (2009) use the Health Survey for England, a repeated cross-section, and the reported jump in their work greatly exceeds the 20/25% gap typically reported in most studies.

strument. We also take this approach, but we introduce two methodological innovations. Firstly, we note that the distribution of retirees exhibits a second feature, namely there is a kink at the default retirement age. The rate of retirees grows fast before the default retirement age, but this rate slows down considerably afterwards. Following recent work by Card et al. (2009) and Dong (2011) we exploit this discontinuity in the density function of retirement in order to produce an additional set of instruments, which allows us to add identification power of our estimator, as well as circumvent weak instrument problems. Secondly, when panel data are available, it is a wide-spread practice to take the average cluster approach described in Lemieux and Milligan, 2008, Battistin et al., 2009, or Dong, 2011). However, as pointed out recently by Petterson-Lidbom (forthcoming), one can exploit the two stage least square interpretation of discontinuity designs (Angrist and Pischke, 2008) and combine the discontinuity approach with standard I.V. panel methods. This has the advantage that comparisons are drawn between the same individual at consecutive points in time (right before and right after the DRA), making it less contentious to use the main assumptions underpinning nonparametric discontinuity techniques, namely comparability of distributions around the threshold and continuity of potential outcomes.

The structure of the article is as follows. Section 2 introduces the econometric methodology, providing an overview of existing discontinuity designs. Section 3 describes the data and present the main results, while section 4 concludes.

2 Estimation Methods: Discontinuity Designs

Our analysis uses the British Household Panel Survey (BHPS hereafter), a representative longitudinal survey that contains employment and retirement histories for each surveyed person as well as other information at individual and household level. We consider the first 16 waves of the data set, corresponding to the period 1991 to 2006 and focus on the sub-population of male individuals. In the analysis, a person was taken as a retiree if (*i*) that was his self-reported job market status, (*ii*) he reported not to have undertaken any paid work during the two weeks prior to the interview and (*iii*) he did not re-enter the job market after retiring, regardless of whether their subsequent job status is employed or unemployed.

The identifying strategy followed in this article exploits that, during the period under consideration, there was a default state pension age (for men) in the U.K. of 65, what induces a number of peculiarities in the distribution of retirees. The estimate of this distribution is plotted in figure 1. The average ratio of retirees at age 64 for our sample

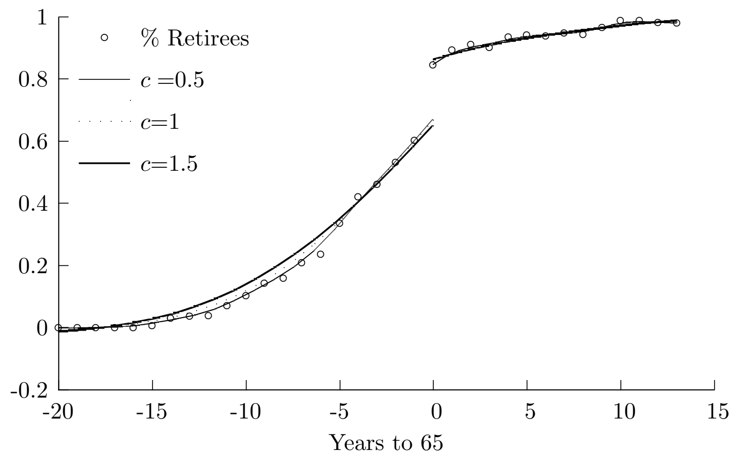

Figure 1: Discontinuities in the proportion of male retirees. The abscissa is $Age - 65$. Local linear estimator with bandwidth $h = c\sigma_x n^{-0.2}$, for $c = 0.5, 1$ and 1.5.

is approximately 60% confirming the findings of previous studies[2] that most people have already retired by the time they reach the DRA. However, the first useful feature of the distribution is the discontinuity at age 65, where the proportion of retirees jumps to about 85%. This discontinuity in the distribution of retirees can be exploited *à la* regression discontinuity (Thistlethwaite and Campbell, 1960, van der Klaauw, 1996, Hahn et al., 2001) to obtain a first set of instrumental variables for retirement in the health-retirement equation. The procedure can be formalised as follows.

Let Y be an outcome of interest with conditional expected value $G(x) = E(Y|X = x)$. In our case Y is health status measured, for instance, as an indicator of depression or the average score in a general health questionnaire. X is a random variable, typically correlated with Y, that determines allocation to treatment status -the latter represented by T, a binary indicator taking value 1 if a person in the sample is treated, and whose conditional expectation is $P(x) = E(T|X = x)$. In the typical regression discontinuity application, allocation to treatment depends on the running variable X exceeding a threshold value x_o. In our case, X denotes an individual's age, T indicates retirement status and $x_o = 65$ (the default retirement age). Perfect compliance with treatment is not a requirement for successful identification -and in our case it is not satisfied[3]. Using Rubin's potential outcomes framework let $Y(1)$ and $Y(0)$ refer to an individual's

[2]See, Banks and Smith (2006), Gruber and Wise (2002, 2004).

[3]Traditionally one distinguishes between designs with perfect compliance, "sharp"RD, and designs with imperfect compliance, "fuzzy". In this paper we are interested in the second type of design.

outcomes with and without the treatment, only one of which is revealed in empirical research,

$$Y = TY(1) + (1-T)Y(0) = \alpha + \tau T.$$

where $\tau = Y(1) - Y(0)$ is the treatment effect parameter. A number of sources[4] show that, if

$$\lim_{x \to x_o^+} P(x) \neq \lim_{x \to x_o^-} P(x)$$

then,

$$E(\tau | X = x_o) = \frac{\lim_{x \to x_o^+} G(x) - \lim_{x \to x_o^-} G(x)}{\lim_{x \to x_o^+} P(x) - \lim_{x \to x_o^-} P(x)} \tag{2.1}$$

The necessary condition for identification is that $E(Y(0)|X = x)$ and $E(Y(1)|X = x)$ are continuous at x_o -a condition we will refer to as continuity of potential outcomes (CPO)[5]. Under additional weak restrictions, Lee (2008) shows that CPO naturally leads to quasi-randomization in small neighbourhoods to the left and right the cut-off point, and this provides the power (and justifies the popularity) of the regression discontinuity. Therefore, evaluation of empirical distributions of pre-determined characteristics just above and below x_o becomes a valid check of the otherwise non-testable CPO assumption.

Estimation in RD designs in this setting admits an Instrumental Variable interpretation[6]. From a parametric point of view, for small $e(n) > 0$, one has the following outcome model in $(x_o - e, x_o + e)$,

$$Y = \beta_0 + h(X) + \tau T + \varepsilon \tag{2.2}$$

where the unknown $h(X)$ can be approximated at x_o by a polynomial series expansion (Angrist and Pischke, 2008), so that[7]

$$Y = \beta_0 + \beta_1(X - x_o) + \ldots + \beta_p(X - x_o)^p + \tau T + \varepsilon \tag{2.3}$$

where ε is uncorrelated with X by assumption. In our case, this implies that age looses its detrimental effect on average health if we restrict attention to a group of people whose age differs only slightly. If the probability of treatment is discontinuous at x_o,

[4]See Hahn et al. (1999), Lee (2008), Angrist and Pischke (2008) or Lee and Lemieux (2010)

[5]Under homogeneous treatment effect the ratio in equation (2.1) identifies τ itself, and in this case only continuity of $E(Y(0)|X)$ is required (Hahn et al., 1999)

[6]Without loss of generality, in what follows we adopt a parametric approach. The equivalent nonparametric take on RD designs can be found in numerous references, including Hahn et al. (1999), Angrist and Pischke (2008) or Dong (2011).

[7]For convenience we abuse the notation slightly and use the same symbol for the error term in equations (2.2) (2.3)

then $D_i = \mathbb{I}(X_i \geq x_o)$ is correlated with T_i but, by hypothesis, uncorrelated with ε. Therefore, D_i stands as a valid instrument for T_i in $(x_o - e, x_o + e)$ and τ can be consistently estimated via 2SLS using D_i and a polynomial in X_i as instruments.

If the discontinuity in the distribution of T given X is small, researchers face a problem of weak identification (Feir et al., 2011). It is well know that weak instruments exacerbate the small sample bias of 2SLS estimators and will render misleading inferential procedures (Bound et al., 1995, Staiger and Stock, 1997, Feir et al., 2011, Kleibergen, 2002). However, a recent paper by Dong (2011) (see also Card et al., 2009), has pointed out that, should a discontinuity in the distribution of treatment be too small, identification of treatment effects is possible if there is a discontinuity in the first derivative of the distribution of treatment -that is, a kink in the distribution of T given X- so that:

$$\lim_{e \to 0} \frac{\partial P(x)}{\partial x}\Big|_{x=x_o+e} \neq \lim_{e \to 0} \frac{\partial P(x)}{\partial x}\Big|_{x=x_o-e}. \tag{2.4}$$

The essential condition for identification is continuity in the first order partial derivatives of potential outcomes. Dong (2011) shows that, under this assumption, it is possible to identify treatment effects when there is a kink in the conditional distribution of T, or a jump, or both -in which case the estimator is a weighted average of the estimator used in RD designs and Kink designs, namely

$$\tau = \frac{\lim_{x \to x_o^+} G(x) - \lim_{x \to x_o^-} G(x) + w_n(\lim_{x \to x_o^+} G'(x) - \lim_{x \to x_o^-} G'(x))}{\lim_{x \to x_o^+} P(x) - \lim_{x \to x_o^-} P(x) + w_n(\lim_{x \to x_o^+} P'(x) - \lim_{x \to x_o^-} P'(x))} \tag{2.5}$$

for a given sequence $\{w_n\}$ such that $\lim_{n \to \infty} w_n = 0$. Continuous differentiability of potential outcomes is not a directly testable assumption. Dong suggests that the adequacy of the kink design can be tested by checking the existence of kinks and jumps in the conditional means of pre-determined variables, although she does not provide a formal discussion regarding the nature of these conditions. A formal analysis can be undertaken borrowing from Lee (2008) and Card et al. (2009), and is done in the Appendix.

Looking at figure 1 it is a priori unclear whether the jump in the discontinuity is sufficiently large to identify the causal effect of retirement on health. However, the figure exhibits a change in the slope after crossing default retirement age. The existence of the kink can be confirmed by a simple OLS regression of the retirement indicator on $D = I(X_i \geq 65)$, $D_i * X_i$ and a fifth polynomial in X_i. The coefficient for the interaction term in such regression was -.0568565 (p=0.000). It was mentioned above that the retirement rate at age 64 is about 60% for a typical year and jumps to about 85% at age 65. The increase in the proportion of retirees up to age 64 is fast, reflected in a large positive, increasing slope of the half of the distribution to the left of x_o. However, the right half of the distribution exhibits an only moderate slope, suggesting that retirement beyond the DRA converges slowly to 1. This feature allows us to build a second set of instrumental variables. Dong (2011) shows that her kink design approach also admits a local I.V. interpretation. Under the premises underpinning the local outcome model in equation (2.2) and its approximation in (2.3) a kink at x_o can be captured by the interaction of D and X, in which case D and $D*X$ are both valid instruments to identify τ via 2SLS using the feasible first stage equation

$$T = \alpha_o + \alpha_1(X - x_o) + \dots \alpha_p(X - x_o)^p + \pi_1 D + \pi_2 D * (X - x_o) + u.$$

In this case, Dong (2011) shows that the estimator of τ is an empirical version of (2.6) with weights $w_1 = cov(T, D)$, $w_2 = cov(T, X * D)$.

2.1 Panel Data

Discontinuity designs have been developed with cross-section data in mind. When repeated cross-section and panel data are available, it is a wide-spread practice to take the average cluster approach described in Lemieux and Milligan (2008), Battistin et al. (2009), or Dong (2011), whereby the relevant endogenous variables are averaged within each wave and across the panel conditional on clusters of the running variable. As noted by Lemieux and Milligan (2008), in a regression discontinuity framework, the resulting estimator of the treatment effect is identical to weighted estimates of individual wave estimators, when the weights used are the number of observations per cell.

As pointed out by Petterson-Lidbom (forthcoming), RD relies on the cut-off value inducing local quasi-experimental randomization, which is the strength, but also Achille's heel, of the method. In practice nonparametric identification requires large amounts of data at the boundary of the threshold value, which is not always available. However if one exploits the panel structure of the data, then estimates via fixed effects (FE) and first-difference (FD) draws comparisons within the same individual, making the treatment and control groups comparable by definition and the assumption of continuous (differentiable) potential outcomes less contentious regardless of the sample size, thus reducing the relevance of choosing a bandwidth. Following this rationale, we suggest the following local outcome model,

$$Y_{it} = \theta_i + \lambda_t + \tau T_{it} + \beta_1(X_{it} - x_o) + \ldots + \beta_p(X_{it} - x_o)^p + \varepsilon_{it} \tag{2.6}$$

$$\begin{aligned} T_{it} &= \theta_i + \lambda_t + +\beta_1(X_{it} - x_o) + \ldots + \beta_p(X_{it} - x_o)^p \\ &+ \pi_1 D_{it} + \pi_2 D_{it} * (X_{it} - x_o) + \nu_{it}. \end{aligned} \tag{2.7}$$

where θ_i and λ_t are individual and period specific coefficients. This model can be estimated via first difference instrumental variables (FD-IV) on the structural equation, with instruments described in the first stage equation. As before the unknown control functions $q(.)$ and $r(.)$ are replaced by polynomial approximations in practice. To test the validity of the instruments, we follow Staiger and Stock (1997), and calculate the first stage test of joint significance (F test), expecting this to exceed a nominal value of ten.

3 Empirical Analysis.

We use the discontinuity design just described to evaluate the effect of retirement on a collection of health-related indicators which can be classified in three groups: mental health indicators, measures of health care utilisation and design check variables. We describe these variables next.

Mental health is often perceived as the dimension of health most exposed to the effects of retirement, and therefore it has received much attention in the literature[8]. Medical and sociological research has suggested that the connexion between both variables could be explained because people who have retired from their career are vulnerable to feeling a role loss, which could lead to psychological distress (Kim and Moen, 2002). On the contrary, it is plausible that retirement from demanding roles might lead to an improvement of mental well-being by reducing the amount of strain that people are subjected to. In the BHPS, mental health is measured with Goldberger's General Health Questionnaire[9], GHQ-12, (Goldberger, 1978). The amount of strain and sense of a role felt by interviewees constitute two of the domains explored by GHQ-12, and this gives us the opportunity of studying whether retirement affect these domains to the point of altering the average mental health status. In the survey, individuals are asked if they have recently felt that they "*were playing a useful part in things*". We created a binary

[8]See, for instance, Johnston and Lee, 2009, Dhaval et al. (2008) or Mein et al., 2003

[9]The answers to the questionnaire are summarised in a twelve point scale that measures the inability to carry out normal functions and the appearance of new and distressing psychological phenomena. Large average scores denote deteriorating mental health.

indicator taking value 1 if an individual answered "*less so*" or "*much less*" to this question. Similarly, GHQ-12 contains the question "*Have you recently felt constantly under strain?*". A binary indicator was created and an individual was allocated value 1 if his answer to this question was "*rather more*" or " *much more*". Apart from the GHQ-12 and the role and strain dummies, BHPS includes a binary indicator taking value 1 if a person reported to "*have any of the health problems or disabilities listed ... anxiety or depression*", which is also included in the analysis.

In addition to these mental health scores, we also considered two additional outcomes, namely migraine and high blood pressure. Increasing evidence suggests that there is a genetic association between migraine and depression (Ahn and Ashizawa, 2010, Stam et al., 2010). In principle, then, if retirement induces a variation in mental health status, its effect should reflect on the incidence of migraines. The medical literature has also recently identified a correlation between depression and high-blood pressure (Licht et al., 2008, Dawood et al., 2009). If retirement affects mental health and this is correlated with blood pressure, then one might observe a variation in self-reported blood pressure. There is a potential confounding effect, because blood pressure might be affected by retirement indirectly, via changes in life-style or diet. However these would be long-term effects that a discontinuity technique is unlikely to capture.

Our measures of health care utilisation are a dummy variable indicating if an individual had at least one inpatient stays in a hospital and a dummy variable indicating if an individual visited a general practitioner during previous year in six or more occasions. In the typical year, the proportion of individuals in the panel that have visited a general practitioner (family doctor) three or more times over the previous 12 month period is about 40% while the proportion of individuals who visit a general practitioner six or more times ranges between 15-20% , so the latter is a relatively infrequent event. Because individuals normally make appointments in their General Practice on their own initiative when they consider that they need medical care, this measure of utilization is not exempt of subjectivity as a subjective indicator of health status. On the contrary, inpatient stays require the qualified opinion of a physician, and therefore a part from measuring utilization, this variable is an objective proxy of medical need and overall health status. If retirement would seriously affect health in the short run, we should observe some variation in the levels of these variables.

To check the validity of the discontinuity designs, we sought kinks or jumps in the conditional distributions of a set of pre-determined outcomes. These were the proportion of individuals without any qualification, the distribution of the running variable for each year in the wave and the amount of time spent doing homework. Our estimating strategy should reveal a significant (positive) effect only in the last case. We also included in this group the proportion of individuals with diabetes. In accordance with the medical literature, diabetes is related to certain diseases and genetic endowment. There is evidence, however, that Type II diabetes is related to sedentary life styles (Risérus et al., 2009), and therefore, in the long-run, retirement might lead to higher diabetes if it conveys a change to a less active life-style. Even then, it is unlikely that the prevalence of diabetes increases in the short run immediately after retirement, and therefore our discontinuity design should not reveal any variation in the prevalence of this disease in the sample.

3.1 The role of education

The BHPS is a representative survey and so, in principle, our design should approximate the population's average treatment effect. Yet, any effects of retirement are likely to be heterogeneous. To take into account this effect, we pay special attention to the roles education and occupation might play in the distribution of treatment effects.

In accordance to human capital theories, a person's schooling decision maximises the present value of lifetime earnings. The higher the rate of discount, the less likely a worker will invest in education, as he discounts heavily the receipt of future income generated by further education. Fuchs (1982) suggests that differences in time preferences are established early in life and remain relatively stable, which suggests that these discount rates will be high still upon retirement. In accordance with Grossman (1972), health promoting activities have a consumption and an investment dimension, the later due in part to the ability of health to generate future income by enabling a person to work. Individuals about to retire might postpone health care utilization if that might incur foregone income or opportunity costs. However, this effect would be more evident among the population of people that discount income at a higher rate. In practice, discount rates are unobservable but in view of this discussion, a given group of people with similar level of schooling will be relatively homogeneous in terms of discount rates. Therefore, we split our sample in three groups in accordance to whether an individual has no qualifications, secondary education or higher education.

Education determines to a certain degree people's skill mix and later occupation in life. A number of recent articles (see Autor et al., 2003, Acemoglu and Autor, 2011 and references therein) have noted that occupational mix can explain evolution of wage differentials via, for example, the introduction of new technologies and off-shoring, both of which can depress returns to certain tasks while boosting returns to others. For instance, Firpo et al. (2011) give the example of debugging and updating software. Consider a country with a group of firms producing software. The firms can subcontract debugging and updating its software overseas, where it can be completed promptly and cheaply. This frees time for the firms' own programmers to concentrate on developing new applications, and thus boosting their productivity. However, off-shoring will depress returns to debugging and increase returns for developers in the country were the firm is located. This channel can further induce different retirement patterns among occupations, an argument that is implicit in (Banks and Smith, 2006), when they mention the disadvantage of older workers during industrial restructuring and technological change as a potential determinant of retirement. People are endowed with heterogeneous mixes of skills, but the argument could be made that people self-select into occupations as to maximise their returns given their knowledge about their own mix of skills. This would result in specific occupations having workers with similar social, emotional or even physical abilities, so that common patterns of reaction to retirement might arise in such occupations. Of course this argument presupposes that individuals have a good understanding of their own abilities, which is a contentious assumption -though perhaps empirically testable. In either case, although we these hypothesis are untested in this article, we do explore the causal relationship of retirement on health by occupational groups. In particular we will separate the sample into a group of manual workers and a group of white collar workers.

3.2 Results.

The results of estimating our panel-discontinuity design are given in Tables 1 to 6 and figures 2 to 4. We begin by assessing the validity of the discontinuity design by looking for jumps or kinks in the figures, as this would suggest the existence of factors other than those considered that might be confounding our estimates. Figure 2 represents the distribution of the running variable for three different years, 1995, 2000 and 2005. The figure suggests that this distribution is smooth in a neighbourhood of the default retirement age, and so the first condition for identification (continuous differentiability of the distribution of the running variable -see Appendix A) seems to be satisfied. Figures 3 and 4 represent scatter plots of the average (across the panel) number of manual workers and people without qualifications at each age cell. These variables are both determined before the event of retirement, and therefore they serve us to further evaluate the conditions required for identification (Appendix A). Neither figure suggests the existence of jumps or kinks in these relationships. Finally, in tables 1 to 6 we observe that our panel data estimates of the effect of retirement on diabetes is insignificant at all levels, for all the considered combinations of level of education and occupation, and therefore we conclude that the requirements described in the appendix hold.

Next we discuss the results in the tables. We estimated model (2.6) using the whole sample and then using three different bandwidths, namely $\pm 10, \pm 8$ and ± 6. This notwithstanding, the estimated coefficients are relatively insensitive to the choice of bandwidth, as one would expect given that we are using panel data, and comparisons are drawn at individual level.

The first conclusion of the study is that, on average retirement does not affect any of the six dimension of mental health considered in this article. The estimated local average treatment effects all appear to be statistically insignificant at all levels, for all bandwidths and regardless of education and occupation classifications. The same conclusion holds for utilisation. Although one could expect that inpatient stays would stay approximately unchanged upon retirement, the number of individuals that visit a GP in six or more occasions in a year remains insignificant across the tables. The exception is for $h = \pm 8, 6$ when the whole sample is considered (Table 1). Then, a negative coefficient of -0.25 (p=0.026) would suggest a considerable reduction in this variable. Yet, the result is not reproduced in any of the remaining tables, so we cast serious doubts on the reliability of this result.

The question might arise if the lack of significance in the results presented here is due to poor identification, in which case the design would fail to capture variation in virtually any variable under consideration. We evaluate this by studying a model of the effect of retirement on time spent in housework. Figure 5 shows local linear regressions for the amount of time spent in housework in three different years (1995, 2000 and 2005). The plots, which are representative of all waves in our dataset, consistently reflect a discontinuity in the amount of time spent in housework upon retirement. This is consistent with individuals having more spare time to invest in activities other than work. The figure suggests a jump of about 3-4 hours per week, on averages. Table 7 collects the results of applying our discontinuity designs to the variable housework. It confirms a jump of between 3 and 5 hours per week and the results are significant for all bandwidths at (at least) 5% significance level. This provides strength to our conclusion that retirement has not effect on any of the studied dimensions of mental health.

4 Conclusion

In this article we have explored the causal effect of retirement on health using a representative sample of the population (the British Household Panel Survey). A number of researchers have pointed out that if retirement affects health the valuation of policies that prolong retirement should account for such effect, since a longer retirement horizon, by postponing changes in health outcomes, would affect the utilization of health services by older adults and this would impact on the projected variation. This notwithstanding, numerous published evidence suggests that there are different experiences of retirement, and therefore, any potential effect of retirement on health is likely to be heterogeneous. We have used a new identification strategy in order to capture the local average causal effect of retirement on a number of outcomes (namely mental health and health care utilisation). Our strategy combines discontinuity designs with panel data. Exploiting discontinuities in the distribution and the density functions of the proportion of retirees conditional on age, we have constructed instrumental variables that were fed into a first-difference instrumental variable panel data model. Proceeding this way, we could take into account the potential endogeneity in the treatment indicator. By exploiting the panel structure of the data, we had the advantage that comparisons are drawn within the same individual over time, so that the assumption of continuous differentiability of potential outcomes typically needed for the validity of discontinuity designs becomes much less contentious and, furthermore, the issue of selecting a bandwidth guaranteeing homogeneity of the treatment and control groups becomes also less fundamental. Our results suggest that the local average treatment effect of retirement on health are largely insignificant, so that this hypothesis can be dismissed. This claim does not depend on the occupational group considered or the level of education of the individuals interviewed. This result also supports previous evidence by Neuman (2008) and Coe and Lindeboom (2008) that also suggests this relationship to be merely nominal.

In common with most empirical work today, one potential inconvenience of our analysis is that it only considers average treatment effects. However, it is the overall distribution of health that is of interest for the policy maker because the average health status might remain constant over time, even when radical changes might be occurring in the distribution of health. To explore this, however, requires estimating distributional effects, and we leave this for future research.

A Appendix

Continuous differentiability of potential outcomes is a necessary condition for the validity of the kink design. However, this is not a directly testable assumption. Dong suggests that the adequacy of the kink design can be tested by checking the existence of kinks and jumps in the conditional means of pre-determined variables, although she does not provide a formal explanation. We provide next a formal analysis of this condition, borrowing from Lee (2008) and Card et al. (2009). Let us introduce the following general scenario.

Assumption 1. (i) (X, W) are random variables (only X is observable). The c.d.f. of W is denoted by $G(w)$. (ii) The conditional distribution of X given W, $F(x|w)$, is twice continuously differentiable at x_o for all w. (iii) The conditional density $f(x_o|w) > 0$ in $\mathcal{A}$, where $\int_{\mathcal{A}} dG(w) > 0$.

Assumption 2. $Y(0) = y_o(X, W)$, $Y(1) = y_1(X, W)$, where y_o, y_1 are real-valued and continuously differentiable at the cut-off, x_o. Finally Z (any pre-determined and observable variable) is such that $Z = z(W)$.

Assumption 3. $\beta_i = Y_i(0) - Y_i(1)$ is such that $\tau = E(\beta_i|X_i = x)$ is continuous differentiable at x_o, and X is independent if β_i conditional on X near x_o, for all w.

As in Lee (2008), W is the unobservable type of an individual -which we assume to be, without loss of generality, a single random variable. Identical individuals will share the same value of W. Assumption 1.ii implies that for each individual, the probability of obtaining an X just below and just above 0 are the same and that, in a neighbourhood about x_o, changes in this probability occur smoothly. The latter is not a requirement for identification in RD designs. By requiring $f(x_o|w) > 0$ we are ruling out situations when individuals can precisely manipulate their X score, what would invalidate the design. Assumption 2 allows outcome to vary with X directly, and not only indirectly through treatment status. Finally, Assumption 3 is required because we are assuming heterogeneous treatment effects. The condition is identical to that in Hahn et al. (1999) for RD designs. In the case of constant treatment effect is can be done without.

For an arbitrary function $H(x)$ denote $\lim_{x \to x_o^+} H'(x) = \lim_{e \to 0} \partial H(x)/\partial x|_{x=x_o+e}$. Given all three conditions, we can introduce the following result.

Proposition 1 *Under Assumptions 1 to 4,* (i) $F(W \leq w|X = x)$ *is continuously differentiable at* x_o*,* (ii) $F(Z \leq z|X = x)$ *is continuously differentiable at* x_o *for any* *predetermined variable* Z*, and* (iii)

$$\tau = \frac{\lim_{x \to x_o^+} G'(x) - \lim_{x \to x_o^-} G'(x)}{\lim_{x \to x_o^+} P'(x) - \lim_{x \to x_o^-} P'(x)} \tag{A-1}$$

This result is proved in the appendix. The key innovation of the proposition is result (ii). Dong (2011) establishes that identification in kink designs requires continuous differentiability of potential outcomes. But this is an untestable assumption. Result (ii) in the proposition establishes a way to verify the validity of the kink design by evaluating that the conditional c.d.f of observable pre-determined variables do not exhibit jumps or kinks about the threshold value x_o. If these exist, the it is unlikely that outcomes will be continuously differentiable. The proof of (i) and (ii) can be found in Card et al. (2009). To prove (iii) note that from equation (**??**), we have that, $Y_i = \alpha_i + \beta_i T_i$, where $\alpha_i = Y(0)$, $\beta_i = Y_i(1) - Y_i(0)$. Then,

$$\begin{aligned} E(Y_i|X = x_o + e) &= E(\alpha_i|X = x_o + e) + E(\beta_i T_i|X_i = x_o + e) \\ &= E(\alpha_i|X = x_o + e) \\ &+ E(\beta_i|X_i = x_o + e)E(T_i|X_i = x_o + e), \end{aligned} \tag{A-2}$$

under conditional independence. Differentiating with respect to x and taking limits, we have

$$\begin{aligned} \frac{\partial}{\partial x}E(Y_i|X = x_o + e) &= \frac{\partial}{\partial x}E(\alpha_i|X = x_o + e) \\ &+ \frac{\partial}{\partial x}E(\beta_i|X_i = x_o + e)E(T_i|X_i = x_o + e) \\ &= \int \frac{\partial y_o(w, v)}{\partial x}\frac{f(x|w)}{f(x)}dF(w) \\ &+ \int y_o(w, v)\frac{\partial}{\partial x}\left(\frac{f(x|w)}{f(x)}\right)dF(w) \\ &+ \frac{\partial E(\beta_i|X = x_o + e)}{\partial x}E(T_i|X = x_o + e) \\ &+ E(\beta_i|X = x_o + e)\frac{\partial E(T_i|X = x_o + e)}{\partial x} \end{aligned} \tag{A-3}$$

A similar result follows for $\frac{\partial}{\partial x}E(Y_i|X = x_o - e)$. Taking limits as $e \to 0$, it follows that,

$$\begin{aligned} & \lim_{e\to 0}\frac{\partial}{\partial x}E(Y_i|X = x_o + e) - \lim_{e\to 0}\frac{\partial}{\partial x}E(Y_i|X = x_o - e) \\ = \quad & E(\beta_i|X = x_o + e)\lim_{e\to 0}\left(\frac{\partial E(T_i|X = x_o + e)}{\partial x} - \frac{\partial E(T_i|X = x_o - e)}{\partial x}\right) \end{aligned} \quad \text{(A-4)}$$

because of the continuous differentiability of potential outcomes and $f(v|w)$ and the continuity of $E(\beta_i|X)$ at x_o.

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Table 1: Local A.T.E., all sample

	(1)	h_{10}	h_8	h_6
High blood pressure	−0.034	−0.024	−0.047	−0.068
	(0.596)	(0.816)	(0.667)	(0.532)
Depression/Anxiety	0.000	0.020	0.033	0.037
	(1.000)	(0.735)	(0.591)	(0.547)
Diabetes	0.005	0.027	0.040	0.020
	(0.820)	(0.468)	(0.313)	(0.602)
Migraine	0.001	0.005	0.046	0.038
	(0.982)	(0.918)	(0.407)	(0.480)
GHQ-12	0.044	0.357	0.467	0.291
	(0.947)	(0.585)	(0.497)	(0.661)
Role	−0.090	−0.050	−0.014	−0.017
	(0.296)	(0.614)	(0.894)	(0.871)
Strain	−0.014	−0.020	0.031	0.000
	(0.904)	(0.856)	(0.786)	(0.999)
Inpatient	0.051	0.091	0.105	0.154
	(0.499)	(0.392)	(0.347)	(0.166)
G.P. Often	−0.154	−0.194	-0.275^{*}	-0.252^{*}
	(0.053)	(0.096)	(0.026)	(0.039)

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

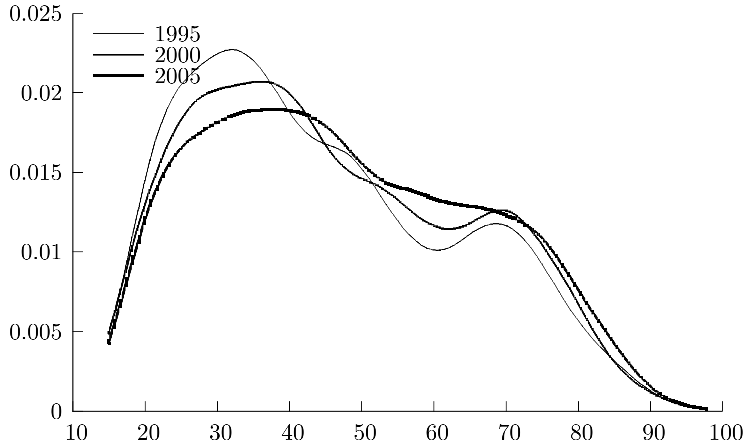

Figure 2: Density function of the running (age) variable for years 1995, 2000 and 2005.

Table 2: Local A.T.E., manual workers

	(1)	h_{10}	h_8	h_6
High blood pressure	-0.113*	-0.105	-0.126	-0.122
	(0.024)	(0.222)	(0.168)	(0.188)
Depression	-0.0592	-0.0326	-0.0416	-0.0521
	(0.152)	(0.527)	(0.427)	(0.311)
Diabetes	0.0372**	0.00419	0.0105	0.0111
	(0.006)	(0.886)	(0.759)	(0.756)
Inpatient	0.0101	0.108	0.123	0.166
	(0.882)	(0.232)	(0.215)	(0.110)
Migraine	0.0370	0.00476	0.0274	0.0114
	(0.383)	(0.915)	(0.528)	(0.785)
Role	-0.0385	0.0521	0.0797	0.0476
	(0.606)	(0.539)	(0.359)	(0.600)
GHQ-12	0.472	0.641	0.714	0.533
	(0.422)	(0.290)	(0.244)	(0.388)
Strain	0.0373	0.0914	0.0948	0.0550
	(0.716)	(0.344)	(0.310)	(0.546)
GP Often	-0.0370	-0.0713	-0.0893	-0.0493
	(0.625)	(0.507)	(0.422)	(0.671)

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3: Local A.T.E.,No qualifications

	(1)	h_{10}	h_8	h_6
High blood pressure	-0.129	-0.146	-0.182	-0.140
	(0.174)	(0.214)	(0.142)	(0.262)
Depression	0.0309	0.0367	0.0444	0.0298
	(0.593)	(0.581)	(0.526)	(0.670)
Diabetes	0.0373	0.0458	0.0385	0.0236
	(0.313)	(0.317)	(0.446)	(0.644)
Inpatient	0.131	0.148	0.161	0.150
	(0.184)	(0.203)	(0.195)	(0.239)
Migraine	0.0271	0.0137	0.0458	0.0424
	(0.576)	(0.819)	(0.465)	(0.517)
Role	0.00866	0.0331	0.0830	0.0665
	(0.933)	(0.771)	(0.488)	(0.582)
GHQ-12	0.0148	0.272	0.421	-0.0947
	(0.982)	(0.707)	(0.584)	(0.904)
Strain	-0.000742	0.0367	0.0445	0.0109
	(0.994)	(0.743)	(0.701)	(0.924)
GP Often	-0.0650	-0.119	-0.171	-0.159
	(0.552)	(0.370)	(0.225)	(0.266)

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 4: Local A.T.E., Secondary Education

	(1)	h_{10}	h_8	h_6
High blood pressure	0.101	0.141	0.125	0.197
	(0.562)	(0.656)	(0.680)	(0.491)
Depression	−0.263	−0.192	−0.142	−0.004
	(0.071)	(0.315)	(0.422)	(0.978)
Diabetes	−0.096	−0.041	−0.018	−0.064
	(0.080)	(0.697)	(0.857)	(0.503)
Inpatient	−0.206	−0.154	−0.043	0.138
	(0.368)	(0.656)	(0.897)	(0.662)
Migraine	0.072	0.159	0.193	0.141
	(0.604)	(0.314)	(0.199)	(0.263)
Role	−0.127	−0.082	0.053	0.074
	(0.619)	(0.786)	(0.858)	(0.785)
GHQ-12	−0.922	0.189	0.810	0.788
	(0.684)	(0.933)	(0.716)	(0.670)
Strain	−0.371	−0.286	−0.144	−0.191
	(0.298)	(0.422)	(0.672)	(0.528)
GP Often	−0.163	−0.292	−0.377	−0.152
	(0.496)	(0.422)	(0.298)	(0.643)

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 5: Local A.T.E., Higher Education

	(1)	h_{10}	h_8	h_6
High blood pressure	0.101	0.073	−0.005	−0.105
	(0.581)	(0.853)	(0.989)	(0.788)
Depression	0.053	0.179	0.116	0.080
	(0.722)	(0.421)	(0.604)	(0.716)
Diabetes	−0.017	−0.055	0.089	0.025
	(0.748)	(0.626)	(0.487)	(0.815)
Inpatient	−0.008	0.205	0.452	0.342
	(0.971)	(0.605)	(0.288)	(0.388)
Migraine	−0.122	−0.117	−0.099	−0.193
	(0.412)	(0.564)	(0.636)	(0.298)
Role	−0.108	0.049	−0.295	−0.300
	(0.705)	(0.896)	(0.452)	(0.420)
GHQ-12	0.883	2.416	0.472	0.917
	(0.694)	(0.340)	(0.842)	(0.672)
Strain	0.077	0.081	−0.043	−0.257
	(0.851)	(0.858)	(0.925)	(0.544)
GP Often	−0.355	−0.451	−0.423	−0.247
	(0.140)	(0.302)	(0.349)	(0.554)

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 6: Local A.T.E., White collar

	(1)	h_{10}	h_8	h_6
High blood pressure	-0.153	-0.105	-0.126	-0.122
	(0.290)	(0.222)	(0.168)	(0.188)
Depression	-0.071	-0.033	-0.042	-0.052
	(0.562)	(0.527)	(0.427)	(0.311)
Diabetes	-0.043	0.004	0.011	0.011
	(0.339)	(0.886)	(0.759)	(0.756)
Inpatient	0.070	0.108	0.123	0.166
	(0.712)	(0.232)	(0.215)	(0.110)
Migraine	0.016	0.005	0.027	0.011
	(0.897)	(0.915)	(0.528)	(0.785)
Role	-0.082	0.052	0.080	0.048
	(0.740)	(0.539)	(0.359)	(0.600)
GHQ-12	-0.410	0.641	0.714	0.533
	(0.832)	(0.290)	(0.244)	(0.388)
Strain	-0.210	0.091	0.095	0.055
	(0.568)	(0.344)	(0.310)	(0.546)
GP Often	-0.057	-0.071	-0.089	-0.049
	(0.772)	(0.507)	(0.422)	(0.671)

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Local A.T.E. Housework

	(1)	h_{10}	h_8	h_6
Housework	3.182^{*}	3.327^{*}	3.898^{*}	5.079^{**}
	(0.013)	(0.049)	(0.030)	(0.004)

p-values in parentheses

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

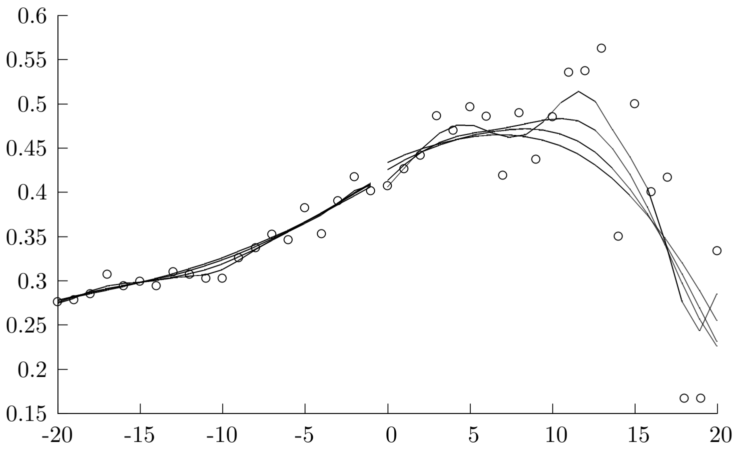

Figure 3: Discontinuities in the proportion of manual workers. The abscissa is $Age-65$. Local linear estimator with bandwidth $h = c\sigma_x n^{-0.2}$, for $c = 0.5, 1, 1.5$ and 2.

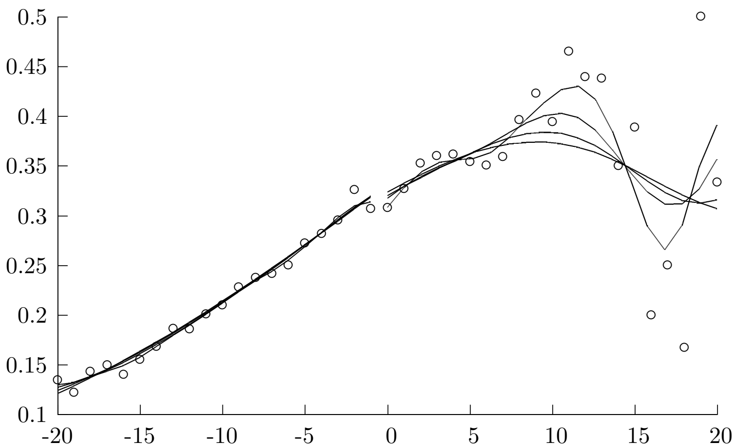

Figure 4: Discontinuities in the proportion of individuals with no qualifications. The abscissa is $Age - 65$. Local linear estimator with bandwidth $h = c\sigma_x n^{-0.2}$, for $c = 0.5, 1, 1.5$ and 2.

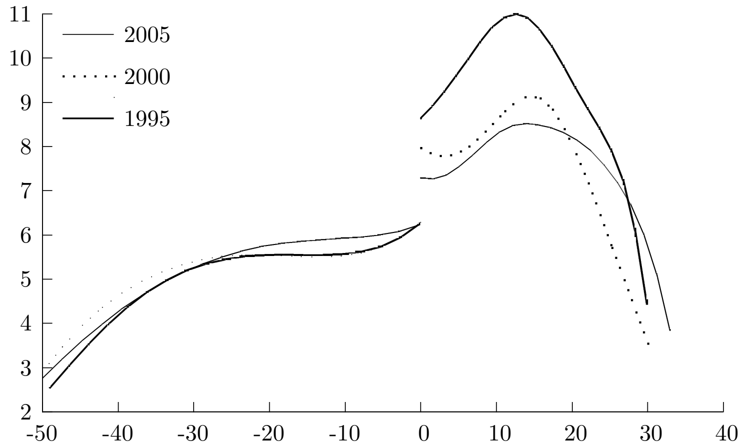

Figure 5: Discontinuities in the amount of time spent in housework (local linear regression), years 1995, 2000 and 2005. The abscissa is $Age - 65$.