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"An Econometric Insight into Health Insurance Demand"

Aporophobia and Racism as Drivers of Health Insurance Demand in the UK (1991–2008)

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ABSTRACT

Interactions between race, income and Health Insurance demand have been largely explored in the literature. However, there are virtually no studies exploring the effects of cross-consumer views on peers' income and race as drivers of Health Insurance demand. More concretely, we suspect that high-income (or white) individuals might be tempted to increase their private Health Insurance demand to avoid undesired meetings with low-income or minority groups in public health facilities. To determine the role of aporophobia and racism within Health Insurance markets, we exploit cross-regional variation in income and minority shares as well as interregional migration in the United Kingdom. We take advantage of 15 years + panel data coming from British Household Panel Survey to implement a DiD framework where we discuss (i) alternative definitions of treatment, (ii) ambitious selections on observables such as PSM-DiD, (iii) wave-heterogenous effects and (iv) a complete set of robustness checks including Rambachan and Roth, 2019 pre-trends deviations from linearity Confidence Intervals. Our final results show some non-significant positive support for our hypothesis, however, because we believe that there are important region-level omitted negative biases, we cannot reject the positive contribution of aporophobia (and racism) to Health Insurance demand.

Key words: Health Insurance, aporophobia, racism, Difference-in-Difference.

DEDICATION

To my ever-supportive family, friends, colleagues, professors and mentors. This is just the beginning of something bigger and brighter.

CONTENTS

LIST OF FIGURES

LIST OF TABLES

1. INTRODUCTION

Perception shapes behavior and behavior shapes everything else.

Health Insurance debate inside and outside the academia has been triggered by Health Insurance Industry failure in the United States (DeNavas-Walt et al., 2013), increasing health expenditure across all aged European countries ("Health at a glance. Europe." n.d.), and, of course, the irruption of Covid-19 global pandemic.

Classic Health Insurance literature usually depicts insurances either as health production machines, either as safety nets against unexpected medical costs or prolonged health leaves (Nyman, 1999; Black et al., 1988). However, the academia has largely overlooked the importance of human perceptions, fears and stereotypes within Health Insurance Economics. In this paper, we thoroughly analyze the contribution of those social perceptions, namely the role of aporophobic and racist attitudes, as drivers of Health Insurance demand.

Data reveals that there is a strong correlation between income and Health Insurance demand in Western European countries (Kaestner and Lubotsky, 2016). Indeed, this dependence is expected given that the demand of Health Insurances increases with available income (as the demand of any other normal good), especially if we take into consideration the free disposal of an alternative inferior good as it is Public Health service. However, traditional Income Effect considerations have hidden deeper behavioral patterns in Health Insurance demand, including social differentiation through consumption and service sharing disutility.[1] More concretely, it may be the case that individuals are (marginally) con-

[1] Economics and Sociology fields have identified social differentiation as a key utility driver in many

suming more privately-run Health Insurances to avoid sharing public facilities with those whom they consider to be “less-deserving", for example low-income or ethnic minority groups. Note that this differentiation mechanism would also show a strong income-Health Insurance correlation, however its underlying motivation would not be income-driven but driven by social considerations.

In this sense, our research question is whether racism and aporophobia play a role in Health Insurance demand decisions. In order to solve this question, we adopt a quasi-experimental design exploiting interregional movements in the United Kingdom and interregional differences in income and minority ratios across them. More concretely, we take advantage of 15 years + panel data coming from British Household Panel Survey (BHPS) to run this research design.

This question is rather relevant for Public Administrations inasmuch as they may be tempted to redesign Public Health investment structures depending on its answer. For instance, if mid- and high-income individuals feel disenchanted with Public Health services, they may opt to withdraw their tax revenues from this budget line. Moreover, if this mechanism is correct, Public Authorities could redirect health expenditures to marketing/education associated campaigns aimed at removing stereotypes, instead of improving the quality of the service *per se*. Alternatively, Public Administrations may consider to engineer novel health facilities or new health service structures which minimize contact across groups.

To provide a compelling answer to our research question, this article is structured as follows: Section 2 presents a brief summary of the existing literature. Section 3 ex-

mundane “economic" activities like eating out (Warde and Martens, 2000). In that sense, *a priori*, it is not unreasonable to believe that social differentiation may explain a portion of Health Insurance demand patterns.

plores different theoretical backgrounds and discusses the pros and cons of each of them to finally select the most convenient one. Section 4 introduces the reader to BHPS survey data and presents some stylized facts about movers, migrations and treatment definitions. Section 5 sets out a general DiD framework while discussing the inconveniences of benchmark specifications and the role of Ommitted Variable Bias (OVB). Section 6 presents a potential set of solutions to previously identified problems including Multivariate Regression Analysis, Propensity Score Matching methods and alternative definitions of treatment. Section 7 covers wave-heterogenous treatment effects and further robustness analyses ranging from clustered errors to deviations from pre-trend linearity (Rambachan and Roth, 2019). Finally, Section 8 concludes and presents some limitations of our analyses.

2. LITERATURE REVIEW

There is a wide literature covering Health Insurance Economics both from classic and behavioral approaches (Currie and Madrian, 1999). Moreover, income and race have played a prevalent role within these analyses. For instance, Goldman et al., 2005 highlights the significant inequality in Health Insurance tenancy between foreign-born and domestic Americans. This gap is particularly worrisome for undocumented migrants, which suffer a double burden, namely socioeconomic and administrative hurdles.

Behavioral Economists have also explored differences in risk and loss-aversion attitudes across different income and racial groups (Baicker et al., 2012; Stuber et al., 2000). Within this body of literature, several authors claim that there exist important administrative and stigma concerns beyond socioeconomic factors which explain unequal access to Health Insurance. However, these rationales have overlooked the role of income and racial segregation coming from the consumer side. More concretely, there is very little empirical work in the demand of private Health Insurances or the usage of alternative Health facilities to avoid sharing Public Health services with certain collectives. Some authors like Cotlear et al., 2015 have described structural administrative differences in health services provision across income groups in Latin America, however their work only brings in qualitative and descriptive arguments.

Its small size notwithstanding, Economics of Education have explored this issue in more detail. For instance, Zhou et al., 2016 explore socioeconomic discrimination in Hong Kong schools, where they prove that social segregation in Hong Kong is not only driven by elite private centers (supply side) but also by upper-middle class students who demand high-quality semi-private institutions (demand side). Similar analyses have been conducted in Israel and post-apartheid South Africa (Agbaria, 2018). All these cases, besides studying the role of educational systems as drivers of socioeconomic differences, explore consumers' agency and the relevance of network effects in cross-group demand differentiation.[2]

These network effects could also exist in Health Insurance scenarios. Assume, for instance, a high-income Group (A) and a low-income Group (B) to be sharing the same health facilities. Individuals in Group B unconditionally demand Public Health services, while the demand of Group A depends negatively on the B/A share of patients in those health facilities. The larger the share of people of Group B, the lower their demand. Individuals in Group A may hold a wide range of B/A ratio elasticities, however, after just a few iterations cascade effects may lead to full exodus of Group A from the public system, even with a reduced share of Group B population living in the area.

Similarly, the realization of B/A ratios may take some time to conform as Group A individuals do need some iterations to confirm that Group B shares are consistent and not driven by reduced-n spurious coincidences.[3] Consequently, we do not expect individuals (i) to immediately demand private Health Insurances after being exposed to new B/A scenarios, neither (ii) to come back into Public Health services once transition has taken place. This framework may lead to constant gaps in Health Insurance demand across income (or ethnic) groups. In this paper we seek to provide compelling empirical evidence of these sorts of patterns and the role of demand-side segregation in Health Insurance markets.

[2] See for instance Friedl et al., 2014 for considerations on network and social-comparison effects on disaster insurance demand.

[3] Note that Group A individuals perceive an imperfect signal of the B/A ratio every time they attend General Practitioner. As a result, they may need several repetitions of this event to emit valid statements.

3. THEORETICAL FRAMEWORK

Given that this piece of work is essentially designed as a method-driven paper rather than a theoretically driven exercise, we will briefly discuss the theoretical implementation of our hypothesis. Let us start by characterizing the demand of Health Insurances H_{irt} by individual i in region r in period t such that

$$H_{irt} = \theta_i + \lambda_t + \delta X_{it}^{'} + \pi S_{rt}^{'} + \epsilon_{irt} \tag{3.1}$$

Where $X_{it}^{'}$ is a vector of individual time-varying personal characteristics such as age, current health status, labor income, etc. θ_i is an individual dummy identifier which controls for individual-level fixed effects, while operating as a proxy for prevalent long-run health status of individual i.[4] λ_t is a set of time fixed effects and $S_{rt}^{'}$ is a vector of region-level time-varying characteristics. Among the components of this vector, we may highlight region-level Public Health investment or region-level private Health Insurance sector penetration. Finally, ϵ_{irt} is an error term normally distributed such that $\epsilon_{irt} \rightsquigarrow \mathcal{N}(0, \sigma_\epsilon)$.

Although the analysis of the main individual contributors of Health Insurance demand (like health status) is of ultimate interest, this paper focuses on the non-zero contribution of the individual (time-varying) characteristic k (X_{kit}), defined as the (un)willingness of individual i to share Public Health facilities with "less-deserving" individuals, namely low-income and/or racialized citizens. In other words, some individuals might experience

[4] This broad definition of long-run or prevalent health status may seem slightly arbitrary, however, θ_i may not only be interpreted in terms of disability from birth, but also in terms of unobservables which explain individual i overall health status, as well as the set of behavioral patterns which affect health and are unlikely to be changed in the short run such as smoking or diet habits (Currie and Madrian, 1999).

disutility from sharing public services with others (especially if the characteristics of the "others" fit within certain stereotypes) and hence, are somehow willing to purchase private Health Insurance (or to get employed in firms which provide this benefit) to avoid these undesired meetings.

However, to study the contribution δ_k of X_{kit} itself presents severe limitations. Racism and aporophobia are poorly estimated unobservables which get largely undetected in survey data (Akee and Casey, n.d.). Moreover, we seldom have access to natural quasi-experiments which allow us to study the contribution of these variables to public services demand. However, under the appropriate assumptions, it is not unreasonable to identify the individual-level contribution of X_{kit} (δ_k) through a revealed preference framework. In other words, we may identify the contribution of aporophobia or racism on Health Insurance demand by analyzing the evolution of both, Health Insurance tenancy and average income / shares of ethnic minorities in region r.

We could then interpret coefficient δ_k as the average of individual coefficients δ_{ki}, which reflect the marginal contribution of income and racial structures on individual i's Health Insurance demand. For this intuition to work, we depend on the strong exclusion restriction (A1) which requires that regional income and race distributions only affect H_{irt} through behavioral attitudes. More concretely, although we acknowledge that average income in region r or share of ethnic minorities in region r are region level characteristics (S_{rt}), we assume that they do only have an impact on individual Health Insurance demand through racism and aporophobia and not through direct mechanisms of type π_k. As a final note on this regard, to avoid notation misunderstandings, even though income and race distributions of region r are region-level characteristics (and consequently they could be referred as the S_{krt} components of vector $S^{'}_{rt}$) we would refer to them as T_{rt}.[5]

Throughout the next few paragraphs we try to persuade the reader about an identification strategy for δ_k. In order to do so, we have adopted a Potential Outcome notation, which has been widely implemented in the literature (Rubin, 2005; Angrist and Pischke, 2008) as it presents a convenient environment for reduced-form estimators derivation. For simplicity, we assume that H_{irt}, T_{rt} and t are binary variables representing Health Insurance tenancy, racial/income distribution of region r, and time, respectively. In this context, T_{rt} equals 1 if and only if r is a "poor" region or "non-white" region. We can put all these intuitions together in equation 3.1 such that:[6]

$$\begin{aligned} H_{irt|T_{rt}=1} &= \theta_i + \lambda_t + \delta X^{'}_{it} + \delta_k + \epsilon_{irt} \\ H_{irt|T_{rt}=0} &= \theta_i + \lambda_t + \delta X^{'}_{it} + \epsilon_{irt} \end{aligned} \tag{3.2}$$

where first differences can be expressed as

$$H_{irt|T_{rt}=1} - H_{irt|T_{rt}=0} = \delta_k + \epsilon_{irt|T_{rt}=1} - \epsilon_{irt|T_{rt}=0} \tag{3.3}$$

Moreover, by using Potential Outcome notation, we can re-define H_{irt} in the following way

$$H_{irt} \begin{cases} H_{1irt} & T_{rt} = 1 \\ H_{0irt} & T_{rt} = 0 \end{cases} \tag{3.4}$$

5 Because our model design is based on the assumption that income and racial shares only affect H_{irt} through X_{kit} we have preferred to call them T_{rt}, instead of S_{krt}, to avoid misunderstandings between δ_k and an hypothetical π_k.

6 Note that under $T_{rt} = 0$, there is no way X_{kit} can have an impact on H_{irt} given that we believe that it is not inherent racism or aporophobia what moves individual i to demand more or less Health Insurances, but her willingness to avoid contact with "less-deserving" individuals. Consequently, we expect δ_k to be irrelevant (i.e. = 0) when $T_{rt} = 0$.

such that $H_{1irt} - H_{0irt} = \delta_k + \epsilon_{1irt} - \epsilon_{0irt}$. Eventually, under Independence Assumption (IA) considerations ($E[T_{rt}\epsilon_{irt}] = 0$) we obtain that $H_{1irt} - H_{0irt} = \delta_k = \tau_{ATT}$, where τ_{ATT} is the Average Treatment Effect on the Treated population.

Nevertheless, in empirical frameworks, identification might not be that straightforward because we never get to observe H_{1irt} and H_{0irt} for the same individual i. Moreover, it seems very difficult to turn on and off region level characteristics like T_{rt}, and, even when observing these variations in T_{rt} (i.e. $T_{r0} = 0$ and $T_{r1} = 1$), it is very unlikely for Stable Unit Treatment Value Assumption (SUTVA) to hold in these contexts ($X_{i0}^{'} \stackrel{?}{=} X_{i1}^{'}$ and $S_{r0}^{'} \stackrel{?}{=} S_{r1}^{'}$). In other words, after a generalized non-exogenous shock in the income/racial distribution of region r, it is indeed very improbable for the rest of regional (and individual) characteristics to remain unchanged.

As a result, if only we could find two individuals i and j, living in two regions r_1, r_2 such that $T_{r_10} = 0$, $T_{r_11} = 1$ and $T_{r_20} = 0$, $T_{r_21} = 0$ we could implement a difference-in-difference estimator

$$\begin{aligned}
\tau_{DiD}^{ATT} &= E[H_{irt}|r = 1, t = 1] - E[H_{irt}|r = 1, t = 0] - (E[H_{jrt}|r = 2, t = 1] - E[H_{jrt}|r = 2, t = 0]) \\
&= E[H_{1irt}|t = 1] - E[H_{0irt}|t = 0] - E[H_{0jrt}|t = 1] - E[H_{0jrt}|t = 0] \\
&= \delta_k + \delta X_{it}^{'} + \lambda_t - \delta X_{jt}^{'} - \lambda_t = \delta_k + \delta(X_{it}^{'} - X_{jt}^{'})
\end{aligned} \tag{3.5}$$

where the first two terms of equation 3.5 represent differences in Health Insurance demand in region 1 after the realization of certain event or the implementation of certain policy which raises T_{rt} from 0 to 1, and the two latter terms refer to the evolution of Health Insurance demand in region 2 where no such a policy or event took place (thus, $T_{r21} = T_{r22}$). In this context, treatment equals 1 if individual lives in region 1 and equals 0 if individual lives in region 2. Hence, if we either ignore the marginal differences between non-k elements of $X_{it}^{'}$ and $X_{jt}^{'}$ or we appropriately control for them (namely, $\tau_{DiD}|X_{it}^{'}$) we could potentially derive consistent estimators of δ_k.

This framework is indeed “ideal" for this type of event studies,[7] but may not be particularly suitable for non-random ($E[T_{rt}\epsilon_{irt}] \neq 0$) or non-material ($E[T_{r0}]\approx E[T_{r1}]$) variations in T_{rt}. For instance, coming back to our main hypothesis, if we were to implement a DiD framework to identify the variation in Health Insurance demand because of changes in the composition of the population in the absence of an exogenous shift, such as an exogenous mass migration shock or a generalized reduction in the available income of the region, it would be very likely for us to end up with biased estimators.

In equation 3.5 the identifying restriction, as in any other standard DiD framework, is the common trend assumption (CTA). CTA imposes the parallel evolution of H_{irt} in both regions r_1, r_2 should the intervention had not taken place.[8] Mathematically,

$$E[\epsilon_{ir1} - \epsilon_{ir0}|r = 1] - E[\epsilon_{ir1} - \epsilon_{ir0}|r = 2] = 0 \tag{3.6}$$

However, in the absence of an exogenous shock there are many good reasons why equation 3.6 and consequently equation 3.5 might not hold. First of all, it is very likely that variations in the income and racial composition of regions 1 and 2 are correlated with idiosyncratic trends within each region. In other words, the fact that one region experiences an increase or a decrease in the mean available income of its population, or the fact that one region receives certain number of foreigners compared to another, is correlated with high probability to the specifics of region r (i.e. non-T_{rt} components of $S_{rt}^{'}$) even when

[7] Please see Wing et al., 2018 for a minute description of DiD designs in Public Health Policy research.

[8] We would progressively demand weaker Independence Assumptions of our variables of interest. See Sections 5, 6 and 7 for more details.

controlling on observables.[9] Consequently,

$$
\begin{aligned}
&E[H_{1irt}|t=1,X_{it}^{'}] - E[H_{0irt}|t=0,X_{it}^{'}] - (E[H_{0jrt}|t=1,X_{jt}^{'}] - E[H_{0jrt}|t=0,X_{jt}^{'}]) \\
&= \tau_{DiD} + (E[\epsilon_{ir1} - \epsilon_{ir0}|r=1,X_{it}^{'}]) - (E[\epsilon_{ir1} - \epsilon_{ir0}|r=2,X_{jt}^{'}]) \neq \tau_{DiD}
\end{aligned}
\tag{3.7}
$$

Beyond violations of CTA at the region level, we may also suffer violations of SUTVA at the individual level. Using our income framework as an illustration, it is very likely that generalized changes in the income distribution of the whole region affect available income of individual i. Controls on observables in this cross-time comparison framework would unlikely avoid bias of non-k components of $X_{it}^{'}$ even when taking first differences.

Finally, there is a further problem related to the characterization of $\delta_k(=\tau_{DiD})$ due to identification concerns of our target variable (racism and aporophobia). The problem can be expressed as follows: Because poverty and migration shocks are frequently expressed in relative terms, rather than in absolute terms, all the regional characteristics in $S_{rt}^{'}$ may be correlated with δ_k. More concretely, high-income regions (or the individuals within those regions if preferred) may define the poverty line at a higher benchmark than poorer regions (or individuals living in poorer regions) will probably do.[10] Consequently, aporophobic (or racist) individuals could interpret differently an income (or racial) shift depending on pre-event levels of T_{rt} and other $S_{rt}^{'}$ components. Based on this intuition, the identification strategy of our parameter of interest $\tau_{DiD}=\delta_k$ gets highly compromised given that treatment's intensity *de facto* varies across regions.

On a side note, even though DiD mass migration shocks in principle do not suffer

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9 See Angrist and Krueger, 1999, where they discuss the limitations of traditional DiD scenarios in large treatment units, using as an example the "Mariel Boat Lift that Didn't Happen".

10 Poverty and racial diversity are frequently exhibited in the literature as relatively rather than absolutely determined (Saez, 2021). In fact, the threshold for classifying an American as "poor" is substantially higher than the cutoff for an Argentinian citizen.

from the previously described SUTVA problems (at least in the short-run), CTA and cross-region intensity of treatment variation may still play a key role when assessing the validity of our DiD framework.

To solve some of the aforementioned problems, we have chosen an alternative specification which enables us to capitalize the benefits of panel data and DiD while minimizing the contributions of these three sources of bias. The intuition goes as follows. Instead of analyzing “exogenous" shocks to the income/racial distribution of region r, we can take advantage of interregional mobility of individuals across time. As a result, we can potentially analyze the effect on Health Insurance demand when individuals move to poorer or more-racialized regions compared to the Health Insurance demand of those who move to richer or whiter regions. The underlying math is very similar, but now, instead of shifting the region as a whole hoping for the exogeneity of this variation and the invariability of the treatment unit, we characterize a treatment variable D_{irt} which demands a weaker assumption, namely migration destination exogeneity. D_{irt} is a $\{0, 1\}$ variable which equals 1 if and only if individual i moves from a “rich" region to a “poor" region and 0 otherwise. Our identification strategy model can be defined as:

$$\begin{aligned}\tau_{DiD} &= E[H_{irt}|r = 2, t = 1] - E[H_{irt}|r = 1, t = 0] - (E[H_{jrt}|r = 3, t = 1] - E[H_{jrt}|r = 1, t = 0]) \\ &= E[H_{1irt}|t = 1] - E[H_{0irt}|t = 0] - (E[H_{0jrt}|t = 1] - E[H_{0jrt}|t = 0]) \\ &= \delta_k + \delta X_{it}^{'} + \lambda_t - \delta X_{jt}^{'} - \lambda_t = \delta_k + \delta(X_{it}^{'} - X_{jt}^{'})\end{aligned} \tag{3.8}$$

where $T_{r_1,t} = 0$, $T_{r_2,t} = 1$ and $T_{r_3,t} = 0$ $\forall t$ (meaning that $D_{irt} = 1$ and $D_{jrt} = 0$).

Although interregional mobility still presents some concerns related to the non-T_{rt} components of $S_{rt}^{'}$ and the non-k time-varying characteristics of $X_{it}^{'}$ of individual i, it presents remarkable improvements compared to the region-level shock design.

a) First, SUTVA problems at the regional level get minimized given that T_{rt} remains unaffected. That is to say, we exploit interregional differences in average income and share of non-white population, while leaving T_{rt} unchanged.

b) Second, although important critics hold, it is more reasonable to bet on the exogeneity of migration destination ($E[D_{irt}\epsilon_{it}] = 0$), meaning to assume that migrating to a slightly richer or to a slightly poorer region than the one you come from is an exogenous decision, rather than betting on the exogeneity of regional economic performance ($E[T_{rt}\epsilon_{it}] = 0$).

c) Third, this framework in fact allows us to endogenously define treatment in a very convenient way under some monotonicity assumptions. In our previous setting, variations in the intensity of treatment were problematic given that δ_k was dependent on the levels of $S^{'}_{rt}$ components like pre-event racial shares or poverty ratios. However, this framework automatically characterizes treatment based on T_{rt} levels. More concretely, by unequally defining treatment based on the region of origin, we can interpret the movement differently to the same region r by the same individual i depending on whether she comes from region r_1 or r_2 (such that $T_{r1t} > T_{rt} > T_{r2t}$). This consideration, demands a strong monotonicity of treatment assumption (A2) which imposes that D_{irt} will always equal 1 when moving to a poorer region (or to a region with higher share of racialized individuals), but at the same time, it generalizes the validity of τ_{DiD} by endogenously defining treatment based on T_{rt}.

d) Finally, the main drawback of this design compared to the income/racial shock framework is the challenge to effectively control by time-varying characteristics $X^{'}_{it}$ of individual i. Migrating usually shifts a countless number of individual characteristics such as income, job status or public services consumption patterns, thus, even though we minimize CTA considerations at the region level, SUTVA's reliability at the individual level gets compromised.

In the next sections we present the data used, our results-driven methodology and an ambitious series of robustness checks (i) to prove our main hypothesis and (ii) to potentially tackle the limitations of our research design including the non-exogeneity of destinations and the variation of X_{it}'.

4. DATA ANALYSIS

4.1. Introduction to BHPS data

To produce our results we have used the British Household Panel Survey (hereafter, BHPS) elaborated by the Economic and Social Research Council of the United Kingdom (ESRC) and the Institute of Economic and Social Research of the University of Essex (IESR),[11] which includes panel data for 18 consecutive waves (1991–2008).[12] There exists a total of 238,996 observations of 32,380 unique individuals over 16 years old in this survey,[13] although, after appropriate data cleaning, a total of 238,917 observations (32,355 individuals) were considered for analysis.[14]

Among these individuals, those who moved just once in the whole period were selected as the population of this study. Individuals who moved more than once were not considered for simplicity. Movement was identified based on the variable “gor-dv" which identifies the administrative region where the individual lives. There exists a total of 13 government-office regions in the United Kingdom, all of which remained unmodified during the whole period of analysis.[15] In order to identify an individual’s movement, we have

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11 This database is available under demand here.

12 In year 2008, the ESCR and the IESR launched a new bi-annual survey design known as the Understanding Society Longitudinal Survey (UKHLS). Although the scope of this survey is broader than the one of BHPS, there was a change in the composition of the interviewees. Consequently, by May 2021, when the data download took placed, there were only 9 UKHSL available waves. Because interregional movements are relatively infrequent throughout someone’s life, we decided to prioritize the time scope of the survey over its observational scope.

13 Although only 16 years old + individuals were eligible for these interviews, 808 observations were reported to be 15 years old. We understand that the inclusion of these individuals answers to 16 year-old-cohort individuals who were 15 when the interview took place.

14 For a complete description of the data cleaning process, please see Annex A.

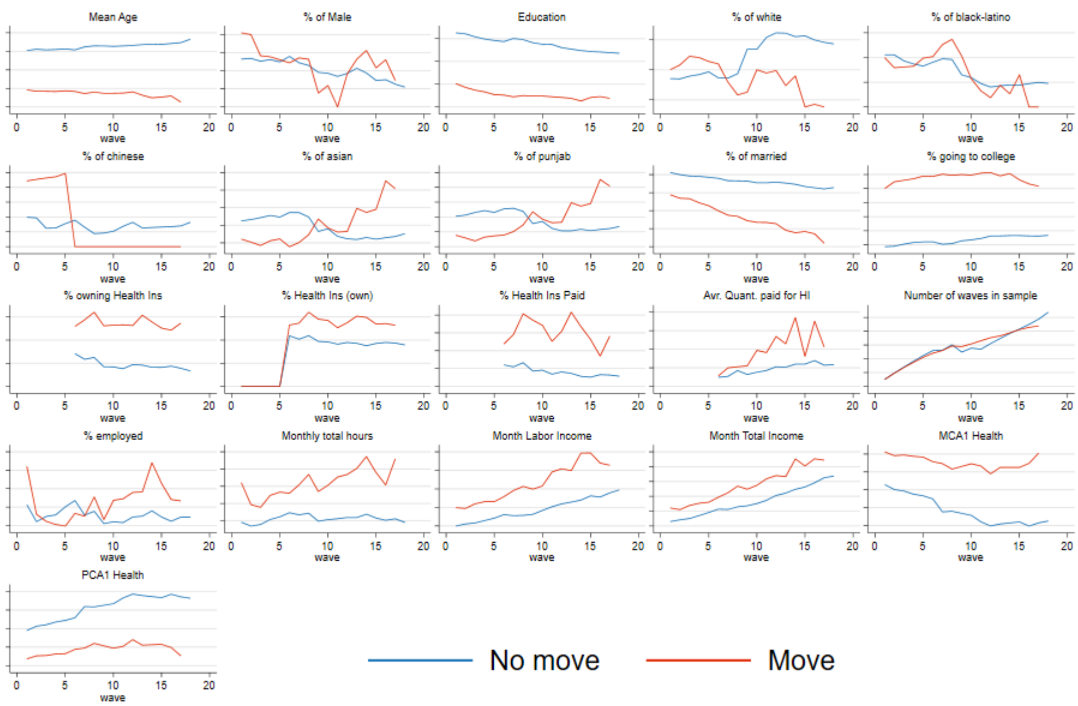
15 For more information about the 13 administrative regions, please see Annex A. Please note that there exist very few observations of movers either coming from or moving to Northern Ireland and Channel

simply parsed variations in the region of residence for each individual.

4.2. Sample Representativeness: Non-Movers vs (Pre-Movement) Movers

Below you may find some summary graphs and statistics about the individuals who did not move compared to those who moved just once **before movement took place**. In order to avoid bias, only those individuals who show up in at least two consecutive waves and only those whose location was available for their whole run have been used as representatives of non-movers.[16]

Figure 4.1. Summary Statistics of One-Time Movers (Pre-Movement) vs Non-Movers



Islands. As a result, the reader should expect some graphs or tables not to report figures for these two regions.

[16] Because for qualifying as a mover, we demand an individual to show up in at least two consecutive waves and to know her region of origin and destination (otherwise movement could not be correctly identified), we have imposed these same criteria to non-movers to avoid bias. Still, we acknowledge that individuals showing up in fewer waves are more likely to be overrepresented in the non-movers' group.

There are some considerations that we need to take into account in order to understand summary Graph 4.1. First of all, because there is decaying number of pre-movement individuals within the moving group, descriptives of this cohort may be poorly estimated in the final waves of the sample. However, and although there exist some differences in levels across moving and non-moving groups, trends are overall fairly similar. More concretely, moving individuals are younger, more educated, more single, they go more to university, have higher rates of Health Insurance ownership, they work more hours, and are slightly richer. All these indicators were expected, thus, it is good evidence of the data quality and representativeness of our sample.

Table 4.1. T-Tests One-Time Movers (Pre-Movement) vs Non-Movers

	No mov.	Move	Diff	SE
Age	44.001	31.872	12.129***	(0.484)
Sex	0.470	0.475	-0.005	(0.013)
Education	3.887	2.795	1.093***	(0.041)
White	0.973	0.967	0.006	(0.004)
Black_latino	0.008	0.010	-0.002	(0.002)
Chinese	0.001	0.001	-0.001	(0.001)
Asian	0.014	0.014	0.000	(0.003)
Punjab	0.013	0.013	0.001	(0.003)
Married	0.481	0.343	0.137***	(0.013)
College	0.114	0.345	-0.231***	(0.008)
Health_ins	0.133	0.224	-0.091***	(0.008)
Health_ins_own	0.065	0.063	0.002	(0.005)
Health_ins_paid	0.168	0.283	-0.115***	(0.015)
Health_ins_paid_q	1.718	1.928	-0.210	(0.333)
Run number	4.617	3.553	1.064***	(0.066)
Job Status	0.539	0.541	-0.002	(0.011)
Hours month	69.355	75.746	-6.391***	(1.628)
HH Month Labor Income	19797.062	23899.220	-4102.158***	(460.772)
HH Month Total Income	2430.282	2578.186	-147.904***	(40.005)
Health MCA 1	-0.037	0.287	-0.323***	(0.023)
Health PCA 1	0.062	-0.478	0.540***	(0.039)

Note: *** p<0.01, ** p<0.05, * p<0.10.

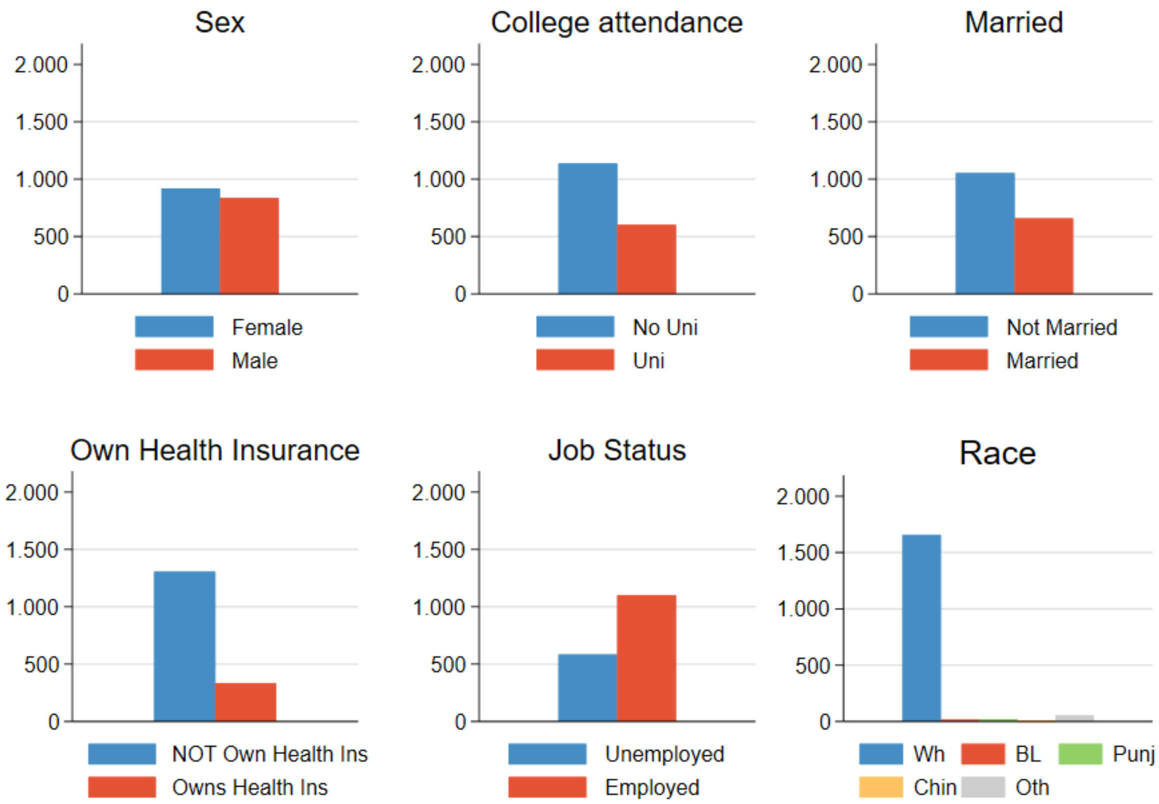
Note too, that this comparison across moving and non-moving groups has been conducted pre-movement, thus we should non interpret unequal evolution of income, employment or Health Insurance demand as the result of migration. In fact, these are more likely to be the cause of the movement than its outcome (with the exception of Health Insurance demand which probably is reflecting increasing income of the pre-movement moving cohort). We know, based on the literature (Poston Jr and Bouvier, 2010), that richer individuals are more likely to move, hence this pattern is not especially worrisome. In addition, it is important to realize that trend differences only emerge after wave 10, where estimators for the pre-movement sub-sample of movers might be poorly identified. As a result, we cannot disregard composition effects to be the drivers of these differences.

As a final note, it should be mentioned that differences in health status across groups are difficult to characterize given that both Principal Components (PCA) and Multiple Correspondence (MCA) decomposition analyses did not identify key drivers explaining overall health of individual *i*. Still, based on the depiction of the average mover, we should expect both PCA and MCA to be reveling that movers are indeed healthier than non-movers.

Regarding movers' sample size, number of movers' observations (21,451) represent around 10% of total non-movers observations (207,725). These observations belong to a total of 1,705 different individuals across all 18 waves and all 13 regions.[17] Finally, in order to conclude this data presentation section we (i) characterize the population of movers, (ii) we introduce some key facts about overall migration movements in the UK based on BHPS data and (iii) we present alternative definitions of treatment.

[17] Please see footnote 15.

Figure 4.2. Summary Statistics of Individual Movers



4.3. Characterization of Movers and Movements

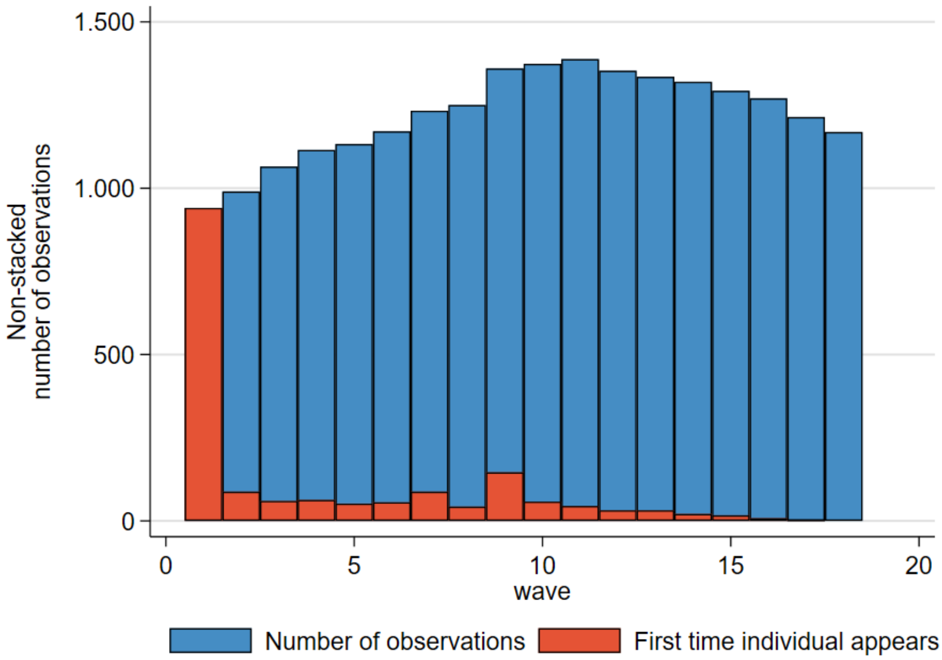
As from Graphs 4.2 and 4.3,[18] we can see that the sample is fairly homogeneous in terms of gender and extremely polarized in terms of race. White movers represent around 95.5% of observations in the sample, a figure fairly similar to the overall number of white citizens in the UK in the year 2001 (91.2%).[19] Small discrepancies in our sample could be explained by (i) administrative concerns and (ii) income biases, which limit the capacity of interviewers to reach these communities.[20] Finally, in terms of the overall consistency

[18] In order to produce Graph 4.2, we have used the cross-time mode to classify individuals across binary bins.

[19] Figure has been extracted from UK census data.

[20] Migrant communities are frequently underrepresented in administrative and survey data because their address is usually not officially registered by public authorities. Furthermore, many migrants (especially the undocumented ones) may be reluctant to answer the queries of public servants because of different

Figure 4.3. Number of Observations of Movers by Wave Compared to First Time Mover Shows Up in Sample



of our sample, good news are that most of the individuals (observations) show up for first time in wave number one (53,7%). Ever since, data shows consistently decaying attrition and addition rates to our sample that may pollute its representativeness among British movers.

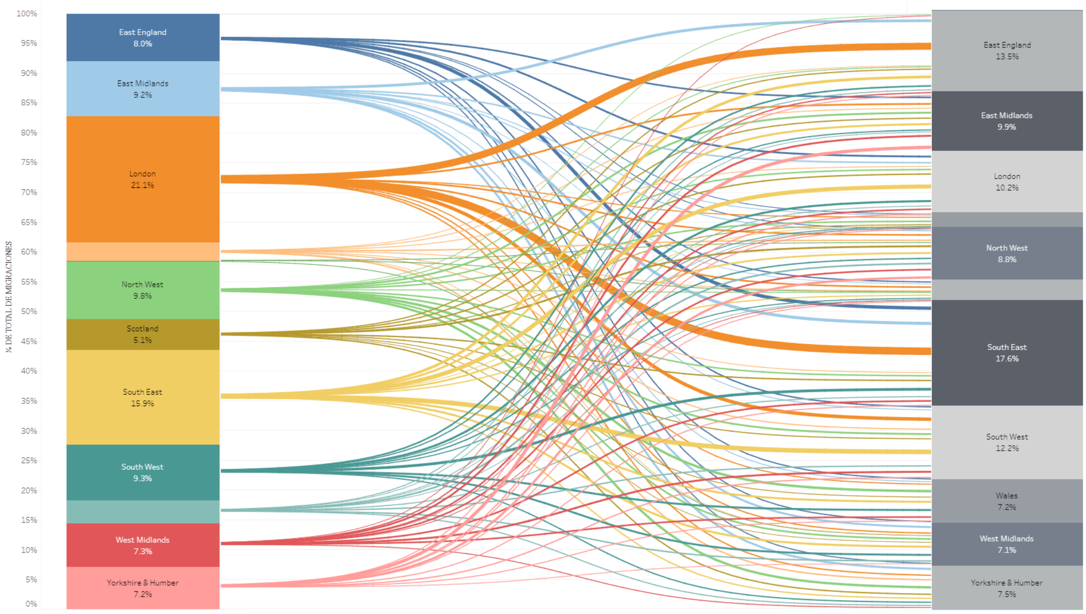
Regarding the origin and destination of these movements (see Sankey Graph 4.4) we observe how migration patters are fairly homogeneous overall. This Sankey graph shows the number of individuals moving from their origin region (left) to their destination region (right). We may highlight two (surprising) remarks derived from this diagram:

i) The densest migration routes are the London-East England and the London-South East paths; and

personal considerations (Goldman et al., 2005). Because of similar situations, low-income individuals are usually underrepresented in survey data too. Migrant communities regularly combine both dimensions, namely racial diversity and low-income status, hence, they are particularly difficult-to-track for BHPS interviewers.

ii) London is the main region of origin (with around 21% of total emigrations) while the South-East (18%) followed by East England (14%) and the South West (12.2%) are the main British immigration destinations.

Figure 4.4. Region of Origin and Region of Destination Sankey Diagram. Coloring by Region of Origin



A priori we were expecting (i) more asymmetric migration patterns and (ii) London standing up as the biggest attraction pole of national immigration, however, from a research-design perspective, it is positive to observe non-negligible migrations across virtually all different combinations of origin and destination regions.[21]

4.4. Alternative Definitions of Treatment

Eventually in order to conclude this section, we proceed to explain the different treatment definitions under consideration in this study. Essentially, this paper characterizes treatment = 1 as every movement from a richer region to a poorer region (and zero otherwise).

21 For a destination based coloring of Graph 4.4, please see Annex B.

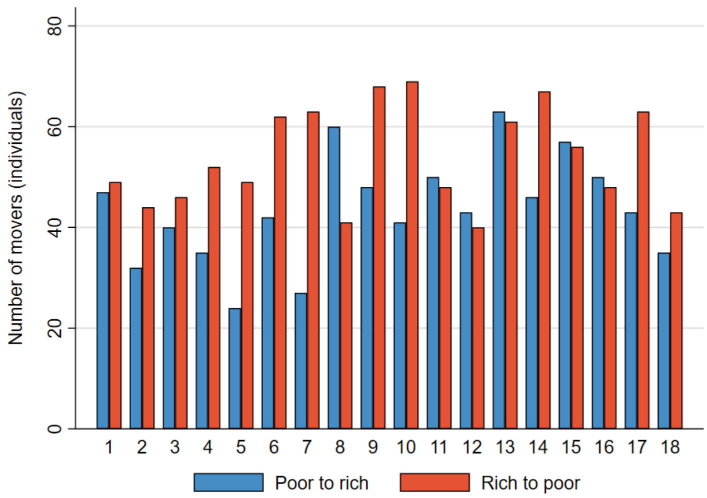
To do so, we have computed the average total household income by region and wave, and we have ranked all regions independently for each wave based on this classification. Eventually, we compare the rankings of the region of origin and the region of destination in the year of movement of individual i ($t = 0$). Similarly, we can define treatment in racial frameworks using the same strategy. More concretely, we define treatment equals one if moving from a whiter region to less-white region or from a more-black/asian/punjab region to a less-black/asian/punjab region.

Furthermore, we can establish different treatment intensities based on the rank difference between origin and destination regions. In that regard we can move from "difference-equals-one" treatments (where all movements are considered) to "difference-equals-twelve" treatments (where only movements from the richest region to the poorest region are considered). For simplicity, we define as "*Progressive treatments*" those which assess all movements (difference equal 1) and as "*Top-to-Bottom treatments*" those which only evaluate some movements (difference $> |1|$). Note that in Top-to-Bottom approaches, individuals whose movements do not comply with the cutoff (i.e. those whose movement difference $< |c|$) are excluded from the analysis, such that we only compare rich-to-poor movers with difference $\geq c$ and poor-to-rich movers with difference $\leq -c$.

Both approaches present some advantages and disadvantages. Progressive approach provides us with a higher number of observations and reinforces our intuitions about exogeneity of treatment. In other words, by comparing unequal Health Insurance demand patterns of individuals coming from the same region r to a slightly richer region r_1 or to slightly poorer region r_2 (such that $T_{r1} \leq \mathrm{T}_{rt} \leq \mathrm{T}_{r2t}$), it is very likely that (i) post-treatment characteristics of movers (X'_{it} with $t > 0$) vary in parallel across r_1 and r_2 immigrants. Moreover, (ii) differences in non-T_{rt} components of S'_{rt} across regions are potentially not too big in this design, thus we get to minimize OVB cofounders. On the disadvantages side, treatment identification may be quite weak. Because we are dealing with broad treatment units (regions) it may be the case that one individual moves from a slightly richer area to a slightly poorer one without even realizing variations in poverty shares at the destination region ($E[T_{r_1t}] \approx E[T_{r_2t+1}]$).

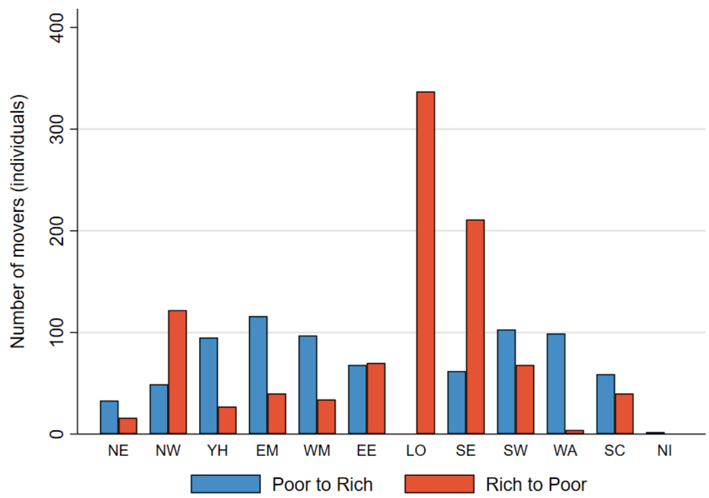
Conversely, Top-to-Bottom treatments may solve the later problem (considering that $E[T_{r_1t}] >> E[T_{r_2t+1}]$), but at the same time they weaken our exogeneity assumption (the more different migration alternatives are, the higher the likelihood of endogeneity biases in our analyses). Similarly, the more different destination regions are across treatment and control groups, the larger the room for region-level OVB and post-movement variations of X'_{it}. Because there exists interesting benefits coming from both sides, these two sets of results are displayed hoping for mutual synergy between them in our fight against OVB and poor identification. Graph 4.5 presents the number of movements from poor to rich ($D_{irt} = 0$) compared to those of rich to poor ($D_{irt} = 1$) using a Progressive definition of treatment. Main conclusions from Graph 4.5 are (i) the cross-wave movement homogeneity and (ii) the prevalence of to-poor movers (969 movements) over to-richer movers (783).

Figure 4.5. Number of Movements by Wave and Treatment Unit (Move to Rich vs Move to Poor)



As a final note, it should be mentioned that individuals coming from the richest and/or the poorest regions cannot experience variation in treatment, meaning they can be interpreted as Always/Never Takers. In order to avoid bias and to properly identify our subject of interest (Compliers), Annex C presents some robustness checks where these individuals are excluded from the sample. See, as an example, Greater London region (LO) in Graph 4.6, which shows no to-rich migrations given that London consistently stands as the richest region in the UK for the whole period of analysis. In fact, when Londoners are excluded from the sample, figures from Graph 4.5 revert and to-rich movements (783) offset to-poor movements (632).

Figure 4.6. Number of Movements by Region of Origin and Treatment Unit (Move to Rich vs Move to Poor)



5. METHODOLOGY AND RESULTS I. A PROGRESSIVE CHARACTERIZATION OF TREATMENT

Throughout the next few paragraphs we adopt an unusual narrative structure to present our results. Because the underlying methodology and mechanisms are very similar across the income and racial scenarios we will focus on the former and leave the latter as a robustness check of the key intuitions derived from the income framework. Let us start by characterizing a simple DiD regression analysis

$$H_{irt} = \lambda_t + \beta_1 D_{irt} + \beta_2 D_{irt} t \tag{5.1}$$

where H_{irt} is our dependent variable, in this case Health Insurance demand, λ_t is a time fixed effect, D_{irt} is our treatment variable, t is a period binary variable $\{0, 1\}$ and β_1, β_2 are parameters. More concretely, β_2 is our parameter of interest ($\tau_{DiD} = \delta_k$). *A priori*, if properly identified, our hypothesis expects $\beta_2 > 0$, meaning that treated individuals, those who are moving to poorer regions ($D_{irt} = 1$), everything else constant, demand larger quantities of Health Insurance. As a final remark, it should be mentioned that migrations take place at some point between normalized period -1 and normalized period 0. For consistency, we have declared

$$t \begin{cases} 0 & wave\_norm < 0 \\ 1 & wave\_norm \geq 0 \end{cases} \tag{5.2}$$

However we should not be surprised if we observe trend deviations starting *wave_norm* =

-1.

This DiD Progressive treatment framework is summarized in Table 5.1 and Graphs 5.1, 5.2 and 5.3 where (1) all sample, (2) only percentile 50 and above and (3) only percentile 75 and above are considered. The reason for including specifications (2) and (3) is strictly related to a matter of compliance as we do not expect individuals from the bottom of the income distribution to manifest aporophobia attitudes when moving to another region (even when the destination region is significantly poorer than the origin region).[22, 23] Regressions have been computed using OLS estimators and numbers in parentheses represent robust standard errors. Please note that for this introductory set of results, rather than including a time fixed effect we have just included a time binary variable.

Table 5.1. Progressive Treatment Benchmark Specifications. No Controls

	(All)	(p50)	(p75)
Treatment	0.015	0.021	0.048
	(0.013)	(0.019)	(0.029)
Time	0.023*	0.012	0.030
	(0.012)	(0.019)	(0.027)
Time × Treatment	-0.051***	-0.062**	-0.058
	(0.016)	(0.025)	(0.036)
Constant	0.228***	0.296***	0.337***
	(0.010)	(0.014)	(0.021)
Observations	12069	5925	3113

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: Health Insurance

There are some positive and negative results coming from these pieces of evidence. First of all, as Rambachan and Roth, 2019 pointed out, parallel pre-trends assumption is a necessary condition for consistent and unbiased identification of τ_{DiD}. In this regard,

[22] Income percentile of individual i is evaluated in period $wave\_norm = -1$.

[23] Because the number of available observations in very distant waves is very limited, we have constrained the time dimension of our analysis to a time range where at least 5% of observations satisfying inclusion considerations were available.

Figure 5.1. DiD Graphical Analysis of All Movers

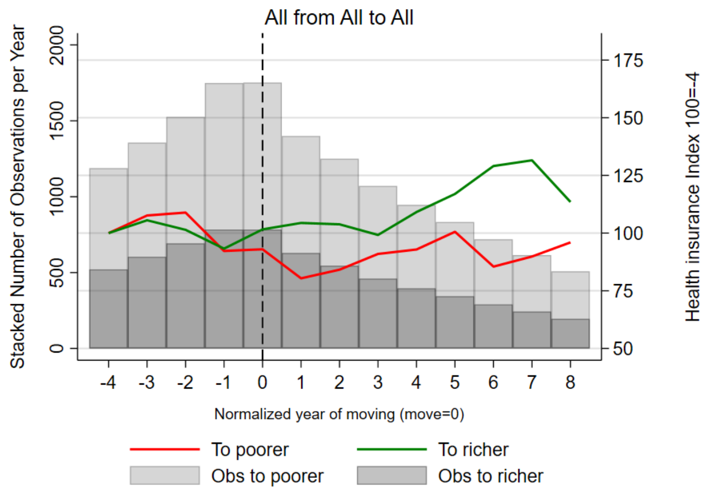


Figure 5.2. DiD Graphical Analysis of >p50 Movers

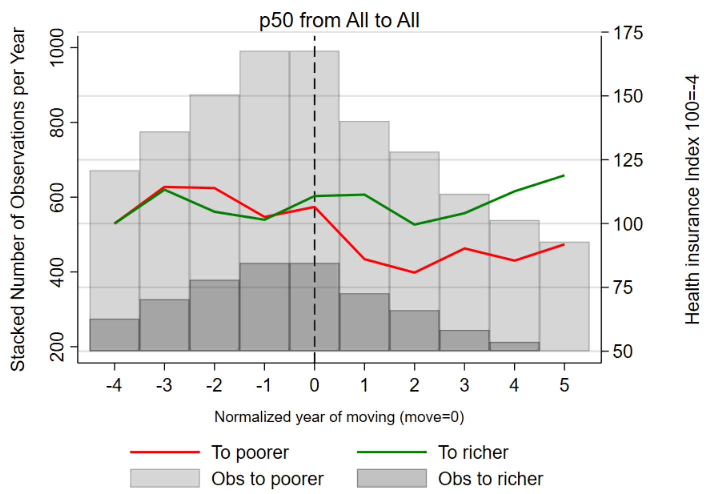
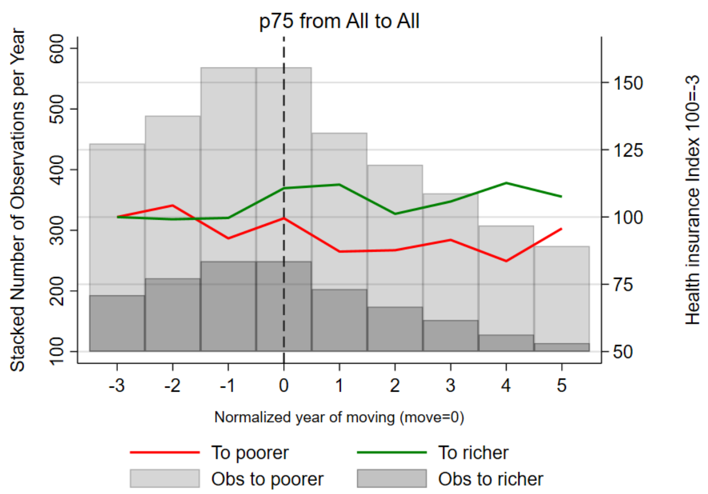


Figure 5.3. DiD Graphical Analysis of >p75 Movers



although further analyses take place in Sections 6 and 7, graphically it seems like we are not that far away from linearity (maybe with the exception of p75 specification). Unfortunately, results are completely contrary to our intuition given that τ_{DiD} is negative for all three specifications (and statistically significant for all and p50 regressions).

However, this set of results, although disappointing, may not be telling the whole story. There are at least four different reasons which may explain the (negative) bias of β_2 coefficient.

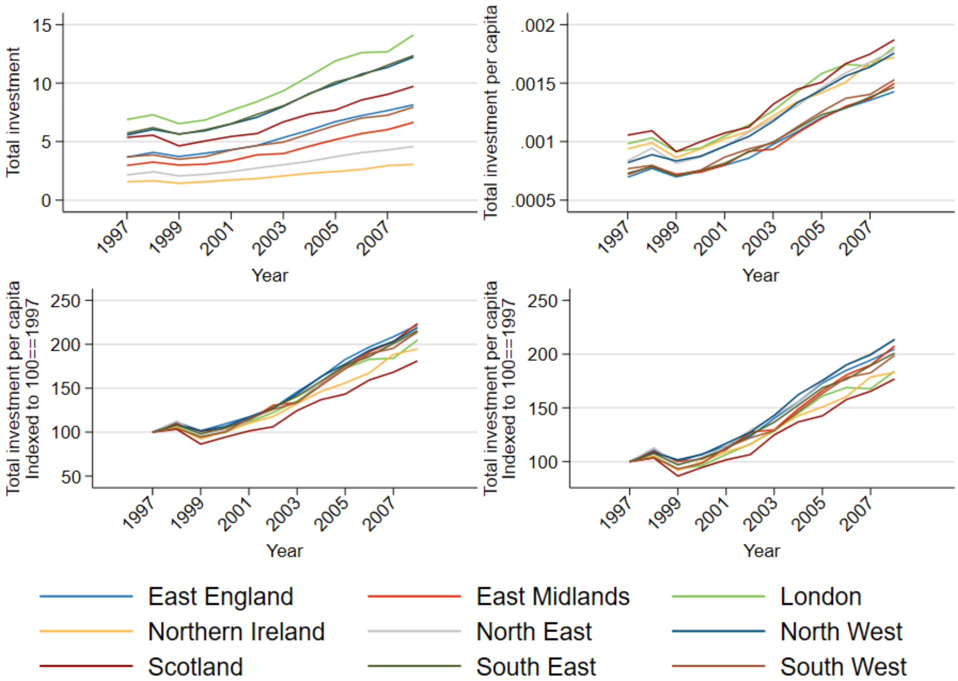
a) Challenge 1 (C1). First source of bias may come from unobserved non-T_{rt} components of $S_{rt}^{'}$. These biases may operate in both directions. For instance, we suspect that poorer regions indeed invest less resources in Public Health services. If that was the case, then our coefficient would be positively (not negatively) biased as migrants may be demanding Health Insurances as a replacement of floundering public services. On the other hand, there are other regional characteristics which may be pushing down our coefficient such as private Health Insurance industry penetration. We expect this sector to be more developed in richer and more urban regions, thus it is reasonable to assume that to-poor movers' Health Insurance demand is downward biased by this cofounder.

   Sources of positive bias coming from deficient Public Health services are easy to tackle by factoring in Public Health investment per capita. Nonetheless, based on the evolution of Public Health investment across different regions, as shown in Graph 5.4, we do not expect large positive biases in our regression analysis.[24, 25] Moreover, note

[24] Data has been extracted from the "UK Public Spending" website, based on the HM Treasury "Public Expenditure Statistical Analysis" information. Unfortunately there is no region-level information prior to 1997, thus we have limited our analysis to the 1997–2008 period. Still, nor do we expect mayor interregional differences in the period 1991–1997.

[25] Annex B shows that there exists a small positive and significant correlation between Public Health

Figure 5.4. Public Health Investment by Region (1997–2008)



that in per capita terms, rich regions like London are not among the largest Public Health investors, hence the probaility of positive bias is relatively small in this setting.[26] Conversely, controlling for potential negative sources of bias is rather tricky and difficult to achieve, so overall, we may expect some negative bias coming from this set of unobserved S'_{rt} components.

b) Challenge 2 (C2). Second source of negative bias may come from potential violations of SUTVA. As mentioned in Section 4, it is very likely that individuals moving to richer regions are on average performing better in terms of job status and total income compared to those individuals who moved to a poorer region. If that is the case, and

investment per capita ranking and average household income ranking, even under fixed time effects considerations. Still the magnitude of this relationship is close to negligible thus we do not expect a significant bias coming from Public Health investment.

[26] Again, we acknowledge that this characterization might be somehow tricky. Because Public Health Investment does not account for private funding, it still may be the case that Londoners are receiving better health quality, given that a lot of them go to private institutions. Still, we do not expect this bias to be particularly significant in our framework.

Figure 5.5. Evolution of Income-Related Variables. To Rich Movers vs To Poor Movers

because we know that Health Insurances are normal goods whose demand increases with income,[27] we should expect poor-to-rich movers to demand more Health Insurances due to Income Effects. In fact, if we compare the evolution of income-related variables of rich-to-poor movers and poor-to-rich movers we can see that our intuitions might be correct in this regard.

As we can see, subjects moving to richer regions perform better in all economic-related variables, namely month labor household income, month total household income, job status (employment) and monthly usual working hours after moving (normalized wave ≥ 0). Moreover, the magnitude of these differences resembles the post-treatment gap in Health Insurance demand, thus *ex ante* we should not reject SUTVA violations to be the main drivers of previously identified negative treatment effects.

c) Challenge 3 (C3). The set of graphs in Figure 5.5 points out another interesting pre-

[27] Please find a scatter plot representing dependence between household income and Health Insurance tenancy in Annex B.

movement difference especially in terms of job status across treatment and control groups. For instance, individuals moving to richer regions experience an unemployment dip a few waves before moving.[28] Consequently, even though pre-movement trends look fairly similar, differences across treated and non-treated individuals might exist in pre-movement periods. If that is the case, and to-rich movers, for instance, are more educated than to-poor movers or have a higher earnings potential (which happens to be the case), we expect some further negative bias coming from this side.

d) Challenge 4 (C4). Finally, as previously pointed out in Section 4, it could be the case that we are not defining treatment properly. Government office regions in the United Kingdom are very large and present important internal differences. As a result, it is very unlikely that migrations to marginally richer or marginally poorer regions produce a shift in the social perception of the treated individual. In other words, in these kinds of migrations is very unlikely that individual i gets to perceive the marginal difference between $T_{r_1 t}$ and $T_{r_2 t+1}$. If no such a realization takes place, then, assuming that Health Insurance demand is a conscious decision, there is no way variations in T_{rt} can have an impact on Health Insurance demand.

To summarize, we have identified four potential sources of bias driving our negative coefficients for β_2. Although there is not a unique solution to all these four problems, there are a few tools which could be brought in to tackle them down. In particular, C1 and C2 may be minimized by controlling on observables at the region (C1) and individual (C2) level. The academia is not very keen to these kinds of research designs given that

[28] Note that this difference could be explained by age differences across treatment and control groups. We know that individuals moving to richer regions are younger than those who move to poorer regions, hence it is possible for employment differences to be driven by very young individuals who are finishing their last years of education, and who move to a richer region after education completion. As a result, employment gap, would not be necessarily related to different unemployment rates across groups, but differences in activity rates.

there is always room for OVB coming from unconsidered or unobserved components of S'_{rt} and X'_{it}. However, in this scenario, it is difficult to come-up with alternative sources of bias at the individual level once income and working hours are factored in. On the other hand, omitted negative biases are still likely at the regional level (i.e. penetration of private Health Insurance sector in region r), hence, even after controlling on observables we would expect some negative bias in β_2. Further analyses looking forward to solving this OVB at the region level are discussed in Sections 6 and 7.

In addition, in relation to C3, although pre-trends were fairly consistent, we can look for more sophisticated tools which maximize the comparability or pre-movement observations such as Propensity Score Matching (PSM). This method looks to redefine equation 3.8 in the following way

$$\begin{aligned}\tau_{DiD}^{PSM} =& E_{p(X'_{it})|D_{irt}=1}\Big[E[H_{1ir1} - H_{1ir0}|p(X'_{it})] - \\ & E[H_{0ir1} - H_{0ir0}|p(X'_{it})]\Big]\end{aligned} \tag{5.3}$$

and consequently, we would need a weaker IA, namely Conditional Independence Assumption (CIA):

$$\epsilon_{ir1} - \epsilon_{ir0} \perp D_{irt}|X'_{it} \tag{5.4}$$

where $p(X'_{it})$ is the propensity score of individual i in period t.

Finally, in regard to C4, as anticipated in Section 4, we might be tempted to redefine our treatment based on a ≥ 1 difference between the income rank of the region of origin and the income rank of the region of destination.

6. METHODOLOGY AND RESULTS II. SELECTION ON OBSERVABLES AND ALTERNATIVE DEFINITIONS OF TREATMENT

6.1. Selection on Observables: Multivariate Regression Analysis and PSM-DiD Estimators

Table 6.1 summarizes the main results from our analysis using a Progressive definition of treatment. For presentation purposes we only report results for p50 specification. Column (1) controls on a complete set of individual observable characteristics,[29] while Column (2) includes covariates at both the individual and region level (i.e. origin region FE, destination region FE and regional health investment per capita). Moreover, Tables 6.2 and 6.3 use a PSM-DiD design where $p(X_{it}^{'})$ has been computed using the same range of variables that were used in Columns (1) and (2) of Table 6.1, respectively. In Table 6.1, estimators have been computed using OLS methods. Nonetheless, in order to partially overcome rigidity concerns, we have generated some polynomial variables when relevant. Numbers in brackets represent robust standard errors.[30]

Regarding, PSM estimators, these have been built using the user-written package diff for Stata16. Underlying propensity scores have been computed using traditional logit estimators. Eventually, matching has been conducted using Kernel-Gaussian weights, rather than traditional k-close-neighbors approaches.[31] Only observations satisfying common

29 Please refer to Annex A for an exhaustive characterization of all relevant variables.

30 Specifications using region level controls include fewer observations given that Public Health investment was not available prior to 1997.

31 Note that Kernel approaches, instead of implementing discrete matching connections, match every

support conditions have been considered for PSM analysis. Finally, because the diff package requires balanced panel data, we have also excluded from the analysis observations with missing Health-insurance demand information.

There are some important takeaways from the previous exercise that we shall comment. Let us start by characterizing our parameter of interest β_2. β_2 is negative for all four specifications and significant in three out of the four. Unfortunately, its magnitude is fairly consistent with the results in Table 5.1, meaning that we do not observe a reduction in the potential negative biases (C1 to C3) that we described in Section 5. Estimators of the rest of the variables are fairly consistent and, in most of the cases, they match our economic intuition.[32] Interestingly enough, health investment parameters present a negative sign which confirms our intuition about people demanding Health Insurances as a replacement of floundering health facilities. In addition, (i) health status is, surprisingly, not a strong predictor of Health Insurance demand (everything else constant)[33] and (ii) all three income-related variables have positive (and significant) effects on Health Insurance demand, thus our previous concerns regarding individual level OVB were justified in this regard.

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observation with each other assigning unequal weights to those connections. Kernel-Gaussian methods use the normal distribution function to assign matching weights to all observations.

[32] The only unexpected estimator's sign is the one for employment. Intuitively, we were expecting a positive contribution of employment on H_{irt}, either through Income Effects mechanisms, either through firm delivering this benefit. Its negativeness though, could be actually reflecting the fact that employed individuals are healthier than the unemployed. Nonetheless, employment coefficient remains within the non-significance scope, hence, we should not be too worried about this result.

[33] This fact could potentially be explained by two reasons. Reason number one being the low predictive power of our PCA and MCA estimators overall, and reason number two being the dual relationship between income and health-insurance demand. This nature is determined by the fact that individuals who can consume it (high-income individuals) usually do not need it (given the strong dependence between income and health), while those who need it (disabled people and those with a high probability of getting ill) usually cannot afford it. These two effects could cancel each other leading to poor cross-sectional identification of Health Insurance demand based on health status.

Table 6.1. Progressive Treatment Benchmark Specifications. Multivariate Regression Analysis

	(1)	(2)
Time	0.010	0.034
	(0.022)	(0.024)
Treatment	0.028	0.026
	(0.022)	(0.031)
Time=1 × Treatment	-0.069**	-0.088***
	(0.028)	(0.032)
Age	0.000	0.001
	(0.004)	(0.004)
Age2	0.000	0.000
	(0.000)	(0.000)
Male	0.075***	0.076***
	(0.020)	(0.021)
Married	0.082***	0.075***
	(0.017)	(0.018)
Maxrun	-0.004**	-0.007***
	(0.002)	(0.002)
Employed	-0.017	-0.034
	(0.022)	(0.023)
Monthly job hours	0.001***	0.001***
	(0.000)	(0.000)
Monthly job hours ^{2}	-0.000***	-0.000***
	(0.000)	(0.000)
HH Monthly labor income	0.000***	0.000***
	(0.000)	(0.000)
HH Monthly labor income^2	-0.000***	-0.000***
	(0.000)	(0.000)
HH Monthly total income	0.000***	0.000***
	(0.000)	(0.000)
HH Monthly labor income^2	-0.000***	-0.000***
	(0.000)	(0.000)
MCA 1	0.039	0.100
	(0.116)	(0.120)
PCA 1	0.004	0.046
	(0.071)	(0.074)
Health investment pc		-101.859**
		(42.315)
FE Race	Yes	Yes
FE Education	Yes	Yes
FE Origin region	No	Yes
FE Destination region	No	Yes
Constant	-0.045	0.029
	(0.088)	(0.112)
Observations	4656	4305

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: Health Insurance

Table 6.2. Progressive Treatment Benchmark Specifications. PSM-DiD

	Mean	SE	P value	Number of obs
Before				1853
Control	0.319***	0.019	0.000	
Treated	0.325***	0.014	0.000	
Diff (T-C)	0.006	0.024	0.785	
After				2461
Control	0.284***	0.016	0.000	
Treated	0.269***	0.011	0.000	
Diff (T-C)	-0.014	0.020	0.468	
Diff-in-Diff	-0.021	0.031	0.498	4314

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

Table 6.3. Progressive Treatment Benchmark Specifications. PSM-DiD with Region Level Controls

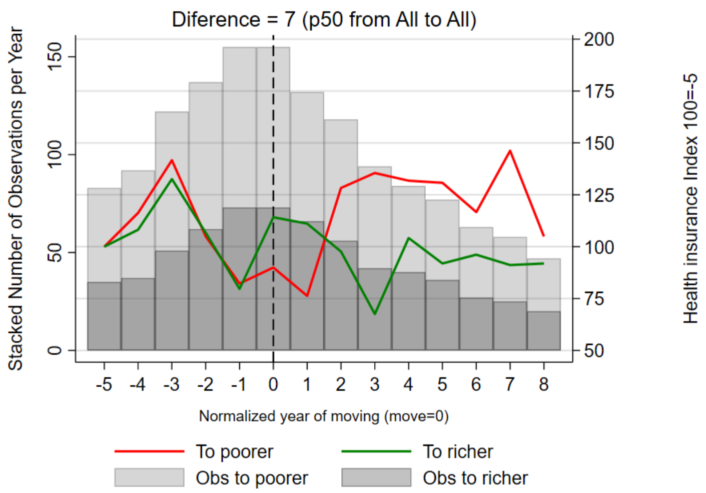
	Mean	SE	P value	Number of obs
Before				1697
Control	0.308***	0.019	0.000	
Treated	0.330***	0.015	0.000	
Diff (T-C)	0.021	0.024	0.382	
After				2240
Control	0.325***	0.018	0.000	
Treated	0.257***	0.012	0.000	
Diff (T-C)	-0.068***	0.021	0.001	
Diff-in-Diff	-0.089***	0.032	0.006	3936

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

6.2. Alternative Definitions of Treatment. Top-to-Bottom Approach

These analyses provide important improvements compared to our benchmark DiD regression framework, especially in terms of OVB minimization, however, they potentially still suffer from identification concerns related to treatment definition (C4). To solve this issue we provide an additional set of results for p50 movers where alternative definitions of treatment are considered. More concretely, we define $D_{irt} = 1$ when individual i moves to a region at least 7 positions below in the regional average income ranking at $wave\_norm = 0$. Analogously, individuals moving to a region at least 7 positions richer than their current region have been assigned a treatment value of zero. Movers who do not comply with any of these conditions have been excluded from the sample.[34, 35] Please find below a set of descriptive graphs and regression analyses characterizing this alternative definition of treatment.

Figure 6.1. DiD Graphical Analysis of p50 Movers when Difference ≥ |7|



[34] Annex C reproduces this whole analysis for Difference ≥ |8| specification.

[35] We have chosen a numerical difference of 7 and 8 as they were the two maximum income differences which had observations for at least three pre-periods. Movements of order 9 or above were extremely infrequent and usually did not contain observations for a non-negligible number of pre- and post-movement periods.

Table 6.4. Top-to-Bottom Treatment. Diff ≥ |7| Specifications. Multivariate Regression Analysis

	(1)	(2)	(3)
Time	-0.016	0.022	0.050
	(0.044)	(0.058)	(0.057)
Treatment	-0.139***	-0.116**	-0.409***
	(0.044)	(0.054)	(0.129)
Time × Treatment	0.029	-0.064	-0.051
	(0.055)	(0.069)	(0.085)
Age		0.013**	0.012*
		(0.006)	(0.006)
Age^2		-0.000*	-0.000
		(0.000)	(0.000)
Male		0.155***	0.187***
		(0.044)	(0.041)
Married		0.114***	-0.007
		(0.036)	(0.042)
Maxrun		0.004	-0.002
		(0.004)	(0.005)
Employment		-0.126**	-0.136***
		(0.052)	(0.052)
Monthly job hours		0.000	0.000
		(0.001)	(0.001)
Monthly job hours ^{2}		-0.000	-0.000
		(0.000)	(0.000)
HH Monthly labor income		-0.000	-0.000
		(0.000)	(0.000)
HH Monthly labor $income^2$		0.000	0.000
		(0.000)	(0.000)
HH Monthly total income		0.000*	0.000**
		(0.000)	(0.000)
HH Monthly total $income^2$		-0.000	-0.000
		(0.000)	(0.000)
MCA 1		-0.017	-0.090
		(0.242)	(0.218)
PCA 1		-0.072	-0.109
		(0.145)	(0.131)
Health Investment pc			-127.939
			(89.105)
FE Race	No	Yes	Yes
FE Education	No	Yes	Yes
FE Origin region	No	No	Yes
FE Origin destination	No	No	Yes
Constant	0.330***	0.092	0.140
	(0.035)	(0.203)	(0.257)
Observations	1127	879	813

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: Health Insurance

Table 6.5. Top-to-Bottom Treatment. Diff ≥ |7| Specifications. PSM-DiD

	Mean	SE	P value	Number of obs
Before				320
Control	0.379***	0.053	0.000	
Treated	0.212***	0.029	0.000	
Diff (T-C)	-0.167	0.060	0.785	
After				413
Control	0.278***	0.037	0.000	
Treated	0.148***	0.023	0.000	
Diff (T-C)	-0.130***	0.043	0.003	
Diff-in-Diff	0.037	0.074	0.615	733

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

Table 6.6. Top-to-Bottom Treatment. Diff ≥ |7| Specifications. PSM-DiD with Region Level Controls

	Mean	SE	P value	Number of obs
Before				302
Control	0.412***	0.056	0.000	
Treated	0.213***	0.030	0.000	
Diff (T-C)	-0.199***	0.063	0.002	
After				370
Control	0.320***	0.048	0.000	
Treated	0.158***	0.024	0.000	
Diff (T-C)	-0.162***	0.054	0.003	
Diff-in-Diff	0.037	0.083	0.653	672

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

Let us start by commenting on Graph 6.1, as it contains very interesting pieces of information. First element that pops up is the robustness of pre-trends, despite the pre-movement high variability of Health Insurance demand. In fact, as pointed out in Section 4, our biggest concern was precisely related to the non-linearity of pre-trends, which could suggest the non-exogeneity of movement or the non-comparability across treatment and control cohorts. However, this graphical evidence suggests that we may not be that far from parallel co-movement. Second interesting fact is the overall development of Health Insurance demand across waves. After movement, we observe how to-rich movers' Health Insurance demand surges compared to the slight decay of Health Insurance demand in to-poor movers. However, to-poor movers' Health Insurance demand bounces back reaching a quasi-constant gap compared to to-rich movers' demand. These results not only match our predictions but are very coherent with our underlying mechanisms and network effects.[36] When moving, to-rich migrants experience a larger increase in income or employability which gets translated, via Income Effect, in rising Health Insurance demand. However, over time, to-poor movers start realizing the socioeconomic background of their neighbors. Stereotypes get reinforced and movers start demanding these private services to avoid sharing their public spaces with (low-income) locals.

In Table 6.4, Column (1) presents our benchmark specification for movement difference $\geq |7|$; while Columns (2) and (3) include different control variables at the individual and regional level. On the other hand, Tables 6.5 and 6.6 are analogous to previous benchmark PSM summary DiD tables. In this case, β_2 becomes insignificant for all five specifications and first positive coefficients emerge when we implement PSM methods. These results match our predictions, namely the larger the intensity of treatment the more

[36] Please see Section 2 for further insights on network effects.

positive β_2. These results hold for Difference $\geq$ $|8|$ specification.[37] Still, taking into consideration the overall evolution of Health Insurance demand across groups shown in Graph 6.1, we consider wave-heterogenous effects to be of ultimate interest for a better interpretation of treatment parameters.

6.3. A Race-Based Characterization of Treatment

Finally, in order to conclude this section, let us provide a reproduction of Tables 6.4 to 6.6 using a Progressive approach, but defining treatment in terms of race instead of income. The underlying methodological process is very similar, only difference being that filtering is not produced anymore based on income (p50, p75, etc.) but based on race. More specifically, only white individuals are considered as part of this sample, as we would not expect racist attitudes within ethnic minorities nor against the prevalent race in the UK. Note that these results, even when considering a Progressive definition of treatment, are more aligned with our initial hypothesis than income-based treatments. However, we acknowledge that there exists a positive correlation between the economic buoyancy of certain region and the number of incoming international immigrants.[38] Consequently, moves towards more ethnically diverse scenarios are likely to be hiding migration towards richer regions. Although dependence between economic rank and racial rank is not a one to one relation, we were fearful of the potential impact of this type of bias, thus we have preferred to show these results as supporting evidence rather than the main target of our analysis.

In this regard, we present the analysis for target treatment variable “other-to-punjab"

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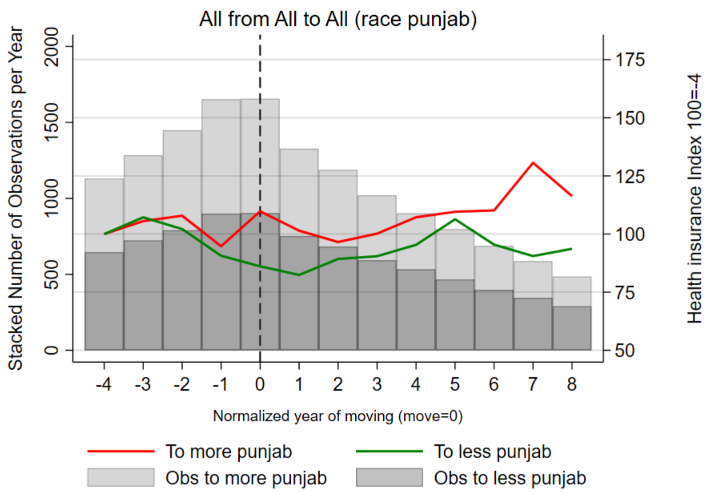
[37] Please see Annex C for a complete set of results involving this specification.

[38] Please find a scatter plot representing dependence between income levels and non-white shares in all 13 regions in Annex B.

which equals 1 if individual i moves to a region with a higher share of Punjab (Indian, Bangladeshi and Pakistani) citizens and 0 otherwise.[39] As we can see in Graph 6.2 and summary Tables 6.7, 6.8 and 6.9, our intuitions were correct and results are aligned with our expectations even in the benchmark specification scenario. Our parameter of interest is positive for all five specifications (and significant, at least at 10% confidence level, for four of them), meaning that movers to more-punjab regions experience an increase in their Health Insurance demand after movement. Once more, we acknowledge that these results may be driven by income and not racial considerations.

Figure 6.2. DiD Graphical Analysis of White Movers (More Punjab vs Less Punjab Region)



To summarize, this section has consistently proven the following points:

i) Our benchmark results are robust to different Selection on Observables processes including Multivariate Regression and PSM methods. There is still plenty of room for (negative) OVB, especially at the region level, but unfortunately our coefficients are

[39] We have conducted these same graphical and regression analyses for Asian and Black-Latino groups. Because results were not materially different across different ethnic groups we do not report these results in the current file.

Table 6.7. Progressive Race-Based (Punjab) Treatment. Multivariate Regression Analysis

	(1)	(2)	(3)
Time	-0.019*	-0.046***	-0.036***
	(0.011)	(0.012)	(0.013)
Treatment	-0.015	-0.008	0.035
	(0.014)	(0.015)	(0.023)
Time × Treatment	0.032*	0.027	0.035*
	(0.017)	(0.019)	(0.020)
Age		0.000	0.001
		(0.002)	(0.002)
Age^2		0.000	0.000
		(0.000)	(0.000)
Male		0.036**	0.036**
		(0.015)	(0.015)
Married		0.051***	0.049***
		(0.011)	(0.011)
Maxrun		-0.001	-0.004***
		(0.001)	(0.001)
Employment		-0.020	-0.030**
		(0.014)	(0.015)
Monthly job hours		0.001***	0.001***
		(0.000)	(0.000)
Monthly job hours^2		-0.000	-0.000*
		(0.000)	(0.000)
HH Monthly labor income		0.000***	0.000***
		(0.000)	(0.000)
HH Monthly labor income^2		-0.000	-0.000
		(0.000)	(0.000)
HH Monthly total income		0.000***	0.000***
		(0.000)	(0.000)
HH Monthly total income^2		-0.000***	-0.000***
		(0.000)	(0.000)
MCA 1		0.060	0.063
		(0.055)	(0.057)
PCA 1		0.026	0.027
		(0.034)	(0.035)
Health Investment pc			-103.905***
			(27.706)
FE Education	No	Yes	Yes
FE Origin region	No	No	Yes
FE Destination region	No	No	Yes
Constant	0.245***	-0.043	0.024
	(0.009)	(0.037)	(0.055)
Observations	11473	9106	8487

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: Health Insurance. Race FE have been excluded from this specification given that only white individuals were considered for analysis.

Table 6.8. Progressive Race-Based (Punjab) Treatment. PSM-DiD

	Mean	SE	P value	Number of obs
Before				3041
Control	0.245***	0.011	0.000	
Treated	0.235***	0.011	0.000	
Diff (T-C)	-0.010	0.016	0.517	
After				5081
Control	0.226***	0.008	0.000	
Treated	0.255***	0.009	0.000	
Diff (T-C)	0.028**	0.012	0.023	
Diff-in-Diff	0.038*	0.020	0.057	8122

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

Table 6.9. Progressive Race-Based (Punjab) Treatment. PSM-DiD with Region Level Controls

	Mean	SE	P value	Number of obs
Before				2814
Control	0.247***	0.012	0.000	
Treated	0.231***	0.011	0.000	
Diff (T-C)	-0.016	0.017	0.327	
After				4254
Control	0.216***	0.009	0.000	
Treated	0.255***	0.010	0.000	
Diff (T-C)	0.039***	0.012	0.003	
Diff-in-Diff	0.055***	0.021	0.009	7068

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

negative (and statistically significant) when a Progressive characterization of treatment is considered.

ii) To minimize identification concerns, while raising treatment's intensity, we have implemented a Top-to-Bottom characterization of treatment. When this definition is adopted, (insignificant) positive coefficients for β_2 finally emerge. This alternative definition seems more "relevant" in IV jargon, but at the same time less exogenous. However, results proved to be consistent across different Selection on Observables specifications. Moreover, results are not only aligned with our intuitions, but they give some support to our underlying mechanisms, thus these results are further analyzed in Section 7 through wave-heterogenous specifications.

iii) Race-based analysis confirms our initial hypothesis too with a significance level above 90% in most of the specifications. Nevertheless, we suspect that these results are driven by income rather than by racial considerations, so they will not be further discussed in the present study.

Given the good feelings derived from Top-to-Bottom definitions of treatment, in the next section we proceed (i) to identify wave-heterogeneous estimators and (ii) to check the robustness of these results under (a) clusterization of errors and (b) Rambachan and Roth, 2019 deviations from pre-trend linearity scenarios.

7. METHODOLOGY AND RESULTS III. WAVE-HETEROGENEOUS TREATMENT EFFECTS AND ROBUSTNESS ANALYSIS

Let us start this concluding section by presenting a wave-heterogeneous model inspired by Duflo, 2001 and based on equation 5.1:

$$H_{irt} = \lambda_t + \beta_1 D_{irt} + \sum_{t=0}^{T} \beta_{2t} D_{irt} \tag{7.1}$$

where the main novelty is that we allow β_2 coefficient to vary across waves. Moreover, in this scenario, rather than our traditional binary time variable, we have used time fixed effects for every wave. Using our Difference $\geq |7|$ Top-to-Bottom specification, we can observe that our previous intuitions were correct, even under Multivariate Regression Analysis considerations. β_{2t} coefficients are negative for the first waves and move towards more positive coefficients along time. Although no β_{2t} coefficient is significant, some of them are close to significance at 90% confidence level. Graphically:

Figure 7.1. Evolution of Robust and Clustered Errors

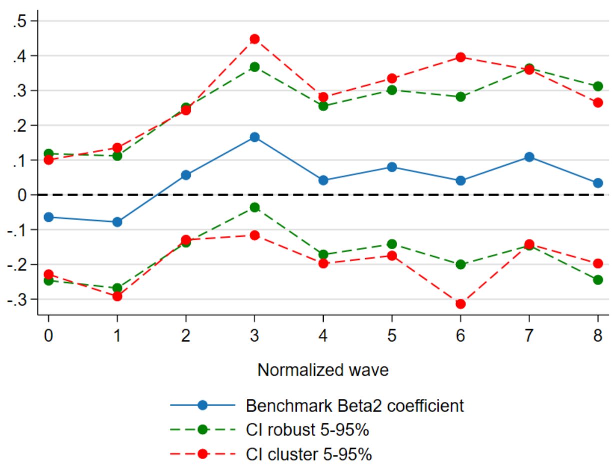


Table 7.1. Top-to-Bottom Treatment. Diff ≥ |7| Specifications. Multivariate Regression Analysis with Wave-Heterogenous effects

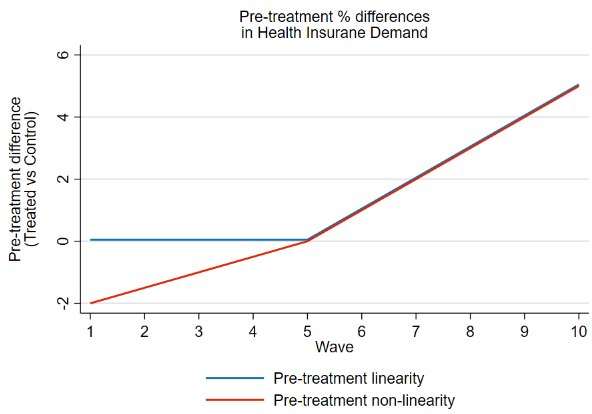
	(1)	(2)
Treatment	-0.143	-0.417
	(0.044)***	(0.129)***
	[0.096]	[0.111]***
Treatment_0	-0.064	-0.137
	(0.093)	(0.115)
	[0.084]	[0.137]
Treatment_1	-0.078	-0.058
	(0.097)	(0.121)
	[0.109]	[0.113]
Treatment_2	0.057	-0.081
	(0.099)	(0.118)
	[0.095]	[0.129]
Treatment_3	0.166	0.138
	(0.103)	(0.127)
	[0.144]	[0.206]
Treatment_4	0.042	-0.057
	(0.109)	(0.136)
	[0.122]	[0.122]
Treatment_5	0.080	-0.017
	(0.113)	(0.125)
	[0.130]	[0.153]
Treatment_6	0.041	-0.117
	(0.123)	(0.131)
	[0.181]	[0.133]
Treatment_7	0.109	-0.061
	(0.130)	(0.162)
	[0.128]	[0.115]
Treatment_8	0.034	0.028
	(0.142)	(0.143)
	[0.118]	[0.156]
Time FE	Yes	Yes
Individual Level Controls	No	Yes
Income related variables	No	Yes
Region Level Controls	No	Yes
Observations	1127	813

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: Health Insurance. Robust standard errors are reported inside (); Clustered standard errors are reported inside []. Significance levels have been assigned to SE rather than coefficients for presentation purposes.

where the blue line represents our benchmark estimators for each β_{2t}, the green dashed line represent 5–95% confidence level interval under robust standard errors and the red line represents region of origin clustered errors following the recommendations in Abadie et al., 2017. As a brief note on clustering, although we have consistently reported robust standard errors throughout this paper, we acknowledge that assignment to treatment (i.e. moving to a richer or poorer region) is necessarily determined at the region level, hence, clustered errors may provide us with better insights on errors distribution.[40] As we can see, results remain insignificant, but they clearly depict an increasing trend which matches our Health Insurance demand network effects considerations.[41]

Despite results not being significant under strict linearity assumptions of pre-trends, following the advice of current literature Rambachan and Roth, 2019, it seems very convenient to redefine our Confidence Intervals based on pre-trends deviations from linearity. The intuition goes as follows: DiD spirit somehow seeks to represent variations in trends across series. However, the term variation (or deviation from linearity if preferred) is very slippery. See as an example Graph 7.2:

Figure 7.2. Deviations from Linearity in Pre-Trends. A Graphical Example



[40] Clustered errors are preferred when we suspect that observations within each group, in this case region of origin, are not iid, that is to say, we expect some unexplained variance in our dependent variable to be correlated across time.

[41] We have considered the possibility of clustering our errors at the individual level, rather than the region level. In fact, in DiD scenarios clustering at the individual level is usually considered the standard practice. However, in this specific case we were particularly concerned about region-level unexplained variance given that region of origin is the main determinant of treatment. On the other hand, considering the no-significance of our robust coefficients, clustering level considerations are not particularly relevant in this situation.

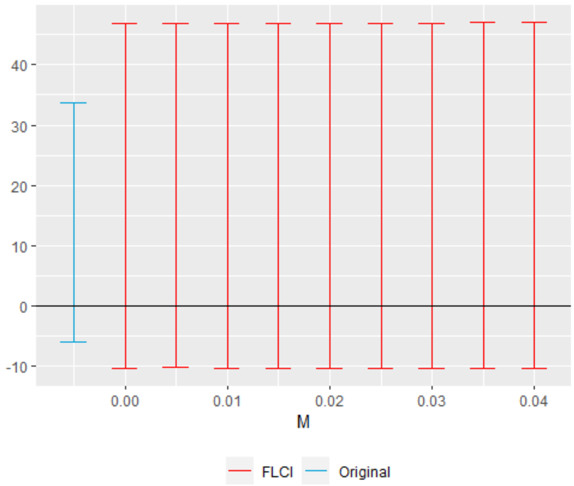
In this case, based on pre-event linearity deviations differences between blue and red lines, it seems reasonable to interpret differently the post-treatment change in trends. As a result, we would like our DiD estimators to take this pre-event information into account, namely variance and pre-movement deviations from linearity. Robust (and clustered) errors take care of the former but the latter has remained largely unattended by the literature for a long time. In a recent paper, Roth and Rambachan suggest to adopt a “Honest DiD" approach where pre-trends deviations are factored in when estimating post-treatment coefficients. More concretely, they suggest to calibrate the significance of post-event estimators based on a parameter M which measures the magnitude of that divergence in standard deviations. Because our estimators were not significant in first place, there is no point in expanding even more our Confidence Intervals, still, just for illustration purposes, we have decided to implement this approach in our β_{27} estimator from Table 7.1.

To produce these results we have derived a slightly different model compared to the one in Table 7.1. More concretely, we have estimated a β_{2t} for every t (including pre-event waves) and we have excluded β_{20} for collinearity concerns. Estimators have been computed using Fixed Linear Confidence Intervals (FLCI) methods and graphical evidence has been elaborated taking as reference RR HonestDiD package in R. In Graph 7.3 we can see alternative confidence intervals for our parameter of interest β_{27} when different M magnitudes are considered.[42]. RR errors are significantly larger but surprisingly constant for different magnitudes of M.[43]

[42] M takes values from 0 to 50% of the standard error of the first post-period coefficient, in our case β_{21}

[43] Although they look all very similar, there exist marginal differences across CIs, which move from (-10.2, 46.8) to (-10.4, 47.0)

Figure 7.3. Confidence Intervals Under Deviations from Pre-Event Linearity



8. CONCLUSION

To summarize, we can state that our treatment effect estimators are far from significant. In fact, results range from significant negative when Progressive definitions of treatment are used to insignificant positive when Selection on Observables methods, wave-heterogeneous and alternative definitions of Treatment are adopted. Still, we believe that there is room for negative bias coming from unobserved (or uncontrolled) variables at the region level. More concretely, we suspect that Private Health Industry penetration could be draining our estimates. In that sense, considering this negative bias, quasi-significant positive results may suggest that there is room for discriminatory attitudes in Health Insurance demand. In addition, race-based estimators suggest a significant positive treatment effect. However, considering the lessons that we have extracted from income-based analyses, we believe that race-based results could be biased by income considerations. As a result, we have decided to ignore these (positive) results.

As a concluding statement, if we take into consideration (i) our non-significant positive and non-significant negative treatment coefficients, and (ii) potentially negative OVB at the region level, we cannot reject our initial hypothesis, i.e. we cannot reject that the contribution of aporophobia (and racial discrimination) in Health Insurance demand is greater than zero at standard confidence levels. Nevertheless, there are important limitations within our research design that we need to highlight.

First of all, realized Health Insurance demand is an imperfect proxy of real Health Insurance demand, what may weaken our revealed preferences framework. Individuals usually get covered by firms or relatives' Health Insurance policies even though they would not have purchased that good by their own. Second, Administrative Regions in the United Kingdom are big and diverse territories with significant internal heterogeneity. Consequently, relevance condition may not be satisfied in some scenarios. In this sense, it might be interesting to exploit postal-code level information in BHPS, only available under official authorization. Third, although we implement Public Health Insurance controls as proxies for Public Health services quality in region, it is true that this variable may be poorly identified. If rich regions have stronger Public Health services despite lower funding, for instance because of Economies of Scale or because large Private Health Insurance sectors in those regions, our parameter of interest β_2 may be positively (and not negatively) biased.

And finally, some general considerations regarding the overall research design and research data are the dubious quality of survey data compared to administrative data,[44] as well as the difficulty that DiD designs face when dealing with time varying characteristics of treatment units. Migrating usually shifts a countless number of personal characteristics and consumption patterns, hence, SUTVA considerations get highly compromised in these frameworks. In addition, although exogeneity of treatment has been consistently assumed throughout this paper, there are good reasons to reject this assumption. For instance, pre-event unequal unemployment dips or differences in age and education profiles across to-poor and to-rich movers, may evidence some endogeneity in migration destination decisions.

As you all know, perception shapes behavior and behavior shapes everything else . . . , even Health Insurance demand.

[44] Attenuation bias is survey data coming from inaccurate or missing responses may be hiding significant positive results for β_2 parameters.

BIBLIOGRAPHY

Abadie, A., Athey, S., Imbens, G. W., & Wooldridge, J. (2017). *When should you adjust standard errors for clustering?* (Tech. rep.). National Bureau of Economic Research.

Agbaria, A. K. (2018). Israeli education and the apartheid in south africa: Ongoing insights. *Intercultural Education*, *29*(2), 218–235.

Akee, R., & Casey, M. (n.d.). Measuring racism and discrimination in economic data.

Angrist, J. D., & Krueger, A. B. (1999). Empirical strategies in labor economics. *Handbook of labor economics* (pp. 1277–1366). Elsevier.

Angrist, J. D., & Pischke, J. (2008). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Baicker, K., Congdon, W. J., & Mullainathan, S. (2012). Health insurance coverage and take-up: Lessons from behavioral economics. *The Milbank Quarterly*, *90*(1), 107–134.

Black, D., Townsend, P., & Davidson, N. (1988). *Inequalities in health: The black report*. Penguin.

Cotlear, D., Gómez-Dantés, O., Knaul, F., Atun, R., Barreto, I. C., Cetrángolo, O., Cueto, M., Francke, P., Frenz, P., Guerrero, R., et al. (2015). Overcoming social segregation in health care in latin america. *The Lancet*, *385*(9974), 1248–1259.

Currie, J., & Madrian, B. C. (1999). Health, health insurance and the labor market. *Handbook of labor economics*, *3*, 3309–3416.

DeNavas-Walt, C., Proctor, B. D., & Smith, J. C. (2013). Income, poverty, and health insurance coverage in the united states: 2012. current population reports p60-245. *US Census Bureau*.

Duflo, E. (2001). Schooling and labor market consequences of school construction in indonesia: Evidence from an unusual policy experiment. *American economic review*, *91*(4), 795–813.

Friedl, A., De Miranda, K. L., & Schmidt, U. (2014). Insurance demand and social comparison: An experimental analysis. *Journal of Risk and Uncertainty*, *48*(2), 97–109.

Goldman, D. P., Smith, J. P., & Sood, N. (2005). Legal status and health insurance among immigrants. *Health Affairs*, *24*(6), 1640–1653.

Health at a glance. europe. (n.d.).

Kaestner, R., & Lubotsky, D. (2016). Health insurance and income inequality. *Journal of Economic Perspectives*, *30*(2), 53–78.

Lambrinos, J. (1981). Health: A source of bias in labor supply models. *The Review of Economics and Statistics*, 206–212.

Mossey, J. M., & Shapiro, E. (1982). Self-rated health: A predictor of mortality among the elderly. *American journal of public health*, *72*(8), 800–808.

Nyman, J. A. (1999). The value of health insurance: The access motive. *Journal of health economics*, *18*(2), 141–152.

Poston Jr, D. L., & Bouvier, L. F. (2010). *Population and society: An introduction to demography*. Cambridge University Press.

Rambachan, A., & Roth, J. (2019). An honest approach to parallel trends. *Unpublished manuscript, Harvard University.[99]*.

Rubin, D. B. (2005). Causal inference using potential outcomes: Design, modeling, decisions. *Journal of the American Statistical Association*, *100*(469), 322–331.

Saez, E. (2021). Public economics and inequality: Uncovering our social nature. *AEA Papers and Proceedings*, *111*, 1–26.

Schansberg, D. E. (2014). The economics of health care and health insurance. *The Independent Review*, *18*(3), 401–420.

Stuber, J. P., Maloy, K. A., Rosenbaum, S., & Jones, K. C. (2000). Beyond stigma: What barriers actually affect the decisions of low-income families to enroll in medicaid?

Villa, J. M. (2016). Diff: Simplifying the estimation of difference-in-differences treatment effects. *The Stata Journal*, *16*(1), 52–71.

Warde, A., & Martens, L. (2000). *Eating out: Social differentiation, consumption and pleasure*. Cambridge University Press.

Wing, C., Simon, K., & Bello-Gomez, R. A. (2018). Designing difference in difference studies: Best practices for public health policy research. *Annual review of public health*, *39*.

Zhou, Y., Cai, T., & Wang, D. (2016). Social segregation in hong kong's schools: 2000–2012. *Chinese Sociological Review*, *48*(3), 248–270.

A. DATA CLEANING APPENDIX

Data cleaning process has been conducted using Stata and R software programs. The cleaning codes are available under demand at carlos.gonzalperez@gmail.com. Data is available under demand too at https://www.ukdataservice.ac.uk/. Finally, questionnaire items and further relevant information can be found here. For more information about the cleaning (and/or methodological) process, please contact Mr. Gonzalez at carlos.gonzalperez@gmail.com

Data cleaning process starts by appending the .dta files for the 18 different waves of indresp (the main survery within BHPS) and selecting the relevant variables. Individuals are identified through a cross-wave unvarying personal identifier (pidp). Moreover, we can extract household information from hhresp, a parallel database which include a time-varying household identifier (hidp) which can be found in indresp too. Cross database merging has been produced using the time varying identifier hidp. Only 117 observations were excluded (all of them belonging to hhresp dataset) during the merging process because of mismatching concerns. Selected variables include a wide variety of personal characteristics that will be presented when relevant. Minor adjustments in key variables took place in the following way

Individual non-health-related variables

- **Sex.** Sex (sex) is a binary variable {Male, Female}. Sex has been replaced by modal sex. This change has affected 2,020 observations either because gender reassignment, either because this information was missing for some waves. Observations where modal sex could not be inferred were deleted (79 observations).

- **Age.** Age (age-dv) is a numerical discrete variable indicating the age of individual *i* at the time of the interview. Interviews are conducted every year in approximately the same period of time of year x (September-December). Age was derived when age was missing using lagged or forward observations. Observations whose age could not be derived were excluded from the original sample (5 observations).

- **Region.** Region (gor-dv) is a numerical categorical variable which identifies the region of residence of individual *i*. There exists a total of 13 administrative regions in the United Kingdom, namely Scotland, Northern Ireland, Wales, North East, North West, Yorkshire and the Humber, West Midlands, East Midlands, South West, South East, East of England, Greater London. These administrative regions have remained unmodified during the whole period of analysis 1991–2008. Note that BHPS contained more granular information on this regard, up to ZIP-code level, but this information is confidential and it can only be accessed under official approval.

- **Education.** Education (hiqual) is a categorical monotonic variable which classifies individuals in 6 different levels of education (with 1 = "Higher Education or above"). Because it is likely that younger cohorts experience an increase in their educational attainments throughout different waves and we understand that education operates as a signal for individual's ability, we have decided to replace education by a max(education) variable. Moreover, we have created the variable *univ* which equals 1 if $education = 1$

- **Race.** Race and Racel-bh originally were two interviewer-derived variables. Note that in UKHLS the imputation of variables race/racel-bh was not done by the interviewer anymore, but based on the self-identification of interviewee *i*. It originally included 18 different categories which were simplified into the following dummy categories: White (if respondent was considered White British, White Irish, White

Welsh, White Scottish or Other White Background); Black-Latino (if individual was considered Mix White and Black Caribbean, Mixed White and Black African, Black/British African, Black British/Caribbean or Other Black Background); Chinese (if Chinese); Punjab (if individual was assigned to an Asian/British Indian, Asian/British Pakistani or Asian/British Bangladeshi background); Asian (if Chinese, Punjab, Mix white and Asian or Other Asian Background); and Other (if Other Mix Background or Other). Note that the Asian category is a non-exclusive dummy as individuals can hold both (or just one) from the following Asian, Chinese and Punjab. Chinese, Punjab, White, Black Latino and Other are indeed exclusive categories.

- **Married.** This information has been extracted from the categorical variable mastat which includes a complete set of marital status. Married is a binary modal variable $\{0, 1\}$ which was built based on the information in mastat and equals 1 if mode(married)=1.

- **Job Status.** Job status is a binary variable that has been constructed based on the BHPS variable jbstat which equals 1 if jbstat was employed, self-employed or on maternity leave at the time of the interview. Alternatively, job-status2 has been defined as a binary variable which equals 1 if individual i usually works more than 10 hours a week.[45] Differences between the two characterizations of job status exist but are not particularly relevant. See a summary table below.

- **Full time.** Full-time status is defined as a categorical variable

$$\{0, 1, 2\}$$

[45] For more information about regular working hours please see total-hours-month variable description.

Figure A.1. Comparison of Alternative Definitions of Job Status

=1 if working more than 10 hours	Working (=1) vs Not-working (=0) No	Yes	Total
No	96,347	20,598	116,945
Yes	5,205	115,750	120,955
Total	101,552	136,348	237,900

based on BHPS jbft-dv variable where 1 stands for full-time paid job, 2 stands for part-time paid job and 0 stands by no-paid job or no job at all. This variable has eventually not been considered for analysis because of the loose definitions of part-time and full-time job status. We expect this variable's information to be confounded by "job-hours" variable.

- **Month total income and Month Labor income.** These variables have been directly extracted from BHPS fimngrs-dv and fimnlabgrs-dv variables, which are derived by the interviewer based on the sum of different income components. They both reflect usual monthly earnings in pounds.

- **Job Hours.** Total job hours have been computed as the sum of 4× (average weekly working hours in the main job) + monthly average working hours in secondary and other jobs. This variable provides an alternative definition of working status and effective total/labor income per hour. 216 individuals working hours were sent to missing given that they claimed to work over 336 hours a month (equivalent to work around 17 hours a day from Monday to Friday or around 11 hours a day from Monday to Sunday).

Household level selected variables

- **Month-total-income-hh and Month-labor-income-hh.** Usual household month total/labor income measured in pounds. These two variables operate as the central income identification variables of our analyses.

- **Maxrun** Maxrun is defined as the maximum number of consecutive runs that individual i shows up in the sample. This variable seeks to capture some unobserved X_{it}' characteristics potentially correlated with this number. For instance, we feared low-income individuals to only show up in sample when they were not financially struggling.

Individual health related variables

Health related variables (excluding Health Insurance variables) are summarized in the main body specifications through Principal Component Analysis (PCA) and Multiple Correspondence Analysis (MCA) main components. As a result, we simply discuss the variables which were included in both multi-level analysis. All the following variables have been built based on a large number of different health related variables available at BHPS.

- **Disability.** Disability is a binary variable which equals 1 if and only if respondent i held an official certification of its disability at the interview time. This strong definition of disability clashes with the definition used in UKHLS, where it got transformed into a self-consideration question.

- **Hlprb-count.** Hlprb-count is discrete numerical variable which counts the number (and not the intensity!) of different health problems that individual i claims to have. BHPS includes 15 different types of health problems ranging from sight to coronary problems.

- **Hllt-count.** Hllt-count is a discrete numerical variable which counts the number (and not the intensity!) of daily activities (including work) that get limited because of health related issues.

- **Hlltwa-count.** Hlltwa-count is a discrete numerical variable which specifies the amount of work which gets limited by health status. It ranges from 0 to 4, with zero not limited at all by health status and four can do nothing.[46]

As a final note, we have decided to exclude from the PCA/MCA analysis "health investment variables" such as the number of health checks that respondent i received in year x and the number of different practitioners that interviewee i visited last year. Although these variables may be a good proxy for health status, they suffer from important biases such as (i) heterogeneous health utility and (ii) available income concerns. For avoiding these types of problems, we have restricted our health variable selection to the aforementioned items.[47]

Individual Health Insurance related variables

- **Health-ins.** Health-ins is the main variable of interest within our DiD framework. It equals 1 if the respondent owns a private health insurance (either own, or via company/family). This variable has been built using as reference variable hlcvr from survey data.

- **Health-ins-own.** Once again, Health-ins-own is a binary variable which equals 1 if the individual holds a private health insurance at her own name (this is, excluding health insurances via relatives). Although this variable might be more accurate in terms of realized Health Insurance demand, it is only available starting from wave 6 of BHPS. In addition, this variable does not capture the fact that some individuals

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[46] There is an appealing field within Health Economics literature which suggests that officially recognized disabled people tend to overemphasize their limitations to justify their condition. Similar concerns exist regarding unemployed people who find in health problems a suitable justification for their job status (Currie and Madrian, 1999).

[47] Several studies (Lambrinos, 1981; Mossey and Shapiro, 1982) show that results are very dependent to health status characterization.

might be willing to pay more for family premiums in Health Insurance policies as a realization of family utilities. Hence, for a non-working partner, having a Health Insurance via his/her spouse, might suggest that his/her spouse is indeed demanding larger amounts of Health Insurance. Because of these limitations we have finally decided to select Health-ins as our target variable. Note that all the analyses presented in the main body have been also conducted using health-ins-own as dependent variable with very similar results and conclusions.

- **Health-ins-paid.** Health-ins-paid is a non-monotonic categorical variable which specifies the payer of the health insurance (conditioned health-ins-own equals 1). Health insurance in this set-up can either be paid directly (1), deducted from wages (2) or fully paid by employers (3).

- **Health-ins-paid-q.** Finally, Health-ins-paid-q is a continuous variable which reflects the amount of money that individual i is paying for her own health insurance if paid directly by her. Although the quality of this variable is surprisingly high, we only have a non-zero answers for a very small share of the population. Moreover, this variable does not control for the fact that some individuals might (un)consciously employ themselves in companies which pay higher premiums for their Health Insurances. Because survey data does not collect any information on the approximate amount of money that the employer is paying on behalf of the employee for their Health Insurance, we have decided to use Health-ins as the basis of our analysis.

B. ADDITIONAL DATA ANALYSIS APPENDIX

In the following section we present some additional data analyses or some data support to broader claims presented in the main body. Additional analyses are simply presented in the same order as discussed in the main body.

Figure B.1. Region of Origin and Region of Destination Sankey Diagram. Coloring by Region of Destination

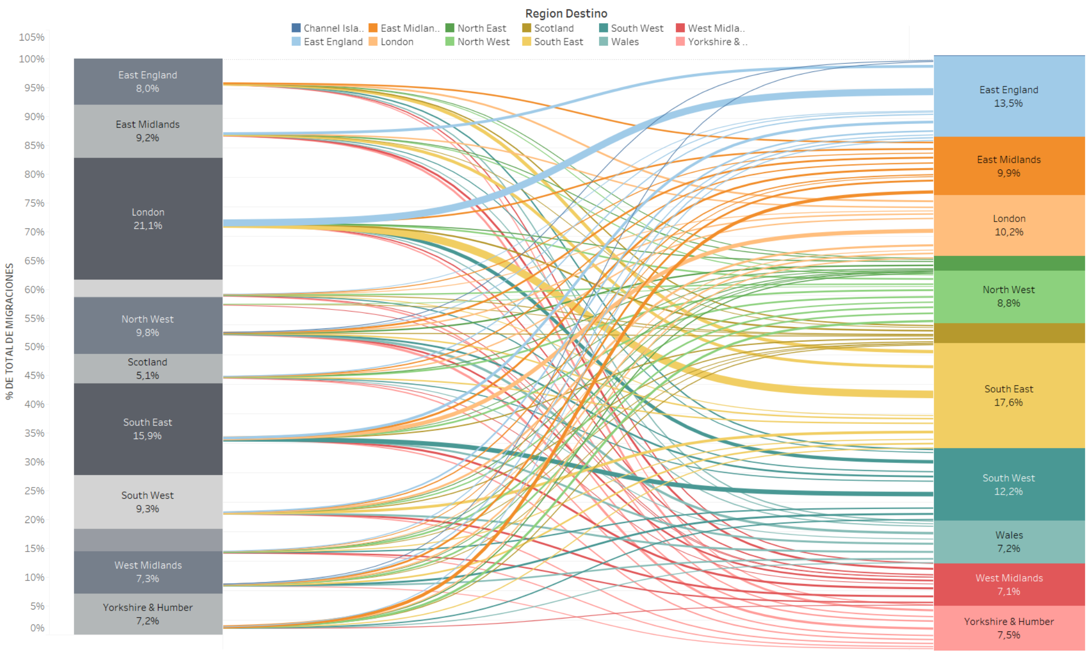
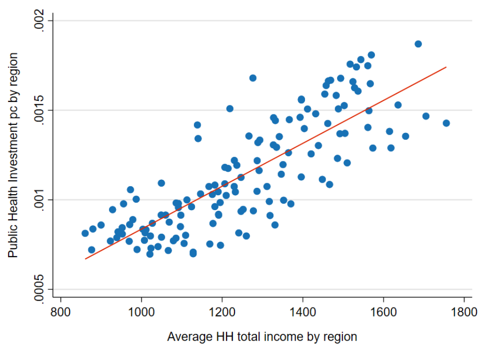
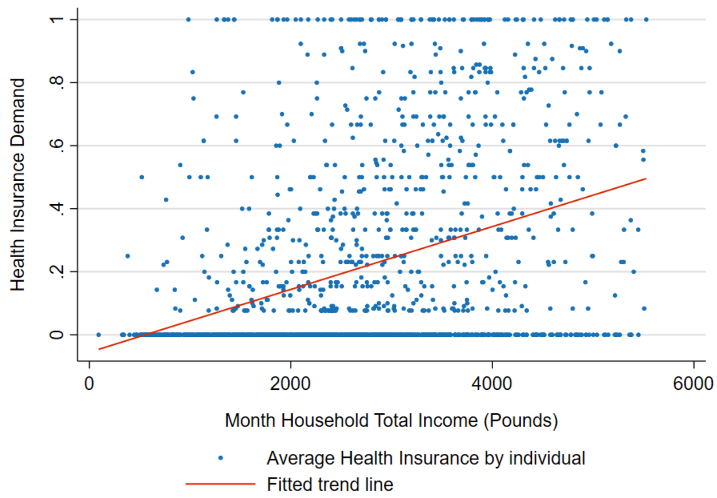


Figure B.2. Public Health Investment per Capita by Region vs Average Household Income by Region



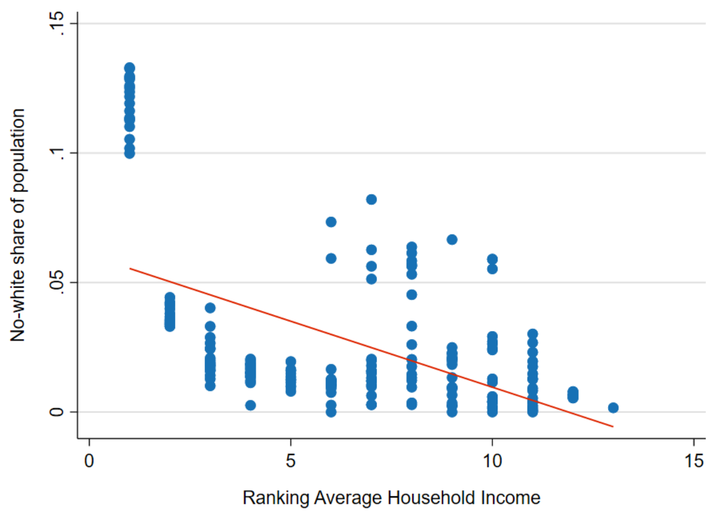
Each point represents one wave-region combination of health investment pc and average household income

Figure B.3. Health Insurance Demand vs Monthly Household Total Income



Each point represents an individual, not an observation. Health Insurance tenancy is presented as the average number of years in which individual i held Health Insurance ($H_{irt} = 1$) or not ($H_{irt} = 0$)

Figure B.4. Average Household Income Regional Ranking vs Share of No-White Citizens Regional Ranking



Each point represents one wave-region combination of household income ranking and share of

non-white in the region

C. ADDITIONAL REGRESSION ANALYSIS APPENDIX

In the following section we present some additional regression analyses or some regression support to broader claims presented in the main body. Additional analyses are simply presented in the same order as discussed in the main body.

Table C.1. Progressive Treatment Benchmark Specifications Excluding London. No Controls

	(All)	(p50)	(p75)
Treatment	-0.012	-0.010	0.002
	(0.015)	(0.021)	(0.033)
Time	0.023*	0.012	0.030
	(0.012)	(0.019)	(0.027)
Time × Treatment	-0.058***	-0.072***	-0.073*
	(0.018)	(0.027)	(0.041)
Constant	0.228***	0.296***	0.337***
	(0.010)	(0.014)	(0.021)
Observations	9592	4552	2332

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: Health Insurance

Figure C.1. DiD Graphical Analysis of All Movers (Excluding London)

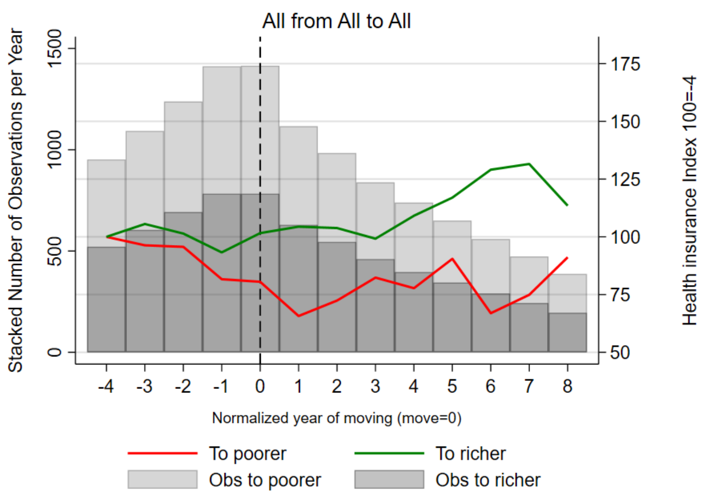


Figure C.2. DiD Graphical Analysis of >p50 Movers (Excluding London)

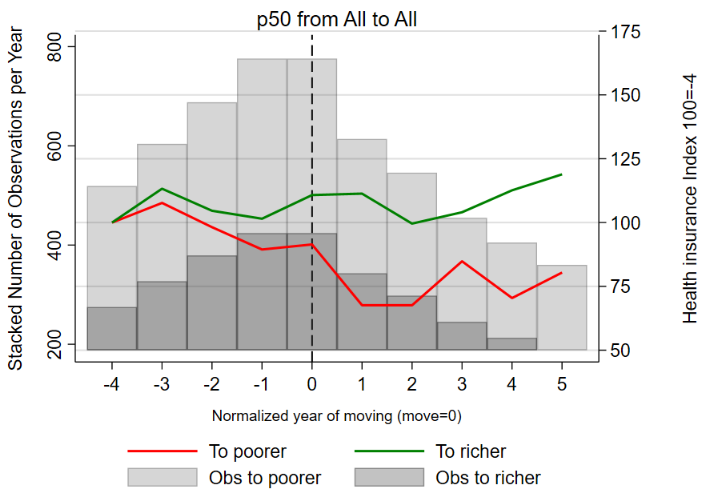


Figure C.3. DiD Graphical Analysis of >p75 Movers (Excluding London)

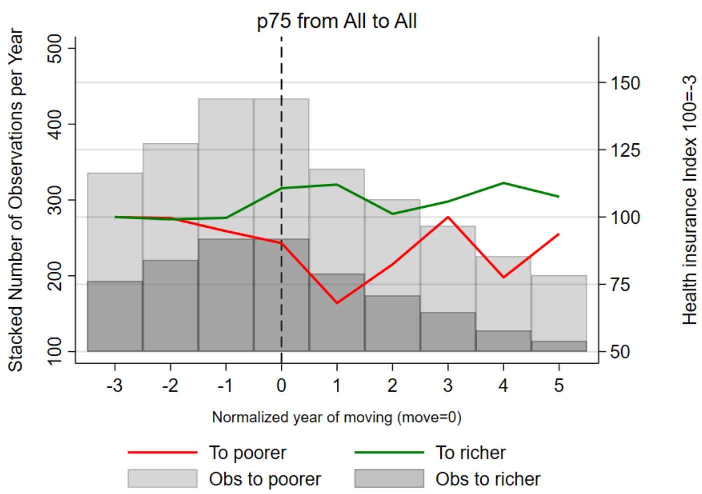


Table C.2. Top-to-Bottom Treatment. Diff ≥ |8| Specifications. Multivariate Regression Analysis

	(1)	(2)	(3)
Time	-0.124*	-0.090	0.002
	(0.067)	(0.089)	(0.100)
Treatment	-0.165**	-0.070	0.105
	(0.072)	(0.099)	(0.200)
Time × Treatment	0.122	-0.051	-0.099
	(0.084)	(0.113)	(0.147)
Age		0.002	-0.009
		(0.009)	(0.010)
Age^2		0.000	0.000*
		(0.000)	(0.000)
Male		-0.081	-0.041
		(0.070)	(0.064)
Married		-0.003	-0.086
		(0.051)	(0.055)
Maxrun		-0.003	-0.011
		(0.005)	(0.008)
Employment		0.014	-0.010
		(0.077)	(0.078)
Monthly job hours		0.000	0.000
		(0.001)	(0.001)
Monthly job $hours^2$		0.000	0.000
		(0.000)	(0.000)
HH Monthly labor income		-0.000***	-0.000**
		(0.000)	(0.000)
HH Monthly labor $income^2$		0.000**	0.000**
		(0.000)	(0.000)
HH Monthly total income		0.000	0.000
		(0.000)	(0.000)
HH Monthly labor $income^2$		-0.000	-0.000
		(0.000)	(0.000)
MCA 1		0.080	0.034
		(0.362)	(0.330)
PCA 1		0.002	-0.014
		(0.213)	(0.198)
Health Investment pc			-112.626
			(137.587)
FE Race	No	Yes	Yes
FE Education	No	Yes	Yes
FE Origin region	No	No	Yes
FE Origin destination	No	No	Yes
Constant	0.333***	0.484**	0.672**
	(0.058)	(0.202)	(0.261)
Observations	488	382	351

Note: *** p<0.01, ** p<0.05, * p<0.10. Dependent variable: Health Insurance

Table C.3. Top-to-Bottom Treatment. Diff ≥ |8| Specifications. PSM-DiD

	Mean	SE	P value	Number of obs
Before				97
Control	0.385***	0.105	0.000	
Treated	0.196***	0.053	0.000	
Diff (T-C)	-0.189	0.118	0.113	
After				190
Control	0.167***	0.045	0.000	
Treated	0.117***	0.031	0.000	
Diff (T-C)	-0.050***	0.054	0.361	
Diff-in-Diff	0.139	0.130	0.285	287

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

Table C.4. Top-to-Bottom Treatment. Diff ≥ |8| Specifications. PSM-DiD with Region Level Controls

	Mean	SE	P value	Number of obs
Before				64
Control	0.341***	0.082	0.000	
Treated	0.207***	0.076	0.009	
Diff (T-C)	-0.135	0.112	0.234	
After				90
Control	0.180***	0.054	0.001	
Treated	0.132***	0.056	0.020	
Diff (T-C)	-0.049	0.077	0.531	
Diff-in-Diff	0.086	0.136	0.529	154

Note: *** p<0.01, ** p<0.05, * p<0.10. SE report robust standard errors

Figure C.4. DiD Graphical Analysis of p50 Movers when Difference > |8|