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Ex Ante Moral Hazard and Anticipatory Behaviour: Some Evidence

Laure B. de Preux

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Abstract

Controversy exists over whether health insurance reduces the individual incentives to invest in prevention activities; there is no consensus on the existence of ex ante moral hazard (EAMH). Past evidence shows that insurance seems to reduce investment in secondary prevention (e.g. check-ups), but have not supported the hypothesis of EAMH in the case of primary prevention (e.g. healthy lifestyles). In this paper, we first review the theoretical predictions in the case of primary and secondary preventions, and their main empirical evidence in the past literature. Then, we extend the general EAMH framework by assuming that healthy lifestyles reduce the probability of illness only in future periods. Assuming that there exists a payoff period before observing the lifestyle consequences, current preventive behaviour will be affected by anticipation of future insurance coverage. We call the effect "anticipatory behaviour" (AB). Therefore, it seems reasonable to test for the existence of EAMH some times before effectively receiving a health insurance. In the United States, Medicare is offered to almost all the population at age of 65. This exogenous variation in health insurance coverage is a natural experiment that allows us to test for EAMH and anticipatory changes in preventive activities. We use the nine waves of the US Health and Retirement Study (HRS) and test whether uninsured individuals change their lifestyle as they approach 65. Our estimates are based on double-robust approach that combine propensity score and regression methods and estimated for three different definitions of the uninsured group. Differences between the insured and uninsured in terms of physical activity and smoking behaviour are similar to the ones predicted by our model of AB. The effect on alcohol drinking behaviour is less clear but DR approach suggests rather the presence of pure EAMH.

1 Introduction

Ex Ante Moral Hazard (EAMH) is the reduction of preventive effort due to health insurance (Arrow, 1963, Pauly, 1968, Shavell, 1979). In the case of illness, the insurance reduces the cost of medical care and may also compensate the individual for her income loss. EAMH assumes that individuals are able to reduce their probability of illness adopting a responsible behaviour, and that these efforts are not directly observable. Theoretical predictions are ambiguous: in their seminal paper, Ehrlich and Becker (1972) concludes that health insurance and preventive effort (referred to as "self-protection") can be complements.

Empirical evidence is also mitigated. Using the only study based on a randomised trial, the RAND experiment, Newhouse & Group (1993) conclude that health insurance does not significantly affect lifestyles. Many authors (Decker, 2005, Card et al., 2004, among others) have used the granting of Medicare at the age of 65 to look at a change in behaviour due to an exogenous change in health insurance. However, it cannot be used as a perfect natural experiment without adjustment because this exogenous change is anticipated.[1] For example, a direct consequence in the case of reimbursed preventive care is that individuals tend to postpone them (e.g. Lichtenberg, 2002) which would bias upwards the effect of insurance on the demand of medical care. The individual anticipation becomes an issue if the benefit of healthy lifestyles are not immediate. In order to test for EAMH, one should take into account that individuals may change their behaviour already before being covered by Medicare because prevention only changes future illness probabilities.

We first develop a theoretical model that extends the classical EAMH framework by taking into account (1) the existence of a payoff period for the benefit of healthy lifestyle and (2) this anticipated insurance coverage. If these assumptions are true, our model predicts that EAMH appears some years before receiving Medicare and that, at the time of the coverage, behaviours have already been adapted.

Second, we test this hypothesis using semi-parametric methods. We combine propensity score and regression methods in a double-robust estimate that is robust if either the selection mechanism or the regression model is correctly specified.

We use the Health and Retirement Study, a biennial survey of Americans of 50 and over. We define the uninsured group based on different definitions that take into account different type of health insurance. We estimate the average effect of

[1]Similarly, when evaluating the New Dear for the Young Unemployment program, Blundell et al. (2004) take into account the possibility that individual could react in anticipation of the program, before being actually eligible.

Medicare and its anticipation effect on the behaviour of the uninsured for different lifestyles: physical activity, drinking and smoking behaviour.

Our results shows that the difference in terms of physical activity and smoking behaviour between the insured and uninsured are in line with the existence EAMH with anticipatory behaviour. Differences in term of smoking are not very significant but rather suggest the presence of pure EAMH.

Our results contribute to the current policy debate on universal coverage. If past evidence has generally rejected the existence of EAMH, insurance coverage may still create incentives to reduce investment in certain types of prevention for a certain part of the population, and this reduction may already appear some times before the receipt of insurance if anticipated.

The structure of the paper is as follows. Section 2 surveys previous economic literature on primary prevention. In Section 3, we present the theoretical model and discuss its predictions. Section 4 discusses the identification approach. Section 5 describes the data, and the empirical results are analysed in Section 6. Finally, Section 7 contains a short conclusion.

2 Insurance and prevention in the literature

Although there is a general consensus on the existence of Ex Post Moral Hazard (EPMH), the existence of EAMH is still debated. In order to understand past evidence of EAMH, one should distinguish between two types of prevention: self-protection, which refers to the individual ability to reduce the probability of illness, and self-insurance, which refers to the individual ability to reduce the size of the future costs of illness. This formal distinction comes from the seminal paper of Ehrlich & Becker (1972). They show that self-insurance and health insurance redistribute income towards the states of good and bad health, whereas self-protection reduces the probability of bad health. This crucial difference leads them to demonstrate that insurance and self-insurance are in theory substitute but that insurance and self-protection can be complements.

The stricto sensu definition of EAMH only concerns activities that reduce the probability of illness, and that are unobserved or uncontractable by the insurance (self-protection). Empirically, self-protection is often associated to (Kenkel, 2000) primary prevention (e.g. lifestyles, vaccinations) whereas self-insurance to secondary prevention (e.g. check-ups, screening procedures) [2], but a clear cate-

[2]There also exists a tertiary prevention that we do not consider here: it consists of all the actions that reduce disability associated with a chronic illness.

gorisation is generally not possible as there are few activities that only affect either the probability or the consequences of illness.

It is crucial to analyse separately the impact of insurance on these two types of prevention as they also often differ in observability and therefore in the extend that they can be controlled by insurance contracts (information asymmetry). Primary prevention is generally not observed and personal investments in those activities are generally not reimbursed.[3] Secondary prevention may be observed by the insurer and eventually reimbursed (Bradley, 2005). A change in secondary prevention, similarly to EPMH, is generally due to a direct price effect of these activities, whereas a change in primary prevention, if not contractible, is due to an indirect effect of insurance. The effect of insurance on non-observed prevention may even be exacerbated if secondary prevention is reimbursed, as the individual will be more likely to demand secondary prevention which reduces the financial consequences of the illness and thus reduces the benefit of investing in primary prevention. This indirect effect of insurance is the EAMH problem. We review here the main evidence of EAMH in the health insurance literature. Therefore, evidence in the case of secondary prevention are instructive but should not be confounded with EAMH.

There is no or very little evidence of EAMH for primary prevention, but an increase in the demand for secondary prevention due to higher insurance coverage is generally observed (Card et al., 2004). Courbage & de Coulon (2004) address both type of prevention: first, to compare the effect of insurance on reimbursed and observable preventive care vs. not observed and not reimbursed care, they estimate the impact of having health insurance on the probabilities of having a breast check and a cervical smear (secondary prevention) vs. the probabilities of exercising and of being a smoker (primary prevention, unobserved and uncovered). Second, in order to take into account unobserved risk aversion that could affect the demand for preventive care and private insurance, they use instrumental variables; they use the political party appurtenance to predict the probability of having insurance. Their results suggest that privately insured individuals compare to individuals only covered by the NHS are significantly more likely to undergo breast screening, but not to have cervical smears, even though both covered by the insurance. The privately insured are also more likely to have a healthier lifestyle.Card et al. (2004) obtained similar results using a regression discontinuity design. Although the probability to visit a doctor increases with coverage, smoking, exercising and the probability of being overweight smoothly evolve with age with no significant

[3]Past literature assumes that lifestyles are not observed and that its costs are not reimbursed, however there is actually the emergence of a new type of health insurance that covers some of the costs of primary prevention.

changes at age 65.

The classical framework to test for the existence of EAMH has been recently extended by Dave and Kaestner (Dave & Kaestner, 2006,2009). They argue for the existence of a direct effect of insurance on behaviour and an indirect effect that goes in the opposite direction: health insurance decreases the incentives to invest in prevention but increases the opportunities to visit the doctor, and greater contact with the medical professionals is likely to influence positively health behaviour. Their empirical approach is based on difference-in-differences (DiD) and difference-in-difference-in-differences (DDD) approaches. Although their evidence of EAMH is relatively weak, it is larger once the positive (indirect) effect of doctor visits is taken into account.

The largest EAMH effect is measured by Stanciole (2007). The author estimates a multivariate probit model where insurance impact the lifestyle choices. This framework supposes that the decision to contract for insurance and the lifestyle choices are sequential but interdependent. His results suggests that insurance strongly encourages heavy smoking, sedentary, and obesity, but insured individuals are less likely to be heavy drinker.

In summary, there exists very little evidence of EAMH. One reason might be that we are omitting part of the whole story. Dave & Kaestner (2009) have suggested that we should account for the indirect effect of doctor advice, Stanciole (2007)'s evidence indicates that there is something that explains the results but that, so far, we haven't controlled for. We are assuming in this paper that this may be due to the anticipation effect, and that the impact of insurance may have already appeared before the change in insurance status. Another explanation may be the existence of positive selection.

Recent theory has suggested the possibility of advantageous selection (Hemenway, 1990, 1992): more risk averse individuals are more likely to be insured and also more likely to invest more in preventive activities. Evidence exists in the case of life insurance (Cawley & Philipson, 1999), long term care insurance (Finkelstein & McGarry, 2006), private insurance (Buchmueller et al., 2008), and car insurance (Chiappori & Salanie, 2000) among others, but it has not been investigated in the case of health insurance so far to our knowledge.

3 The Formal Model

As mentioned above, the formal model of self-insurance, self-protection and health insurance was introduced by Ehrlich & Becker (1972). We modify their model of self-protection and assume that the benefits of lifestyle are not instantaneous but only appear in the future. Consequently, individuals have an incentive to reduce their preventive efforts already before receiving Medicare.

We sketch a very simple model of self-protection where the individual maximises expected utility by choosing her investment in health related behaviour and consumption at each period. Utility is state dependant. In each period, the individual can be either in good health ($h = g$) or in bad health ($h = b$). Expected utility in period t is

$$U_t = [1 - \pi_t(L_{t-1})]u_t^g(L_t, x_t^g, 0) + \pi_t(L_{t-1})u_t^b(L_t, x_t^b, c_t m_t^b) + \delta U_{t+1} \tag{1}$$

where L_t is the lifestyle chosen at period t before the individual knows her health status in that period. The higher L, the more healthy the lifestyle. x_t^h is the commodity good consumed at period t with health status h, m_t is medical care received if ill at time t (otherwise 0) and c_t is the coinsurance rate. π_t is the probability of being sick at time t and depends on L_{t-1}, the lifestyle chosen at period $t-1$. The probability of illness is decreasing in the level of lifestyle, but the marginal effect of lifestyle is decreasing. δ is a discount factor. The budget constraint is given by

$$p_x x_t^h + p_L L_t + c_t p_m m_t^h \leqslant I_t \tag{2}$$

where p_x, p_L, p_m are the constant prices of the commodity good, the lifestyle and medical care respectively and I_t is the exogenous income received at period t with health status h. We assume that the marginal utilities of the commodity good and medical care are positive but decreasing, but that the marginal utility of lifestyles is negative and increasing. We restrict the marginality utility of each type of good to be independent of the consumption of the other goods. We assume that the goods are measured in units that represents a price of 1, so that each price is equal to one. Moreover, we assume that there is no inter-temporal transfer of income (no borrowing or lending). The only inter-temporal effect is the benefit of lifestyle: the investment in lifestyle in period t reduces the probability of sickness in period $t + 1$.

We assume that the individual first chooses the optimal lifestyle for the period t before knowing her health status, and then, once the health status is revealed, chooses the commodity good x_t^h. We assume that the amount of medical care m_t is decided by the doctor in the case of illness. Using the Bellman's Principle, we can solve the maximisation problem backwards. The optimal x_t^h solves

$$Max_{x_t} \;\; u_t^h(L_t^*, x_t^h, m_t^h) \; s.t. \; x_t^h + L_t + c_t m_t^h \leqslant I_t \tag{3}$$

which gives $x_t^{h*} = x_t^h(L_t^*, m_t^h, I_t)$.

The optimal L_t solves

$$\begin{aligned} Max_{L_t} \quad EU_t = \;& [1 - \pi_t(L_{t-1})]u_t^g(I_t - x_t^{g*} - L_t) + \pi_t(L_{t-1})u_t^b(I_t - x_t^{b*} - L_t - c_t m_t) \\ & + \delta\{[1 - \pi_{t+1}(L_t)]u_{t+1}^g(I_t - x_{t+1}^{g*} - L_{t+1}) \\ & + \pi_{t+1}(L_t)u_{t+1}^b(I_t - x_{t+1}^{b*} - L_{t+1} - c_{t+1}m_{t+1})\} \\ & + \delta^2 U_{t+2} \end{aligned} \tag{4}$$

The first order condition (FOC) gives

$$MC_t = \underbrace{\frac{\partial u_t^g}{\partial L_t} + \pi_t \left\{ \frac{\partial u_t^b}{\partial L_t} - \frac{\partial u_t^g}{\partial L_t} \right\}}_{(a)} = -\delta \underbrace{\frac{\partial \pi_{t+1}}{\partial L_t}}_{(b)} \underbrace{\left\{ u_{t+1}^b - u_{t+1}^g \right\}}_{(c)} = MB_t \tag{5}$$

where the LHS represents the marginal cost (MC) and the RHS the marginal benefit at time t with (a) the direct cost of lifestyle on current utility, (b) the marginal productivity of lifestyle, and (c) the future utility gain from better health.

If the individual is insured at time t but the insurance does not reimburse preventive care, insured and uninsured will choose the same level of lifestyle. If the individual is uninsured at time $t+1$, her future benefits of today lifestyle are twofold: the reduction of future probability of illness (b) and the gain from better health as she saves on the medical care consumption (c). However, if the individual is insured in the second period, the latter gain (c) is reduced and is even equal to zero if the individual is fully insured (coinsurance rate equal to zero) which removes all the future benefits of a healthy lifestyle.

In the case of Medicare, time t corresponds to the period before receiving Medicare and time $t+1$ to the period after 65 years when every one is covered by Medicare. The anticipatory effect is even stronger is the lifestyle benefit appears in more than one period. Suppose that the benefits of lifestyles are still perceptible in π_{t+1}, π_{t+2}, π_{t+3}. The FOC in equation 5 becomes now

$$\pi_t \left\{ \frac{\partial u_t^g}{\partial L_t} - \frac{\partial u_t^b}{\partial L_t} \right\} = -\delta \frac{\partial \pi_{t+1}}{\partial L_t} \left\{ u_{t+1}^b - u_{t+1}^g \right\} -\delta^2 \frac{\partial \pi_{t+2}}{\partial L_t} \left\{ u_{t+2}^b - u_{t+2}^g \right\} -\delta^3 \frac{\partial \pi_{t+3}}{\partial L_t} \left\{ u_{t+3}^b - u_{t+3}^g \right\} \tag{6}$$

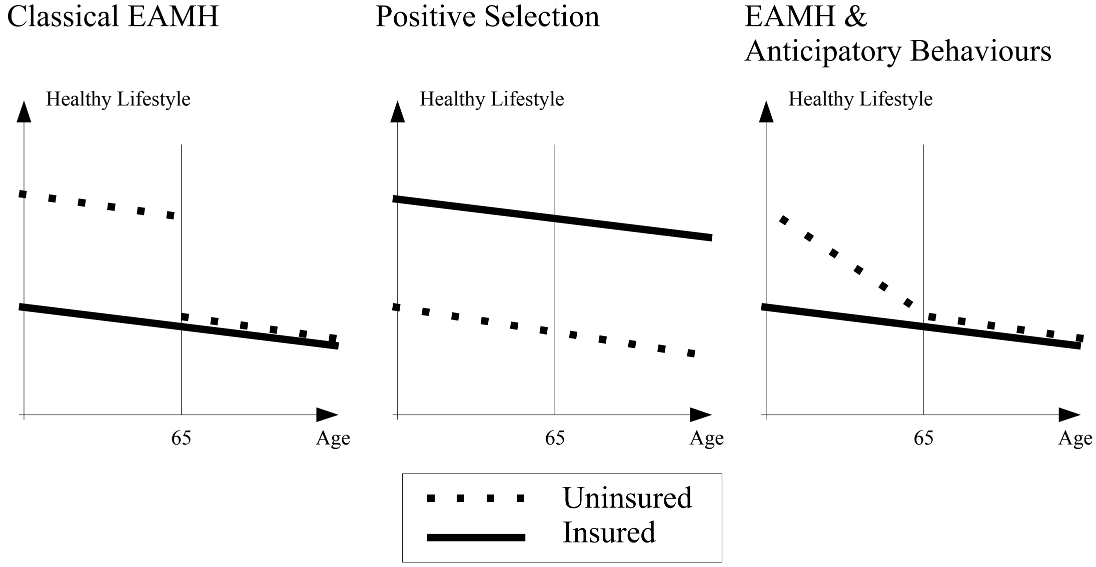
If the individual is uninsured at all periods, her marginal benefit of lifestyle is the marginal productivity of lifestyle and the future utility gain from better health for all the next three periods. However, if she is insured at time $t + 3$ (and she knows it), the marginal benefit of lifestyle is reduced as the difference between u_{t+3}^b and u_{t+3}^g diminishes and is equal to zero in the case of full coverage. The closer the individual is of the time she receives an insurance, the smaller the marginal benefit of healthy lifestyles. Finally, there is no effect of insurance at time t if it does not cover lifestyles. In this paper, we call this phenomena *EAMH with anticipatory behaviour* (AB). Therefore, in the case of Medicare, we expect individuals to reduce their investment in healthy lifestyles the closer they get to 65 years old and to observe no difference afterwards.

Figure 1 illustrate the main possible relationship between lifestyle and insurance. The first graph represents the classical hypothesis of EAMH. Positive selection assumes that insured individuals are more risk averse and thus invest more in prevention at all times. Uninsured individuals, possibly more risk neutral, are not affected by the granting of Medicare. Finally, the last graph illustrates the assumption of EAMH with anticipatory behaviour.

4 Identification strategy

We use the granting of Medicare to almost all Americans at the age 65 to analyse the impact of an anticipated exogenous change in health insurance on lifestyles. Most Americans have a health insurance of some sort before 65 years old (military insurance, insured by their employer, privately purchased, etc.) but a few of them do not have one or it is not continuous and quite uncertain. We use the continuously insured individual as our control group as they have been continuously exposed to the treatment and Medicare only prolongs their health insurance, and the uninsured or temporally insured as our treatment group as they experience an expected change in exposure at the age of 65. In what follows, we will refer to the insured and uninsured to distinguish between the two groups. But this appellation

Figure 1: Ex Ante Moral Hazard - Different Impacts



does not always correspond precisely to the their actual coverage up to age 65, that is, it must be clear that the uninsured actually refers to treated group and that after 65 years, this group is insured.

We seek to measure the average treatment effect (ATE), but, as the uninsured group only represents a sub-sample of the population that is not representative, very often only the average treatment effect on the treated (ATET) is measured, i.e. the impact of having an insurance on the previously uninsured.

The classical EAMH hypothesis postulates that the uninsured will adopt a less healthy lifestyle once insured post 65 because health insurance removes the financial consequences of illness. Dave & Kaestner (2009) among others have used the granting of Medicare to test for a change in lifestyle due to insurance at age 65. However the granting of Medicare cannot be considered as a natural experiment as the change in insurance status is non-random and anticipated. Our theoretical model in Section 3, has shown that, if the consequences of a less cautious lifestyle take some years to appear, individuals who anticipate Medicare will change their lifestyle before 65 years old. As we do not know when the anticipation of Medicare has an effect on lifestyles, if any, we use flexible methods that not only allow us to identify an effect of Medicare on lifestyles before 65 years old (if there is AB), but also after 65 years old (if there is no AB, but a pure EAMH effect). We focus on individuals aged between 59 and 68 years old.

Control and treated groups are defined based on their insurance status between ages 61 and 64 (various definitions are used, they are described in details in Section 5.1). Let U_i be equal to 0 if the individual is assigned to the insured (control) group or equal to 1 if the individual is allocated to the uninsured (treatment) group. Contrary to the classical program evaluation approach, the control group here represents the individuals that have already been treated. The two groups have different treatment status *before* the exogenous change in their health insurance and are all treated *after* 65 years old.

Our model in Section 3 predicts that, if the individual knows that the consequences of her lifestyle will only appear in the future when she is insured, she will reduces today already her investment in healthy lifestyle. However, when she starts decreasing her effort depends on when she believes she will perceive the consequences. As her believes cannot be observed, we implement flexible models allowing for a change in behaviour in at least 6 years before receiving Medicare.[4] Our identification strategy is to measure the impact of age on lifestyles allowing for different effects between the groups at all ages without imposing a specific age at which Medicare could influence the lifestyles of the uninsured. It also allows the identification of the pure EAMH when individuals are fully covered post 65.

The difference between the two groups at the different ages is measured using double-robust estimators. This method combines propensity score and regression methods and remains consistent if either one or the other method is correctly specified (Lunceford & Davidian, 2004).[5] Propensity score methods recreate post-experiment a random allocation to treatment. This is possible if the confounding factors are observable. As insurance group allocation is defined on the basis of insurance coverage between 61 and 64 years old, we use information at the ages 59 and 60 to estimate the propensity score, assuming that the variables at theses ages are not affected by the allocation of the insurance group defined in the future nor the change in health insurance coverage. A drawback of propensity score methods is that they do not allow us to distinguish between the direct effect of insurance and possible indirect effects, for example due to the opportunity to see a doctor that would encourage a healthier behaviour (Dave & Kaestner, 2009). This is however possible using a flexible parametric model.

Regression methods using difference-in-differences (DiD) have been widely used to estimate the impact of a change in policy (Ashenfelter, 1978, Ashenfelter & Card, 1985), and in particular to estimate the impact of Medicare (Dave & Kaestner, 2009, Decker, 2005). The main purpose of the DiD model is to compare the mean of the outcome variable between the two groups before and after the treatment.

[4]We also want to observe the individual just after receiving Medicare to allow for the classical EAMH effect. Ideally, we would of course prefer to observe more time periods before the age of 65 but we are limited by our data and the size of the sample.

[5]In the on-line Appendix, we first implement separately propensity score and regression methods.

Adding interactions terms permits to disentangle direct and indirect effects. We extend Dave & Kaestner (2009)'s approach by allowing for more possible indirect effects and also estimate the models using non-linear models that better fit the data.

As the interviews are conducted every two years, for each method we compare individuals and their lifestyles by couple of years; the effect of insurance on lifestyles is measure at ages 59/60, 61/62, 63/64, 65/66 and 67/68. The main reason for comparing individuals by couple of years is to compare the same group of individuals at all (couple of) ages. Otherwise, some individuals would only be observed at odd ages and the other at even ages. Shall the AB appears before, our empirical approaches would not allow us to identify it.

4.1 Double-Robust Estimator

Rubin (1973) suggests to combine propensity score and covariate adjustment methods to obtain robust and efficient estimators. Based on the work of Robins & Rotnitzky (1995) and Robins et al. (1995), Scharfstein et al. (1999) develop an estimator combining propensity score matching and covariates to adjust for missing outcome variables. Lunceford & Davidian (2004) adapt it to the case of non-random treatment allocation (if the non-random treatment allocation is based on observables). This approach has been referred to in the literature as double-robust as "it remains consistent when either a model for the treatment assignment mechanism (the PS) or a model for the distribution of the counterfactual data is correctly specified" (Bang & Robins, 2005, p.962). In both cases, the unbiasedness of the estimator relies on the ignorability of treatment assignment assumption.

The form of the double-robust estimator is similar to the inverse probability estimator but augmented for an expression involving the predicted values of the regression model that permit to increase efficiency (Lunceford & Davidian, 2004). As we are interested in the impact of insurance at different ages, we estimate the double-robust estimator of the average treatment effect using Emsley et al. (2008)'s implementation but adapt it to measure separately the effect at different ages $a = [59/60, 61/62, 63/64, 65/66, 67/68]$.

$$ATE_{DR,a} = \frac{1}{N}\sum_{i=1}^{N}\frac{U_i L_{i,a} - (U_i - \hat{p}_i)l_{1,a}(X_i)}{\hat{p}_i} - \frac{1}{N}\sum_{i=1}^{N}\frac{(1-U_i)L_{i,a} - (U_i - \hat{p}_i)l_{0,a}(X_i)}{1-\hat{p}_i} \tag{7}$$

where $L_{i,a}$ is the lifestyle of individual i at age a, $l_{U,a}(X) = E(L_i|U_i = U, X_i, Age =$

a) is the predicted (lifestyle) value at ages a of the regression models estimated separately for the insured ($U = 0$) or the uninsured ($U = 1$), and $\hat{p}_i$ is the estimated propensity score.

The estimation of the propensity score is explained in detail in the on-line Appendix. We estimate first the following regression model (1)

$$\begin{aligned} L_{ia} &= \alpha + \beta X_i + \sum_{t=61/62}^{67/68} \eta_t A_{it} + \delta U_i + \sum_{t=61/62}^{67/68} \gamma_t A_{it} U_i + \varepsilon_{ia} \\ & for \;\; i = 1, ..., N \;\; and \;\; a = 59/60, ..., 67/68 \end{aligned} \tag{8}$$

where X_i is a set of covariates including a dummy for doctor visits, A_i are age dummies and $A_i U_i$ is the interaction term between the uninsured group and the age dummies that allow for a different effect of age for the uninsured. In order to allow for the possibility of indirect effect, we extend equation **??** by adding (model 2) an interaction term equal to one if an uninsured individual has seen the doctor after 65 years old ($\beta_{D65U} D65U_i$, see Dave & Kaestner, 2009). Finally, we extend model 2 by replacing the doctor dummy by a set of indicator of doctor visits at the different age range to allow for a different effect of doctor over the ages (model 3).

The sampling variance can be estimated as

$$\begin{aligned} V(ATE_{DR,a}) &= \frac{1}{N^2} \sum_{i=1}^{N} [\frac{U_i L_{i,a} - (U_i - \hat{p}_i) l_{1,a}(X_i)}{\hat{p}_i} \\ &- \frac{(1 - U_i) L_{i,a} - (U_i - \hat{p}_i) l_{0,a}(X_i)}{1 - \hat{p}_i} - ATE_{DR,a}]^2 \end{aligned} \tag{9}$$

Similarly to the DiD approach, the common support of the covariates maybe an issue; the more the confounding factors with lack of overlap between the two groups, the more untrustworthy the model-based extrapolations are (Rubin, 1977) as the effect will be determined by one group or the other depending on its predominance on different regions of the control variables (Lunceford & Davidian, 2004). Therefore, as a final robustness check, we also estimate the model restricting first the controls to the ones having a PS in the range of PS of the uninsured individuals.

5 Data

The Health and Retirement Study (HRS) is a longitudinal household survey that began in 1992 and that has been repeated every two years, adding regularly cohorts to maintain a representative sample of the 50 years old and older population. We use the first nine waves of the HRS and briefly describe here the key data for the analysis.[6]

In order to concentrate on the impact of Medicare on behaviour pre and post 65, we consider only the individuals aged between 59 and 68 years old. We drop individual who do not report Medicare after 65 as these individuals would not anticipate this insurance coverage and thus would bias our results. We also drop disabled at all waves if they report being disabled in at least one wave.

We analyse three types of lifestyle. The physical activity variable is an indicator whether the individual reports having some vigorous physical activities at least three or more times a week.[7] To study the impact of insurance on drinking behaviour, we use an indicator of daily alcohol consumption and a count variable[8] equal to the average daily number of alcoholic drinks per week. Finally, two variables are used to analyse smoking behaviour:[9] the average number of cigarettes smoked per day and a dummy variable indicating whether the individual has quit smoking if she has ever smoked.

5.1 Definitions of the uninsured group

The uninsured group refers to a sub-sample of individuals; a respondent is consider either as insured or uninsured, but this classification does not change with age. In order to measure the sensitivity of our results due to the choice of insurance coverage, we use three different definitions.

The insurance status is based on two indicators of insurance coverage at the ages 61/62 and 63/64 (i.e. for the two interviews preceding the one at 65-66 years). An indicator is equal to one if the individual reports some types of insurance coverage (specified below) for the current period. If the indicator of health insurance is equal to zero for at least one of the two waves before 65/66 years old, the individual is considered as uninsured.[10] There are two main reasons for considering an

[6] More details are provided in the on-line Appendix.

[7] This question has only been asked until wave 6.

[8] It is only measured from the third wave.

[9] The questions about smoking only consider cigarettes and unfortunately no other type of smoking (pipes or cigars).

[10] We have also tried more stringent definitions where the individuals must be uninsured at both waves to be considered as uninsured, but the results remain practically unchanged.

individual as uninsured if she has been uninsured at least for one of the two waves. First we want to considered uninsured individuals for whom Medicare will make the most important change. Second, Schoen & DesRoches (2000) show that people currently uninsured or having been recently uninsured are much more likely to encounter care access and cost problems than the continuously insured. We therefore classify individuals facing the same risk due to their insurance status in the same group.

The three definitions come from three different insurance indicators at the ages 61/62 and 63/64. The first definition (*All Types*) consider all types of health insurance, i.e. it is equal to 1 if the respondent reports any type of insurance either private or public including Medicaid, military insurance or Medicare. The second definition (*Private Only*) captures privately insured individuals only: it is equal to 1 if the individual reports being insured by an employer provided insurance or any other insurance other than provided by the government. The last definition (*Private & Public*) is very similar to *"Private Only"* but also considers the military insurance. Apart from the veteran insurance, the government only provide need-specific[11] insurance coverages before the age of 65. Someone may be covered by Medicaid at the age of 40 because ill and very poor, but may no longer be eligible at the age of 60 because richer. Private insurances are less need-specific and the individual may have it for many years, either because she has a stable job paying for it or because she pays for it without the intention to stop. Similarly, military insurance is provided when the military becomes a veteran and she keeps it until 65 years old. Therefore, this latter definition considers insurances coverages that are less volatile and more independent of the health status compare to the other ones provided by the government. It is a good compromise between the two other and we present the results more specifically for this definition. For all these definitions, life insurance and LTC are not taken into account.

5.2 Descriptive statistics

Descriptive statistics are presented for the 4th wave (1998). Table 1 is for the whole sample whereas Tables 2 and 3 split the sample by uninsured definition.

The characteristics of the two groups are generally significantly different from one another. In terms of physical activity, the insured are more likely to exercise and to smoke less or to have quit smoking. Alcohol consumption is generally not different between the two groups, except that individuals with private type of insurance are more likely to drink alcohol more frequently. However, when

[11]Temporary and only for very specific reasons.

they drink, both groups drink approximately the same. Insured individuals are significantly more likely to have LTC insurance or life insurance. Differences in term of the specific plans vary accordingly to the various definitions.

6 Results

Results using the "Private & Public", "All Types" and "Private Only" definitions are presented in Tables 4, 5 and 6 respectively. For each estimate, we report the ATE, the analytical standard errors, the P-values assuming that the errors are asymptotically normally distributed, and the number of observations used. The regression models are estimate using probit if the dependant variable is binary, or negative binomial if the dependant variable is a count variable. As discussed above, Models 2 and 3 specifically allow for a possible indirect effect of doctor on the uninsured once they receive Medicare.

In the case of vigorous physical activity, the ATE is always negative. The uninsured are less likely to exercise but the difference is generally the largest at 63/64 and/or at 65/66 and reduces by 67/68. In the case of "All Types" definition, the difference is however often the largest around 67/68 suggesting the presence of pure EAMH as well. In any case, the difference is significantly negative at the ages 63/64 and larger than in the previous age range which is the effect to be expected in the case of AB. Observing large differences at the ages 65/66 cannot be disentangle from AB or pure EAMH due to the question referring to the previous 12 months.

Model 1, that does not allow for doctor indirect effect, tends to have lower ATE after 65 and is more likely to reject the assumption of pure EAMH, but as this model is more restrictive, estimates from Models 2 and 3 should be preferred. The effect of being uninsured at the ages 63/64 is about 8 percentage points (difference between the two group in their probability to report vigorous physical activities) using "Private & Public" and "All Types" definitions, and is around 6 percentage points when using the "Private Only" definition.

The probability to quit smoking is significantly smaller for the uninsured group already at the ages 59/60. When significant, the difference varies between 7.6 to 12 percentage points. Then, the negative difference tends to increase with age. In the case of "Private & Public" definition, the difference is about 7.6 percentage points at ages 59/60 and raises up to 38 in Model 3 at the ages 67/68. The estimates based on the CS have a smaller spread, from 12 percentage points at 59/60 to 20.3 at 67/68 based on the same definition. The same pattern is observed using the other definitions although the figures vary. The difference between the groups in term of the number of cigarettes they smoke per day also increases over the years with the uninsured generally more likely to smoke more with a peak at 65/66. Based on the "Private & Public" definition, the uninsured smoke on average 1 cigarettes more than the insured group at the ages 61/62 but up to 5 cigarettes at 65/66 years old. The consumption afterwards remains relatively constant. The same conclusions can be drawn from the two other definitions. This pattern of consumption is precisely the one predicted by EAMH with AB.

Finally, using the most flexible models (3 with or without limiting it to the CS) the difference in the probability to drink daily varies similarly to the one expected in the case of AB and certainly in the case of pure EAMH. Models 1 and 2 produce estimates that are generally not different from zero, however, based on Model 3, uninsured individuals have a significantly higher probability to drink daily already at ages 63/64 but the difference is always larger at the ages 65/66 ranging from 3.3 percentage points based on the "Private Only" definition to 6 using the "All Types" definition. The number of alcoholic drinks is also significantly different between the two groups using Model 3 at ages 65/66 with estimates varying from 1 to 3.9 drinks depending on the definitions and the difference weakly persists in the next age range. This result do not exclude the possibility of EAMH, however it does not support the assumption of AB.

6.1 Summary of the results, discussion and limitations

We use three different definitions to characterise the insured and uninsured groups. We start with semi-parametric approaches to remove the bias pre-treatment associated with observable differences between the insured and uninsured. It allows us to obtain estimates ATET measured in term of the differences and the change in differences between the two groups without imposing a functional form. Then, in order to better understand the underlying mechanisms that could explain these differences, we estimate linear and non-linear models to measure possible indirect effects due to the change in health insurance. Finally, we combine these methods into one estimator that is robust to the miss-specification of one of its two approaches. Our preferred definition is the "Private & Public" as it does not include need-specific and/or temporary health insurance provided by the government (Medicare and Medicaid), but takes into account the military insurance that is generally continuous until the recipe of Medicare. However, the three definitions lead to fairly similar conclusions.

Apart from the MDiD that never lead to significant estimate, all our results support the assumption of EAMH with AB. The probability to exercise at least three times a week shows a significant drop for the uninsured around the ages 63/64 for all the methods that varies between 4 to 8 percentage points or more (CS). The difference remains significant afterwards and is generally higher if we take into account possible positive effect of doctor visits.

The probability to quit smoking is always lower for the uninsured group and the difference tends to increase over the years. Differences are up to 10 percentage points at the ages 59/60 but increase up to 15 at ages 67/68 using either PSM or regression models. It reaches about 40 in the DR approach at the ages 67/68 but about half of this when limiting the sample to the CS which may be less sensitive to the presence of outliers. The difference between the number of cigarettes smoked per day is generally not significant at 59/60, but the difference becomes significant after that and tends to continuously increases. At the ages 67/68, PSM estimates differences smaller than 2 cigarettes, whereas the DR approach estimates the difference around 5 cigarettes which is lower than the DiD estimates. When using the "Private & Public" definition, the difference is the largest at the ages 65/66 and reduces afterwards. The continuous presence of a significant difference between the two groups suggests that propentious selection may be present. However, as the difference increases over time and already before the granting of Medicare, it does not reject either the possibility of EAMH with AB.

Alcohol consumption analysis provides us with much weaker results and it is difficult to disentangle pure EAMH from AB. Apart for the "Private Only" definition, the probability to drink daily is always higher for the uninsured around 63/64 and sometimes thereafter, but tends to zero at 67/68 years old. PSM suggests that the difference is the largest before 65 years old ranging between 1.5 to 3 percentage point, but the difference is never significant in the case of "Private Only"definition. DiD estimates are much higher and the difference is generally the largest around 56/66 years old around 15 percentage points. DR estimates however are never significant before 65. The difference is between 3 to 6 percentage points at ages 65/66 and generally decreases afterwards. Similarly, the number of drinks seems to be higher for the uninsured before 65 years old based on matching, never using regression methods, and generally only significantly higher after 65 based on DR with difference of about 1 drink using "Private & Public" and about 4 using the other two definitions.

One issue that none if these methods can exclude is the possibility of selection on unobservables. Risk aversion certainly affects the decision to contract an insurance and the lifestyle choice.[12] However, if risk aversion is constant over time, it cannot

[12]We have tried to control for income risk aversion but it was never significant and did not

explain the change in differences that we observe at different ages.

Finally, we must say that the main limitation of our approach, similar to other articles using the granting of Medicare to study the impact of change in health insurance is the conclusion that these changes around 65 years old are due to Medicare once we control for the covariates. We have used observational data and cannot guarantee that these effects are not due to another phenomena in the mid 60s.

7 Conclusion

Most of the previous research on EAMH has found very little evidence of the phenomena. We postulate here that this may be due to the choice of experiment: in the case of Medicare, the exogenous change in insurance status for the uninsured at the age of 65 is known and expected. If individuals believe that there exists a payoff period for the benefits of healthy lifestyle and if, in their early 60s, they anticipate that they will soon be covered, then they may reduce their effort to invest in healthy lifestyles already before receiving a health insurance. If this postulate is true, it may explain why past research has failed to identify EAMH.

In this paper, we have first discussed the evidence on the impact of insurance on primary prevention in order to better understand the possible implications of insurance coverage on certain types of prevention. Although insurance generally increases the demand for secondary prevention, there is no consensus in the case a primary prevention, the classical EAMH. Second, we have proposed a simple theoretical model that explains how insurance influences behaviour if it is anticipated and if the benefits of lifestyle are not immediate. Finally, we have applied different identification methods.

The probability to exercise at least 3 times a week differs between the insured and uninsured groups as predicted by EAMH & AB. The difference becomes significantly larger from 63 years old and increases up to 66 and then remains fairly constant. The smoking behaviour, measured by the probability to quit smoking, and the number of cigarette smoked per day cannot exclude the presence of EAMH and AB, but also suggests the presence of propentious selection. Finally the drinking habit, measured by the probability to drink daily and the average number of drinks per week, suggests the presence of pure EAMH although the three empirical approaches provide us with relatively weak estimates. Accounting for a positive effect of doctor visits generally increase the EAMH effect.

affect the results.

Our results cannot be generalised to the whole population. Although in some approaches we have considered the whole sample, descriptive statistics suggest that the two groups are quite different. Matching methods focus on the treated group and try to find similar controls but disregarded the ones that were too different. In the parametric approaches, we always presented the results also limited to the CS and we believe that this results are more reliable (there were also more moderate). Therefore, our results only approximate the ATET.

Our results are in line with past evidence on EAMH; the phenomena may exists from 65 years in some cases and is larger if we account for the indirect effect of Medicare, but the main effect seems to appear before receiving Medicare, possibly due to AB. The classical theoretical framework should be reformulated to account for possible AB and, possibly as well, for the existence of positive selection. Moreover, access to care and doctor advice should be taken into account as they are likely to influence primary prevention (Dave & Kaestner, 2009). A better understanding of these phenomena is necessary for future empirical research.

Table 1: Descriptive Statistics 1

	(1)	(2)	(3)	(4)	(5)
		Wave 4			**All**
	mean	**min**	**max**	**count**	**count**
male	0.460	0	1	5,739	42,832
age	63.230	59	68	5,739	42,832
white	0.837	0	1	5,738	42,820
black	0.133	0	1	5,738	42,820
other	0.030	0	1	5,738	42,820
hispanic	0.070	0	1	5,736	42,806
high school	0.389	0	1	5,730	42,757
some college	0.194	0	1	5,730	42,757
college and above	0.179	0	1	5,730	42,757
married	0.727	0	1	5,739	42,832
partnered	0.027	0	1	5,739	42,832
divorced/separated	0.108	0	1	5,739	42,832
widowed	0.111	0	1	5,739	42,832
works full-time	0.273	0	1	5,739	42,832
works part-time	0.063	0	1	5,739	42,832
unemployed	0.005	0	1	5,739	42,832
partly retired	0.130	0	1	5,739	42,832
retired	0.432	0	1	5,739	42,832
# years worked	33.610	0	55	5,739	42,832
job requires some physical activity	0.166	0	1	5,629	41,700
household total assets (in 1992$)	322,510	-361,509	74,204,064	5,739	38,392
# parents alive	0.276	0	2	5,608	41,626
household's # children	3.449	0	20	5,701	42,358
census: West	0.170	0	1	5,739	42,820
census: South	0.412	0	1	5,739	42,820
SAH	3.263	1	5	5,736	42,811
visited the doctor (2 years)	0.918	0	1	5,679	42,632
Lifestyle					
vigorous physical activity >2/week (waves 1-6)	0.507	0	1	5,737	27,826
has ever smoked cigarettes	0.619	0	1	5,689	42,562
smokes now	0.178	0	1	5,739	42,602
quit smoking	0.710	0	1	3,523	26,124
# cigarettes smoked per day	3.195	0	140	5,739	31,438
has ever drunk alcohol	0.509	0	1	5,739	42,827
drinks daily (waves 4-9)	0.074	0	1	5,739	36,205
# days/week with alcohol (waves 4-9)	1.103	0	7	5,739	36,137
# drinks/day when drinks (waves 4-9)	0.684	0	24	5,722	36,096
# drinks/Week (waves 4-9)	2.534	0	144	5,722	36,076
Covered					
by government	0.448	0	1	5,719	42,666
by CHAMPUS/VA	0.042	0	1	5,720	42,678
by Medicare	0.402	0	1	5,720	42,677
by Medicaid	0.039	0	1	5,717	42,646
by employer	0.578	0	1	5,739	42,832
by other health insurance	0.191	0	1	5,713	42,451
number of insurance plans	0.618	0	4	5,588	39,803
life insurance	0.737	0	1	5,694	42,449
LTC insurance	0.102	0	1	5,562	41,985
Uninsured definitions					
“All Types”	0.153	0	1	4,448	31,941
“Private & Public”	0.205	0	1	4,448	31,941
“Private Only”	0.237	0	1	4,448	31,941

Notes: Columns 1-4 are the descriptive statistics for wave 4, column 5 are the number of observations for all the waves. LTC: Long Terme Care.

Table 2: Descriptive statistics by uninsured groups (Wave 4)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	All Types					Private & Public					Private Only				
	insured		uninsured			insured		uninsured			insured		uninsured		
	count	**mean**	**count**	**mean**	**difference**	**count**	**mean**	**count**	**mean**	**difference**	**count**	**mean**	**count**	**mean**	**difference**
male	3,768	0.480	680	0.443	0.078**	3,538	0.481	910	0.447	0.080***	3,395	0.477	1,053	0.464	0.048*
age	3,768	62.990	680	62.910	0.092	3,538	63.000	910	62.890	0.196	3,395	63.000	1,053	62.900	0.173
white	3,768	0.861	680	0.726	0.126***	3,538	0.872	910	0.719	0.154***	3,395	0.875	1,053	0.730	0.144***
black	3,768	0.117	680	0.222	-0.087***	3,538	0.107	910	0.236	-0.129***	3,395	0.105	1,053	0.223	-0.114***
other	3,768	0.022	680	0.052	-0.039***	3,538	0.021	910	0.045	-0.025***	3,395	0.020	1,053	0.047	-0.030***
Hispanic	3,767	0.044	679	0.187	-0.170***	3,537	0.040	909	0.168	-0.154***	3,394	0.040	1,052	0.149	-0.131***
high school	3,762	0.406	679	0.333	0.074*	3,532	0.409	909	0.341	0.072**	3,390	0.409	1,051	0.351	0.060**
some college	3,762	0.209	679	0.127	0.084***	3,532	0.216	909	0.121	0.0954***	3,390	0.212	1,051	0.148	0.070***
college and above	3,762	0.203	679	0.083	0.148***	3,532	0.213	909	0.072	0.166***	3,390	0.214	1,051	0.088	0.148***
married	3,768	0.764	680	0.596	0.157***	3,538	0.782	910	0.570	0.255***	3,395	0.782	1,053	0.598	0.227***
partnered	3,768	0.021	680	0.046	-0.020*	3,538	0.019	910	0.046	-0.025***	3,395	0.018	1,053	0.045	-0.026***
divorced/separated	3,768	0.097	680	0.156	-0.042*	3,538	0.087	910	0.182	-0.127***	3,395	0.088	1,053	0.164	-0.112***
widowed	3,768	0.096	680	0.165	-0.077***	3,538	0.092	910	0.162	-0.075***	3,395	0.091	1,053	0.154	-0.063***
works full-time	3,768	0.287	680	0.275	0.006	3,538	0.302	910	0.219	0.095***	3,395	0.308	1,053	0.212	0.110***
works part-time	3,768	0.058	680	0.096	-0.041**	3,538	0.058	910	0.086	-0.025*	3,395	0.057	1,053	0.084	-0.019
unemployed	3,768	0.003	680	0.012	-0.013***	3,538	0.003	910	0.009	-0.009**	3,395	0.003	1,053	0.009	-0.009**
partly retired	3,768	0.137	680	0.119	0.031	3,538	0.141	910	0.108	0.0529**	3,395	0.141	1,053	0.111	0.044**
retired	3,768	0.432	680	0.359	0.102***	3,538	0.414	910	0.445	-0.036	3,395	0.410	1,053	0.455	-0.057**
# years worked	3,768	34.900	680	31.420	4.979***	3,538	35.250	910	30.950	7.013***	3,395	35.390	1,053	31.090	6.607***
job requires some physical activity	3,709	0.157	659	0.225	-0.089***	3,480	0.161	888	0.195	-0.012	3,339	0.162	1,029	0.187	0.000
household total assets (in 1992$)	3,768	330,990	680	146,226	191,799***	3,538	345,541	910	136,352	237,049***	3,395	351,785	1,053	144,629	235,281***
# parents alive	3,704	0.295	666	0.246	0.021	3,478	0.304	892	0.220	0.084***	3,337	0.306	1,033	0.227	0.081***
household's # of children	3,748	3.346	672	3.891	-0.926***	3,519	3.311	901	3.887	-0.826***	3,377	3.310	1,043	3.814	-0.720***
census: West	3,768	0.167	680	0.156	0.001	3,538	0.167	910	0.156	0.001	3,395	0.167	1,053	0.159	-0.005
census: South	3,768	0.398	680	0.543	-0.185***	3,538	0.393	910	0.524	-0.141***	3,395	0.383	1,053	0.538	-0.160***
SAH	3,765	3.338	680	3.054	0.341***	3,535	3.402	910	2.878	0.619***	3,392	3.402	1,053	2.949	0.558***
visited the doctor (2 years)	3,741	0.937	668	0.823	0.126***	3,515	0.937	894	0.852	0.085***	3,374	0.939	1,035	0.859	0.081***

Notes: SAH: self-assessed health. Differences between the two groups are tested using t-test assuming equal variances. Stars convention: * for p<.05, ** for p<.01, and *** for p<.001.

Table 3: Descriptive statistics by uninsured groups (continued)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)
	All Types					Private & Public					Private Only				
	insured		**uninsured**			**insured**		**uninsured**			**insured**		**uninsured**		
	count	**mean**	**count**	**mean**	**difference**	**count**	**mean**	**count**	**mean**	**difference**	**count**	**mean**	**count**	**mean**	**difference**
Lifestyle															
vigorous physical activity >2/week (waves 1-6)	3,767	0.525	679	0.457	0.114***	3,537	0.539	909	0.417	0.161***	3,394	0.540	1,052	0.431	0.141***
has ever smoked cigarettes	3,747	0.614	675	0.621	0.008	3,519	0.606	903	0.648	-0.028	3,377	0.603	1,045	0.652	-0.044*
smokes now	3,768	0.154	680	0.260	-0.089***	3,538	0.145	910	0.270	-0.123***	3,395	0.143	1,053	0.260	-0.125***
quit smoking	2,299	0.747	419	0.578	0.150***	2,133	0.760	585	0.579	0.182***	2,037	0.762	681	0.598	0.177***
# cigarettes smoked per day	3,768	2.648	680	4.921	-2.402***	3,538	2.489	910	4.966	-2.759***	3,395	2.478	1,053	4.663	-2.706***
has ever drunk alcohol	3,768	0.537	680	0.406	0.166***	3,538	0.551	910	0.385	0.193***	3,395	0.552	1,053	0.402	0.174***
drinks daily (waves 4-9)	3,768	0.069	680	0.088	-0.007	3,538	0.071	910	0.078	-0.003	3,395	0.071	1,053	0.077	0.003
# days/week with alcohol (waves 4-9)	3,768	1.111	680	1.044	0.182	3,538	1.142	910	0.942	0.284**	3,395	1.147	1,053	0.953	0.298**
# drinks/day when drinks (waves 4-9)	3,758	0.661	677	0.773	-0.066	3,528	0.672	907	0.702	0.037	3,385	0.673	1,050	0.696	0.006
# drinks/Week (waves 4-9)	3,758	2.365	677	2.997	-0.256	3,528	2.398	907	2.711	-0.097	3,385	2.409	1,050	2.630	-0.150
Covered															
by government	3,760	0.420	677	0.323	0.144***	3,530	0.392	907	0.459	-0.093***	3,387	0.368	1,050	0.525	-0.182***
by CHAMPUS/VA	3,762	0.052	677	0.012	0.046***	3,532	0.054	907	0.017	0.047***	3,389	0.026	1,050	0.110	-0.086***
by Medicare	3,761	0.367	678	0.302	0.094***	3,531	0.346	908	0.400	-0.039	3,388	0.347	1,051	0.391	-0.035
by Medicaid	3,760	0.029	677	0.056	-0.007	3,530	0.007	907	0.133	-0.187***	3,387	0.007	1,050	0.117	-0.165***
by employer	3,768	0.675	680	0.165	0.606***	3,538	0.709	910	0.163	0.633***	3,395	0.733	1,053	0.158	0.646***
by other health insurance	3,755	0.198	677	0.111	0.159***	3,526	0.203	906	0.114	0.171***	3,383	0.206	1,049	0.116	0.170***
number of insurance plans	3,663	0.725	673	0.168	0.651***	3,437	0.762	899	0.164	0.674***	3,294	0.788	1,042	0.163	0.690***
life insurance	3,745	0.792	676	0.543	0.297***	3,517	0.806	904	0.552	0.319***	3,376	0.804	1,045	0.591	0.279***
LTC insurance	3,649	0.115	658	0.041	0.097***	3,419	0.118	888	0.047	0.089***	3,279	0.118	1,028	0.056	0.086***
Uninsured definitions															
"All Types"	3,768	0.000	680	1.000	-0.909***	3,538	0.000	910	0.747	-0.652***	3,395	0.000	1,053	0.646	-0.559***
"Private & Public"	3,768	0.061	680	1.000	-0.854***	3,538	0.000	910	1.000	-0.895***	3,395	0.000	1,053	0.864	-0.779***
"Private Only"	3,768	0.099	680	1.000	-0.819***	3,538	0.040	910	1.000	-0.858***	3,395	0.000	1,053	1.000	-0.880***

Notes: LTC: long-term care. Differences between the two groups are tested using t-test assuming equal variances. Stars convention: * for p<.05, ** for p<.01, and *** for p<.001.

Table 4: DR approach - "Private & Public" definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Vigorous physical activity				**Quit smoking**				**Drink daily**				**# cigarettes smoked per day**				**# alcoholic drinks per week**			
	ATE	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**
Model 1																				
age 59/60	-0.005	0.022	0.812	5,231	-0.076	0.027	0.005	3,526	-0.005	0.015	0.743	3,852	0.261	0.526	0.619	2,926	0.312	0.422	0.460	3,841
age 61/62	-0.040	0.025	0.105	4,335	-0.063	0.027	0.020	3,373	0.004	0.013	0.766	4,634	1.088	0.515	0.035	3,740	25.319	25.166	0.314	4,616
age 63/64	-0.080	0.029	0.005	3,517	-0.115	0.029	0.000	3,065	0.012	0.014	0.381	5,026	1.379	0.521	0.008	4,147	-0.297	0.330	0.368	5,010
age 65/66	-0.058	0.034	0.082	2,345	-0.109	0.032	0.001	2,356	0.005	0.015	0.734	3,868	1.585	0.476	0.001	3,868	0.005	0.416	0.991	3,860
age 67/68	-0.011	0.046	0.802	1,478	-0.141	0.036	0.000	1,779	-0.008	0.015	0.578	2,982	1.459	0.430	0.001	2,982	-3.767	4.254	0.376	2,977
Model 2																				
age 59/60	-0.078	0.022	0.000	5,231	-0.077	0.027	0.004	3,526	0.038	0.015	0.009	3,852	0.692	0.527	0.189	2,926	0.854	0.430	0.047	3,841
age 61/62	-0.042	0.025	0.093	4,335	-0.064	0.027	0.017	3,373	0.004	0.013	0.744	4,634	1.110	0.516	0.031	3,740	31.062	30.864	0.314	4,616
age 63/64	-0.082	0.029	0.004	3,517	-0.117	0.029	0.000	3,065	0.013	0.014	0.362	5,026	1.413	0.522	0.007	4,147	-0.256	0.327	0.434	5,010
age 65/66	-0.130	0.034	0.000	2,345	-0.167	0.032	0.000	2,356	0.012	0.015	0.421	3,868	2.055	0.477	0.000	3,868	0.473	0.428	0.270	3,860
age 67/68	-0.089	0.046	0.050	1,478	-0.205	0.036	0.000	1,779	-0.002	0.015	0.890	2,982	1.984	0.430	0.000	2,982	-3.344	4.560	0.463	2,977
Model 3																				
age 59/60	-0.073	0.022	0.001	5,231	-0.076	0.027	0.004	3,526	0.008	0.014	0.571	3,852	0.335	0.525	0.523	2,926	0.243	0.423	0.565	3,841
age 61/62	-0.045	0.025	0.074	4,335	-0.061	0.027	0.023	3,373	0.003	0.013	0.797	4,634	1.117	0.516	0.030	3,740	27.549	27.431	0.315	4,616
age 63/64	-0.079	0.029	0.006	3,517	-0.123	0.029	0.000	3,065	0.015	0.014	0.271	5,026	1.476	0.525	0.005	4,147	-0.131	0.320	0.683	5,010
age 65/66	-0.101	0.034	0.003	2,345	-0.345	0.032	0.000	2,356	0.035	0.015	0.017	3,868	4.499	0.481	0.000	3,868	1.004	0.434	0.021	3,860
age 67/68	-0.060	0.046	0.189	1,478	-0.380	0.036	0.000	1,779	0.021	0.015	0.169	2,982	4.411	0.437	0.000	2,982	-2.258	4.292	0.599	2,977
Model 3-CS																				
age 59/60	-0.062	0.023	0.006	5,193	-0.120	0.027	0.000	3,496	-0.007	0.015	0.652	3,794	0.724	0.532	0.173	2,895	0.081	0.411	0.845	3,800
age 61/62	-0.043	0.025	0.086	4,307	-0.053	0.027	0.049	3,340	0.001	0.013	0.917	4,562	1.519	0.524	0.004	3,697	0.291	0.583	0.617	4,570
age 63/64	-0.079	0.029	0.006	3,497	-0.118	0.029	0.000	3,039	0.010	0.014	0.478	4,969	1.357	0.531	0.011	4,110	-0.244	0.311	0.432	4,971
age 65/66	-0.032	0.034	0.339	2,332	-0.177	0.032	0.000	2,337	0.046	0.015	0.002	3,834	5.189	0.487	0.000	3,843	1.587	0.371	0.000	3,835
age 67/68	-0.009	0.046	0.851	1,474	-0.203	0.035	0.000	1,766	0.032	0.015	0.030	2,956	5.076	0.449	0.000	2,963	1.395	0.331	0.000	2,958

Notes: The regression models used with binary and count dependant variables are probit and negative binomial respectively. CS: the sample is restricted to the common support.

Table 5: DR estimates - "All Types" definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Vigorous physical activity				**Quit smoking**				**Drink daily**				**# cigarettes smoked per day**				**# alcoholic drinks per week**			
	ATE	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**
Model 1																				
age 59/60	-0.017	0.023	0.470	5,231	0.034	0.029	0.230	3,525	-0.007	0.014	0.595	3,850	0.207	0.589	0.726	2,926	0.416	0.508	0.413	3,841
age 61/62	0.000	0.026	0.993	4,335	-0.072	0.029	0.013	3,368	0.014	0.014	0.341	4,631	1.556	0.585	0.008	3,740	8.881	8.702	0.307	4,616
age 63/64	-0.086	0.030	0.004	3,517	-0.131	0.030	0.000	3,058	0.034	0.017	0.041	5,021	1.933	0.575	0.001	4,147	0.070	0.364	0.848	5,010
age 65/66	-0.043	0.035	0.228	2,345	-0.123	0.032	0.000	2,349	0.014	0.016	0.385	3,864	1.916	0.538	0.000	3,868	0.121	0.465	0.794	3,860
age 67/68	-0.046	0.048	0.330	1,478	-0.172	0.036	0.000	1,776	0.005	0.019	0.804	2,982	1.863	0.504	0.000	2,982	-3.037	3.642	0.404	2,977
Model 2																				
age 59/60	0.012	0.023	0.600	5,231	-0.104	0.029	0.000	3,525	0.049	0.014	0.000	3,850	0.482	0.590	0.414	2,926	0.926	0.512	0.070	3,841
age 61/62	-0.002	0.026	0.945	4,335	-0.074	0.029	0.010	3,368	0.014	0.014	0.309	4,631	1.581	0.586	0.007	3,740	11.069	10.836	0.307	4,616
age 63/64	-0.088	0.029	0.003	3,517	-0.134	0.030	0.000	3,058	0.036	0.017	0.034	5,021	1.964	0.575	0.001	4,147	0.122	0.361	0.735	5,010
age 65/66	-0.104	0.036	0.004	2,345	-0.184	0.032	0.000	2,349	0.029	0.016	0.068	3,864	2.254	0.538	0.000	3,868	0.683	0.479	0.154	3,860
age 67/68	-0.113	0.047	0.017	1,478	-0.237	0.036	0.000	1,776	0.019	0.019	0.322	2,982	2.191	0.505	0.000	2,982	-2.717	3.947	0.491	2,977
Model 3																				
age 59/60	-0.055	0.023	0.017	5,231	-0.107	0.029	0.000	3,525	0.012	0.014	0.370	3,850	0.056	0.583	0.924	2,926	-0.479	0.502	0.339	3,841
age 61/62	-0.004	0.026	0.873	4,335	-0.068	0.029	0.017	3,368	0.013	0.014	0.360	4,631	1.554	0.584	0.008	3,740	7.478	7.389	0.312	4,616
age 63/64	-0.087	0.030	0.003	3,517	-0.143	0.030	0.000	3,058	0.039	0.017	0.020	5,021	2.122	0.579	0.000	4,147	0.289	0.352	0.412	5,010
age 65/66	-0.088	0.036	0.014	2,345	-0.364	0.032	0.000	2,349	0.045	0.016	0.005	3,864	5.069	0.544	0.000	3,868	3.941	0.519	0.000	3,860
age 67/68	-0.097	0.047	0.041	1,478	-0.409	0.036	0.000	1,776	0.037	0.019	0.056	2,982	4.597	0.510	0.000	2,982	1.331	3.255	0.683	2,977
Model 3-CS																				
age 59/60	-0.058	0.023	0.013	5,207	-0.096	0.028	0.001	3,502	-0.008	0.014	0.547	3,801	1.186	0.589	0.044	2,899	-0.417	0.514	0.418	3,809
age 61/62	0.001	0.025	0.960	4,319	-0.058	0.028	0.039	3,349	0.010	0.014	0.461	4,571	1.192	0.595	0.045	3,707	0.761	0.916	0.406	4,582
age 63/64	-0.083	0.029	0.005	3,505	-0.135	0.030	0.000	3,045	0.033	0.017	0.049	4,978	1.863	0.592	0.002	4,123	0.177	0.368	0.630	4,985
age 65/66	-0.088	0.036	0.013	2,338	-0.180	0.031	0.000	2,343	0.060	0.016	0.000	3,839	3.349	0.559	0.000	3,852	3.305	0.495	0.000	3,844
age 67/68	-0.097	0.048	0.042	1,476	-0.216	0.035	0.000	1,771	0.051	0.019	0.007	2,963	3.235	0.534	0.000	2,970	3.038	0.387	0.000	2,965

Notes: The regression models used with binary and count dependant variables are probit and negative binomial respectively. CS: the sample is restricted to the common support.

Table 6: DR estimates - "Private Only" definition

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)	(19)	(20)
	Vigorous physical activity				**Quit smoking**				**Drink daily**				**# cigarettes smoked per day**				**# alcoholic drinks per week**			
	ATE	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**	**ATE**	**se**	**P-value**	**N**
Model 1																				
age 59/60	-0.010	0.019	0.575	5,231	0.010	0.024	0.693	3,526	-0.010	0.011	0.346	3,852	1.056	0.538	0.050	2,926	0.232	0.354	0.513	3,841
age 61/62	-0.022	0.022	0.322	4,335	-0.063	0.025	0.011	3,373	-0.003	0.010	0.737	4,634	1.354	0.478	0.005	3,740	158.174	157.818	0.316	4,616
age 63/64	-0.061	0.025	0.016	3,517	-0.110	0.026	0.000	3,065	0.008	0.011	0.489	5,026	1.418	0.524	0.007	4,147	-0.132	0.262	0.615	5,010
age 65/66	-0.053	0.030	0.071	2,345	-0.092	0.028	0.001	2,356	0.002	0.012	0.838	3,868	1.152	0.397	0.004	3,868	0.070	0.420	0.868	3,860
age 67/68	-0.015	0.040	0.706	1,478	-0.106	0.031	0.001	1,779	-0.006	0.013	0.676	2,982	0.978	0.360	0.007	2,982	-6.528	7.792	0.402	2,977
Model 2																				
age 59/60	-0.067	0.019	0.000	5,231	-0.080	0.024	0.001	3,526	-0.010	0.011	0.354	3,852	1.071	0.539	0.047	2,926	0.723	0.368	0.049	3,841
age 61/62	-0.023	0.022	0.303	4,335	-0.064	0.025	0.010	3,373	-0.003	0.010	0.751	4,634	1.371	0.478	0.004	3,740	188.302	187.907	0.316	4,616
age 63/64	-0.062	0.025	0.014	3,517	-0.112	0.026	0.000	3,065	0.008	0.011	0.476	5,026	1.443	0.524	0.006	4,147	-0.108	0.260	0.678	5,010
age 65/66	-0.105	0.030	0.000	2,345	-0.150	0.028	0.000	2,356	0.007	0.012	0.555	3,868	1.550	0.398	0.000	3,868	0.507	0.466	0.277	3,860
age 67/68	-0.071	0.040	0.072	1,478	-0.169	0.031	0.000	1,779	-0.001	0.013	0.929	2,982	1.401	0.361	0.000	2,982	-5.969	8.314	0.473	2,977
Model 3																				
age 59/60	-0.010	0.019	0.575	5,231	-0.079	0.024	0.001	3,526	-0.012	0.011	0.259	3,852	1.022	0.535	0.056	2,926	0.209	0.360	0.561	3,841
age 61/62	-0.025	0.022	0.269	4,335	-0.062	0.025	0.011	3,373	-0.004	0.010	0.707	4,634	1.391	0.478	0.004	3,740	174.867	174.532	0.316	4,616
age 63/64	-0.060	0.025	0.017	3,517	-0.115	0.026	0.000	3,065	0.010	0.011	0.371	5,026	1.475	0.525	0.005	4,147	-0.040	0.256	0.877	5,010
age 65/66	-0.090	0.030	0.003	2,345	-0.205	0.028	0.000	2,356	0.050	0.012	0.000	3,868	2.648	0.399	0.000	3,868	0.788	0.472	0.095	3,860
age 67/68	-0.055	0.040	0.167	1,478	-0.218	0.031	0.000	1,779	0.039	0.013	0.003	2,982	2.413	0.363	0.000	2,982	-4.925	7.927	0.534	2,977
Model 3-CS																				
age 59/60	-0.033	0.019	0.080	5,189	-0.076	0.024	0.002	3,499	-0.012	0.011	0.264	3,792	0.398	0.545	0.465	2,894	-0.487	0.316	0.123	3,798
age 61/62	-0.023	0.023	0.304	4,302	-0.056	0.025	0.023	3,343	-0.006	0.010	0.536	4,559	1.268	0.487	0.009	3,694	0.630	0.717	0.379	4,567
age 63/64	-0.061	0.025	0.017	3,494	-0.109	0.026	0.000	3,040	0.006	0.011	0.614	4,966	1.400	0.526	0.008	4,107	-0.225	0.253	0.374	4,968
age 65/66	-0.085	0.030	0.005	2,332	-0.307	0.028	0.000	2,335	0.033	0.012	0.007	3,830	4.547	0.407	0.000	3,839	1.803	0.311	0.000	3,831
age 67/68	-0.049	0.040	0.216	1,472	-0.320	0.031	0.000	1,767	0.026	0.013	0.045	2,952	4.206	0.375	0.000	2,959	1.718	0.309	0.000	2,954

Notes: The regression models used with binary and count dependant variables are probit and negative binomial respectively. CS: the sample is restricted to the common support.

References

Ai, C. & Norton, E. C. (2003). Interaction terms in logit and probit models. *Economics Letters*, 80, 123–129.

Arrow, K. J. (1963). Uncertainty and the welfare economics of medical care. *The American Economic Review*, 53(5), 34.

Ashenfelter, O. (1978). Estimating the effect of training programs on earnings. *The Review of Economics and Statistics.*

Ashenfelter, O. & Card, D. (1985). Using the longitudinal structure of earnings to estimate the effect of training programs. *The Review of Economics and Statistics*, 67(4), 648–60.

Bang, H. & Robins, J. (2005). Doubly robust estimation in missing data and causal inference models. *Biometrics*, 61, 962–972.

Becker, S. O. & Ichino, A. (2002). Estimation of average treatment effects based on propensity scores. *The Stata Journal*, 2(4), 20.

Blundell, R., Dias, M., Meghir, C., & Reenen, J. (2004). Evaluating the employment impact of a mandatory job search program. *Journal of the European Economic Association*, 2(4), 569–606.

Blundell, R. & Dias, M. C. (2008). Alternative approaches to evaluation in empirical microeconomics. *cemmap working paper*, (26), 125.

Bradley, R. (2005). A semi-parametric model for asymmetric information in health plan markets. *Economic Inquiry*, 43(4), 812–822.

Buchmueller, T. C., Fiebig, D., Jones, G., & Savage, E. (2008). Advantageous selection in private health insurance: The case of australia. *CHERE Working Paper*, 2, 1–35.

Caliendo, M. & Kopeinig, S. (2005). Some practical guidance for the implementation of propensity score matching. *IZA Discussion Paper*, 1588, 1–32.

Cameron, A. C. & Triverdi, P. (2005). Microeconometrics: Methods and applications. *Cambridge: Cambridge University Press.*

Card, D., Dobkin, C., & Maestas, N. (2004). The impact of nearly universal insurance coverage on health care utilization and health: Evidence from medicare. *NBER Working Paper Series*, 10365.

Cawley, J. & Philipson, T. (1999). An empirical examination of information barriers to trade in insurance. *The American Economic Review*, 89(4), 827–46.

Chiappori, P. & Salanie, B. (2000). Testing for asymmetric information in insurance markets. *Journal of Political Economy*, 108, 56–78.

Courbage, C. & de Coulon, A. (2004). Prevention and private health insurance in the u.k. *The Geneva Papers on Risk and Insurance*, 29(4), 719–727.

Dave, D. & Kaestner, R. (2006). Health insurance and ex ante moral hazard: Evidence from medicare. *NBER Working Paper Series*, 12764.

Dave, D. & Kaestner, R. (2009). Health insurance and ex ante moral hazard: evidence from medicare. *International Journal of Health Care Finance and Economics*, 9(4), 1–24.

Decker, S. L. (2005). Medicare and the health of women with breast cancer. *The Journal of Human Resources*, 40(4), 948–968.

Dehejia, R. & Wahba, S. (1999). Causal effects in nonexperimental studies: Reevaluating the evaluation of training programs. *Journal of the American Statistical Association*, 94(448), 1053–1062.

Dehejia, R. & Wahba, S. (2002). Propensity score-matching methods for nonexperimental causal studies. *The Review of Economics and Statistics*, 84(1), 151–161.

Drake, C. (1993). Effects of misspecification of the propensity score on estimators of treatment effect. *Biometrics*, 49, 1231–1236.

Ehrlich, I. & Becker, G. S. (1972). Market insurance, self-insurance, and self-protection. *The Journal of Political Economy*, 80(4), 623–648.

Eichler, M. & Lechner, M. (2002). An evaluation of public employment programmes in the east german state of sachsen-anhalt. *Labour Economics*, 9, 143–186.

Emsley, R., Lunt, M., Pickles, A., & Dunn, G. (2008). Implementing double-robust estimators of causal effects. *The Stata Journal*, 8(3), 334–353.

Finkelstein, A. & McGarry, K. (2006). Multiple dimensions of private information: Evidence from the long-term care insurance. *The American Economic Review*, 96(4), 938–58.

Heckman, J., Ichimura, H., Smith, J., & Todd, P. (1998). Characterizing selection bias using experimental data. *Econometrica*, 66(5), 1017–1098.

Heckman, J. J., Ichimura, H., & Todd, P. E. (1997). Matching as an econometric evaluation estimator: Evidence from evaluating a job training programme. *The Review of Economics Studies*, 64(4), 51.

Hemenway, D. (1990). Propitious selection. *The Quarterly Journal of Economics*, 105(4), 1063–1069.

Hemenway, D. (1992). Propitious selection in insurance. *Journal of Risk and Uncertainty*, 5(3), 247–51.

Imai, K., King, G., & Stuart, E. A. (2008). Misunderstandings between experimentalists adn observationalist about causal inference. *Journal of the Royal Statistical Society*, 171(2), 481–502.

Imbens, G. (2004). Nonparametric estimation of average treatment effects under exogeneity: A review. *Review of Economics and Statistics*, 86(1), 4–29.

Imbens, G. M. & Wooldridge, J. M. (2008). Recent developments in the econometrics of program evaluation. *Working Paper*, 14251.

Kenkel, D. S. (2000). Prevention. *Handbook of Health Economics*, (Chapter 31), 1675–720.

Lichtenberg, F. (2002). The effects of medicare on health care utilization and outcomes. *Frontiers in Health Policy Research*, 5(3).

Lunceford, J. K. & Davidian, M. (2004). Stratification and weighting via the propensity score in estimation of causal treatment effects: a comparative study. *Statist. Med.*, 23(19), 2937–2960.

Moreno-Serra, R. (2007). Matching estimators of average treatment effects: a review applied to the evaluation of health care programmes. *HEDG Working Paper*.

Moreno-Serra, R. (2009). Health programme evaluation by propensity score matching: Accounting for treatment intensity and health externalities with an application to brazil. *HEDG Working Paper*, (09/05).

Newhouse, J. P. & Group, T. I. E. (1993). Free for all? lessons from the rand heatlh insurance experiment. *Harvard University Press*.

Pauly, M. (1968). The economics of moral hazard: Comment. *The American Economic Review*, 58(3), 531–7.

Puhani, P. A. (2008). The treatment effect, the cross difference, and the interaction term in nonlinear "difference-in-differences" models. *IZA Discussion Paper*, 3478, 1–10.

Robins, J. & Rotnitzky, A. (1995). Semiparametric efficiency in multivariate regression models with missing data. *Journal of the American Statistical Association*, 90(429), 122–129.

Robins, J., Rotnitzky, A., & Zhao, L. (1995). Analysis of semiparametric regression models for repeated outcomes in the presence of missing data. *Journal of the American Statistical Association*, 90(429), 106–21.

Rosenbaum, P. & Rubin, D. (1984). Reducing bias in observational studies using subclassification on the propensity score. *Journal of the American Statistical Association*, 79(387), 616–524. Discusses missing values.

Rosenbaum, P. R. & Rubin, D. B. (1983). The central role of the propensity score in observational studies for causal effects. *Biometrika*, 70(1), 41–55. Seminal Paper on Propensity Score.

Rosenbaum, P. R. & Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *The American Statistician*, 39(1), 33–8.

Rubin, D. & Thomas, N. (1996). Matching using estimated propensity scores: Relating theory to practice. *Biometrics*, 52(1), 249–264.

Rubin, D. B. (1974). Estimating causal effects of treatments in randomized and nonrandomized studies. *Journal of Educational Psychology*, 66(5), 688–701.

Rubin, D. B. (1977). Assignement to treatment group on the basis of a covariate. *Journal of Educational Statistics*, 2, 1–26.

Rubin, D. B. (1997). Estimating causal effects from large data sets using propensity scores. *Annals of Internal Medicine*, 127, 757–763. Easy to read.

Scharfstein, D., Rotnitzky, A., & Robins, J. (1999). Adjusting for nonignorable drop-out using semiparametric nonresponse models. *Journal of the American Statistical Association*, 94(448), 1096–120.

Schoen, C. & DesRoches, C. (2000). Role of insurance in promoting access to care - uninsured and unstably insured: The importance of continuous insurance coverage. *Health Services Research*, 35(1).

Shavell, S. (1979). On moral hazard and insurance. *The Quarterly Journal of Economics*, 93(4), 541–562.

Smith, J. A. & Todd, P. E. (2005). Does matching overcome lalonde's critique of nonexperimental estimators? *Journal of Econometrics*, 125, 305–353.

Stanciole, A. (2007). Health insurance and life style choices: Identifying the ex ante mh. *IRISS Working Papers*, (2007-10).

Todd, P. (2008). Matching estimators. *The New Palgrave - A Dictionary of Economics Online*, Second Edition.

A List of Acronyms

AB	Anticipatory Behaviour
ATE	Average Treatment Effect
ATET	Average Treatment Effect on the Treated
BRFSS	Behavioural Risk Factor Surveillance System (a telephone survey)
BS	Balanced Sample
CSA	Common Support Assumption
DiD	Difference-in-Differences
DR	Double-Robust
EAMH	Ex Ante Moral Hazard
EPMH	Ex Post Moral Hazard
FOC	First Order Condition
HIE	Health Insurance Experiment
HMO	Health Maintenance Organisation
HRS	Health and Retirement Study
IPW	Inverse Probability Weight
IV	Instrumental Variable(s)
LHS	Left Hand Side
MB	Marginal Benefit
MC	Marginal Cost
NHS	National Health Service (UK)
PA	Physical Activity
PSID	Panel Study of Income Dynamics
PSM	Propensity Score Matching
RAND	Research ANd Development Coporation
RHS	Right Hand Side
UBS	Unbalanced Sample