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Does employment-based private health insurance increase the use of covered health care services? A matching estimator approach

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Abstract This study estimates the effect of employment-based private health insurance (EPHI) on the use of covered health care services based on Danish survey data collected in 2009. The paper provides some of the first estimates of how EPHI affects the use of health care services in a Scandinavian context. The effect of EPHI is estimated using propensity score matching. This method is shown to provide plausible estimates given the institutional setting of EPHI in Denmark and a wide set of relevant covariates. Considering the full sample of occupationally active, it is found that EPHI does not significantly affect the probability of having had any hospitalisations, physiotherapist, chiropractor, psychologist, specialist, or ambulatory contacts within a 12 month period. Restricting the analysis to the subsample of privately employed, the estimated effects for ambulatory contacts and hospitalisation are somewhat higher and statistically significant. More precisely, it is found that EPHI increases the probability of hospitalisation from 5.1 to 8.5% and the probability of having had any ambulatory contacts from 17.9 to 23.3% among the privately employed.

Keywords Duplicate health insurance · Demand for health care · Moral hazard · Matching estimator · Denmark

JEL Classification C31 · I11

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Abbreviations

EPHI Employment-based private health insurance
ATT Average treatment effect on the treated

Introduction

The framework of a tax-financed health care system supplemented by employment-based private health insurance (EPHI) is found in many countries worldwide, such as Canada, Australia, the United Kingdom, France, Spain, Portugal, Sweden, and Norway (Aarbu 2010; Colombo and Tapay 2004; Mossialos and Thomson 2002). The Danish health care system is no exception. During the recent decade, Danish employers have increasingly taken out private health insurance on behalf of their employees. The percentage with some sort of private health insurance coverage through their workplace has gone from 5% in 2002 to 32% of the employed in 2009 (Copenhagen Economics 2008; Statistics Denmark 2010; The Danish Insurance Association 2010). The EPHI schemes taken out by the Danish employers primarily cover elective surgery at private hospitals and clinics, thereby allowing employees to circumvent waiting times for treatment at public hospitals or accommodate their preference for private treatment. Hence, the coverage provided by this type of private health insurance may be classified as primarily duplicate in relation to the tax-financed health care system (OECD 2004). Some private insurance schemes also provide free access to physiotherapy, chiropractic care, and psychological counselling, however, often with a limitation on annual number of consultations (Kjellberg et al. 2010).

Economic theory predicts that private health insurance induces moral hazard in the use of health care services for which the demand is price elastic by lowering the price that patients are facing at the point of use, thereby leading to higher utilization levels (Arrow 1963; Pauly 1968). In addition to moral hazard, private health insurance may also increase the use of health care through risk reductions, i.e. because the desired level of utilisation is greater under the financial certainty created by insurance than under uncertainty (de Meza 1983; Vera-Hernández 1999), an income transfer effect (Nyman and Maude-Griffin 2001; Pauly 1968), and supplier-induced demand (Evans 1974).[1] Institutional barriers such as the use of gatekeepers and restrictions in the coverage provided by the private insurers may moderate the effect of private health insurance.

The aim of this study is to estimate the effect of EPHI on the use of covered health care services based on Danish survey data collected in 2009. The following health care services are considered: physiotherapy, chiropractic care, psychological counselling, specialist care, ambulatory care, and hospitalisation. These are the main benefits covered by EPHI in Denmark. In a policy context the answer to this question adds to our knowledge of the extent to which EPHI generates horizontal inequity in the use of health care services. As such, the results of the study are of relevance to policy makers in the various countries with universal health care systems and duplicate EPHI; in particular in Denmark, where EPHI was tax-exempted and thus implicitly subsidised at the time of writing. The causal effect of EPHI is distinguished from selection effects by applying a propensity score matching estimator. This approach is based on the identifying assumption that there is no selection on unobservables after conditioning on a set of covariates. Sensitivity analysis indicated that this assumption is plausible in the present study, given the wide set of relevant covariates available in the data and the institutional setting of EPHI in Denmark. However, the results are found to be quite

[1] I am not able to distinguish empirically between these four channels in the present study.

sensitive to possible deviations from the assumption of conditional mean independence. The method of matching differs from regression methods in that it emphasises common support and avoids the functional form assumptions that are implicit in parametric methods (Bryson et al. 2002).

The study contributes to the existing literature in several ways. First, the effect of EPHI on the total use of health care services has not previously been studied in Denmark or any of the other Scandinavian countries.[2] To the best knowledge of the author, the data used in the present study contain the most detailed information on private health insurance coverage in the Danish population available to date. In this way, the results of the study generate knowledge within an institutional setting where empirical findings are still limited. Moreover, while matching estimators have traditionally been used to evaluate effects of labour market programmes (Imbens and Wooldridge 2009), the use of the method to identify the impact of health insurance is more limited (see e.g. Barros et al. 2008; Jones et al. 2006; Johar 2009).

The remainder of the paper is organised as follows. The next section provides the background for the empirical analysis, followed by accounts of the propensity score matching estimator and the data used in the empirical analysis. Subsequently, the results are reported and some robustness checks are undertaken. Finally, the methods and results of the study are discussed, and conclusions are drawn.

Background and empirical evidence

Employment-based private health insurance in Denmark

The Danish health care system is a comprehensive tax-financed system with universal access. General practitioner and specialist visits, out-patient ambulatory care as well as hospitalisation are free at the point of use for all citizens. General practitioners act as gatekeepers in the sense that in most cases a referral from a general practitioner is needed to be able to access more specialised treatment. The general practitioners play a crucial role in ensuring that the principle of keeping treatment at the lowest effective care-level (i.e. the so-called LEON-principle) is followed. Copayment and waiting time are frequently used to ration the use of health care services for which demand is price or time sensitive. There is considerable private copayment for adult dental care, prescription medication, physical therapy, chiropractic care, and psychological counselling (Strandberg-Larsen et al. 2007). Private copayment accounted for about 14% of total health expenditures in 2009 (OECD 2009). For other types of treatment, mainly elective surgery, there may be waiting time for treatment at public hospitals. This has attracted a considerable amount of public and political attention over time (Madsen 2010). Emergency and acute care is only available at public hospitals, whereas elective surgery is also performed private hospitals and clinics (The Ministry of Interior and Health 2010).

Following legislation that tax-exempted employees for the value of private health insurance premiums, the share of the employed with private health insurance through their

[2] However, the research area of EPHI has received increasing attention in Denmark in recent years. About the time when this study was submitted to the International Journal of Health Care Finance and Economics, Søgaard et al. (2011) published a report in which they analysed the effect of EPHI on the use of tax-financed health care services in Denmark based on information from the customer registers of the commercial insurance companies linked with various registers. Moreover, Borchsenius and Hansen (2010) and Pedersen (2011) have analysed how EPHI affects sickness absence in Denmark, to mention a few recent contributions. These studies do, however, differ from the present studies in various respects.

workplace has gone from negligible in 2002 to 32% of the employed in 2009 (Statistics Denmark 2010; The Danish Insurance Association 2010). Motivated by equity considerations, the tax-exemption was contingent on the insurance being offered to all employees in a company. The decision to offer private health insurance is that of the employer. In 2007, private health insurance (individually purchased and employment-based) made up 1.6% of the total Danish health expenditure (OECD 2010).

The EPHI contracts are supplied by commercial insurance companies. The exact benefits differ slightly between insurance companies, just like policies are often tailored to specific firms. As previously mentioned, EPHI may be classified as primarily duplicate in relation to the tax-financed health care system given that its primary function is to cover diagnostics and some types of elective surgery at private facilities for treatments that are also available within the tax-financed health care system, but usually with some waiting time. In addition, the EPHI contracts are increasingly being used for health care services where co-payment is common, e.g. physiotherapy, chiropractic care, and psychological counselling. However, often with a limitation on the annual number of consultations (Kjellberg et al. 2010).

In 2009, the total gross compensations paid out by the commercial insurers were distributed as follows: 67% covered operations and the like, 9% covered psychological counselling, 17% covered physiotherapy, chiropractic care and the like, and 7% covered other types of treatments (The Danish Insurance Association 2010).

Premiums are either paid by employers or, for about 26% of the insured based on the data used in this paper, deducted from the pre-tax income of the employees. As previously mentioned, the premium for fully employer paid insurance is not subject to income tax when insurance is offered to all employees in a company. This implies an indirect tax subsidy of about 40–60% of the premium. The annual premium per employee varies depending on the coverage level and the size of the buying company. Larger companies generally pay a smaller premium per employee because the scope for risk pooling increases with company size. There is no risk rating of premiums within companies due to the conditions of the tax-exemption, but it is likely to occur between companies. The average premium per person has been constant around DKK 1000/USD 187.71 since 2003, but increased to DKK 1428/USD 268.04 in 2009 (The Danish Insurance Association 2010).[3]

While it is possible that screening of firms occurs, insurance eligibility within the firm is usually not restricted by health requirements, again due to the tax-exemption. However, there may be a deferred period for treatment of existing conditions and limitations on the annual number of consultations with physiotherapists, chiropractors, and psychologists.

In addition to EPHI, some employers also have company health schemes in place, which provide prevention and treatment of work-induced injuries, typically with physiotherapy, chiropractic care, massage, and reflexology. The health schemes differ from EPHI in the sense that they do not provide any type of elective surgery at private facilities, and that they treat only work-induced injuries.

Duplicate private health insurance coverage can also be purchased from the commercial insurance companies on an individual basis. The benefits are roughly the same as for the EPHI contracts, but premiums are not subject to special tax treatment and are risk rated based on age. In 2009, the pool of individuals who had taken out private health insurance through a commercial insurance company on an individual basis included approximately 100,000 individuals according to industry figures from The Danish Insurance Association (2010). In addition, more than two millions Danes (approximately 42% of the adult population)

[3] The figures are calculated as total premium income of the commercial insurers divided by the number of insured. Conversion from DKK to USD is undertaken using the March 2011 average exchange rate of 532.75 (Danske Bank 2011).

were covered by private health insurance through the non-profit mutual insurance company 'denmark' in 2009 (Health Insurance denmark 2009). This type of private health insurance is mainly complementary to the tax-financed health care system in that it primarily covers co-payments for treatment in the public health care system. Approximately 25% of the members of 'denmark' are also partly reimbursed for elective surgery at private hospitals.

Despite some overlap in coverage between the individually purchased and employment-based insurance contracts, some individuals hold both (23% of the sample of employed described in the data section are covered by both EPHI and 'denmark'). The effects of membership of 'denmark' and company health schemes on the use of health care are not subject to analysis in this paper; they are, however, taken into account when analysing the effect of EPHI.

The empirical literature

There is a large and growing empirical literature seeking to identify the effect of private health insurance on the use of health care services. The majority of these studies consider private health insurance that is purchased on an individual basis (Christiansen et al. 2002; Gerfin and Schellhorn 2006; Höfter 2006; Holly et al. 1998; Jones et al. 2006; Pedersen 2005; Riphahn et al. 2003), some consider employment-based contracts (Barros et al. 2008; Chiappori et al. 1998; Ruthledge 2009; Stabile 2001), and other again consider both, either combined (Schokkaert et al. 2010) or separately (Buchmueller et al. 2004).[4] This section focuses on the identification strategies used in the literature and briefly summarises the results.

Identification of the effect of private health insurance is complicated by the fact that in most settings there is likely to be some sort of selection into private health insurance, either adversely (Rothschild and Stiglitz 1976) or advantageously (de Meza and Webb 2001; Finkelstein and McGarry 2006; Hemenway 1990), which may cause insurance status to be endogenous in models of health care use.

The most far-reaching study of the impact of insurance on health care use to date is the RAND Health Insurance Experiment, which randomly assigned approximately 6,000 US citizens to insurance plans with varying levels of cost sharing (Manning et al. 1987).

The greater part of the empirical literature is, however, based on observational data. A few studies have estimated the effect of private health insurance on the use of health care services using various count data models, treating insurance as exogenous i.e. relying on selection on observables, using extensive sets of control variables to mitigate potential selection bias (Christiansen et al. 2002; Pedersen 2005; Stabile 2001). Along a similar line, Barros et al. (2008) argued that selection on observables is plausible in the context of private health insurance given exclusively to civil servants and their dependents in Portugal and applied a matching estimator, and Søgaard et al. (2011) estimated the effect of EPHI on the use of tax-financed health care services in Denmark using propensity score matching.

In the larger share of the literature, the potential endogeneity of private health insurance status is taken into account by using various bivariate modelling strategies, including joint estimation of insurance and health care use (Buchmueller et al. 2004; Schokkaert et al. 2010) and various two-stage estimation procedures (Cameron et al. 1988; Coulson et al. 1995; Harmon and Nolan 2001; Höfter 2006; Holly et al. 1998; Riphahn et al. 2003; Savage and Wright 2003; Schellhorn 2001; Vera-Hernández 1999). Jones et al. (2006) identified the effect of private health insurance using both joint estimation of insurance status and health care use, and binary probit and matching estimators assuming exogeneity of insurance.

[4] A few studies did not explicitly state whether they analysed employment-based or individually purchased contracts (Cameron et al. 1988; Coulson et al. 1995).

The functional forms applied in the various models of health care use are generally determined by the nature of the dependent variable as well as computational convenience rather than explicit theoretical considerations.

When the model of insurance choice is non-linear, the various bivariate models of insurance choice and health care use are in principal identified by functional form due to non-linearity in the structure of the error terms. It is, however, preferable (and required in the linear case) to find an instrumental variable, i.e. one or more variables affecting the probability of having private health insurance (the relevance condition) but not the use of health care services (the exclusion restriction) and exclude this from the utilization equation for more robust identification. In the following, the instruments for health insurance used in the empirical literature to date are summarised and discussed.

Holly et al. (1998) used age squared and body mass index squared as instrumental variables without providing any explicit justification for their validity. Schellhorn (2001) used differences between Swiss cantons regarding the availability of private health insurance and premium levels for identification. A number of studies used different socioeconomic characteristics as instrumental variables. Buchmueller et al. (2004) excluded an indicator of public sector employment from the utilization equation. This restriction was argued to be theoretically valid given that all public employees are offered private health insurance contracts and most of them take up these contracts, while public sector employment is not expected to impact neither health status nor the use of care. Höfter (2006) used dummies for being self-employed, in a permanent job, and a measure of risk as instrumental variables for insurance.[5] Vera-Hernández (1999) used measures of social class, occupation, and some interaction terms as instrumental variables for insurance. Harmon and Nolan (2001) used education as instrumental variable. Finally, Jones et al. (2006) used lagged information on whether individuals had access to employer-provided free or subsidized health care or insurance as instrumental variable for privately paid insurance.

The majority of the studies did not provide any explicit theoretical justification for the untestable exclusion restrictions; thereby emphasizing the point made by Barros et al. (2008) that theoretically valid instrumental variables are hard to find when seeking to identify the effect of private health insurance on health care use.

Another branch of the literature relied on different natural experiments, which could provide plausible exogenous variation in insurance status without theoretical justification. Chiappori et al. (1998) identified the effect of private health insurance on the use of health care services using exogenous variation in coverage stemming from a policy change which implied that one subgroup was exposed to a 10% copayment-rate for physician services while no change occurred for another subgroup. Along a similar line, Ruthledge (2009) used variation in health plan offers across employers in the US to separate the effects of moral hazard and adverse selection. Anderson et al. (2010) exploited a sharp change in insurance coverage rates in the US that occurs when young adults age out of their parents' insurance plans and used a regression discontinuity design to estimate the effect of private health insurance coverage. Kaestner and Khan (2010) estimated the effect of ageing into prescription drug coverage under Medicare Part D on the use of prescription medicine and health care services using difference-in-difference regression.

Finally, Gerfin and Schellhorn (2006) estimated non-parametric bounds around the effect of different levels of deductibles in the basic health insurance in Switzerland on the use of health care under various assumptions. They relied on bounds developed by

[5] The measure of risk was defined by an interaction between the number of individuals depending on the head of the household and a continuous score based on age-sex factors provided by one of the largest insurers in the market.

Manski and Pepper (2000) that presumed a priori knowledge of the sign of the treatment effect combined with exclusion restrictions.

Considering the findings of the empirical literature, the vast majority of the studies found some evidence in favour of private health insurance increasing the use of health care services, which is consistent with the presence of moral hazard. In addition, several studies found that the significance and size of the positive effect varied across different types of health care services, insurance schemes, and population groups.

Methodology

When assignment to EPHI is not random, the difference in average health care use between insured and uninsured yields a biased estimate of how EPHI affects the use of health care services (Rubin 1974). In this study, this fundamental identification problem is handled by using matching to estimate the average treatment effect on the treated (ATT)[6]:

$$\tau_{ATT} = E\left[\tau \,|D = 1\right] = E\left[Y^1 \,|D = 1\right] - E\left[Y^0 \,|D = 1\right] \tag{1}$$

where $D \in \{0, 1\}$ denotes a binary indicator of treatment (i.e. EPHI coverage), Y^1 and Y^0 denote the potential outcomes of interest (i.e. use of health care services) for treated and controls, respectively, X denote a vector of covariates, and E is the population mean operator.

The estimation of the ATT parameter requires that the treatment effect for each individual is independent of the treatment status of the other individuals. Moreover, Heckman et al. (1998) and others have shown that an assumption of mean independence of potential outcomes given X as stated in (2) and the overlap condition stated in (3) suffice to identify the ATT using the method of matching.

$$E\left[Y^1 \,|D = 1, X\right] = E\left[Y^1 \,|D = 0, X\right] = E\left[Y^1 \,|X\right] \tag{2}$$

$$P\left(D = 1 \,|X = x\right) < 1 \tag{3}$$

Matching treated and controls on the propensity score $P(X)$ as opposed to the full dimensional X due to the curse of dimensionality, one also needs to check covariate balance (Rosenbaum and Rubin 1983):

$$D \perp X \,\Big|\, \hat{P}\left(X\right) \tag{4}$$

This study matches treated and controls using kernel matching. Standard errors including the variance due to the estimation of the propensity score and the imputation of common support are obtained by bootstrapping. This has been shown to provide valid inference for kernel matching (Abadie and Imbens 2008).

Data

The empirical analysis is based on cross-sectional survey data on the Danish population aged 18–75. The data were collected in June 2009 using an internet-based questionnaire.

[6] This is the relevant measure when the interest centres on the effect of treatment on the group of individuals who actually received the treatment, and it is neither feasible nor policy relevant to treat everybody in the population (Heckman 1997).

The pilot-tested final questionnaire was e-mailed to a sample of 13,246 respondents via YouGov Zapera's Denmark panel.[7] In total 5,447 respondents answered the questionnaire, which corresponds to a response rate of 41%. Moreover, the dataset contains inverse probability weights based on age, gender, and region of residence. The questionnaire and the data collection process, including analyses of non-response and representativity, are fully documented in Kiil and Pedersen (2009).

For the purpose of the present study the sample is restricted to the subsample of occupationally active, given that individuals outside the labour force do not have EPHI by definition. This restriction reduces the sample size from 5,447 to 3,301 individuals.

Employment-based private health insurance (treatment)

EPHI status is measured by a dummy variable which equals one for individuals who are covered by private health insurance through their workplace and zero otherwise. An intrinsic problem in studies of private health insurance is how to account for different types of insurance coverage and avoid that controls hold some sort of insurance. In the current study, this problem is handled as follows. Individuals who do not know their insurance status were dropped from the data, reducing the sample size from 3,301 to 3,068. Moreover, 207 individuals who are covered by private health insurance through the employer of a family member and 172 individuals who have purchased private health insurance from a commercial insurance company on an individual basis were also dropped from the data. It is questionable whether it is possible to control appropriately for selection into these two alternative types of private health insurance. Hence, it was chosen to restrict the dataset in order to ensure the plausibility of the conditional mean independence assumption throughout the analysis. The resulting sample thus includes 2,689 individuals, of whom 41% are covered by private health insurance through their own employer. Within the group of individuals with EPHI, 70% receives the insurance free of charge, 26% pays the premium themselves out of their pre-tax income, and 4% do not know how the premium is paid.

Health care use (outcomes)

The use of health care services is captured by a set of outcome variables measuring contacts to physiotherapists, chiropractors, psychologists, specialists, ambulatory health care providers, and hospitalisations.[8] These are the main types of health care services covered by the EPHI schemes available in the Danish market. The outcome variables are defined as dummy variables indicating whether the individual had one or more contacts to the provider in question or was hospitalised in the 12 months prior to the interview. The choice of dummy variables indicating whether any use took place is motivated by the fact that the main choice individuals are facing is whether to see a given health care provider or not, while further visits are, to a large extent, out of their control (Barros et al. 2008; Gerfin and Schellhorn

[7] YouGov Zapera's Denmark panel is an actively managed internet-based panel containing 38,600 members in Denmark as of July 2009. The panel meets the Esomar international code on marketing and social research practice. This implies among other things that its members are recruited through a wide selection of channels in order to ensure an appropriate demographic balance, and that panel members must log on with a password when participating in surveys in order to ensure that the intended person completes the survey (YouGov Zapera Ltd. 2009).

[8] Ambulatory care is defined as hospital contacts without actual hospitalisation, such as examinations, scans, same-day surgery, and control visits.

Table 1 Descriptive statistics for health care use within the previous 12 months by EPHI status

	All employed	EPHI	No EPHI	Two-sided test for equality (EPHI vs. no EPHI)
	Mean	Mean	Mean	z-Statistic
Share with any contacts				
Physiotherapists	0.177	0.203	0.159	−2.956***
Chiropractors	0.129	0.147	0.117	−2.325**
Psychologists	0.056	0.054	0.057	0.327
Specialists	0.275	0.273	0.277	0.207
Ambulatory care	0.251	0.231	0.265	1.991**
Hospitalisation	0.089	0.083	0.093	0.826
N	2,636	1,092	1,544	

** Significance at 5% level; *** significance at 1% level

2006). Moreover, a dummy variable captures the majority of the variation in outcomes due to a large number of zeros and ones in the number of contacts.

Table 1 shows some descriptive statistics for the outcome measures of health care use for the full sample of employed and separately by EPHI status.

It is seen from Table 1 that the share of the employed with at least one physiotherapist or chiropractor contact during the previous 12 months is significantly higher for the group of individuals with EPHI than for those who rely exclusively on the tax-financed health care system, while the opposite relationship holds for ambulatory care. This is somewhat surprising given that the privately insured enjoy preferential access to elective surgery at private hospitals and clinics.

Covariates

A set of potential covariates was selected based on economic theory and previous empirical findings, taking into consideration the particular institutional features of the Danish health care system. The set of covariates includes variables that may reasonably be expected to influence both the probability of having EPHI and the use of health care services, subject to the condition that they should not be affected by EPHI coverage or the anticipation of getting it. The condition that the covariates should not be affected by EPHI coverage or the anticipation of it is accommodated by including variables that may reasonably be assumed to be either largely fixed over time for the study population or unaffected by EPHI coverage. In addition, some random variation is needed in order to ensure that the overlap condition is satisfied.

EPHI coverage is most likely not randomly distributed within the workforce, and selection into this type of insurance may occur at various levels. For the EPHI contracts available in the Danish market, selection is mainly expected to occur at the firm level because the insurance contracts are free or heavily subsidised for the employee contingent on the policy being offered to all employees in a company. However, it cannot be ruled out that some extent of selection may also occur at the individual level, since some employees are required to pay the premium out of their pre-tax wage when taking out private health insurance through their workplace. In this case employees face an actual choice and may reject the insurance offer.

This is the case for about 26% of the employees with EPHI based on the data used in this paper.[9]

The selected covariates may be broadly classified into three groups. The first group includes the following characteristics related to the workplace: size, sector, and the presence of a health scheme. The size of the workplace has previously been found to affect the probability of employers offering insurance in the context of the Norwegian health care system and is thus included (Seim et al. 2007). The sector of employment is included because EPHI is mainly a private sector phenomenon in Denmark (Kjellberg et al. 2010). However, it is noted that the extent to which these characteristics affect health care used is uncertain. As for company health schemes, which differ from EPHI in the sense that they treat work-induced injuries only and do not provide any type of elective surgery at private facilities, the expected association with EPHI is ambiguous. While the most likely relationship among the two fringe benefits is that both tend to be offered by the same employers, i.e. those who assign a high value to having healthy employees, it is also possible that employers choose to offer company health schemes instead of EPHI. Company health schemes may reasonably be expected to increase the use of the health care services to which they give free access.

The second group of covariates includes the following basic demographic and socioeconomic variables: gender, age, marital status, region of residence, income, education level, occupational status, and membership of the non-profit mutual insurance company 'denmark'. Socioeconomic and demographic variables have previously been shown to affect the probability of having EPHI in Norway, Spain, Denmark, and the United Kingdom (Aarbu 2010; Besley et al. 1999; King and Mossialos 2005; Kjellberg et al. 2010; Rodríguez and Stoyanova 2008). The theoretical importance of the various demographic and socioeconomic characteristics is motivated by the human capital approach as developed by Grossman (1972). In the Grossman-model, the demand for medical care is derived from the demand for health. Assuming that the costs of producing health as well as the benefits from being healthy differ with among other things demographic and socioeconomic characteristics, it is clear the these characteristics will also affect the demand for health care. Moreover, the inclusion of income is intended to measure the consumption possibility set, which is expected to affect the demand for EPHI directly as well as through the ability to self-insure. Moreover, region of residence is included in order to capture geographical variation in the occupational structure (Danish Agency for Science 2008) as well as the pattern of health care use that has been found to exists in Denmark (Bech and Lauridsen 2009). Finally, membership of 'denmark' is included based on an expectation that the members of 'denmark' are less likely to accept an offer of EPHI in the cases where the premium is deducted from the pre-tax income, due to the overlap in coverage between the two types of insurance. Moreover, membership of 'denmark' has been shown to increase the use of selected health care services in Christiansen et al. (2002) and Pedersen (2005).

The third group of covariates includes eight dummy variables indicating the presence of selected chronic conditions. These variables are intended to proxy the need for health care. Perceived health was deliberately not included as a measure of need, since this variable has frequently been argued to be endogenous with respect to the use of health care (Barros et al. 2008; Windmeijer and Santos Silva 1997). Overall, the employer's decision to offer EPHI may be affected by the health related variables as well as the sociodemographic variables to the extent that the decision is affected by the characteristics and preferences of current and potential employees, as suggested in the economic literature (Bundorf 2002; Feldman et al.

[9] Previous empirical evidence shows that fully employer paid EPHI and EPHI which is paid for out of the pre-tax income of the employee may reasonably be considered jointly in the Danish setting, even though the underlying decision processes differ somewhat (Kiil 2011).

1997; Glied and Zivin 2004). Considering the theoretical relationship between the health of the employee and the employer's decision to offer EPHI, two opposite effects may be at play (Grepperud and Iversen 2011). On the one hand, it may be the case that companies with high sickness absence or those operating in industries exposed to considerable health risks may be relatively more inclined to purchase EPHI, i.e. adverse selection at the company level.[10] On the other hand, it is also possible that companies using highly educated and specialised labour, which is hard to replace in the case of illness, are more likely to invest in the health of their employees by taking out EPHI, assuming that EPHI reduces sickness absence. If sickness absence decreases with the qualification and education level of the employee, which is most likely the case, these effects are opposite. Empirical evidence based on company-level data from Norway indicates that both effects may be present (Seim et al. 2007).[11]

Table 2 shows descriptive statistics for the full set of covariates for the full sample of occupationally active and separately by EPHI status. Respondents who answered 'don't know' or 'other' than the categories specified in the questionnaire to one or more of the explanatory variables are dropped from the data before commencing on the analysis, reducing the sample size further from 2,689 to 2,636 individuals.[12] The main motivation for this data restriction is that it is questionable whether the individuals in the 'don't know' and 'other' groups have anything in common. For the variable measuring gross household income, which was plagued by a particularly large number of missing values, two dummies were generated that equal one whenever respondents don't know or do not wish to disclose their income, respectively, and zero otherwise.

It is seen from Table 2 that the individuals with EPHI differ significantly from those who do not have EPHI on the majority of the covariates. In particular, the expectation that EPHI is mainly a private sector phenomenon and that it is more frequently offered in larger companies are confirmed by Table 2. Likewise for the demographic, socioeconomic, and health-related variables, where the differences between the groups with and without EPHI, respectively, are by and large as expected.

Results

The propensity score matching estimator was implemented following the practical guidelines laid out in Bryson et al. (2002) and Caliendo and Kopeinig (2005). The estimations were performed in Stata/IC 12 using version 3.1.5 of the 'psmatch2' module written by Leuven and Sianesi (2003). Treated and controls were matched using kernel matching with an Epanechnikov kernel and a bandwidth of 0.04. Sensitivity analyses, which are available from the author upon request, showed that the results are insensitive to reducing the bandwidth to 0.02 or increasing it to 0.06 and 0.08, respectively. In all cases the analyses were restricted to

[10] As for adverse selection at the individual level, this relationship is based on an assumption of asymmetric information, implying that the price at which insurance is offered to a company does not increase proportionally with expected payouts for the company.

[11] More specifically, Seim et al. (2007) found that the probability of companies offering EPHI to some or all of their employees increases with company size and profit, the share of younger employees, the education level of the staff of employees, and operating in one of several industries considered to be particularly exposed to health risks (including building and construction, farming, forestry, and mining).

[12] An alternative strategy would have been to impute the missing values.

Table 2 Descriptive statistics for the covariates by EPHI status

	All employed	EPHI	No EPHI	Two-sided test for equality (EPHI vs. no EPHI)
	Mean	Mean	Mean	z-Statistic
Sociodemographic variables				
Male	0.527	0.574	0.493	4.118***
Age	45.207	43.975	46.078	−4.624***
Married	0.574	0.590	0.564	1.344
# Children in household	0.589	0.652	0.545	2.958***
# Adults in household	1.955	1.950	1.959	−0.286
Northern Jutland	0.089	0.068	0.104	−3.240***
DKK 0–400/USD 0–75 (1,000)	0.179	0.139	0.207	−4.490***
DKK 400–800/USD 75–150 (1,000)	0.497	0.478	0.511	−1.669*
DKK 800+/USD 150+ (1,000)	0.227	0.287	0.184	6.205***
Don't know income	0.013	0.007	0.017	−2.132**
Do not wish to disclose	0.084	0.089	0.081	0.717
Basic or high school education	0.129	0.124	0.133	−0.690
Vocational education	0.263	0.295	0.241	3.098***
Higher education	0.593	0.568	0.611	−2.213**
Other education	0.015	0.014	0.016	−0.379
White-collar worker	0.769	0.816	0.735	4.847***
Skilled worker	0.073	0.076	0.070	0.591
Unskilled worker	0.076	0.078	0.075	0.258
Self-employed	0.083	0.030	0.120	−8.227***
Member of 'denmark'	0.551	0.562	0.542	1.026
Health-related variables				
Asthma	0.059	0.055	0.062	−0.708
Allergies	0.236	0.252	0.225	1.574
Diabetes	0.039	0.038	0.040	−0.341
Hypertension	0.134	0.123	0.143	−1.467
Emphysema	0.018	0.017	0.018	−0.319
Arthritis	0.138	0.109	0.159	−3.644***
Osteoporosis	0.011	0.008	0.012	−1.003
Tinnitus	0.079	0.072	0.084	−1.051
Employer-related variables				
1–4 employees	0.106	0.040	0.152	−9.200***
5–9 employees	0.067	0.055	0.076	−2.105**
10–49 employees	0.278	0.256	0.293	−2.0886**
50–249 employees	0.272	0.281	0.266	0.849
250+ employees	0.277	0.367	0.212	8.752***

Table 2 continued

	All employed	EPHI	No EPHI	Two-sided test for equality (EPHI vs. no EPHI)
	Mean	Mean	Mean	z-Statistic
Company health scheme	0.287	0.417	0.195	12.399***
Public employer	0.358	0.066	0.565	−26.303***
Indep. public employer	0.038	0.040	0.036	0.621
Private employer	0.594	0.886	0.387	25.736***
Other employer	0.011	0.007	0.013	−1.388
N	2,636	1,092	1,544	

* Significance at 10% level; ** significance at 5% level; *** significance at 1% level

the region of common support by dropping treated individuals with propensity scores outside the range of propensity scores for the controls.[13]

Table 3 presents the ATT estimates for the sample of all employed for various specifications of the propensity score in order to investigate which factors drive the correlation between EPHI coverage and health care use. Each column of results in Table 3 represents a separate propensity score specification, and the results of the various logit models used to estimate the propensity scores are reported in Appendix A.

It is seen from Table 3 that the sample of employed contains 1,092 individuals with EPHI (41.4%) and 1,544 controls who rely exclusively on the tax-financed health care system before common support is imposed. Model I does not include any covariates. Comparing the raw differences in means, it is found that the probability of having used physiotherapy or chiropractic care within the previous 12 months is significantly higher for the group of individuals with EPHI, while the probability of having had any ambulatory contacts is significantly lower. The use of the remaining types of health care services does not differ significantly depending on EPHI status. In Model II a set of demographic variables were added to the propensity score. These variables include information on gender, age, marital status, household composition, and region of residence. Model III adds a set of socioeconomic variables measuring income, education level, occupational status, and membership of the non-profit mutual insurance company 'denmark'. Model IV adds the objective health measures defined by a set of dummy variables indicating the presence of eight chronic conditions. The majority of the estimated relationships between EPHI coverage and health care use are not changed markedly by adding demographic, socioeconomic, and health-related variables to the propensity score. However, the estimate of how EPHI affects the use of ambulatory care is gradually adjusted upwards and becomes less significant as more covariates are accounted for. Model V adds a set of dummy variables measuring the size of the workplace. Besides from reducing the estimates slightly, this is seen to have very little effect on

[13] It was considered to apply the inverse probability weights available in the dataset to the matching estimator. However, assuming that the expected value of the error term given the covariates is zero, which is not implausible, it may be shown that weighting is not needed. This approach is frequently chosen in microeconometric studies that emphasize a causal interpretation (Cameron and Trivedi 2005, pp. 818–821). Moreover, it was found that the weighted estimates of all statistically significant coefficients do not differ notably from the unweighted. Hence, applying probability weights would not change the main results of the study notably. The weighted estimates are not given here for brevity, but are available from the author upon request.

Table 3 Average treatment effect on the treated (ATT) estimates for all employed, n = 2,636

	Model I	Model II	Model III	Model IV	Model V	Model VI	Model VII	
	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	Baseline prob.
Outcomes (any contacts)								
Physiotherapy	0.045 (0.015)***	0.050 (0.015)***	0.043 (0.015)***	0.049 (0.016)***	0.048 (0.016)***	0.036 (0.018)**	0.023 (0.026)	0.178
Chiropractic care	0.031 (0.013)**	0.029 (0.013)**	0.028 (0.013)**	0.030 (0.015)**	0.029 (0.014)**	0.020 (0.015)	0.005 (0.024)	0.142
Psychological counselling	−0.003 (0.008)	−0.004 (0.009)	−0.005 (0.010)	−0.004 (0.010)	−0.001 (0.010)	−0.008 (0.012)	−0.013 (0.016)	0.068
Specialist care	−0.004 (0.019)	0.013 (0.018)	0.009 (0.018)	0.015 (0.018)	0.016 (0.019)	0.015 (0.020)	0.020 (0.028)	0.256
Ambulatory care	−0.034 (0.016)**	−0.032 (0.017)*	−0.031 (0.017)*	−0.025 (0.019)	−0.023 (0.019)	−0.027 (0.020)	0.033 (0.023)	0.193
Hospitalisation	−0.009 (0.011)	−0.007 (0.011)	−0.011 (0.012)	−0.008 (0.013)	−0.003 (0.012)	−0.001 (0.011)	0.028 (0.014)	0.055
# Of treated				1,092				
# Of controls				1,544				
Summary measures of matching quality								
Logit model pseudo R^2 before matching		0.023	0.063	0.065	0.080	0.108	0.381	
Logit model pseudo R^2 after matching		0.000	0.000	0.001	0.001	0.001	0.008	
Median bias before matching		13.048	8.727	6.018	6.402	6.599	6.402	
Median bias after matching		0.200	0.641	0.701	0.415	1.314	2.475	
# Of treated off common support		0	1	0	0	0	76	
Covariates	None	Demographic	Demographic	Demographic	Demographic	Demographic	Demographic	
	(diff. in means)		Socioeconomic	Socioeconomic	Socioeconomic	Socioeconomic	Socioeconomic	
				Health conditions	Health conditions	Health conditions	Health conditions	
					Employer size	Employer size	Employer size	
						Health scheme	Health scheme	
							Employment sector	

* Significance at 10% level; ** significance at 5% level; *** significance at 1% level. Standard errors for the ATTs are bootstrapped with 200 replications

the relationship between EPHI status and health care use. Model VI adds a dummy variable indicating whether individuals work for a company with a health scheme providing prevention and treatment of work-induced injuries, typically with physiotherapy, chiropractic care, massage, or reflexology. Except for hospitalisation this reduces the estimated effects of EPHI, indicating that the presence of a company health scheme increases both the probability of having EPHI and the use of health care services. Finally, Model VII includes a set of dummy variables indicating sector of employment in the specification of the propensity score. This is seen to affect the ATT estimates notably. More specifically, the estimated effects for the use of physiotherapy, chiropractic care, and psychological counselling are further reduced, indicating that private sector employment increases both the probability of having EPHI coverage and the use of these health care services. On the contrary, the estimated effects for specialist contacts, ambulatory treatments, and hospitalisations change sign from negative to positive when sector of employment is included in the propensity score. This indicates that private sector employment increases the probability of having EPHI coverage and reduces the use of these health care services simultaneously.

The sharp increase in the R^2 of the logit model used to estimate the propensity score indicates that sector of employment is a very important determinant of EPHI coverage. According to the odds ratios from the logit model used to estimate the propensity score reported in Appendix A, the odds of having EPHI are 10 times larger for individuals working for independent public companies and 43 times larger for private sector employees compared to public sector employees, holding all other observed variables constant. For Models I–VI the share of treated outside the common support is low, and the distributions of the propensity scores (which are assessed graphically in Appendix B) do not give rise to concern. However, it is seen from Table 3 that the number of treated individuals off the common support increases from none to 76 when sector of employment is included in the estimation of the propensity score. Hence, it is possible that the method used to impose common support affects the results of Model VII. It was therefore assessed how the results are affected if common support is imposed by dropping controls with propensity scores outside the range of propensity scores for the treated individuals or not imposed at all. In these additional analyses, the estimated effects for specialist and ambulatory care as well as hospitalisation were somewhat larger than in the main model where common support was imposed by dropping treated individuals with propensity scores outside the range for the controls. Moreover, the estimates for ambulatory care and hospitalisation reached statistical significance. This implies that accounting for sector of employment, the sample contains a group of individuals who are very likely to have EPHI (to an extent that there are no appropriate controls) and at the same time are likely to use the health care services in question. Hence, it is meaningful to implement the matching estimator for the subsample of private sector employees rather than including sector of employment in the propensity score, thereby forcing a perfect match in terms of this characteristic (Reynolds and DesJardins 2009).

Table 4 presents the ATT estimates of how EPHI affects the use of covered health care services for the subsample of private sector employees. This sample contains 968 individuals with EPHI coverage (61.9%) and 597 controls before common support is imposed.

It is seen from Table 4 that insisting on a perfect match in terms of sector of employment changes the pattern of results somewhat. For one thing, the probabilities of having used the health care services in question do not differ significantly depending on EPHI status in Model VIII, which does not include any covariates. Also in contrast to the analysis of the full sample, the estimates of how EPHI affects the use of physiotherapy and chiropractic care do not reach statistical significant in any model specification when the analysis sample is restricted to the privately employed. Another notable difference is that the estimate of how EPHI affects the

Table 4 Average treatment effect on the treated (ATT) estimates for private sector employees, n = 1,565

	Model VIII	Model IX	Model X	Model XI	Model XII	Model XIII	
	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	ATT (std. err.)	Baseline prob.
Outcomes (any contacts)							
Physiotherapy	0.036 (0.022)	0.026 (0.024)	0.019 (0.026)	0.030 (0.025)	0.021 (0.031)	0.023 (0.030)	0.182
Chiropractic care	0.026 (0.018)	0.011 (0.019)	0.013 (0.022)	0.010 (0.022)	0.015 (0.026)	0.001 (0.026)	0.149
Psychological counselling	−0.004 (0.011)	−0.012 (0.013)	−0.011 (0.016)	−0.010 (0.015)	−0.007 (0.015)	−0.016 (0.020)	0.069
Specialist care	−0.009 (0.021)	−0.013 (0.027)	0.002 (0.030)	0.009 (0.028)	0.025 (0.029)	0.019 (0.032)	0.257
Ambulatory care	0.016 (0.022)	0.022 (0.023)	0.050 (0.024)**	0.053 (0.024)**	0.064 (0.026)**	0.054 (0.024)**	0.179
Hospitalisation	0.006 (0.015)	0.006 (0.015)	0.010 (0.018)	0.008 (0.017)	0.027 (0.016)*	0.034 (0.016)**	0.051
# Of treated			968				
# Of controls			597				
Summary measures of matching quality							
Logit model pseudo R^2 before matching		0.043	0.179	0.185	0.239	.266	
Logit model pseudo R^2 after matching		0.000	0.002	0.003	0.006	.006	
Median bias before matching		17.168	14.734	10.592	12.411	13.926	
Median bias after matching		0.785	1.824	0.890	2.132	2.494	
# Of treated off common support		0	17	12	20	76	
Covariates	None	Demographic	Demographic	Demographic	Demographic	Demographic	
	(diff. in means)		Socioeconomic	Socioeconomic	Socioeconomic	Socioeconomic	
				Health conditions	Health conditions	Health conditions	
					Employer size	Employer size	
						Health scheme	

* Significance at 10% level; ** significance at 5% level. Standard errors for the ATTs are bootstrapped with 200 replications

probability of having had any ambulatory contacts within the previous 12 months increases notably and reaches statistical significance when the set of socioeconomic variables are included in the propensity score. This implies that the socioeconomic variables increase the probability of having EPHI coverage and reduce the probability of having used ambulatory care simultaneously. Likewise, the estimate of how EPHI affects the probability of being hospitalised increases notably when the size of the workplace is included and reaches statistical significance with the inclusion of company health scheme in the analysis of the privately employed. Finally, considering the results of the most comprehensive model specification, the ATT estimates based on Model XIII presented in Table 4 are quite similar to those based on Model VII for the full sample (presented in Table 3). However, the effects on ambulatory care and hospitalisation are seen to be somewhat higher and statistically significant when the sample is restricted to private sector employees only. More precisely, EPHI is found to increase the probability of having had any ambulatory contacts within the previous 12 months by 3.3 percentage points for the full sample and 5.4 percentage points for the subsample of private sector employees. Likewise, EPHI increases the probability of hospitalisation by 2.8 percentage points for the full sample and 3.4 percentage points when restricting the analysis to the subsample of privately employed. In both cases, the estimates based on the full sample are statistically insignificant, while the estimates for the privately employed are significant at the 5% level. Finally, it is noted that the estimated effects may be interpreted in relation to the baseline probabilities, i.e. the probabilities of having used the health care service in question among the controls. This shows that EPHI increases the probability of hospitalisation from 5.1 to 8.5% and the probability of having had any ambulatory contacts within a 12 month from 17.9 to 23.3% when the analysis is restricted to the subsample of privately employed. Considering the full sample of occupationally active, EPHI does not significantly affect the probability of having used any of the health care services in question within the 12 months prior to the interview. Along with Table 3 the evidence presented in Table 4 thus suggests that some unexplained variation between public and private sector employees remain when considering the sample of all employed and including sector of employment in the propensity score.

Matching quality

The summary measures of matching quality reported in Tables 3 and 4 provide some evidence that matching balances the observable characteristics. The pseudo R^2 from the logit estimation of the propensity score indicates how well the covariates explain the probability of treatment. The low values of the pseudo R^2 statistics after matching across model specifications and study populations indicate that overall matching have succeeded in balancing the covariates between the treated and the control groups. Balancing tests performed separately for each covariate included in the estimation of the propensity scores are available from the author upon request. The median absolute standardized bias is taken over all the covariates included in the estimation of the propensity score. The standardization allows for comparisons across variables and, for a given x_i, comparisons before and after matching. Following Rosenbaum and Rubin (1985), the standardized differences for a single covariate before and after matching are calculated as:

$$\begin{aligned} B_{before}\,(x_i) &= 100 \cdot \frac{\bar{x}_{i1} - \bar{x}_{i0}}{\sqrt{v_1(x_i) + v_2(x_i)/2}} \\ B_{after}\,(x_i) &= 100 \cdot \frac{\bar{x}_{i1M} - \bar{x}_{i0M}}{\sqrt{v_1(x_i) + v_2(x_i)/2}} \end{aligned} \tag{5}$$

where $\bar{x}_{i1}$ denotes the sample means for the subsample of treated and $\bar{x}_{i0}$ denotes the sample means for the subsample of controls, both as a percentage of the square root of the average of the sample variation in the treated and control groups. The post-matching standardized difference $B_{after}(x_i)$ is restricted to consider only treated individuals that fall on the common support. The largest bias reductions are found for the subsample of privately employed, indicating that the restriction of the sample produces a pool of more similar individuals, as indicated by the main results. The theoretical literature does not seem to provide any formal criteria by which to judge the size of the standardized bias (Becker and Muendler 2008). However, the absolute level of median bias after matching found in this study is in the same range as other microeconometric evaluation studies (e.g. Lechner 2002; Sianesi 2004; Becker and Muendler 2008).

Robustness checks

This section assesses the sensitivity of the results with respect to the main identifying assumption of conditional mean independence by performing several robustness checks. Conditional mean independence implies that after conditioning on the propensity score, the probability of having EPHI should be unrelated to unobserved variables that may also affect health care use. For an unobserved variable to be a source of bias, it must thus affect the process that leads to EPHI coverage as well as the use of health care services. The robustness checks include (1) supplementary analyses of the relationships between EPHI and several variables that may affect both the probability of EPHI ownership and the use of health care services, (2) an assessment of the extent to which an unobserved variable must influence the selection process in order to reverse the results, and (3) joint parametric estimation of the probability of having EPHI and health care use.

Supplementary analyses

In the analysis of how EPHI affects the use of covered health care services, it may be argued that the identifying assumption of conditional mean independence relies on several partial assumptions to hold. Following the approach of Barros et al. (2008), the robustness of these partial assumptions is assessed by analysing the relationships between EPHI and several variables that may affect both the probability of having EPHI and the use of health care services, conditioning on the set of covariates included in the estimation of the propensity score. The variables considered in this section were not included in the propensity score either due to endogeneity concerns, i.e. concerns that they may be affected by EPHI status, or because there were no compelling reason as to include them. In order to make as few assumptions about functional form as possible, the supplementary analyses discussed in the following are also performed using propensity score matching. The full results of the various analyses are available from the author upon request.

Firstly, for the assumption of conditional mean independence to hold it must be the case that employers who offer EPHI do not select their employees in a different manner than those not offering EPHI based on health variables other than those included in the estimation of the propensity score. Given that employers are not allowed to ask questions related to health at any point during recruitment and employment (The Ministry of Employment 1996), it is unlikely that the employers who offer EPHI are able to select their employees in a different manner than those not offering EPHI based on unobservable health characteristics.

Secondly, it must hold that the privately insured are not on average unobservably healthier because they have enjoyed more years of preferential access to some types of health care services or for other reasons. If this was the case, there would be an endogeneity problem and the estimates would be biased downwards. Given that EPHI did not gain foothold in Denmark until 2003, it is not very likely that EPHI has affected the health of the insured just yet. An interesting robustness test would have been to repeat the analyses of how EPHI affects health care use with contacts before 2003 as a placebo outcome variable.[14] However, the dataset used in this paper does not contain information on health care use before 2003. Instead, the relationship between EPHI ownership and health is assessed by analysing the relationships between EPHI coverage and a dummy variable for poor or very poor self-assessed health status (versus fair, good, or excellent health) and the standardised measure of health EQ-5D, respectively, matching on a propensity score including the full set of covariates discussed in the data section. EPHI ownership was not significantly related to any of these measures of health at the commonly considered levels of statistical significance.

Along a similar line, it must thirdly be the case that individuals do not purposely select themselves into jobs with EPHI based on some unobserved characteristic that is also associated with the use of health care. Given the existence of a comprehensive universal tax-financed health care system and the fact that the value of EPHI makes up only a negligible small share of the total compensation package, individuals are not expected to purposely select themselves into jobs with EPHI in Denmark.[15] Moreover, given that EPHI is mainly a private sector phenomenon; many other characteristics of private sector jobs, such as wages and fringe benefits in general, may well be expected to have more influence on the choice of job. Nevertheless, there is still the theoretical possibility that those who expect to use more health care, e.g. because they are sicker, more focused on health, or more risk averse, are more likely to end up in jobs offering private health insurance. In order to investigate whether the privately insured are more focused on health or more risk averse than their counterparts without EPHI, the relationships between EPHI coverage and several risky lifestyle habits and preventive efforts were investigated using propensity score matching. These analyses show that after matching on the set of covariates, the group of individuals with EPHI do not differ significantly from those without EPHI with respect to smoking, drinking, exercising habits, bicycle helmet use, influenza vaccinations, and participation in screening programs for cervical- and breast cancer among women. Likewise, analyses of self-reported financial and health-related risk preferences (measured on a scale from one to ten) did not reveal any statistically significant relationships.

Fourthly, it is possible that the presence of company-level selection into EPHI, e.g. because companies with high sickness absence or those using highly educated and specialized labour are relatively more inclined to purchase EPHI, is not fully captured by the variables included in the propensity score. This issue is investigated by analysing the relationship between EPHI coverage and trade union affiliation. This analysis revealed a negative relationship between EPHI coverage and membership of a trade union in the federation of trade unions for workers (abbreviated by LO) or the federation of trade unions for professional and managerial staff graduated from universities (abbreviated by AC) relative to other trade unions or no union. This indicates that some company level selection remains after conditioning on the propensity score. In relation to this, it is noted that LO have not had EPHI high on their agenda when negotiating contracts, and they have a large share of hourly paid workers among their

[14] Thanks to an anonymous referee for pointing this out.

[15] More precisely, the value of EPHI makes up less than 0.5% of the average money wages for the permanently employed in Denmark (Statistics Denmark 2009b; The Danish Insurance Association 2010).

members, who are traditionally less likely to be offered EPHI than employees in companies primarily employing salaried workers. Although several occupational and employer-related variables are included in the estimation of the propensity score, it thus appears that these variables do not completely capture the existing differences between occupational groups.

Rosenbaum bounds

The extent to which an unobserved variable must influence the selection process in order to reverse the results found by the matching estimator may be assessed using the bounding approach suggested by Rosenbaum (1995). Recent applications of this approach can be found in Aavik (2001), Caliendo et al. (2005), and Johar (2009) among others.

Following the exposition in Becker and Caliendo (2007), the rationale behind the Rosenbaum (1995) bounds may be illustrated by considering a binary outcome which is a function of observed covariates x and unobservables u for a matched pair i and j, and letting P_i and P_j denote the probabilities of treatment. The odds ratio of receiving the treatment, i.e. having EPHI coverage, is:

$$\frac{\frac{P_i}{1-P_i}}{\frac{P_j}{1-P_j}} = \frac{P_i\left(1-P_j\right)}{P_j\left(1-P_i\right)} = \frac{\exp\left[\beta x_i + \gamma u_i\right]}{\exp\left[\beta x_j + \gamma u_j\right]} \tag{6}$$

which is equivalent to $\exp[(\gamma(u_i - u_j)]$ for a matched pair with comparable observed covariates. In other words, the matched pair differs only by a factor of γ and the difference in their unobserved covariates u. The odds ratio is one either if the unobserved variables do not differ $(u_i = u_j)$ or if they do not affect the probability of treatment $(\gamma = 0)$. In this case there is no hidden or unobserved selection bias. The Rosenbaum (1995) bounds assess how the matching estimates are affected by changing the values of γ and $(u_i = u_j)$. Assuming for simplicity that the unobserved covariate is a dummy variable with $u_i \in \{0, 1\}$, Rosenbaum (1995) showed that (6) implies that the odds ratio that one of the matched individuals is treated can be bounded by:

$$\frac{1}{e^{\gamma}} \leq \frac{P_i\left(1-P_j\right)}{P_j\left(1-P_i\right)} \leq e^{\gamma} \tag{7}$$

The pair of matched individuals have the same probability of treatment if $e^{\gamma} = 1$. For $e^{\gamma} = 2$, individuals who appear to be similar in terms of observed covariates could differ in their probability of treatment by as much as a factor of two, etc.

Aavik (2001) suggested testing the significance of the treatment effect for various values of e^{γ} using a non-parametric Mantel-Haenszel (1959) test statistic:

$$Q_{MH} = \frac{\left|Y_1 - \sum_{s=1}^{S} E\left(Y_{1s}\right)\right| - 0.5}{\sqrt{\sum_{s=1}^{S} Var\left(Y_{1s}\right)}} = \frac{\left|Y_1 - \sum_{s=1}^{S}\left(\frac{N_{1s}Y_s}{N_s}\right)\right| - 0.5}{\sqrt{\sum_{s=1}^{S}\frac{N_{1s}N_{0s}Y_s\left(N_s - Y_s\right)}{N_s^2\left(N_s - 1\right)}}} \tag{8}$$

which compares the number of positive outcomes in the treatment group against the same expected number given that the treatment effect is zero. The number of treated and controls in stratum s are denoted by N_{1s} and N_{0s}, respectively. Y_{1s} denotes the number of positive outcomes for the treated individuals, Y_{0s} denotes the number of positive outcomes for the controls, and Y_s denotes the total number of positive outcomes in stratum s, which reflects the estimated propensity score. Rosenbaum (1995) showed that, for a fixed e^{γ} and $u \in \{0, 1\}$, Q_{MH} can be bounded by two known distributions that move apart as e^{γ} increases, reflecting

uncertainty about the test statistics in the presence of unobserved selection bias. Let Q^{+}_{MH} and Q^{-}_{MH} denote the test statistics given that the treatment effect is over- and underestimated, respectively (Becker and Caliendo 2007):

$$Q^{+}_{MH} = \frac{\left|Y_1 - \sum_{s=1}^{S} \tilde{E}^{+}_{s}\right| - 0.5}{\sqrt{\sum_{s=1}^{S} Var\left(\tilde{E}^{+}_{s}\right)}} \tag{9}$$

and

$$Q^{-}_{MH} = \frac{\left|Y_1 - \sum_{s=1}^{S} \tilde{E}^{-}_{s}\right| - 0.5}{\sqrt{\sum_{s=1}^{S} Var\left(\tilde{E}^{-}_{s}\right)}} \tag{10}$$

where $\tilde{E}_s$ and $Var\left(\tilde{E}_s\right)$ are the large sample approximations to the expectation and variance of the number of successful participants when u is binary and for a given γ.

These two bounds were estimated for values of e^{γ} in the interval from 1 to 2 using version 1.1.5 of the 'mhbounds' module written by Becker and Caliendo (2006).[16] For the analysis of how EPHI affects the use of health care services, the direction of the bias potentially caused by unobserved variables is not obvious. In particular, it is noted that selection on observables and unobservables need not have the same pattern.

Considering the Rosenbaum (1995) bounds for the most comprehensive model specification estimated on the full sample of occupationally active (i.e. Model VII), it is found that the ATT estimates are quite sensitive to unobserved selection bias. For all health care services, the results are sensitive to unobserved bias that would change the odds of having EPHI by a factor of 1.6 or less.

If there is positive unobserved selection in the sense that the individuals who are most likely to have EPHI are also more likely to use health care, then the estimated effects overestimate the true treatment effects. In this case, Q_{MH} is too high and should be adjusted downwards. The bounds indicate that the estimated effects of EPHI on the probability of having had any hospitalisations, chiropractor, psychologist, or specialist contacts are most sensitive to positive unobserved selection. On the contrary, the estimates for physiotherapy and ambulatory contacts are more sensitive to negative unobserved selection. The effect of EPHI on the probability of having used physiotherapy within a 12 month period becomes positive and statistically significant at the 5% level if negative unobserved selection reduces the odds of having EPHI by a factor of 1.35. Likewise, the effect on hospitalisation becomes significantly positive at the 5% level for unobserved selection that reduces the odds of having EPHI by a factor of 1.25. Considering the subsample of privately employed, the results are generally found to be less sensitive to unobserved selection bias, and in some cases the direction of sensitivity differs. In particular, the estimated effects on physiotherapy, specialist, and ambulatory contacts are most sensitive to positive unobserved selection and hence most likely to be overestimated, while the opposite relationship holds for the remaining health care services.

[16] The bounds were estimated around ATT estimates based on one-to-one nearest neighbour matching with a radius of 0.01 and no replacement. The reason for using this matching algorithm rather than kernel matching is that the Rosenbaum (1995) bounds are unsuitable for kernel matching. However, it was checked and confirmed that the ATT estimates based on one-to-one nearest neighbour matching with a radius of 0.01 and no replacement do not differ significantly from the estimates based on kernel matching. Hence, the difference in matching algorithms is unimportant in this context.

The full results for the various bounds discussed in this section are available from the author upon request.

Joint parametric model

The final robustness check involves estimating a joint parametric model of received treatment D and outcome Y that relaxes the assumption of conditional mean independence by allowing for correlation between unobservables. For binary treatment and outcomes the joint model is naturally specified using the bivariate probit model[17]:

$$\begin{aligned} &Y = 1\left(\beta_1 X + \alpha D - U > 0\right), D = 1\left(\beta_2 X + \pi Z - V > 0\right), \\ &(U, V) \sim N\left(\begin{pmatrix} 0 \\ 0 \end{pmatrix}, \begin{pmatrix} 1 & \rho \\ \rho & 1 \end{pmatrix}\right) \end{aligned} \tag{11}$$

where β_1 and β_2 are vectors of coefficients for the covariates X, α is the coefficient for the treatment D, π is the coefficient for the instrumental variable Z, and U and V are unobserved latent variables that follow a bivariate standard normal distribution with correlation coefficient ρ. Identification of the effect of D on Y is obtained by the non-linearity of the bivariate normal distribution (Wilde 2000). However, an additional source of identification can be utilized if an instrumental variable, Z, which affects D but not Y directly, is available.[18] Assuming that the model is correctly specified $\rho \neq 0$ implies that D is endogenous with respect to Y. The joint parametric model thus allows one to check whether selection on unobservables is present by assessing the significance of the correlation coefficient ρ. Consistent estimation of the unknown parameters can be obtained by the method of maximum-likelihood.

In this study, EPHI status is instrumented using the set of dummy variables measuring the size of the workplace in terms of employees. The relevance criterion is likely to be fulfilled for this instrumental variable given that larger companies generally pay a smaller premium per employee because the scope for risk pooling increases with company size. Moreover, previous empirical evidence found the probability of companies purchasing EPHI to their employees to be increasing with company size (Seim et al. 2007). It may be argued that the exclusion restriction is likely to be fulfilled as well based on the reasoning that after conditioning on the set of covariates, there is little reason to believe that the use of health care should depend on employer size.

Appendix C reports the correlation coefficients and corresponding likelihood-ratio tests of significance for the various model specifications accounted for in the results section in order to assess the identifying assumption of propensity score matching that there is no selection on unobservables. Except for chiropractic care, the correlation coefficients are insignificant at the commonly considered levels of statistical significance for all model specifications. Assuming that the model is correctly specified, this implies that EPHI coverage is exogenous in the analysis of health care use. The evidence from the joint parametric model thus indicates that overall the identifying assumption of no selection on unobservables cannot be rejected. The significant correlation coefficients for the analyses of chiropractic care are large and negative, indicating that the individuals with EPHI are less likely to use chiropractic care irrespective of insurance status after conditioning on the available set of covariates. The results of the joint parametric model thus indicate that the effect of EPHI on the use of chiropractic care may be underestimated by propensity score matching.

[17] A related estimator is the two-stage least squares estimator, but due to the discrete nature of both treatment and outcomes, this will at best be an approximation.

[18] The latter is an additional exogeneity restriction, also referred to as the exclusion restriction.

Discussion

The finding that EPHI increases the probability of having had one or more hospitalisations or ambulatory contacts (including examinations, scans, same-day surgery, and control visits) among the privately employed corresponds well with the classification of EPHI as primarily duplicate in relation to the tax-financed health care system and the fact that 67% of the total gross compensations paid out by the commercial insurers were allocated towards operations and the like in 2009 (The Danish Insurance Association 2010). The predominantly positive but largely insignificant estimates of how EPHI affects health care use for the full sample of occupationally active as well as the use of physiotherapy, chiropractic, and specialist consultations among the privately employed may have several possible explanations. As previously mentioned, the non-existent or limited effect of EPHI may reflect the use of gatekeepers as well as restrictions in the coverage provided by the commercial insurers. In particular, private insurance patients in Denmark must, like everybody else, obtain a referral to for instance elective surgery, typically from their general practitioner who acts as a gatekeeper in this respect.[19] Moreover, the private insurance schemes often impose a limitation on the annual number of physiotherapy, chiropractic, and psychological counselling sessions that are covered (Kjellberg et al. 2010). Finally, it must be stressed that this study considers only the probability of having had any contacts within a 12 month period; it does not differentiate between tax-financed and privately paid contacts. Hence, another possible, and perhaps more likely, explanation of the absence of a significant effect of EPHI is that of substitution, i.e. that duplicate EPHI shifts the use from tax-financed contacts to privately paid contacts, while the total use of health care stays the same. The recent finding of Søgaard et al. (2011) that EPHI reduces the use of tax-financed health care services supports this hypothesis.

The difference in the results for the full sample of occupationally active and the subsample of privately employed may indicate that some unexplained variation between public and private sector employees remain after conditioning on the propensity score. Such difference may be attributable to among other things differences in the skill mix of the workforce and the pay and conditions of employment between the two sectors, which are not completely captured by the variables included in the propensity score. Another factor that may have attributed to the difference is the fact that only very few public employers offer EPHI to their employees. Hence, the full sample contains a group of individuals who are very likely to have EPHI, for which it is difficult to find appropriate controls. The initial robustness checks indicate that possible violations of the conditional mean independence assumption are most likely at the company level, and that unobserved heterogeneity may have biased the results somewhat upwards. However, the vast majority of the checks do not contradict the identifying assumption; as a matter of fact it suggests that the conditional mean independence assumption is plausible. Given that the results are found to be quite sensitive to possible deviations from the identifying assumption of conditional mean independence, some caution when interpreting the results is advisable. However, one should keep in mind that the Rosenbaum (1995) bounds do not assess whether unobserved selection is actually present in a given setting.

[19] The general practitioners have no financial incentives to restrict the number of referrals to more specialised care. However, they play a crucial role in ensuring that the principle of keeping treatment at the lowest effective care-level (i.e. the so-called LEON-principle) is followed. Moreover, a set of guidelines agreed on by the Danish Medical Association and the Danish Insurance Association in 2008 state that it is the responsibility of the general practitioners to ensure that patients are treated based on medical needs rather than whether they have private health insurance or not (The Danish Insurance Association 2011). Hence, it is likely that the general practitioners, due to their general gatekeeper role, reduce the scope for moral hazard.

For policy purpose, the results of the present study do not say anything about whether the use of health care services without EPHI is efficient or inefficiently high or low. Hence, it is not possible to evaluate how the increase in use induced by EPHI affects the welfare for society based on the results of this study. However, the finding that EPHI induces some extent of moral hazard in the use of ambulatory care among private sector employees, thereby generating horizontal inequity in the use of this type of health care should nevertheless be of relevance to policy makers in Denmark and other countries with universal health care systems and duplicate EPHI.

Like all studies, there are some methodological limitations to this study. Considering first the data, the use of data collected using an internet-based questionnaire constitutes a source of bias if the individuals who can be reached through the internet differ from those without internet access on the characteristics that are subject to investigation. Given that 86% of the Danish population had internet access in their homes in 2009 (Statistics Denmark 2009a) and this study restrict the analysis to the occupationally active, the use of an internet-based questionnaire is not expected to be a major issue. Although in line with what is commonly seen in internet-based surveys (Cook et al. 2000; Sheehan 2006), the response rate of 41% is not impressive and may be argued to hamper the ability to make inferences about the study population. However, the extent of bias entailed by a low response rate is a function of the response rate itself as well as differences between respondents and non-respondents on the variables of interest. In the present study, it is possible that the respondents differ from those who did not answer the questionnaire by having a greater interest in the subject of the survey, i.e. private health insurance. Such an interest could be spurred by being strongly for or against private health insurance, and it may be positively or negatively related to health and health care use. Hence, while caution should always be exercised when using survey data, there are no obvious reasons to believe that the results of this study are systematically biased by non-response. While representativity issues cannot be dismissed with complete certainty, it is, however, worth noting that as previously discussed, the application of inverse probability weights based on age, gender, and region of residence does not change the results notably. Moreover, the use of self-reported data on health care use calls for a brief discussion. Based on the findings of a review of the empirical literature on the use of self-reported health care data (Bhandari and Wagner 2006), some extent of underreporting is expected to be present in the data, and the estimates for the use of inpatient care are expected to be more precise than those for outpatient care. The inaccuracies are, however, not expected to bias the results of this study in any particular direction. Finally, the definition of treatment in studies of how private health insurance affects the use of covered health care services is not straight forward. In accordance with what is common practice in the empirical literature, this study defines treatment as EPHI coverage, i.e. potential use of private care. An alternative approach would be to define treatment as actual use of private care, given that this is the channel through which EPHI is expected to affect the total use of health care services. This would, however, make it very hard to justify the assumption of selection on observables. As a consequence of this, and in order to comply with the literature, treatment is defined as EPHI coverage in this study.

Considering next the econometric method, there are advantages as well as disadvantages associated with matching estimators. The main advantages of matching estimators are the avoidance of functional form assumptions, emphasis on common support, and most importantly the lack of need for exclusion restrictions. On the negative side, the identifying assumption of conditional mean independence poses a challenge. Several robustness checks were performed in order to assess the sensitivity of the results with respect to this assumption. Overall, the robustness checks indicate that the conditional mean independence assumption

is plausible in the present study, given the institutional setting of EPHI in Denmark and the comprehensive set of covariates included in the propensity score, thus placing confidence in the main findings of the study. Finally, it is possible that the stable-unit treatment assumption does not hold in the analyses of how EPHI affects health care use. For one thing individuals with EPHI may release capacity in public hospitals, thereby facilitating quicker access for those who rely exclusively on the tax-financed health care system. If this is the case, the treatment effect for individual i is not independent of the treatment status of the other individuals. However, EPHI may also bring along a slide in the indications for treatment, such that the capacity in the public hospitals remains unchanged or even decreases (Propper and Green 2001). In the context of the Danish health care system, there is no evidence as to which effect dominates. Hence, it is uncertain in which direction a potential violation of the stable-unit treatment assumption may bias the results.

Conclusion

During the recent decade, Danish employers have increasingly taken out private health insurance primarily covering elective surgery at private facilities on behalf of their employees. The overall maintained hypothesis deduced from economic theory is that private health insurance increases the use of covered health care services, all else equal. The findings of this study show that EPHI increases the probability of having had one or more hospitalisations or ambulatory contacts within a 12 month period among the privately employed, thereby generating some extent of horizontal inequity in the use of these types of health care services. However, the predominantly positive but largely insignificant estimates of how EPHI affects health care use for the full sample of occupationally active as well as the use of physiotherapy, chiropractic, and specialist consultations among the privately employed indicate that individuals generally do not exploit the presence of EPHI to increase their use of health care services. The limited effect of EPHI was possible foreseeable given the presence of institutional barriers such as gatekeepers and restrictions in the coverage provided by the private insurers as well as substitution effects causing individuals to shift the use from tax-financed to privately paid contacts rather than increase the total use.

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Appendix A: Propensity scores

See Tables 5 and 6.

Table 5 Results of the logit models used to estimate the propensity scores for the sample of all employed, n = 2,636

	Model II Odds ratio (std. err.)	Model III Odds ratio (std. err.)	Model IV Odds ratio (std. err.)	Model V Odds ratio (std. err.)	Model VI Odds ratio (std. err.)	Model VII Odds ratio (std. err.)
Sociodemographic variables						
Male	1.468 (0.119)***	1.539 (0.132)***	1.522 (0.132)***	1.459 (0.128)***	1.447 (0.130)***	1.157 (0.132)
Age	1.123 (0.032)***	1.077 (0.033)**	1.080 (0.033)**	1.062 (0.033)*	1.058 (0.034)*	1.154 (0.044)***
Age^2	0.998 (0.000)***	0.999 (0.000)***	0.999 (0.000)***	0.999 (0.000)**	0.999 (0.000)**	0.998 (0.000)***
Married	1.242 (0.121)**	1.007 (0.107)	1.003 (0.106)	0.999 (0.107)	0.981 (0.108)	1.210 (0.165)
# Children in household	0.974 (0.049)	0.960 (0.050)	0.955 (0.050)	0.963 (0.051)	0.974 (0.052)	0.952 (0.065)
# Adults in household	0.918 (0.054)	0.810 (0.058)***	0.815 (0.058)***	0.832 (0.060)**	0.844 (0.062)**	0.838 (0.078)*
Northern Jutland	0.614 (0.091)***	0.608 (0.092)***	0.604 (0.092)***	0.629 (0.096)***	0.653 (0.102)***	0.607 (0.115)***
DKK 400–800/USD 75–150 (1,000)[a]		1.608 (0.215)***	1.593 (0.214)***	1.541 (0.209)***	1.556 (0.216)***	1.280 (0.219)
DKK 800+/USD 150+ (1,000)[a]		3.093 (0.504)***	3.052 (0.498)***	2.844 (0.471)***	2.839 (0.480)***	1.771 (0.378)***
Don't know income[a]		1.105 (0.488)	1.106 (0.490)	1.098 (0.491)	1.125 (0.515)	1.164 (0.618)
Do not wish to disclose[a]		2.391 (0.453)***	2.360 (0.448)***	2.253 (0.435)***	2.301 (0.453)***	1.375 (0.340)
Vocational education[b]		1.334 (0.198)*	1.336 (0.199)*	1.355 (0.205)**	1.350 (0.208)*	1.200 (0.223)
Higher education[b]		0.877 (0.121)	0.874 (0.121)	0.883 (0.124)	0.902 (0.130)	1.247 (0.218)
Other education[b]		1.131 (0.418)	1.164 (0.432)	1.140 (0.431)	1.179 (0.453)	1.125 (0.506)
Skilled worker[c]		0.847 (0.140)	0.869 (0.145)	0.943 (0.159)	0.910 (0.157)	0.594 (0.122)**
Unskilled worker[c]		0.994 (0.165)	1.005 (0.168)	1.029 (0.174)	1.047 (0.180)	0.544 (0.109)***
Self-employed[c]		0.227 (0.046)***	0.227 (0.046)***	0.467 (0.113)***	0.493 (0.120)***	0.234 (0.058)***
Member of 'denmark'		1.188 (0.101)**	1.188 (0.101)**	1.168 (0.101)*	1.153 (0.101)	1.163 (0.128)
Health-related variables						
Asthma			0.830 (0.154)	0.845 (0.160)	0.867 (0.167)	0.930 (0.226)
Allergies			1.125 (0.114)	1.126 (0.115)	1.146 (0.119)	1.156 (0.154)
Diabetes			0.978 (0.216)	0.953 (0.212)	0.927 (0.211)	1.176 (0.345)
Hypertension			0.982 (0.129)	0.985 (0.131)	1.001 (0.136)	0.996 (0.169)
Emphysema			1.100 (0.362)	1.131 (0.379)	1.092 (0.373)	1.013 (0.424)

Table 5 continued

	Model II Odds ratio (std. err.)	Model III Odds ratio (std. err.)	Model IV Odds ratio (std. err.)	Model V Odds ratio (std. err.)	Model VI Odds ratio (std. err.)	Model VII Odds ratio (std. err.)
Arthritis			0.742 (0.096)**	0.754 (0.099)**	0.709 (0.095)***	0.629 (0.104)***
Osteoporosis			0.791 (0.336)	0.782 (0.334)	0.923 (0.406)	1.151 (0.618)
Tinnitus			0.939 (0.149)	0.995 (0.159)	1.021 (0.167)	0.868 (0.175)
Employer-related variables						
5–9 employees[d]				1.978 (0.498)***	1.789 (0.457)**	2.316 (0.627)***
10–49 employees[d]				2.223 (0.479)***	2.007 (0.437)***	3.498 (0.793)***
50–249 employees[d]				2.448 (0.533)***	2.078 (0.459)***	4.636 (1.095)***
250+ employees[d]				3.799 (0.828)***	3.016 (0.668)***	7.197 (1.731)***
Company health scheme					2.520 (0.237)***	3.145 (0.395)***
Indep. public employer[e]						9.881 (2.545)***
Private employer[e]						43.150 (6.677)***
Other employer[e]						9.091 (4.271)***
Constant	0.091 (0.055)***	0.177 (0.115)***	0.161 (0.105)***	0.087 (0.060)***	0.080 (0.056)***	0.000 (0.000)***
Log likelihood	−1746.50	−1675.92	−1671.88	−1645.17	−1595.94	−1102.71
LR χ^2	83.38 (df = 7)	224.54 (df = 18)	232.62 (df = 26)	286.05 (df = 30)	384.51 (df = 31)	1370.96 (df = 34)
Pseudo R^2	0.023	0.063	0.065	0.080	0.108	0.383

* Significance at 10% level; ** significance at 5% level; *** significance at 1% level. Conversion from DKK to USD is undertaken using the March 2011 average exchange rate of 532.75 (Danske Bank 2011)

[a] Reference level for the income dummies is DKK 0–400/USD 0–75 (1,000)

[b] Reference level for the education dummies is basic or high school education

[c] Reference level for the occupation dummies is white-collar worker

[d] Reference level for the employer size dummies is 1–4 employees

[e] Reference level for the sector of employment dummies is public employee

Table 6 Results of the logit models used to estimate the propensity scores for subsample of private sector employees, n = 1,565

	Model IX Odds ratio (std. err.)	Model X Odds ratio (std. err.)	Model XI Odds ratio (std. err.)	Model XII Odds ratio (std. err.)	Model XIII Odds ratio (std. err.)
Sociodemographic variables					
Male	0.888 (0.097)	1.167 (0.148)	1.156 (0.149)	1.075 (0.145)	1.079 (0.148)
Age	1.226 (0.042)***	1.167 (0.046)***	1.175 (0.046)***	1.136 (0.047)***	1.149 (0.049)***
Age^2	0.998 (0.000)***	0.998 (0.000)***	0.998 (0.000)***	0.999 (0.000)***	0.998 (0.000)***
Married	1.585 (0.202)***	1.337 (0.201)*	1.342 (0.203)*	1.332 (0.210)*	1.302 (0.208)*
# Children in household	0.957 (0.065)	0.968 (0.074)	0.956 (0.073)	0.979 (0.078)	0.986 (0.080)
# Adults in household	0.944 (0.070)	0.849 (0.086)	0.856 (0.087)	0.881 (0.093)	0.888 (0.095)
Northern Jutland	0.532 (0.101)***	0.549 (0.112)***	0.559 (0.115)***	0.611 (0.131)**	0.595 (0.130)**
DKK 400–800/USD 75–150 (1,000)[a]		1.434 (0.260)**	1.416 (0.259)*	1.292 (0.248)	1.320 (0.261)
DKK 800+/USD 150+ (1,000)[a]		2.581 (0.608)***	2.490 (0.591)***	1.998 (0.496)***	1.990 (0.506)***
Don't know income[a]		1.008 (0.615)	0.984 (0.593)	0.863 (0.533)	0.878 (0.550)
Do not wish to disclose[a]		1.676 (0.434)**	1.584 (0.414)*	1.365 (0.376)	1.388 (0.393)
Vocational education[b]		1.363 (0.267)	1.345 (0.265)	1.297 (0.269)	1.363 (0.289)
Higher education[b]		1.416 (0.261)*	1.386 (0.258)*	1.388 (0.273)*	1.443 (0.291)**
Other education[b]		0.863 (0.408)	0.922 (0.437)	0.858 (0.425)	0.917 (0.471)
Skilled worker[c]		0.449 (0.093)***	0.452 (0.094)***	0.516 (0.112)***	0.464 (0.104)***
Unskilled worker[c]		0.429 (0.087)***	0.431 (0.089)***	0.381 (0.082)***	0.384 (0.085)***
Self-employed[c]		0.064 (0.014)***	0.063 (0.014)***	0.209 (0.053)***	0.210 (0.054)***
Member of 'denmark'		1.212 (0.148)	1.217 (0.150)	1.244 (0.160)*	1.225 (0.160)
Health-related variables					
Asthma			0.944 (0.257)	0.999 (0.288)	1.048 (0.308)
Allergies			1.298 (0.195)*	1.253 (0.196)	1.232 (0.195)

Table 6 continued

	Model IX Odds ratio (std. err.)	Model X Odds ratio (std. err.)	Model XI Odds ratio (std. err.)	Model XII Odds ratio (std. err.)	Model XIII Odds ratio (std. err.)
Diabetes			1.712 (0.615)	1.468 (0.540)	1.356 (0.506)
Hypertension			1.202 (0.231)	1.234 (0.249)	1.286 (0.267)
Emphysema			0.756 (0.337)	0.773 (0.368)	0.782 (0.375)
Arthritis			0.654 (0.117)**	0.603 (0.113)***	0.570 (0.110)***
Osteoporosis			1.222 (0.745)	1.537 (0.970)	1.862 (1.209)
Tinnitus			0.811 (0.175)	0.859 (0.193)	0.899 (0.207)
Employer-related variables					
5–9 employees[d]				2.685 (0.749)***	2.373 (0.675)***
10–49 employees[d]				4.105 (0.952)***	3.575 (0.843)***
50–249 employees[d]				6.026 (1.477)***	4.645 (1.166)***
250+ employees[d]				11.766 (3.013)***	8.521 (2.235)***
Company health scheme					3.074 (0.485)***
Constant	0.037 (0.027)***	0.070 (0.058)***	0.058 (0.049)***	0.022 (0.020)***	0.016 (0.014)***
Log likelihood	−996.08	−854.92	−848.36	−792.75	−764.94
LR χ^2	88.6 (df = 7)	370.91 (df = 18)	384.03 (df = 26)	495.26 (df = 30)	550.87 (df = 31)
Pseudo R^2	0.043	0.178	0.185	0.238	0.265

* Significance at 10% level; ** significance at 5% level; *** significance at 1% level. Conversion from DKK to USD is undertaken using the March 2011 average exchange rate of 532.75 (Danske Bank 2011)

[a] Reference level for the income dummies is DKK 0–400/USD 0–75 (1,000)

[b] Reference level for the education dummies is basic or high school education

[c] Reference level for the occupation dummies is white-collar worker

[d] Reference level for the employer size dummies is 1–4 employees

Appendix B: Assessment of common support

See Figs. 1 and 2.

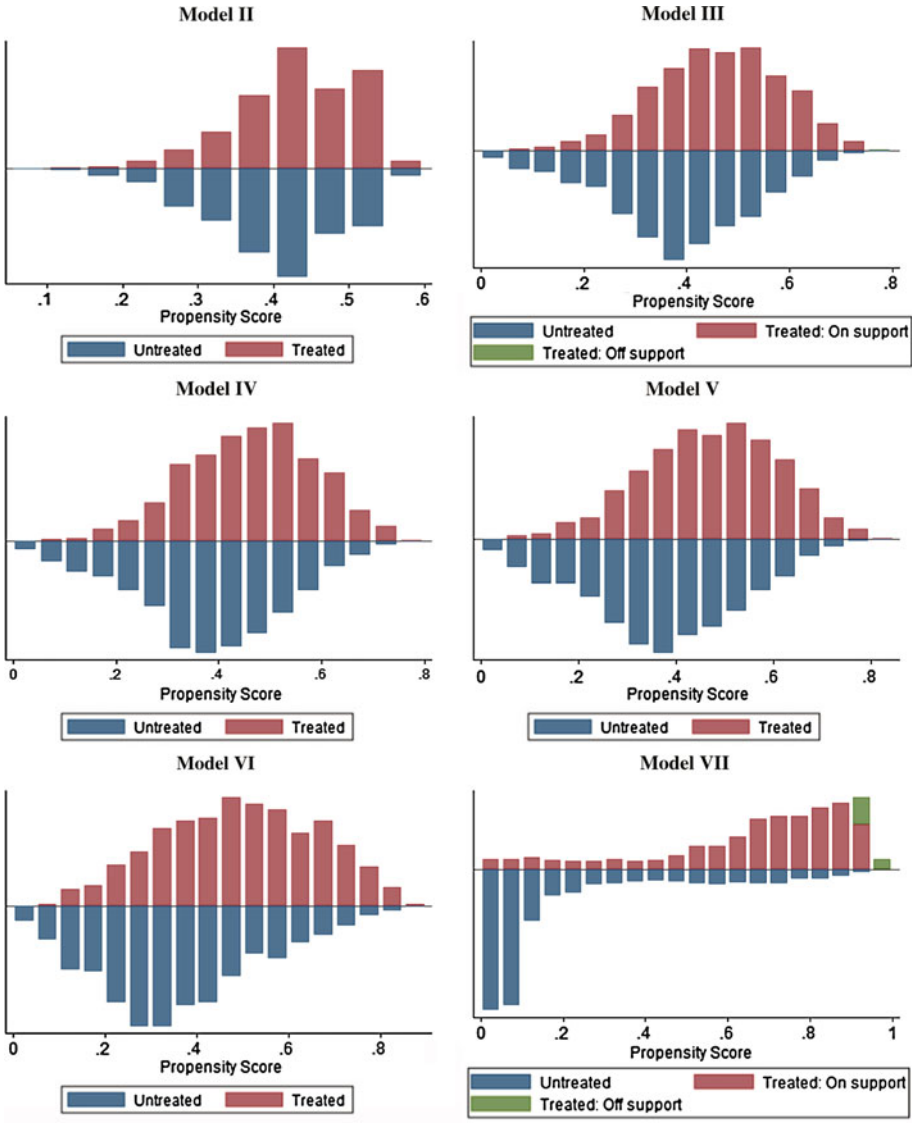

Fig. 1 Propensity scores for treated and non-treated for all employed, n = 2,636

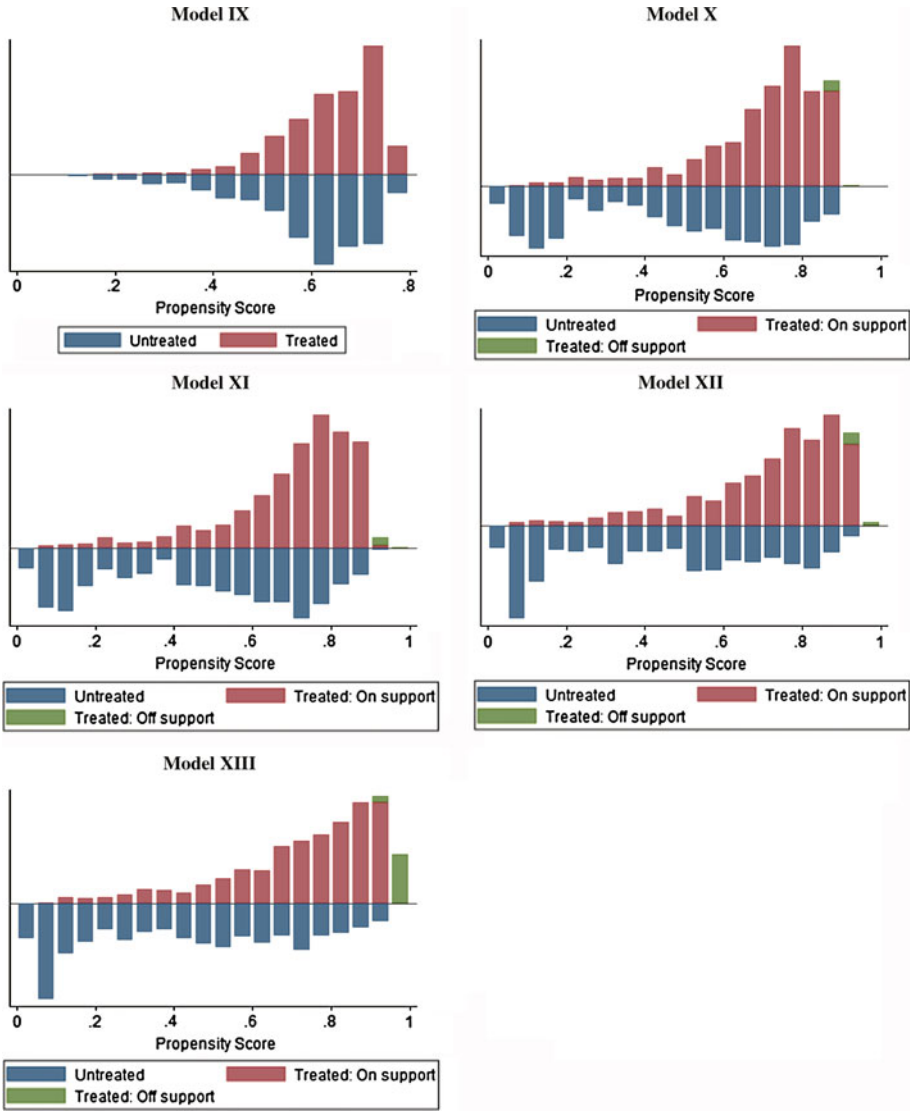

Fig. 2 Propensity scores for treated and non-treated for private sector employees, n = 1,565

Appendix C

See Table 7.

Table 7 Correlation coefficients from the joint parametric models

	Model I		Model II		Model III		Model IV		Model VI		Model VII	
	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value
All employed, n = 2,636												
Physiotherapy	−0.008 (0.169)	0.964	−0.021 (0.194)	0.915	−0.203 (0.248)	0.427	−0.216 (0.254)	0.411	−0.227 (0.328)	0.514	−0.165 (0.180)	0.383
Chiropractic care	−0.254 (0.179)	0.155	−0.184 (0.189)	0.329	−0.407 (0.204)	0.083	−0.445 (0.189)	0.051	−0.431 (0.202)	0.088	−0.397 (0.139)	0.017
Psychological counselling	0.096 (0.215)	0.663	0.262 (0.231)	0.285	0.467 (0.316)	0.193	0.466 (0.333)	0.210	0.244 (0.327)	0.461	0.240 (0.220)	0.274
Specialist care	0.049 (0.147)	0.740	−0.030 (0.164)	0.854	−0.049 (0.240)	0.837	−0.128 (0.242)	0.599	−0.204 (0.304)	0.513	0.160 (0.164)	0.326
Ambulatory care	−0.059 (0.151)	0.233	−0.056 (0.160)	0.727	−0.088 (0.224)	0.696	−0.131 (0.227)	0.568	0.027 (0.265)	0.919	0.136 (0.200)	0.492
Hospitalisation	−0.046 (0.217)	0.363	−0.068 (0.230)	0.766	−0.039 (0.401)	0.922	−0.035 (0.399)	0.931	0.365 (0.404)	0.491	0.494 (0.259)	0.100
	Model VIII		Model IX		Model X		Model XI		Model XIII			
	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value		
Private sector employees, n = 1,565												
Physiotherapy	−0.102 (0.112)	0.363	−0.163 (0.123)	0.185	−0.268 (0.179)	0.153	−0.249 (0.197)	0.223	−0.116 (0.246)	0.640		
Chiropractic care	−0.101 (0.122)	0.407	−0.096 (0.129)	0.457	−0.230 (0.182)	0.222	−0.289 (0.182)	0.134	−0.328 (0.200)	0.126		
Psychological counselling	−0.026 (0.154)	0.867	0.073 (0.166)	0.663	0.022 (0.270)	0.933	0.064 (0.287)	0.821	−0.017 (0.292)	0.953		
Specialist care	0.079 (0.102)	0.438	−0.001 (0.110)	0.986	0.081 (0.179)	0.651	0.102 (0.180)	0.571	0.182 (0.211)	0.393		
Ambulatory care	0.047 (0.106)	0.657	−0.018 (0.116)	0.878	−0.080 (0.199)	0.688	−0.044 (0.202)	0.829	0.139 (0.233)	0.555		
Hospitalisation	0.064 (0.147)	0.663	0.007 (0.160)	0.963	0.161 (0.279)	0.573	0.224 (0.260)	0.413	0.473 (0.239)	0.116		

Table 7 continued

	Model I		Model II		Model III		Model IV		Model VI		Model VII	
	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value	ρ (std. err.)	p value
Covariates	None (diff. in means)		Demographic		Demographic Socioeconomic		Demographic Socioeconomic Health conditions		Demographic Socioeconomic Health conditions Health scheme		Demographic Socioeconomic Health conditions Health scheme Employer sector	

The reported p values are based on likelihood ratio tests of $\rho = 0$. This table does not include Model V and Model XII. These models extended the set of covariates by including the set of dummy variables measuring the size of the workplace, which was used to instrument EPHI in the joint parametric model

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