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Can the use of Electronic Health Records in General Practice reduce hospitalizations for diabetes patients? Evidence from a natural experiment.

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Abstract

Disease management programmes (DMP) in the general practice sector are increasingly used to improve health of chronically ill patients, reduce hospitalizations and thereby costs. The aim of this paper is to estimate the causal effects of the enrolment of general practices (GP) in a DMP based on Electronic Health Records (EHR) on diabetes patients total hospitalizations, diabetes related hospitalizations and hospitalizations with diabetes and cardiovascular related Ambulatory Care Sentive Conditions (ACSC). We use a rich nationwide panel dataset (2004-2013) with information of stepwise enrolment of GPs in the EHR program. As a control group we use GPs who never enrolled. Following the recent literature on causal inference with panel data, we use a standard propensity score matching estimator where we also match on pre-treatment outcomes. This allows controlling for all the unobservable confounders which were already present in the pre-treatment outcomes. Alternative, we use a difference in difference as well as a parametric model with a continuous treatment specification and find similar results. Our results show that enrolment in EHR reduced diabetes patients' risk of hospitalizations by more than 10%. The results are comparable with studies on EHR programs from California and the magnitudes of the effects are comparable to DMPs including both EHR and financial incentives.

JEL classification:I12, I18

Keywords: Disease management, General Practice, Ambulatory Care Sensitive Conditions (ACSC), propensity score matching

1. Introduction

It is well perceived that access to health care overall is associated with lower hospitalization rates (Bindman et al. 1995; Bunker, Frazier, and Mosteller 1994; Roemer et al. 1975; Starfield 1995). Starfield argues that it is important to uncover what it is about access that is most contributory to good outcomes. She points to primary care as a neglected explanatory variable (Starfield 1995). In a later review paper she concludes that evidence suggests that primary care reduce illness and death (Starfield, Shi, and Macinko 2005).

More recent studies have investigated whether primary care disease management, the use of electronic health records, organizational improvements and the introduction of financial incentives in primary care, affect hospitalization rates.

Two branches of studies are interesting to compare. The first branch of the studies is on the effect of financial incentives as e.g. pay for performance (P4P) programs of which the English Quality and Outcome Framework (QOF) is probably the most studied (Eijkenaar et al. 2013). This literature focuses on the effect of the financial incentives in the P4P programs but tend to ignore that the introduction of P4P is often accompanied by the introduction of electronic health records (EHR). A well-known problem with this literature is the problem of separating the effect of EHR from the effect of P4P (Eijkenaar et al. 2013).

The second branch of the literature relates to the effect on hospitalizations of introducing electronic health records (EHR) in primary care (Cebul et al. 2011; Han et al. 2016; Reed et al. 2013; Reed et al. 2012). This literature emerged around the introduction of the Health Information Technology for Economic and Clinical Health (HITECH) Act in US in 2009. The HITECH Act offered providers financial incentives to show meaningful use of EHR until 2015. After 2015 the Act will put penalties on providers failing to show such meaningful use.

This paper focuses on the effect on hospitalizations of introducing EHR in primary care in a European country with a National Health System comparable to the UK system. The focus will be on diabetes care. The effect of primary care disease management programs (DMP) on reducing hospitalizations for diabetes patients has been the subject in a handful of recent studies in health economic and clinical journals (Dusheiko et al. 2011; Iezzi, Lippi Bruni, and Ugolini 2014; Reed et al. 2013; Han et al. 2016). Most studies find a favorable association between the intensity of DMP participation and hospitalizations. Few studies however are

able to estimate causal relationships.

Dusheiko, Doran et al (2011) assess the association between performance on quality indicators and potentially preventable hospitalizations (Amulatory Care Sensitive Conditions - ACSC) for 8000 GP clinics in a 3 years dataset. They find an impact on short-term acute hospitalizations. In another study the impact on cost has been assessed using patient level data for 5 mio patients with covariates at small area level and QOF indicators at GP level. They find that stroke is the only therapeutic area were cost has been reduced as an effect of the DMP.

Harrison et al (2014) use non-incentivised activities as a control for incentivized activity in the QOF and it is probably the study on the QOF where results are closer to have causal interpretation (Harrison et al. 2014). This study show that ACSC hospitalization are 10% lower for incentivized therapeutic areas after the QOF as compared to non incentivized areas.

A more low-powered financial scheme has been introduced in the Emilia Romagna region in Italy and has been studied using patient level data. The most comprehensive and recent study on this program use data for around 160.000 diabetes patients observed over 3 years. Using count models on panel data they show that an increase on 100 Euros in the financial incentives paid to GPs reduce diabetes ACSC with 1 % (Iezzi, Lippi Bruni, and Ugolini 2014).

Han et al (2016) analyzed the impact of using diabetes registries in a group of GP practices in Western New York. The study is based on GPs self-reported use of diabetes registries and cross sectional claims data and find significant association between use of diabetes registries and lower risk of preventable hospitalizations and emergency department visits.

Another low-powered scheme has been analyzed in California where the use of EHR has been hypothesized to influence hospitalizations for diabetes patients. (Reed et al. 2013) use data for around 160.000 diabetes patients from a total population of 2.5 mio individuals above 35 years of age to assess the impact of EHR participation. This is, to our knowledge, the only study in the area, with data on participants and non-participants before and after participation thereby enabling an analytical setup valid for causal interpretation. They find that EHR participation reduce ACSC hospitalizations with approximately 10%. Interestingly this rate is very close to the findings in (Harrison et al. 2014) on the effectiveness of the QOF. This may indicate that non-financial incentives may have an effect comparable to financial incentives in the case of general practice. This is of course soft evidence as the context in the two studies is different and they are not comparable directly. A recent study by (Kolstad

2013) however point in the same direction. He finds that intrinsic incentives on US surgeons had a 3 time higher impact on physician behavior than extrinsic incentives (Kolstad 2013).

Contribution of the paper

The literature on the effects of DMP in diabetes care is mainly based on association studies and before- and after analysis. This paper contributes to the literature in various ways. We are able to estimate the causal effect a non-financial DMP with a convincing identification strategy. In particular, having access to extensive data on several observable characteristics as well as several periods of pre-treatment outcomes, allows us to deal with both observable and unobservable confounders. Furthermore the study analyses the effect of EHR in the context of a tax financed National Health System whereas most of this literature relates to effect of the US HITECH Act from 2009.

Context - the Danish health system

Denmark is, like other Nordic countries, characterised by being a tax financed Welfare state and health care is almost entirely based on tax financed services with equal access for all (Carl Hampus Lyttkens 2016). Primary care is characterised by self-employed general practitioners acting as gate-keepers to specialised care (Olsen 2016).

Danish GPs work on a national contract with the Regions of which there are 5. The remuneration scheme is mixed with 70% fee for service and 30% capitation. The contract details not only services and reimbursement but also opening hours and required postgraduate education. Typical GP's office receives 95% of its operating income from public funds. The contracts cover reimbursable services and a fee schedule. The contract is re-negotiated every 2 years.

Practice units in Denmark are fairly small, on average close to 2 GPs per unit plus nurses and secretaries. The average number of patients per full time GP is around 1,500 and patients have on average, about 7 GP contacts annually, including clinic consultations, home visits, and telephone consultations.

Over the past few years a decrease in solo practices has been seen and is expected to accelerate, in part because of the GP age structure, with many GPs retiring and new GPs not wanting to practice alone. This latter workforce trend is pointing toward a new model with employed GPs, particularly in rural areas.

The EHR program

The natural experiment we consider in this study is comparable with the Californian case studied by (Reed et al. 2013) as it is based on the use of EHR. The DMP were introduced as a pilot study/development project with a limited number of participants in 2006-10. Then in the National contract, agreed between the Association of General Practice and the Association of Danish Regions in 2011, participation were made mandatory and GPs were obliged to enroll in the program within three years. In this study we assess the effect of GPs participating in 2011 and 2012 as restricting analyses to participants enrolling after it became mandatory is expected to reduce selection bias.

The time of enrollment was not random. However, we expect that it is exogenous after controlling for all the observable characteristic as well as the pre-treatment outcomes. An anecdotal explanation for the exogenous variation in timing of enrolment relates to differences in the possibility of the IT systems (11 different system is used) to integrate the EHR technology. In fact, some of the systems could not be immediately integrated with the EHR. As there is no reason to believe that use of a specific IT system is correlated with the quality of disease management and therefore hospitalizations, this is likely to create exogenous variation in EHR enrolment. Unfortunately, as we do not observe which IT system is used by GPs, we cannot further exploit this exogenous variation.

The potential benefits of introducing EHR is well known from the literature on the US HITECH Act and is often divided in the effect of implementing diabetic registries and the effect of clinical decision support (Patel, Reed, and Grant 2015). The Danish system includes both components.

The EHR system increase the information available at the point of care and allows the GP to plan for a better monitoring of the patients. For example, it allows the GP to get an overview on which diabetes patients have not had their annual control or who have an HbA1C level above (or below) the target level. It can also be used in the consultation with the patient and allows for individual planning of treatment targets with the individual patient. Hence the EHR is expected to increase quality of treatment by increasing the GPs planning and overview of the patient population. Even though participation where made mandatory in the 2011 agreement, no enforcement mechanisms existed and GP's were given 3 years to enrol.

Structure of the paper

The paper is structured as follows. In section 2 we describe the selection process. Section 3 describes the dataset used. Section 4 discusses our identification strategy. Section 5 shows the results. Section 6 provides several robustness checks and Section 7 concludes.

2. Selection into the EHR program

The British QOF and the Italian pay for compliance programs were introduced to all GPs at the same time, which limit the possibility to define a proper control group and therefore establish causal relationships. The Californian EHR program was introduced successively and without systematic association to GPs diabetes care quality. Hence enrollment can be interpreted as pseudo random. This study identifies the effect of EHR by neutralizing time trends and including a patient level fixed effect to account for patient level heterogeneity. Even though the Danish program became mandatory in 2011 the time of participation were largely voluntary until the end of 2013. This means that we face a potential problem of self-selection of GPs into the program.

We now discuss the potential factors that might drive the selection into EHR enrolment.

Interest in diabetes treatment: As the program initially was developed around diabetes treatment we believe that the first movers may have a specific interest in diabetes. GPs with special interest in diabetes are also expected to do better in terms hospitalizations even without participation in the program. As this difference in performance is likely to be present in the pre-treatment period, our main identification strategy will capture this by including 7 years of pre-treatment outcomes.

Practice size: Several studies claim that practice size affect EHR adoption and health outcome (Gans et al. 2005; Han et al. 2016; Ketcham, Baker, and MacIsaac 2007; Wang et al. 2006). Hence we expect participating GPs to be larger than non-participants. Practice size can also have impact on hospitalization. Fortunately, practice size is observed in our data and include as a control variable. Moreover, we restrict our analysis to GPs with more than 10 diabetes patients.

IT knowledge: As the program is based on an IT solution it may be that participants are more

skilled or better organized to deal with new technology. As this can also affect hospitalizations, we include "*Use of email consultations*" to proxy for IT skills, moreover the differential in the attitude towards new technology is likely to present in the pre-treatment periods already and captured by including the pre-treatment outcomes.

Characteristics of the patients on the list: As implementation of a DMP requires a certain amount of excess capacity, it may be that GPs with less deprived or frail patients may be more likely to participate. We control for several patients characteristics. In particular, we use all the variables included in the Danish Deprivation Index (DADI).

GP's characteristics: GP's characteristics such as age and gender composition might influence both participation in the EHR and hospitalizations. Although we only observe few GP's characteristics, as GP's composition is pretty much stable over time in Denmark, we expect that the inclusion of the pre-treatment outcome capture these potential confounders.

3. Data

Definition of treatment and control groups

General practices participating in the DMP are identified using data from the Danish Quality Unit of General Practice (DAK-e). We observe monthly the percentages of visits in the clinic which have been registered in the EHR system from 2006 to 2013. We consider two different treatment definitions, a binary treatment and continuous treatment. Differently from Reed et al. (2013) who use a threshold of 80% EHR usage to define treatment, we define our binary treatment indicator equal to one if in a given year the median EHR usage reaches 70%. The reason of using 70% is that, once this threshold has been reached, GPs have access to quality feedback. As a robustness check we also consider yearly median usage in a parametric model. The number of treated GPs per year is reported in Table 1.

(Insert table 1: Number of treated GP's per year)

Our control group consists of 558 GPs who never enrolled in the EHR until the end of our evaluation period 2013. We consider two different treated cohorts. The first cohort consists of

68 GPs who enrolled in 2011 and stay enrolled until 2013. For this cohort we can estimate the instantaneous effect in 2011, the effect after 1 year of treatment in 2012, and the effect of 2 years of treatment in 2013. The second cohort consists of 288 GPs who enrolled in 2012 and stay enrolled until 2013. For this cohort we can only estimate the instantaneous effect in 2012 and the 1 year effect in 2013.

We do not expect any effect heterogeneity between the two cohorts, but we do expect the treatment effects to be different for different time of exposure (i.e., 0, 1 or 2 years). Unfortunately, we can only compare the instantaneous and the 1 year effects between the two cohorts as we only have data until 2013.

The total number of GPs in the first cohort is then 626. In the second cohort our sample consists of 846 GPs. Our final samples are obtained as follow. We start with 1579 GPs who are observable in the whole period 2004-2013. We then exclude 55 GPs with less than 10 diabetes patient in any year and 52 GPs who had less than 900 patients listed in total in any year. Of the remaining GPs, as we mentioned, 558 never enrolled in EHR and they are used as control group. The 2011 treatment group then consist of GPs that in 2011 reach a median EHR usage of 70% or above, without doing this in any year before (52 GPs). We also drop 4 GPs who reach the threshold in 2011 but don't in 2012 or 2013. This leaves us with 68 GPs in the 2011 treatment group. The 2012 treatment group is defined in the in the same way and, after dropping 124 GPs who are treated in the previous years and 15 who are treated in 2012 but not in 2013, consists of 288 GPs.

Definition of the diabetes population

Diabetes patients were identified using an algorithm suggested by the national Danish diabetes register, which is comparable to the algorithm suggested by WHO. Diabetes patients are hence identified based on the presence of more than 3 HbA1C measurements provided by the GP, a prescription of diabetes medications or a diabetes hospitalization[1].

[1] Patients are required to be above 18 and alive and living in Denmark primo 2013 and to have received minimum one service by a general practice in 2008. In addition one out of the three following criteria must be meet: 1) The patients has redeem at least one prescription for anti-diabetic drugs with ATC code A10A* or/and A10B* in 2008. ATC-kode A10BA02* is excluded for women between age 20-40. 2) The patients have received at least three blood sugar or HbA1c tests in 2008 (either from their general practioner or a specialist in the primary

There is a risk of composition bias if enrolment in the DMP involves a systematic increase in the number of a certain type of diabetes patients defined by the algorithm.

Figure 1 below shows the average annual number of diabetes patients in the 2011 treatment group and control group. The treatment group has larger number of diabetes patients. This rest on the fact that these practices, in general are larger. As the trend seems to be parallel – also after treatment - we don't expect composition bias to be a problem. However, to further avoid this issue we only consider diabetes patients who are listed with the same GPs in the period 2010-2013. As a robustness check we also run our analysis on the unrestricted population of diabetes patients.

(Insert Figure 1: Average number of diabetes patients and average age in the treatment and control group: 2004-2013)

Figure 1 also shows the average age of the diabetes in each year. The mean age is increasing quite dramatically over the years. This is reflected in a general upward trend in hospitalizations as we show shortly below. However, the average age is almost identical between the treated and the control group, thus we do not need to control for age in estimating the effect of EHR.

Hospitalization data

The outcome – or dependent variables are various definitions of hospitalization rates for diabetes patients. Information on hospitalizations is obtained from the Danish National Patient Register covering all somatic in- and outpatient treatment. We assess three different hospitalization rates: 1) mean diabetes inpatient hospitalizations per diabetes patient 2) mean total inpatient hospitalizations per diabetes patient 3) ACSC hospitalizations for diabetes and cardiovascular inpatient hospitalizations. As most of the comparable studies we

sector). 3) The patient is registered with one of following ICD10 codes in the National Patient Register: DE10, DE11, DE12, DE13, DE14, DO24, DH360.

use the AHQR definition of ACSC hospitalizations [2].

Figure 2 below show the trend in mean observed hospitalization rates for the treatment and control GPs in our sample before matching. Our main identification strategy does not rely on a common trend assumption, but for total hospitalizations and diabetes hospitalization it seems reasonable to say that the common trend assumption holds – even in the observed rates without conditioning on observables covariates and before matching. The ACSC rates are more volatile.

(Insert figure 2a-b: Observed hospitalization rates per diabetes patient by treatment states in the period 2004-2013)

The ACSC hospitalization per diabetes patient varies between 3% and 6% in the period of observation. ACSC definitions varies in the literature and it is therefore of interest to look at the rates in comparable studies. A Danish study by (Schiotz et al. 2011) compares Danish ACSC rates with rates from Kaiser Permanente health care plans in the US. This study reports diabetes ACSC rates of around 1 per 100 patients above 65 years of age for Denmark and around half of these rates for Kaiser Permanente in the US (Schiotz et al. 2011). (Reed et al. 2013) find ACSC rates per diabetes patient around 7% for California, and (Iezzi, Lippi Bruni, and Ugolini 2014) have rates per diabetes patient around 5% for the Emilia Romagna region in Italy (8,000 ACSCs for 165,000 diabetes patients). (Dusheiko M 2011) only look at ACSC admission coded as emergency admission and find rates of 6-7 per 10.000 person years for UK. In comparison we find a rate of 0,7% emergency ACSC diabetes admissions per diabetes patient. OECD publishes a health indicator of uncontrollable diabetes hospital admissions but use a different definition than the ACQR ACSC definition. However for comparison it may of interest to notice that Denmark is close to the average OECD rate of uncontrolled diabetes admission, UK and Italy is well below and US is above the OECD average (OECD 2013)[3].
Diabetes hospitalizations rates varies between 10% and 22% in the period with a slightly higher rate for the control group throughout the period and a tendency of a larger increase in

[2] Agency for Healthcare Research and Quality. Quality Indicators: Guide to Prevention Quality Indicators: Hospital Admission for Ambulatory Care Sensitive Conditions. AHRQ; 2004.
[3] http://dx.doi.org/10.1787/health-data-en

the control group after treatment in 2011.
Total hospitalizations vary between 30% and 60% and increase over time. The treatment and the control group show a parallel trend but the treatment group seems to face a lower rate of increase after 2011.

Covariates for matching

Socioeconomic characteristics of the diabetes patients are provided by Statistics Denmark. The data include information on age, gender, level of education, employment status, family income, whether the patient live alone, ethnicity (Danish or other ethnicity). We have chosen to include variables used in the Danish Deprivation Index (DADI), derived for primary care. This include the share of diabetes patients with the following characteristics on the GPs list; 1) unemployed between 20 and 59 years of age 2) patients between 25 and 59 years of age without secondary education 3) patients between 25 and 65 years of age with low income 4) patients between 18 and 59 years of age on public benefits 5) Share of 0 to 16-year-old children in families with low income 6) patients with non-western ethnicity 7) patient above 30 years of age who lives alone 8) Share of patients above 70 years of age with a low level of disposable income.

Information on practice style or **treatment pattern** is based on data from the Danish National Health Service Register (NHSR), which contains information about the activities of health professionals contracted with the tax-funded public healthcare system (including general practitioners (GPs). As GP's are partly paid by fee for services we can use the fee structure to give an indication of the treatment pattern of the GP. We include the following treatment pattern variables for the GPs diabetes patients; total number of visits, number of HbA1C measurements, number of annual control visits, use of diabetes medication, number of e-mail visits and number of telephone visits.

Table 2 shows the difference in mean observable characteristics between treated and control for the 2011 and 2012 cohorts. As expected, treated and control GPs differs with respect to several of those variables. The treatment groups have significantly larger practices and more consultations with the diabetes patients both standard, per e-mail and by phone. We do not find much difference in patient characteristics except that patients of GPs in the 2012

treatment group seem to have slightly lower morbidity, measured by the Charlson index, than patients of GPs in the control group. Furthermore there seems to be some regional variations in enrolment.

(Insert table 2a-b: Covariates and bias before matching for the 2011 and 2012 cohort)

4. Identification strategy

Identification with panel data

Let's start by introducing some notation. We denote by D_i our treatment indicator which is equal to 1 if GP i participate in the DMP in 2011, we denote by $Y_{i,t}$ the observed outcome of GP i at time t, and by $X_{i,t}$ our set of GPs and patients observable characteristics. Under the stable unit treatment value assumption (SUTVA), we denote by $Y_{i,t}^1$ and $Y_{i,t}^0$ the potential outcomes that GP i would get at time t with and without participation in the DMP. Note that only one, of the two potential outcomes is observed for each GP according to their treatment status as described in the following observational rule:

$$Y_{it} = D_i Y_{i,t}^1 + (1 - D_i) Y_{i,t}^0$$

The ATET at time t can be defined as:

$$\begin{aligned} ATET_t &\equiv E\left(Y_{i,t}^1 - Y_{i,t}^0 \middle| D_i = 1\right) \\ &= \underbrace{E\left(Y_{i,t} \middle| D_i = 1\right)}_{Identified} - E\left(Y_{i,t}^0 \middle| D_i = 1\right) \end{aligned}$$

The first term of the $ATET_t$ is identified by the expected value of the outcome in the treated group. The second term requires the counterfactual mean potential outcome under control for the treated, which is unobservable, as each individual can only belong either to the treatment or to the control group in a given time period. Therefore, to identify the $ATET_t$ we need to impose assumptions which enable us to express $E\left(Y_{i,t}^0 \middle| D_i = 1\right)$ in terms of observable quantities.

PSM with pretreatment outcomes

We first consider a conditional independence assumption (CIA), where we include in the conditioning variables also pretreatment outcomes.

Assumption CIA (Conditional Independence)

$$E\left(Y^0_{i,k+\tau}\middle|D_i = 1, X_{i,k} = x, Y_{i,k-1} = y_{k-1}, Y_{i,k-2} = y_{k-2}, \dots\right)$$
$$= E\left(Y^0_{i,k+\tau}\middle|D_i = 0, X_{i,k-1} = x, Y_{i,k-1} = y_{k-1}, Y_{i,k-2} = y_{k-2}, \dots\right)$$

CIA assumes that conditional on the pre-treatment outcomes and the covariates there is no selection bias. Including pre-treatment outcomes allow us to control for all the unobservable confounder which were also present in the pre-treatment periods. We also need to impose the following common support assumption:

Assumption CSM (Common Support Matching)

$$\mathrm{P_x} \equiv \Pr\left(D_i\middle|X_{i,k} = x, Y_{i,k-1} = y_{k-1}, Y_{i,k-2} = y_{k-2}, \dots\right) < 1, \forall\, x \in supp(X) and\ \forall\, y \in supp(Y)$$

CMS ensures that each treated unit has at least one comparable control unit.

It is easy to show that under CIA and CSM we can identify all the ATETs, indeed

$$ATET_t = E\left(Y_{i,t}\middle|D_i = 1\right) - E\left(E\left(Y_{i,t}\middle|X_{i,k} = x, Y_{i,k-1} = y_{k-1}, Y_{i,k-2} = y_{k-2}, \dots\right)|D_i = 1\right)$$

As the expectation $E\left(E\left(Y_{i,t}\middle|X_{i,k} = x, Y_{i,k-1} = y_{k-1}, Y_{i,k-2} = y_{k-2}, \dots\right)|D_i = 1\right)$ only depends upon observable variables the $ATET_t$ is identified. In practice the $ATET_t$ can be estimated by any matching estimator. The main idea of this class of estimators is to compare each treated unit with control units which are similar in terms of covariates (including the pre-treatment outcomes). We will use the propensity scored based matching estimator of Huber, Lechner, and Steinmayr (2015), which is the one suggested in the simulation study of Huber, Lechner, and Wunsch (2011) . This estimator compares treated and control with similar values of the propensity score $\mathrm{P_x}$.

Comparison of DiD and Matching

Alternatively to matching on pre-treatment outcomes (simply matching) one could also use Difference-in-Differences (DiD). Let $t = k$ be the last pre-treatment period (2010 in our data), together with Assumption CSM (excluding the pre-treatment outcomes), DiD imposes the following common trend assumption:

Assumption CT (Common Trend)

$$E\left(Y_{i,k+\tau}^{0}\middle|D_i = 1, X_{i,k} = x\right) - E\left(Y_{i,k}^{0}\middle|D_i = 1, X_{i,k} = x\right) =$$
$$E\left(Y_{i,k+\tau}^{0}\middle|D_i = 0, X_{i,k} = x\right) - E\left(Y_{i,k}^{0}\middle|D_i = 0, X_{i,k} = x\right), \forall\, x \in supp(X)$$

Assumption CT is equivalent to assume that, conditional on the observable covariates, the selection bias is constant over time. It is easy to see that the $ATET_{k+\tau}$ is then identified as

$$ATET_{k+\tau} = E\left(Y_{i,k+\tau}\middle|D_i = 1\right) - E\left(E\left(Y_{i,k+\tau}\middle|D_i = 0, X_{i,k} = x\right)|D_i = 1\right)$$
$$-E\left(Y_{i,k}\middle|D_i = 1\right) - E\left(E\left(Y_{i,k}\middle|D_i = 0, X_{i,k} = x\right)|D_i = 1\right)$$

Having panel data, this can be estimated by using the same matching estimator (without the pre-treatment outcomes) using the first difference $\Delta Y_{k+\tau} = Y_{k+\tau} - Y_k$ instead of $Y_{k+\tau}$ as an outcome.

Both (Imbens 2009) and Lechner (2013) argue that matching on pre-treatment outcomes is preferable to DiD. The two identification strategies, however, are based on assumptions which are not nested, in the sense that in general the violation of one does not exclude the other.

DiD allow for the presence of selection bias as soon as it is time constant and there are no anticipation effects while matching allows for anticipation effects but assumes zero selection bias conditional on the observed covariates and on pre-treatment outcomes. Only when the selection bias is zero in both pre- and post-treatment periods, the two approaches leads to the same results.

DiD allows for time invariant unobserved confounders. Matching, on the other hand, requires all the unobservable confounders to be already present in the pre-treatment periods. (Chabé-Ferret 2015) provides a simple model in which matching is consistent if the selection bias is due to transitory shocks only, while DiD is consistent if the selection bias is due only to a permanent individual fixed effects. He also shows that it is not possible to combine the two approaches in order to get rid of both sources of bias. In fact if one try to condition also on

pre-treatment outcomes in a DiD, the resulting estimator is only consistent under the same CIA assumption imposed by matching. (Chabé-Ferret 2015) also shows that conditioning on several pre-treatment outcomes might help reducing the bias of matching in the presence of permanent individual fixed effects.

Given the richness of our data and the consideration we made in section 2, matching is preferable in our setting. In fact, we arguably observe many GPs and patients characteristics as well as 7 years of pre-treatment outcomes which make the CIA likely to hold.

5. Results

We first estimate Propensity scores (one for each outcome) with a probit model. We report the probits marginal effects. Figure 3 below show the overlap of the propensity score between treated and control units.

(**Insert figure 3a-b**: Common support)

Figure 3a show propensity scores for the 2011 treatment group and the matched controls. It appears that control GPs are more concentrated in low propensity score region. However, there seems to be overlap such that for each treated GP's it is possible to find proper match among control GP's. Figure 3b show that the common support is much better for the 2012 cohort which may rest on the fact that we have a much larger treatment group but also that selection may be less of a problem for the late participants as they may be more inclined to participate because it was made mandatory and not because they have special interests in diabetes or IT. Looking closely to potential support issues, for the different outcomes the maximum number of observations off-support is 2 and in most cases is only one. We therefore omit to report the support tables.

Figure 4a-b show the reduction in bias after matching (we report the tables with the post-matching covariates' differences in the appendix). There is no statistically significant difference between treated and control in terms of observable (see table in the appendix) and, as the graph below shows, the overall bias reduction is good.

(**Insert figure 4a-b**: reduction in bias after matching)

Table 3 shows the ATET estimates of the PSM estimator.

(**Insert table 3**: PSM ATET)

The treatment effect for the 2011 cohort is significant and negative after two years of observation for all hospitalization rates. The average ACSC hospitalizations are in this case reduced by 0.01, which compared to the average for the whole population in 2010 (0.042) gives a reduction at about 24%. Diabetes hospitalization is significantly reduced by 0.022 after two years of participation. With an average hospitalization rate of 0.17 this implies a reduction of about of 13%. The estimated treatment effect for the total hospitalizations is -0.066 which compared to the average hospitalization rate before treatment (0.40) indicates a reduction of 17%.

For the 2012 cohort we find treatment effects of comparable sizes already after 1 year of participation. We have run, a falsification test in both cohorts using the last pre-treatment year as an outcome – i.e. 2010 for the 2011 cohort and 2011 for the 2012 one. As the true treatment effect has to be necessarily zero (assuming no anticipation effects) in the pre-treatment periods, PSM estimate only the selection bias in those periods, which, if constant over time, has to be zero under our assumptions. All the estimated selection biases are insignificant as expected, except for the one of diabetes hospitalizations in the 2011 cohort. However, this selection bias, which is only significant at the 10% level, is positive. This indicates that the true effects might be larger in magnitude than the one we estimate. Note that this finding is not very robust. In fact, although always positive the estimated selection bias is often not statistically significant in the robustness checks presented in the next section.

6. Robustness checks

Unrestricted diabetes population

We have undertaken a range of robustness checks. First of all we have estimated the effects in a population where we do not restrict the diabetes patients to be with the same GP in the period 2010-2013. This is done to test for composition bias – i.e. to test if treatment involves changes in the average characteristics of the diabetes patient between the treatment and control group. One hypothesis could be that the treatment group because of the use of EHR would identify more diabetes patient and/or diabetes patient with less severe disease progression and hence less risk of hospitalization. If this is the case the treatment effect may simply be due to the composition of the population and not in a reduced risk of hospitalization per se. We have prevented this possibility, by restricting the analysis to diabetes patients who have been with the same GP in the period 20-2013, which we now relax. Table 4 show estimated treatment effect with the unrestricted diabetes population.

(Insert table 4: PSM ATET with an unrestricted diabetes population)

The estimated treatment effects are pretty much the same for the 2012 cohort, while only the effect on ACSC hospitalization in 2013 is significant and a bit lower than the one of the restricted population for the 2011 cohort. Overall the results do not provide strong evidence of a composition bias.

DiD estimates

We also estimate our effects using a difference-in-differences where we condition on the same covariates as in the PSM, excluding the pre-treatment outcomes. Table 5 show that the treatment effects in general are quite comparable although generally higher than the PSM estimates for the 2011 cohort. Furthermore, we find significant effects already in 2012 for diabetes hospitalizations and total hospitalizations. Estimates for the 2012 cohort are very similar to the PSM matching, except for the effect on diabetes hospitalizations which is not statistically significant.

(table 5: DiD ATET)

Parametric model with continuous treatment

To assess the role of treatment intensity more explicitly we use median EHR usage in a given year as an alternative treatment. To evaluate the impact of this variable on our outcomes we need to use, a parametric model where we maintain the same CIA imposed by PSM. In particular we estimate by OLS the following linear regression:

$$Y_{i,t+k} = c + \delta EHR_{median} + \delta_1 Y_{i,t-1} \dots \delta_6 Y_{i,t-6} + \mathrm{X}'\beta + \varepsilon_i$$

where k=1,2, δ is the effect of interest and EHR_{median} is our treatment (median usage).

(**Insert table 6**: Parametric model)

Table 6 shows that the effects are in general very similar for the 2012 cohort. For the 2011 cohort only the effect on ACSC hospitalization is significant.

7. Conclusion

We have estimated the effect of GP participation in an EHR program introduced in Denmark with the aim of improving primary care for diabetes patients. Our results show that the introduction if the EHR reduces ACSC hospitalizations by around 24%. Similarly diabetes and total hospitalizations are reduced by app 16%. Our findings are robust to several sensitivity checks and different models. The reduction in hospitalizations is in the high end compared to the previous results in the related literature.

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Appendix

Probits marginal effects 2011 Cohort

Table A1: Estimated marginal effects ACSC hospitalizations

Variable name	Marginal effect	S.e.
Consultations	0.01**	0.01
Influenza vaccinations	0.15*	0.09
Preventive visits	0.02*	0.01
Number of e-mail consultations	0.02*	0.01
Number of HbA1C measurements	-0.03*	0.05
List size	0.00***	0.00
Charlson index	0.07*	0.06
Homevisits	0.04*	0.04
Numbner of telephone consultations	-0.01**	0.01
Share of unemployed between 20 and 59 years of age	7.51*	12.11
Share of 25-59 years of age without secondary education	5.08*	3.88
Share of 25-65 years of age with low income	-3.80*	8.52
Share of 18-59 years of age on public benefits	13.10*	8.87
Share with non-western ethnicity	0.09*	4.40
Share of unemployed between 20 and 59 years of age	3.83*	3.39
Share of 25-59 years of age without secondary education	-7.55**	3.80
D_region2	-0.08**	0.04
D_region3	-0.01*	0.04
D_region4	-0.06*	0.05
D_region5	-0.15**	0.06
Y_ACSC_dia_cvd2004	0.64**	0.32
Y_ACSC_dia_cvd2005	-0.10*	0.36
Y_ACSC_dia_cvd2006	-0.52*	0.39
Y_ACSC_dia_cvd2007	-0.76*	0.45
Y_ACSC_dia_cvd2008	-0.52*	0.38
Y_ACSC_dia_cvd2009	-0.66*	0.36
Y_ACSC_dia_cvd2010	0.04*	0.36

Table A2: Estimated marginal effects diabetes hospitalizations

Variable name	Marginal effect	S.e.
Consultations	0.01**	0.01
Influenza vaccinations	0.13*	0.09
Preventive visits	0.02*	0.01
Number of e-mail consultations	0.02*	0.01
Number of HbA1C measurements	-0.02*	0.05
List size	0.00***	0.00
Charlson index	0.06*	0.06
Homevisits	0.01*	0.04
Numbner of telephone consultations	-0.01**	0.01
Share of unemployed between 20 and 59 years of age	8.74*	12.31
Share of 25-59 years of age without secondary education	4.24*	3.92

Share of 25-65 years of age with low income	-4.68*	8.60
Share of 18-59 years of age on public benefits	14.51*	9.00
Share with non-western ethnicity	-1.13*	4.27
Share of unemployed between 20 and 59 years of age	3.35*	3.43
Share of 25-59 years of age without secondary education	-6.60*	3.82
Central Denmark Region	-0.07*	0.04
Region of Southern Denmark	0.02*	0.04
Capital Region of Denmark	-0.06*	0.05
Region Zealand	-0.14**	0.06
Y_inpatient_diabetes2004	0.38*	0.21
Y_inpatient_diabetes2005	-0.09*	0.21
Y_inpatient_diabetes2006	-0.15*	0.22
Y_inpatient_diabetes2007	-0.35*	0.22
Y_inpatient_diabetes2008	-0.49**	0.22
Y_inpatient_diabetes2009	-0.02*	0.18
Y_inpatient_diabetes2010	0.22*	0.15

Table A3: Estimated marginal effects total hospitalizations

Variable name	Marginal effect	S.e.
Consultations	0.01**	0.01
Influenza vaccinations	0.14*	0.09
Preventive visits	0.02*	0.01
Number of e-mail consultations	0.02*	0.01
Number of HbA1C measurements	-0.02*	0.05
List size	0.00***	0.00
Charlson index	0.04*	0.06
Homevisits	0.01*	0.04
Numbner of telephone consultations	-0.01**	0.01
Share of unemployed between 20 and 59 years of age	8.62*	12.06
Share of 25-59 years of age without secondary education	4.61*	3.92
Share of 25-65 years of age with low income	-6.10*	8.57
Share of 18-59 years of age on public benefits	12.65*	8.94
Share with non-western ethnicity	-1.14*	4.35
Share of unemployed between 20 and 59 years of age	3.28*	3.49
Share of 25-59 years of age without secondary education	-6.84*	3.84
Central Denmark Region	-0.08*	0.04
Region of Southern Denmark	0.01*	0.04
Capital Region of Denmark	-0.06*	0.05
Region Zealand	-0.16**	0.06
Y_inpatient2004	0.04*	0.10
Y_inpatient2005	-0.02*	0.11
Y_inpatient2006	0.04*	0.10

Y_inpatient2007	-0.02*	0.10
Y_inpatient2008	-0.16*	0.11
Y_inpatient2009	-0.05*	0.09
Y_inpatient2010	0.08*	0.08

Probits marginal effects 2012 Cohort

Table A4: Estimated marginal effects ACSC hospitalizations

Variable name	Marginal effect	S.e.
Consultations	0.01*	0.01
Influenza vaccinations	0.01*	0.11
Preventive visits	0.07***	0.02
Number of e-mail consultations	0.03*	0.02
Number of HbA1C measurements	0.02*	0.05
List size	0.00***	0.00
Charlson index	-0.06*	0.07
Homevisits	0.08*	0.06
Numbner of telephone consultations	-0.02***	0.01
Share of unemployed between 20 and 59 years of age	-30.90*	15.88
Share of 25-59 years of age without secondary education	10.17**	4.87
Share of 25-65 years of age with low income	1.01*	10.86
Share of 18-59 years of age on public benefits	33.83***	11.10
Share with non-western ethnicity	-2.74*	4.38
Share of unemployed between 20 and 59 years of age	-7.50*	4.19
Share of 25-59 years of age without secondary education	-1.09*	4.62
Central Denmark Region	-0.06*	0.06
Region of Southern Denmark	0.06*	0.06
Capital Region of Denmark	0.07*	0.07
Region Zealand	0.01*	0.07
Y_ACSC_diab2004	-0.51*	0.73
Y_ACSC_diab2005	-0.86*	0.72
Y_ACSC_diab2006	-0.08*	0.67
Y_ACSC_diab2007	-0.99*	0.72
Y_ACSC_diab2008	-0.39*	0.68
Y_ACSC_diab2009	0.31*	0.59
Y_ACSC_diab2010	0.01*	0.61

Table A5: Estimated marginal effects diabetes hospitalizations

Variable name	Marginal effects	S.e.
Consultations	0.01*	0.01
Influenza vaccinations	0.01*	0.11
Preventive visits	0.07***	0.02
Number of e-mail consultations	0.03*	0.02
Number of HbA1C measurements	0.02*	0.05

List size	0.00***	0.00
Charlson index	-0.05*	0.08
Homevisits	0.08*	0.06
Numbner of telephone consultations	-0.02***	0.01
Share of unemployed between 20 and 59 years of age	-31.04*	15.88
Share of 25-59 years of age without secondary education	9.35*	4.87
Share of 25-65 years of age with low income	1.67*	10.87
Share of 18-59 years of age on public benefits	35.60***	11.08
Share with non-western ethnicity	-2.35*	4.37
Share of unemployed between 20 and 59 years of age	-7.29*	4.21
Share of 25-59 years of age without secondary education	-0.85*	4.61
Central Denmark Region	-0.05*	0.06
Region of Southern Denmark	0.08*	0.06
Capital Region of Denmark	0.07*	0.07
Region Zealand	0.04*	0.07
Y_inpatient_diabetes2004	-0.20*	0.22
Y_inpatient_diabetes2005	-0.16*	0.26
Y_inpatient_diabetes2006	-0.08*	0.25
Y_inpatient_diabetes2007	-0.21*	0.26
Y_inpatient_diabetes2008	-0.23*	0.21
Y_inpatient_diabetes2009	-0.05*	0.23
Y_inpatient_diabetes2010	0.07*	0.20

Table A6: Estimated marginal effects total hospitalizations

Variable name	Marginal effect	S.e.
Consultations	0.01*	0.01
Influenza vaccinations	0.03*	0.12
Preventive visits	0.07***	0.02
Number of e-mail consultations	0.03*	0.02
Number of HbA1C measurements	0.02*	0.05
List size	0.00***	0.00
Charlson index	-0.10*	0.08
Homevisits	0.08*	0.06
Numbner of telephone consultations	-0.02***	0.01
Share of unemployed between 20 and 59 years of age	-32.17**	15.83
Share of 25-59 years of age without secondary education	10.53**	4.87
Share of 25-65 years of age with low income	-0.60*	10.83
Share of 18-59 years of age on public benefits	33.91***	11.11
Share with non-western ethnicity	-2.11*	4.38
Share of unemployed between 20 and 59 years of age	-7.10*	4.23
Share of 25-59 years of age without secondary education	-1.63*	4.64
Central Denmark Region	-0.06*	0.06

Region of Southern Denmark	0.07*	0.06
Capital Region of Denmark	0.06*	0.07
Region Zealand	0.01*	0.07
Y_inpatient2004	-0.05*	0.12
Y_inpatient2005	0.16*	0.13
Y_inpatient2006	0.01*	0.12
Y_inpatient2007	-0.12*	0.13
Y_inpatient2008	-0.08*	0.12
Y_inpatient2009	0.03*	0.11
Y_inpatient2010	0.07*	0.10

Standardized bias after matching 2011 Cohort

Table A7: Bias in covariates after matching ACSC hospitalizations – 2011 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	7.3418	7.2725	4	0.23	0.816
Influenza vaccinations	0.3534	0.34931	3.2	0.19	0.852
Preventive visits	1.7268	1.6485	8	0.46	0.647
Number of e-mail consultations	0.88502	0.84826	4.7	0.24	0.808
Number of HbA1C measurements	0.04461	0.04728	-1.1	-0.06	0.95
List size	2433.4	2364.4	5.2	0.26	0.795
Charlson index	0.76299	0.7548	3.3	0.2	0.842
Homevisits	0.14666	0.14168	2.1	0.12	0.901
Numbner of telephone consultations	5.0596	5.2148	-6.9	-0.42	0.674
Share of unemployed between 20 and 59 years of age	0.0015	0.00148	1.1	0.07	0.944
Share of 25-59 years of age without secondary education	0.01139	0.01195	-12.8	-0.76	0.448
Share of 25-65 years of age with low income	0.00352	0.00356	-1.5	-0.11	0.915
Share of 18-59 years of age on public benefits	0.00276	0.00282	-4	-0.24	0.814
Share with non-western ethnicity	0.00341	0.00363	-4.8	-0.4	0.689
Share of unemployed between 20 and 59 years of age	0.01345	0.01377	-6.7	-0.37	0.715
Share of 25-59 years of age without secondary education	0.01086	0.01108	-3.9	-0.25	0.802
Central Denmark Region	0.16667	0.17353	-1.7	-0.1	0.917
Region of Southern Denmark	0.37879	0.37984	-0.2	-0.01	0.99
Capital Region of Denmark	0.27273	0.26849	0.9	0.05	0.957
Region Zealand	0.0303	0.03699	-2.5	-0.21	0.833
Y_ACSC_dia_cvd2004	0.04123	0.0352	14.8	0.89	0.376
Y_ACSC_dia_cvd2005	0.03401	0.03656	-7	-0.44	0.663
Y_ACSC_dia_cvd2006	0.03046	0.03166	-3.3	-0.24	0.807
Y_ACSC_dia_cvd2007	0.02794	0.0265	4.9	0.36	0.722
Y_ACSC_dia_cvd2008	0.0315	0.0321	-1.7	-0.12	0.905
Y_ACSC_dia_cvd2009	0.03447	0.03394	1.4	0.09	0.931
Y_ACSC_dia_cvd2010	0.04185	0.03647	14	1	0.317

Table A8: Bias in covariates after matching diabetes hospitalizations – 2011 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	7.3526	7.2939	3.4	0.21	0.835
Influenza vaccinations	0.35469	0.36199	-5.7	-0.34	0.735
Preventive visits	1.7491	1.6783	7.2	0.41	0.683
Number of e-mail consultations	0.93151	0.91818	1.7	0.08	0.934
Number of HbA1C measurements	0.04394	0.03894	2	0.13	0.899
List size	2438.1	2399	2.9	0.15	0.884
Charlson index	0.75931	0.73377	10.4	0.64	0.524
Homevisits	0.1448	0.15749	-5.3	-0.31	0.753
Numbner of telephone consultations	5.0776	5.1758	-4.3	-0.27	0.79
Share of unemployed between 20 and 59 years of age	0.0015	0.00145	4.2	0.28	0.778
Share of 25-59 years of age without secondary education	0.01135	0.01184	-11.3	-0.67	0.504
Share of 25-65 years of age with low income	0.0035	0.00364	-5.7	-0.4	0.686
Share of 18-59 years of age on public benefits	0.00279	0.00275	2.8	0.16	0.87
Share with non-western ethnicity	0.0034	0.00339	0.2	0.02	0.986
Share of unemployed between 20 and 59 years of age	0.01344	0.01387	-9.1	-0.55	0.584
Share of 25-59 years of age without secondary education	0.01081	0.01167	-15.5	-0.96	0.34
Central Denmark Region	0.16418	0.19153	-6.9	-0.41	0.682
Region of Southern Denmark	0.37313	0.37589	-0.6	-0.03	0.974
Capital Region of Denmark	0.26866	0.24266	5.5	0.34	0.733
Region Zealand	0.02985	0.03569	-2.2	-0.19	0.851
Y_inpatient_diabetes2004	0.09419	0.09023	6.4	0.36	0.717
Y_inpatient_diabetes2005	0.08425	0.07742	10.6	0.68	0.499
Y_inpatient_diabetes2006	0.088	0.08322	7.6	0.52	0.601
Y_inpatient_diabetes2007	0.09069	0.08813	4.1	0.29	0.773
Y_inpatient_diabetes2008	0.09846	0.09607	3.3	0.25	0.805
Y_inpatient_diabetes2009	0.13325	0.11799	20	1.3	0.196
Y_inpatient_diabetes2010	0.16791	0.15002	19.1	1.25	0.214

Table A9: Bias in covariates after matching total hospitalizations – 2011 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	7.3526	7.3438	0.5	0.03	0.975
Influenza vaccinations	0.35469	0.35429	0.3	0.02	0.985
Preventive visits	1.7491	1.6355	11.5	0.66	0.512
Number of e-mail consultations	0.93151	0.81863	14.4	0.75	0.455
Number of HbA1C measurements	0.04394	0.03591	3.2	0.21	0.837
List size	2438.1	2418.2	1.5	0.07	0.942
Charlson index	0.75931	0.75622	1.3	0.08	0.94
Homevisits	0.1448	0.12912	6.6	0.45	0.65

Numbner of telephone consultations	5.0776	5.2533	-7.8	-0.47	0.637
Share of unemployed between 20 and 59 years of age	0.0015	0.00144	4.6	0.31	0.755
Share of 25-59 years of age without secondary education	0.01135	0.01186	-11.7	-0.69	0.491
Share of 25-65 years of age with low income	0.0035	0.00351	-0.6	-0.05	0.963
Share of 18-59 years of age on public benefits	0.00279	0.00273	3.8	0.22	0.826
Share with non-western ethnicity	0.0034	0.00331	1.8	0.16	0.877
Share of unemployed between 20 and 59 years of age	0.01344	0.01368	-5	-0.29	0.772
Share of 25-59 years of age without secondary education	0.01081	0.01118	-6.7	-0.44	0.664
Central Denmark Region	0.16418	0.19285	-7.2	-0.43	0.668
Region of Southern Denmark	0.37313	0.40141	-6.4	-0.33	0.739
Capital Region of Denmark	0.26866	0.22583	9.1	0.57	0.569
Region Zealand	0.02985	0.04043	-4	-0.33	0.742
Y_inpatient2004	0.26524	0.2497	11.6	0.74	0.462
Y_inpatient2005	0.25634	0.25054	4.9	0.32	0.75
Y_inpatient2006	0.28761	0.28449	2.3	0.15	0.884
Y_inpatient2007	0.28959	0.28768	1.3	0.08	0.933
Y_inpatient2008	0.29277	0.28826	3.1	0.23	0.82
Y_inpatient2009	0.35629	0.33307	14.9	0.97	0.333
Y_inpatient2010	0.40534	0.40048	2.7	0.15	0.88

Standardized bias after matching 2012 Cohort

Table A10: Bias in covariates after matching ACSC hospitalizations – 2012 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	6.93	7.03	-5.50	-0.65	0.51
Influenza vaccinations	0.33	0.33	-3.6	-0.44	0.66
Preventive visits	1.7268	1.6485	8	0.56	0.58
Number of e-mail consultations	0.88502	0.84826	4.7	-0.04	0.97
Number of HbA1C measurements	0.04461	0.04728	-1.1	-0.06	0.96
List size	2433.4	2364.4	5.2	0.26	0.55
Charlson index	0.76299	0.7548	3.3	0.2	0.94
Homevisits	0.14666	0.14168	2.1	0.12	0.24
Numbner of telephone consultations	5.0596	5.2148	-6.9	-0.42	0.54
Share of unemployed between 20 and 59 years of age	0.0015	0.00148	1.1	0.07	0.75
Share of 25-59 years of age without secondary education	0.01139	0.01195	-12.8	-0.76	0.97
Share of 25-65 years of age with low income	0.00352	0.00356	-1.5	-0.11	0.82
Share of 18-59 years of age on public benefits	0.00276	0.00282	-4	-0.24	0.72
Share with non-western ethnicity	0.00341	0.00363	-4.8	-0.4	0.84
Share of unemployed between 20 and 59 years of age	0.01345	0.01377	-6.7	-0.37	0.63
Share of 25-59 years of age without secondary education	0.01086	0.01108	-3.9	-0.25	0.64

Central Denmark Region	0.16667	0.17353	-1.7	-0.1	0.52
Region of Southern Denmark	0.37879	0.37984	-0.2	-0.01	0.52
Capital Region of Denmark	0.27273	0.26849	0.9	0.05	0.94
Region Zealand	0.0303	0.03699	-2.5	-0.21	0.65
Y_ACSC_dia_cvd2004	0.04123	0.0352	14.8	0.89	0.93
Y_ACSC_dia_cvd2005	0.03401	0.03656	-7	-0.44	0.80
Y_ACSC_dia_cvd2006	0.03046	0.03166	-3.3	-0.24	0.74
Y_ACSC_dia_cvd2007	0.02794	0.0265	4.9	0.36	0.39
Y_ACSC_dia_cvd2008	0.0315	0.0321	-1.7	-0.12	0.48
Y_ACSC_dia_cvd2009	0.03447	0.03394	1.4	0.09	0.42
Y_ACSC_dia_cvd2010	0.04185	0.03647	14	1	0.23

Table A11: Bias in covariates after matching diabetes hospitalizations – 2012 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	6.9271	6.9735	-2.6	-0.31	0.755
Influenza vaccinations	0.32871	0.33422	-3.9	-0.48	0.633
Preventive visits	1.7846	1.7727	1.2	0.15	0.884
Number of e-mail consultations	0.85006	0.8431	0.9	0.09	0.926
Number of HbA1C measurements	0.0808	0.08117	-0.1	-0.01	0.991
List size	2289	2235.3	4.6	0.49	0.625
Charlson index	0.7303	0.71707	5.5	0.7	0.483
Homevisits	0.14814	0.13036	7.5	1.08	0.279
Numbner of telephone consultations	5.2541	5.348	-4	-0.51	0.611
Share of unemployed between 20 and 59 years of age	0.0014	0.00139	1.2	0.17	0.869
Share of 25-59 years of age without secondary education	0.01157	0.01174	-3.6	-0.44	0.659
Share of 25-65 years of age with low income	0.00374	0.00385	-3.8	-0.5	0.615
Share of 18-59 years of age on public benefits	0.00287	0.00283	2.2	0.26	0.791
Share with non-western ethnicity	0.00388	0.00399	-2	-0.27	0.788
Share of unemployed between 20 and 59 years of age	0.01297	0.01324	-5	-0.64	0.525
Share of 25-59 years of age without secondary education	0.01131	0.01162	-5	-0.62	0.533
Central Denmark Region	0.19512	0.18675	2	0.25	0.799
Region of Southern Denmark	0.26829	0.27886	-2.5	-0.28	0.777
Capital Region of Denmark	0.30314	0.30116	0.4	0.05	0.959
Region Zealand	0.14286	0.12447	5.3	0.65	0.518
Y_inpatient_diabetes2004	0.08209	0.08167	0.6	0.07	0.94
Y_inpatient_diabetes2005	0.08514	0.08587	-1.2	-0.15	0.88
Y_inpatient_diabetes2006	0.09095	0.0934	-3.6	-0.47	0.639
Y_inpatient_diabetes2007	0.09843	0.09727	1.8	0.24	0.814
Y_inpatient_diabetes2008	0.11217	0.11023	2.4	0.33	0.743
Y_inpatient_diabetes2009	0.13459	0.13289	2.2	0.29	0.774
Y_inpatient_diabetes2010	0.15795	0.14821	10.7	1.51	0.132

Table A12: Bias in covariates after matching total hospitalizations – 2012 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	6.9271	7.029	-5.6	-0.68	0.497
Influenza vaccinations	0.32871	0.33612	-5.2	-0.64	0.521
Preventive visits	1.7846	1.7697	1.5	0.18	0.856
Number of e-mail consultations	0.85006	0.8478	0.3	0.03	0.976
Number of HbA1C measurements	0.0808	0.0905	-2.9	-0.3	0.763
List size	2289	2221.7	5.8	0.62	0.536
Charlson index	0.7303	0.71965	4.5	0.56	0.573
Homevisits	0.14814	0.12801	8.4	1.37	0.17
Numbner of telephone consultations	5.2541	5.4256	-7.3	-0.93	0.355
Share of unemployed between 20 and 59 years of age	0.0014	0.00142	-1	-0.14	0.886
Share of 25-59 years of age without secondary education	0.01157	0.01171	-3	-0.37	0.71
Share of 25-65 years of age with low income	0.00374	0.00385	-4	-0.53	0.599
Share of 18-59 years of age on public benefits	0.00287	0.0028	4.1	0.49	0.625
Share with non-western ethnicity	0.00388	0.00409	-3.9	-0.52	0.607
Share of unemployed between 20 and 59 years of age	0.01297	0.0132	-4.3	-0.55	0.585
Share of 25-59 years of age without secondary education	0.01131	0.01161	-4.8	-0.6	0.547
Central Denmark Region	0.19512	0.16806	6.6	0.84	0.401
Region of Southern Denmark	0.26829	0.28301	-3.5	-0.39	0.694
Capital Region of Denmark	0.30314	0.30881	-1.2	-0.15	0.883
Region Zealand	0.14286	0.13871	1.2	0.14	0.887
Y_inpatient2004	0.26694	0.26433	1.9	0.26	0.799
Y_inpatient2005	0.2775	0.27332	3.2	0.42	0.676
Y_inpatient2006	0.29274	0.2877	3.6	0.48	0.631
Y_inpatient2007	0.297	0.29607	0.7	0.09	0.929
Y_inpatient2008	0.31694	0.30854	5.6	0.78	0.433
Y_inpatient2009	0.37425	0.36954	2.9	0.37	0.715
Y_inpatient2010	0.41557	0.40279	6.6	0.89	0.376

Figures and tables

Figure 1a: Number of diabetes patients – 2011 cohort	Figure 1b: Mean age of diabetes patients – 2011 cohort

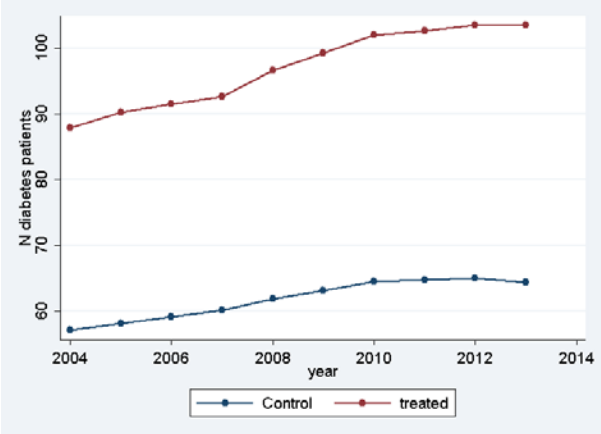


Figure 1a: Number of diabetes patients –2012 cohort

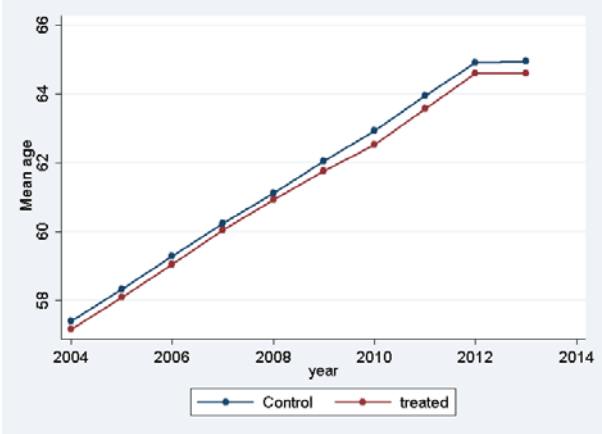
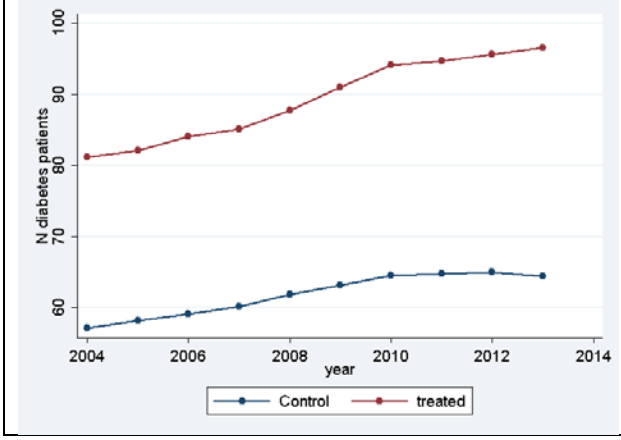


Figure 1b: Mean age of diabetes patients – 2012 cohort



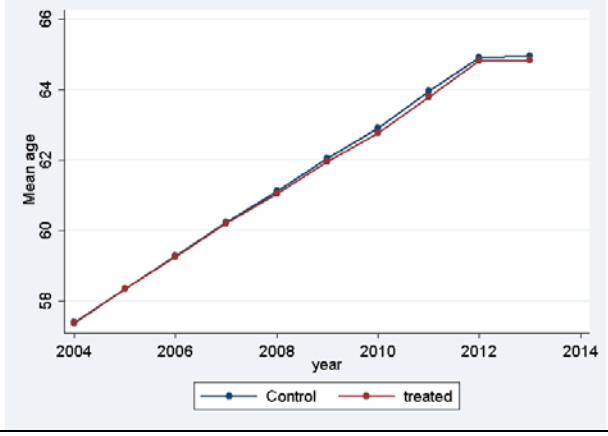


Figure 2a: Trend in outcomes – 2011 cohort

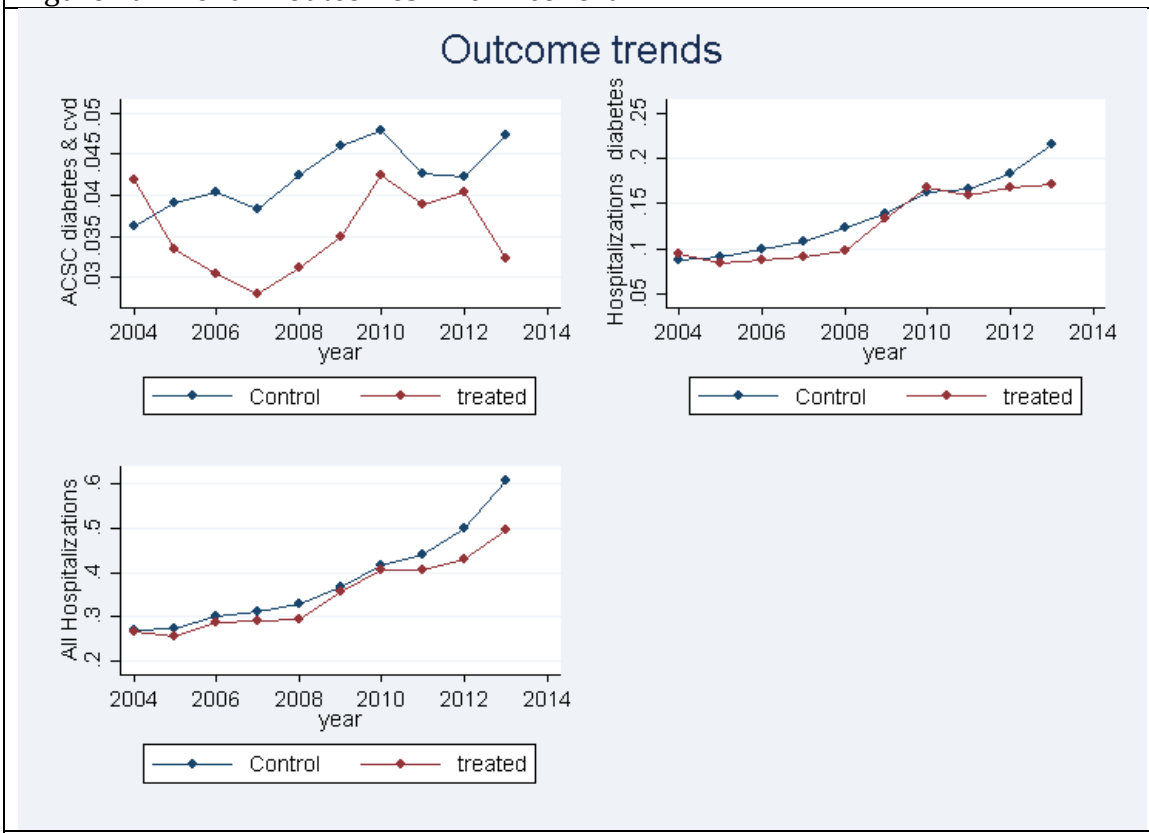


Figure 2b: Trends in outcome – 2012 cohort

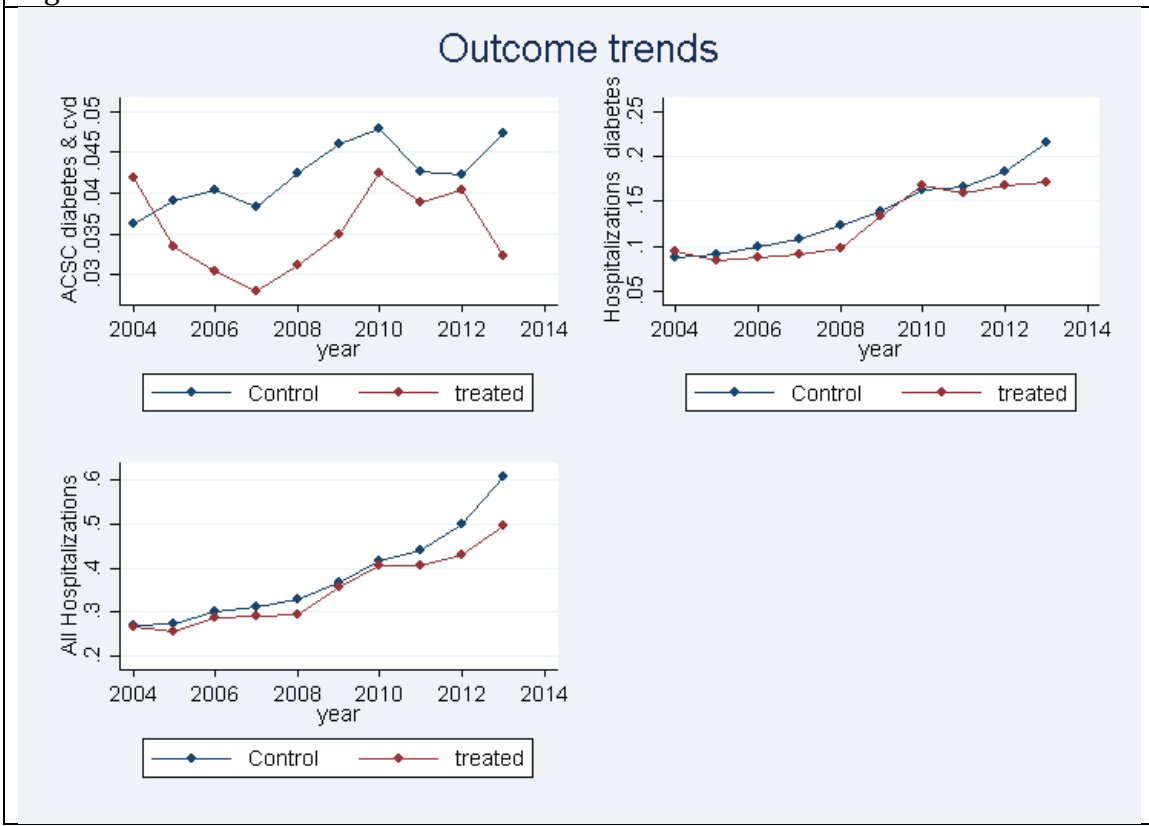


Figure 3a: Common Support – 2011 cohort

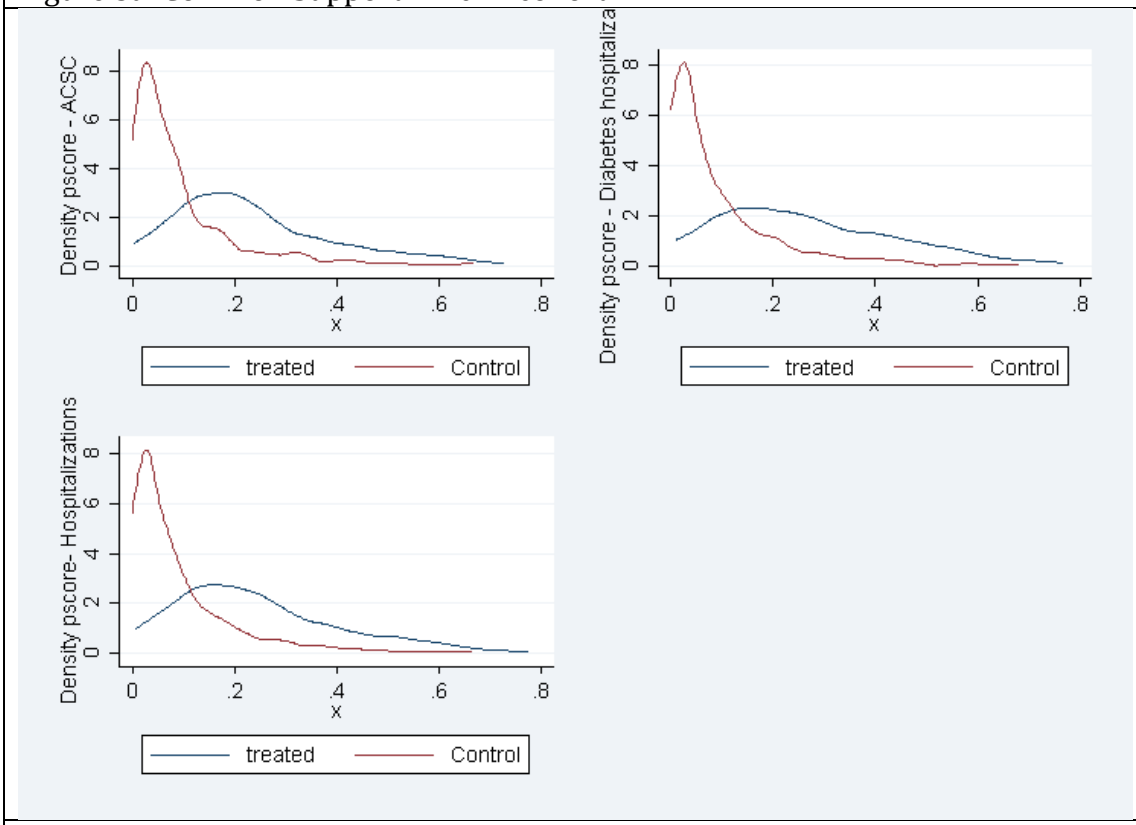


Figure 3b: Common support – 2012 cohort

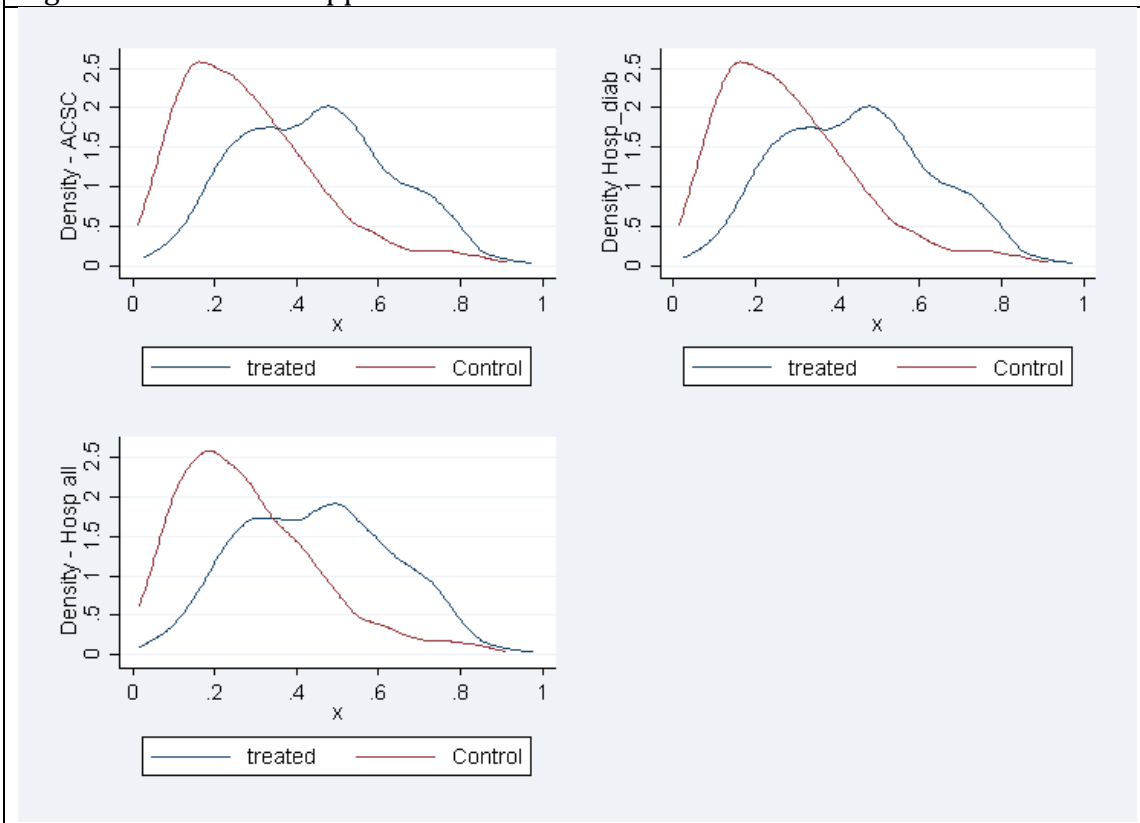
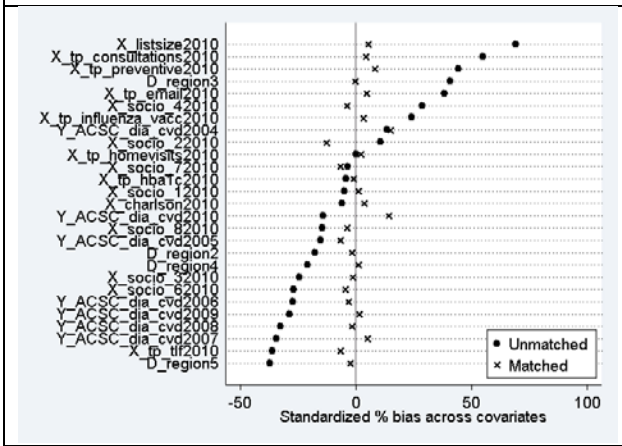
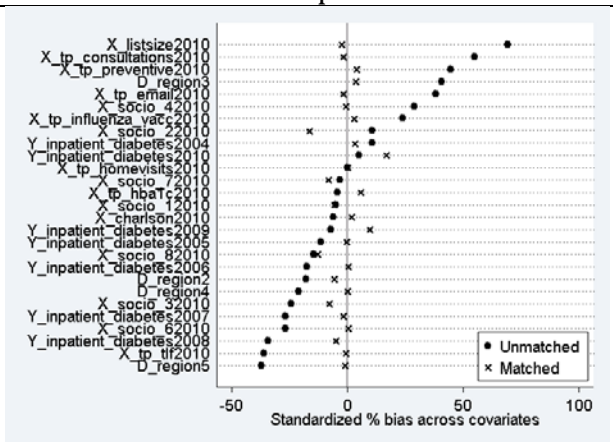


Figure 4a: Reduction in bias after matching – 2011 cohort

ACSC



Diabetes hospitalizations



Total hospitalizations

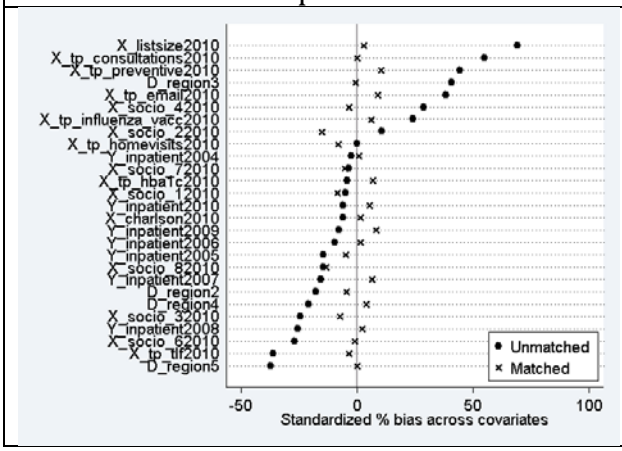
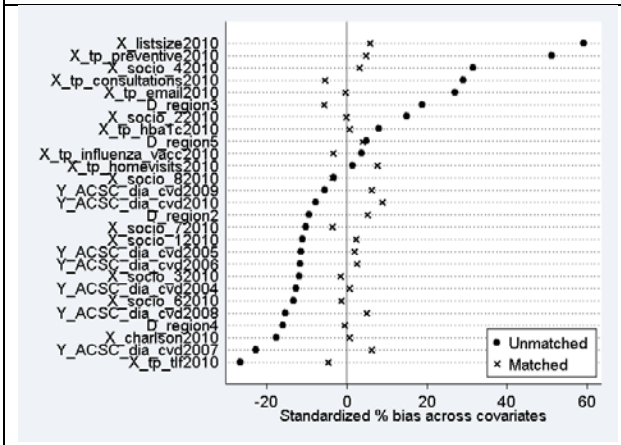
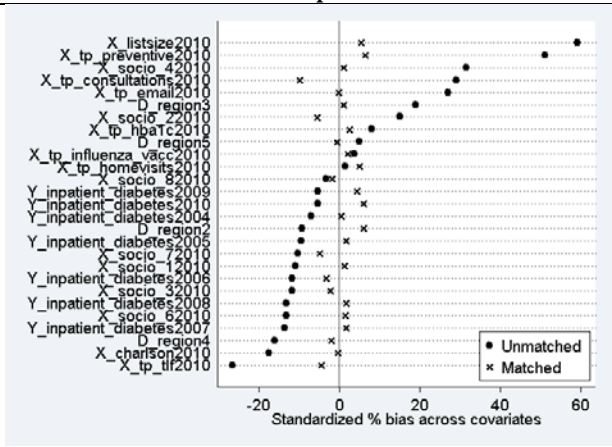


Figure 4b: Reduction in bias after matching – 2012 cohort

ACSC



Diabetes hospitalizations



Total hospitalizations

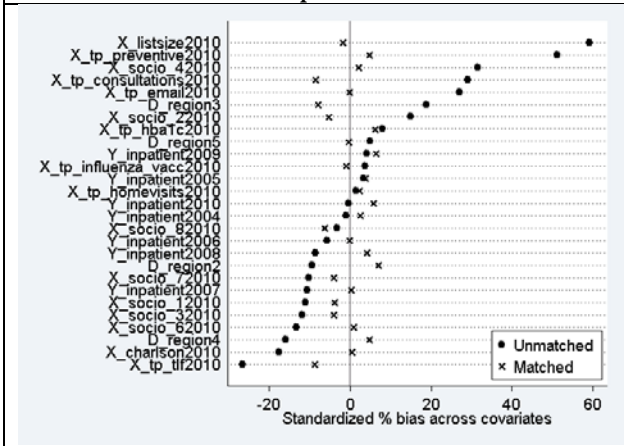


Table 1: Number of treated GPs by year

Year	Number of treated
2013	534
2012	422
2011	120
2010	43
2009	30
2008	10
2007	2
2006	3

Table 2a: Bias in covariates before matching – 2011 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	7.35	6.41	55.1***	3.98	0.00
Influenza vaccinations	0.35	0.32	24.1*	1.72	0.09
Preventive visits	1.73	1.29	44.5**	3.37	0.00
Number of e-mail consultations	0.94	0.64	38.2**	2.84	0.01
Number of HbA1C measurements	0.04	0.05	-4.30	-0.31	0.76
List size	2550.40	1623.90	69.2***	6.58	0.00
Charlson index	0.76	0.77	-6.10	-0.49	0.63
Homevisits	0.14	0.14	-0.20	-0.01	0.99
Numbner of telephone consultations	5.05	5.88	-36.3**	-2.62	0.01
Share of unemployed between 20 and 59 years of age	0.00	0.00	-5.10	-0.36	0.72
Share of 25-59 years of age without secondary education	0.01	0.01	10.80	0.79	0.43
Share of 25-65 years of age with low income	0.00	0.00	-24.4*	-1.69	0.09
Share of 18-59 years of age on public benefits	0.00	0.00	28.9**	2.10	0.04
Share with non-western ethnicity	0.00	0.00	-27*	-1.76	0.08
Share of unemployed between 20 and 59 years of age	0.01	0.01	-3.40	-0.24	0.81
Share of 25-59 years of age without secondary education	0.01	0.01	-14.60	-0.99	0.33
Central Denmark Region	0.16	0.23	-17.90	-1.33	0.19
Region of Southern Denmark	0.37	0.19	40.7**	3.47	0.00
Capital Region of Denmark	0.28	0.38	-21.10	-1.59	0.11
Region Zealand	0.03	0.13	-37.4**	-2.41	0.02
Y_ACSC_diab2004	0.02	0.02	3.60	0.31	0.75
Y_ACSC_diab2005	0.02	0.02	-5.40	-0.42	0.68
Y_ACSC_diab2006	0.01	0.02	-170	-1.16	0.25
Y_ACSC_diab2007	0.01	0.02	-38.8**	-2.52	0.01
Y_ACSC_diab2008	0.02	0.02	-24.1*	-1.81	0.07
Y_ACSC_diab2009	0.02	0.02	-26.2*	-1.83	0.07
Y_ACSC_diab2010	0.02	0.03	-160	-1.12	0.27
Y_inpatient_diabetes2004	0.09	0.09	10.70	0.82	0.41
Y_inpatient_diabetes2005	0.08	0.09	-11.50	-0.87	0.39
Y_inpatient_diabetes2006	0.09	0.10	-17.50	-1.20	0.23
Y_inpatient_diabetes2007	0.09	0.11	-26.8*	-1.88	0.06
Y_inpatient_diabetes2008	0.10	0.12	-34.3**	-2.30	0.02
Y_inpatient_diabetes2009	0.13	0.14	-7.30	-0.53	0.60
Y_inpatient_diabetes2010	0.17	0.16	4.80	0.35	0.73
Y_inpatient2004	0.27	0.27	-2.50	-0.19	0.85
Y_inpatient2005	0.26	0.27	-14.40	-1.02	0.31
Y_inpatient2006	0.29	0.30	-9.70	-0.72	0.47
Y_inpatient2007	0.29	0.31	-15.50	-1.18	0.24
Y_inpatient2008	0.29	0.33	-25.7*	-1.74	0.08
Y_inpatient2009	0.36	0.37	-7.70	-0.55	0.58

Y_inpatient2010	0.41	0.42	-60	-0.41	0.68

Table 2b: Bias in covariates before matching – 2012 cohort

Variable name	Treated	Control	SBias	t-stat	P-value
Consultations	6.94	6.41	29.1***	3.96	0.00
Influenza vaccinations	0.33	0.32	3.70	0.51	0.61
Preventive visits	1.79	1.29	51.2***	6.94	0.00
Number of e-mail consultations	0.85	0.64	27***	3.65	0.00
Number of HbA1C measurements	0.08	0.05	7.90	1.15	0.25
List size	2312.50	1623.90	59.2***	8.48	0.00
Charlson index	0.73	0.77	-17.7**	-2.44	0.02
Homevisits	0.15	0.14	1.40	0.19	0.85
Numbner of telephone consultations	5.25	5.88	-26.6***	-3.60	0.00
Share of unemployed between 20 and 59 years of age	0.00	0.00	-11.10	-1.48	0.14
Share of 25-59 years of age without secondary education	0.01	0.01	15**	2.07	0.04
Share of 25-65 years of age with low income	0.00	0.00	-11.80	-1.62	0.11
Share of 18-59 years of age on public benefits	0.00	0.00	31.6***	4.39	0.00
Share with non-western ethnicity	0.00	0.00	-13.4*	-1.82	0.07
Share of unemployed between 20 and 59 years of age	0.01	0.01	-10.30	-1.41	0.16
Share of 25-59 years of age without secondary education	0.01	0.01	-3.30	-0.44	0.66
Central Denmark Region	0.19	0.23	-9.40	-1.28	0.20
Region of Southern Denmark	0.27	0.19	18.9**	2.66	0.01
Capital Region of Denmark	0.30	0.38	-16.1**	-2.20	0.03
Region Zealand	0.15	0.13	4.90	0.68	0.50
Y_ACSC_diab2004	0.02	0.02	-4.90	-0.66	0.51
Y_ACSC_diab2005	0.02	0.02	-13.5*	-1.77	0.08
Y_ACSC_diab2006	0.02	0.02	-10.50	-1.39	0.17
Y_ACSC_diab2007	0.02	0.02	-15**	-1.98	0.05
Y_ACSC_diab2008	0.02	0.02	-11.40	-1.52	0.13
Y_ACSC_diab2009	0.02	0.02	-0.70	-0.10	0.92
Y_ACSC_diab2010	0.02	0.03	-10.20	-1.34	0.18
Y_inpatient_diabetes2004	0.08	0.09	-70	-1.00	0.32
Y_inpatient_diabetes2005	0.09	0.09	-9.60	-1.30	0.19
Y_inpatient_diabetes2006	0.09	0.10	-11.80	-1.57	0.12
Y_inpatient_diabetes2007	0.10	0.11	-13.7*	-1.83	0.07
Y_inpatient_diabetes2008	0.11	0.12	-13.2*	-1.78	0.08
Y_inpatient_diabetes2009	0.13	0.14	-5.40	-0.72	0.47
Y_inpatient_diabetes2010	0.16	0.16	-5.50	-0.73	0.46
Y_inpatient2004	0.27	0.27	-1.10	-0.15	0.88
Y_inpatient2005	0.28	0.27	3.30	0.45	0.66
Y_inpatient2006	0.29	0.30	-5.80	-0.79	0.43
Y_inpatient2007	0.30	0.31	-10.60	-1.42	0.16
Y_inpatient2008	0.32	0.33	-8.50	-1.12	0.26

Y_inpatient2009	0.38	0.37	4.10	0.56	0.58
Y_inpatient2010	0.42	0.42	-0.30	-0.05	0.96

Table 3: Results propensity score matching (PSM)

	2011 cohort				2012 cohort		
	2010	2011	2012	2013	2011	2012	2013
ACSC	0.0059241	0.0002109	-0.0002604	-0.0104047***	-0.0040758	-0.0033655	-0.0102456***
P-value	0.2110871	0.9631068	0.9504285	0.0053596	0.1240907	0.2141682	0.0001169
Diabetes hosp.	0.0244306**	-0.0045558	-0.0094105	-0.0222247*	0.0000868	-0.0120956	-0.0307051***
P-value	0.0375975	0.6614946	0.4078382	0.0747898	0.9903893	0.1688058	0.0022755
Hospitalizations	0.0253683	0.0037581	-0.0300782	-0.066014**	-0.0157841	-0.0187223	-0.0520517***
P-value	0.244657	0.8542559	0.1591017	0.0283663	0.3220916	0.2572937	0.0067269

* p<0.1 **p<0.05 ***p<0.01

Table 4: Results PSM with unrestricted diabetes population

	2011 cohort				2012 cohort		
	2010	2011	2012	2013	2011	2012	2013
ACSC	-0.0011294	-0.0001433	0.0012459	-0.006678**	-0.0040758	-0.0033655	-0.0102456***
P-value	0.766625	0.9703121	0.7164146	0.0240121	0.1240907	0.2141682	0.0001169
Diabetes hosp.	0.0106946	-0.0104315	-0.0012316	-0.0165222	0.0000868	-0.0120956	-0.0307051***
P-value	0.3101719	0.2821927	0.9081989	0.1396961	0.9903893	0.1688058	0.0022755
Hospitalizations	0.0153952	0.0101215	-0.0329671	-0.0444927	-0.0157841	-0.0187223	-0.0520517***
P-value	0.4286128	0.5724002	0.1451467	0.137578	0.3220916	0.2572937	0.0067269

* p<0.1 **p<0.05 ***p<0.01

Table 5: Results DiD

	2011 cohort				2012 cohort		
	2010	2011	2012	2013	2011	2012	2013
ACSC	-0.0016393	0.0020886	-0.0065571	-0.0128439***	-0.0036141	-0.0062931*	-0.0110822***
P-value	0.7350033	0.6969453	0.2036216	0.0089177	0.2761952	0.0752057	0.0029444
Diabetes hosp.	0.009831	-0.0064942	-0.0193907*	-0.0367354**	0.0067338	-0.0023119	-0.0163951
P-value	0.3802431	0.517593	0.0881787	0.0359894	0.364515	0.7725498	0.1052003
Hospitalizations	-0.0161059	-0.0251179	-0.0598618**	-0.0796132**	-0.0047826	-0.0079213	-0.0479765**
P-value	0.5097608	0.2520813	0.0182358	0.0167327	0.7455924	0.6426272	0.0124527

* p<0.1 **p<0.05 ***p<0.01

Table 6: Results parametric model with continuous treatment

	2011 cohort				2012 cohort		
	2010	2011	2012	2013	2011	2012	2013
ACSC	0.001734	-0.0027063	-0.0003975	-0.0106872**	-0.00303	-0.0030923	-0.0119923***
P-value	0.6983231	0.5097739	0.9343434	0.021421	0.3344114	0.3249524	0.0001722
Diabetes hosp.	0.0242748	-0.0047313	0.003756	-0.0168853	0.0025631	-0.0061103	-0.0285366***
P-value	0.0493032	0.6081169	0.7357578	0.1466196	0.6893824	0.4155148	0.0005567
Hospitalizations	0.0458273*	-0.0549186***	-0.0392228	-0.0502863	-0.0172318	-0.029984*	-0.0578585***
P-value	0.0734075	0.0063916	0.1059995	0.1227777	0.2371128	0.0725191	0.0028212

* p<0.1 **p<0.05 ***p<0.01