

Is sick absence related to commuting travel time? - Swedish Evidence Based on the Generalized Propensity Score Estimator*

Anders Karlström[†]

Transport and Economics, Royal Institute of Technology, SE-100 44 Stockholm, Sweden

Gunnar Isacsson

National Road and Transportations Research Institute, P.O. Box 760, S-781 27 Borlänge, Sweden.

May 15, 2009

*We are grateful for financial support from the Swedish National Road Administration and VINNOVA (the Swedish Governmental Agency for Innovation Systems). We acknowledge helpful comments and support by Mårten Palme and Ingemar Svensson. Computational assistance was provided by Aron Tesfaghebriel.

[†]Corresponding author.

Abstract

This paper focuses on the effects of commuting time on sickness insurance utilization by applying a generalized propensity score estimator to a large sample of Swedish employees. We analyse the effect of commuting time both on the probability of using sickness insurance at all and on the probability that an individual on sick leave is on so-called partial sick leave rather than being completely absent from work. Insurance utilization is in both cases defined as being ill for more than 14 days. The results indicate, in general, that individuals do not use sickness insurance because of their commuting time. However, commuting time seems to increase the risk of being on sick leave among females with relatively low annual wage earnings. The results indicate, furthermore, a relatively weak and negative relationship between the probability of being on partial sick leave and commuting time in the group of individuals who have utilized sickness insurance. The latter result applies to both men and women.

1 Introduction

Commuting is an important aspect of daily life for many individuals. For instance, many americans spend more time commuting than on vacation¹. Hence, commuting is an important characteristic of an employment relationship, and is therefore an important aspect of the labour market. Considering if or where to work, the trade-off between wage and commuting travel time has been extensively studied² both theoretically and empirically. In this paper we focus on the effect of commuting on one aspect of labour supply, viz. longer term (more than 14 days) absenteeism due to sick leave.

Work absenteeism due to sick leave is significant in a labour supply perspective. During the period 1983-2001, the average sick absence in the the original 12 EU countries (EU12) was 1.7%. However, there are many countries with much higher absence, for instance Netherlands (4.1%), Norway (3.2%), and France (2.4%) during the same time period, while it was 4.2% in Sweden. In this paper, we will investigate active employees in the work force in Sweden. During 2002 there were 7.2% who were on sick leave for more than 14 days at least once among active employees in the work force (see Section 2).

Sick leave is, furthermore, an aspect of the individual's decision on labour force participation when modelling daily labour supply. In this respect it is related to the issue of discrete adjustments of the individual's labour supply; that is, adjustments along the so-called 'extensive margin'. In addition, commuting time and commuting costs are both examples of fixed costs that create non-convexities in standard models of labour supply, and that are directly relevant to the decision on participation (see Cogan, 1981, and Blundell and Macurdy, 1999, section 6.5).

There are several reasons as to why commuting travel time and other characteristics of commuting may be related to absenteeism and sick leave (see Kosolowsky et al., 1995, for a comprehensive treatment). First of all, there may be direct ef-

¹American Community Survey. Retrieved December 27, 2007, from <http://www.census.gov/acs/www/>.

²See, e.g., van Ommeren (1998), van Ommeren et al. (2000), Rouwendal (2004), Isacsson and Swardh (2007) and Isacsson et al. (2007).

fects on health. There is a body of research on commuting and ill health. In particular commuting by car has been studied³. For instance, analyzing data from a commute survey in southern California, Novaco and Collier (1994) show that commuting stress is related to distance. The interpretation is that the commuting situation is a behavioural constraint, leading to aversion and frustration⁴. In particular, this holds for congested traffic conditions. Hennessy and Wiesenthal (1999) and Stokol (1978) use measurement intensive (but small sample size) interview data to show that drivers are more stressed during congested traffic. Lucas and Heady (2002) show that workers with flexible working hours report less driver stress than those without flextime. Moczulski et al. (2007) report that students with a long drive to university are more likely to suffer from overweight than those with a short drive. But evidence reported by Evans and Wener (2006) suggests that commuting by train may also be stressful. They report that among a group of train commuters to Manhattan those with a longer commute had higher elevations of salivary cortisol levels relative to the resting base line levels⁵. Individuals with a longer train commute also tended to perceive higher levels of stress according to the results of Evans and Wener (ibid).

It is likely that part of the absenteeism linked to commuting is more indirect. On the margin, commuting is yet another obstacle to overcome to go to work when you already suffer from physical or mental illness. As part of the sickness insurance programme in Sweden, this problem is explicitly handled. The individual is in fact entitled to taxi for the work trip, if he/she then can go to work. This feature of the sickness insurance system should, in principle, make the commuting trip less important as a determinant of sick leave.

Hence, there are reasons to believe that there may be a relationship between commuting characteristics and workplace absenteeism. Indeed, such a significant relationship has repeatedly been reported in the literature. Taylor and Pocock

³Public transit has also been extensively studied. Travel time reliability is a stress factor both for car in congested conditions, as well as for public transit. See, e.g., Wener et al. (2004).

⁴Evans (1994) studies the occupational stress of bus drivers and finds that traffic congestion is a factor for elevated health risks.

⁵Cortisol is a hormone that is often used to measure stress.

(1972) showed that commuting is related to work absenteeism⁶, both in terms of number of days and number of absence spells. They also show that car drivers were more absent than transit riders. For transit riders, Wener et al. (2003) report some evidence that work absence increased if number of transfers exceeded two. Another piece of evidence that work absence and impedance related to commuting is related is provided by Novaco et al. (1990). However, as noted by Costa et al. (1988), most of these studies are based on data from a single workplace, and the number of individuals with longer commutes may be few, limiting the possibility in establishing a relationship, if present. One notable aspect of the present study is, therefore, the sample size. Our data sample includes some 1.7 million observations in total, which is quite large compared to typical sample sizes in the cited studies above (with typical sample sizes of about 2000). On the other hand, we do not have data on short-term sick leave, so we will focus on longer sick leaves, rather than short term sick absence. We will discuss the data in more detail in Section 2.

Another feature of the present study is that geographical space is represented at a finer (low-level) scale. While many studies⁷ have focused on the regional differences in social security utilization, also sickness insurance, using data on a regional or municipality level, we believe that it is important to account for differences also within a municipality. In Sweden, many municipalities are quite large and quite heterogeneous, which makes the geographical configuration of households and workplaces even more important to account for⁸.

In this paper, we will use two different indicators of sick leave. The first is *full-time* sick leave, which simply means that the individual is not working at all during the spell. The second is *part-time* sick leave. Sweden is one of few European countries which allows for part-time sick leave⁹, which means that the individual can be on sick leave only a part of the day, or a part of the work-week.

⁶See also citations in the, somewhat outdated, review by Costa et al. (1988).

⁷RFV (2003).

⁸There are some 290 distinct municipalities in Sweden. A municipality in Sweden is, furthermore, the smallest geographical unit of government with a right to decide on the local tax rate.

⁹Part time sick leave was introduced 2006 in Finland.

This opens for the possibility that individuals that are too sick to work full-time, but can work part-time do not have to be on full-time sick leave. For instance, a person that is recovering from illness can slowly go back to work as work ability is improving. There is a potential demand for partial sick leave: in a survey 32% of the respondents on (full-time) sick leave indicated that they wanted to work more, considering the present ability to work (Eklund et al., 2004). Other studies have shown that the total sick absence may increase rather than decrease, since the length of spells tend to increase if the individual is on part-time sickness.

Finally, when analyzing sick leave and commuting, gender differences should be accounted for. It is well-known that commuting patterns among men and women differ. This is also reflected in both the labour and transport literature, as well as the literature on ill health and commuting¹⁰. In a recent study, Black et al (2007) focus on the large geographical variation in female labour supply across the US. Although there are many factors at play, they conclude that female workers are highly sensitive to commuting travel times when making their labour force participation decisions. This finding can be supported by the ill health literature. For instance, Novaco and Collier (1994) showed that women suffers from greater stress for longer commuting distances, arguing that women perceive more stress spillover from commuting to home and work.

There are also significant gender differences in utilization of the part-time sick leave instrument. The probability is doubled that a woman is on part-time sick leave from the start of a spell, compared to a man (Eklund et al, 2004). In this paper we will show that although there are substantial differences in how the part-time sick leave instrument is used, the (significant) relationship with commuting travel time is fairly stable between men and women. That is, we are not able to support the hypothesis that women are more sensitive to commuting travel time than men, in this respect.

This paper is organized as follows. In Section 2 we present the data. The

¹⁰Gender differences is prevalent, but not present in every aspect of commuting. For instance, Wener et al (2004) could not find gender differences when studying certain aspects of public transit, and Lucas and Heady (2002) found no gender differences when studying the effect of flexible working hours.

empirical approach to estimate the effect of commuting on sickness absence is presented in 3. Section 4 presents the results and section 5 concludes.

2 Data

Our data is derived from two different sources. One is based on administrative registers in which all individuals permanently living in Sweden are included (the LISA database), and the other one is a travel time database (which is part of the so-called SAMPERS system). In this section we will give a brief background of each, and also provide basic descriptive statistics.

The LISA database contains information on all individuals permanently living in Sweden. It is based on two different registers. The first is the income and wealth register consisting of tax return data and information on separate income components from different parts of the income security system on all individuals registered as taxpayers in Sweden. The second is the Enterprise and Workplace register compiled by Statistics Sweden, which contains information on all employers and workplaces in Sweden. These two registers are linked to connect every employed individual to his/her workplace.

For each individual we also have data on sick leave spells with sickness insurance. For each spell we observe starting date, end date, and variables related to sickness insurance utilization. The outcome variables of interest is part-time sick leave and full-time sick leave. The data set only includes data for individuals that have been recorded to be on sick leave for at least 15 days during a spell (episode). In Sweden, sickness insurance is handled by the employer during the first 14 days, so the register data only includes sickness spells that lasted at least 15 days (and where sickness insurance was utilized). Thus, individuals may have had many sickness episodes, each lasting less than 15 days, without being recorded to be on sick leave in our database.

We will use a binary representation of the outcome variables. An individual is considered to be on sick leave if he/she has at least one spell (at least 15 days) with sickness insurance during the year under study (2002). An individual is

considered to be not absent if there were no recording of spells longer than 14 days. By part-time sick leave, we mean that they have at least one day recorded as part-time sick leave¹¹. With full-time sickness, we mean that an individual has at least one day sickness insurance (recorded in the database) and that he/she has no days with part-time sick leave.

We use data from 2002 on individuals that are employed, as defined by Statistics Sweden. Individuals who were self-employed and students are not included. For our application, we also need to know the place of residence and the location of the workplace. Since this is yearly data, the place of residence is the place where the individual was registered November 1st 2002. The workplace is also defined by Statistics Sweden, and it is defined as the workplace from which most of the individual's income was earned during the year. The data may be less accurate for individuals switching workplace late in 2002. The place of residence and the location of the workplace are recorded on a fairly low geographic level. For 2002, Sweden is partitioned into Small Area Market Statistics (SAMS), which is based on homogeneous areas in terms of households.

Our second main source of data is a travel time database which is a part of the SAMPERS database, which in turn is part of a model for transport policy forecasting and evaluation¹². In this database, the geographical zones are not identical to SAMS, used in the LISA database. Instead, the transportation analysis zones (TAZs) are typically aggregated from SAMS (with minor exceptions). Our database includes 9141 TAZs. For each origin-destination pair¹³, according to TAZs, there are several variables available in the database. These include travel distances in kilometers, travel time by car, in-vehicle time by public transit, waiting time for public transit, travel cost for both car and public transit, etc. In effect, all these can be used as measures of impedance related to commuting. Travel

¹¹An individual is considered to be on part-time sick leave if he/she had less than 100% of compensation from the sickness insurance. There are three levels available, 25%, 50%, and 75%, but we make no distinction between these levels in this study.

¹²See Algers and Beser (2000).

¹³Not every pair of TAZs has a value, but there are some 22 million values in the travel time database for peak hour car.

times are also decomposed into peak and off-peak. Outside the major cities, travel times by car during peak and off-peak are very strongly correlated. For public transit, there are differences between off-peak and peak travel times. We believe that travel time for peak-hour is more relevant when studying work trip commuting. In this study we have therefore chosen to use peak-hour travel time for car, since it is the dominating mode of transport for work trips, in particular outside the major cities. As we will see later, we have reasons to deal with the largest city, Stockholm, separately.

Each employed individual in the data base has a place of residence (SAMS zone). However, the zone of workplace is not available for each individual. In the final data set, there were some 1.7 million individuals; that is, individuals who were employed during 2002 and for which we can impute a travel time between place of residence and place of work.

3 Generalized Propensity Score

The purpose of this paper is to investigate the relationship between sickness absence indicators, on the one hand, and commuting travel time, on the other. Clearly, commuting distance is an endogenous variable and cannot be treated as if it were randomly assigned to individuals; that is, we must rely on observational data to estimate the effect of commuting time on sickness absence. This implies certain problems regarding the possibility of estimating the causal effect of commuting time on sickness absence (see Rosenbaum, 2002). Commuting travel time is, for example, typically strongly related to gender and income. Likewise, sickness absence may be, and often is, related to the same socio-economic characteristics as commuting (in fact, income and gender is typically correlated with sick leave). Therefore, to assess the effect of commuting time on sickness absence, we would like to compare an individual who is absent from work because of sickness to another 'similar individual' who is not sickness absent. Since we do not have experimental data, which is often the case in transportation research, we will employ the generalized propensity score (GPS) estimator as outlined by Hirano and

Imbens (2004) to deal with the problem of not comparing 'similar individuals' to estimate the effect (see also Imai and van Dyk, 2004).

The GPS estimator is a generalisation of the propensity score estimator (Rosenbaum and Rubin, 1983). The latter is suitable for the case of estimating 'treatment effects' when the treatment is binary whereas the former is suitable for estimating the effect of a continuous treatment or a dose-response relationship. In our case the 'dose' is commuting travel time and the 'response' is utilization of sickness insurance. An important aspect of the propensity score estimator is that we can test whether the treated and the control groups are indeed 'similar to each other' by applying a t-test to the means of each covariate in the two groups. This is referred to as 'covariate balance' (see for example Rosenbaum, chapter 10). There is also a corresponding test of covariate balance when applying the GPS estimator that we outline below.

More specifically, when applying the GPS estimator we assume that the distribution of outcomes is conditionally independent of the value of each level of the treatment. Hirano and Imbens (2004) refer to this assumption as 'weak unconfoundedness'. Furthermore, and following the terminology from Hirano and Imbens (2004) (and the treatment effect literature in general), we assume that we have a random sample of individuals, indexed by $i = 1, \dots, N$. For each individual, there is a discrete outcome $Y_i(T_i)$ indexed $0, \dots, J$, which may depend on the level of treatment $T_i \in [T_0, T_1]$. In our case, T_i is the travel time from home to the workplace. For each individual, we observe a vector of characteristics $X_i \in \mathfrak{R}^K$, along with the outcome Y_i , and treatment T_i . Now the objective is to estimate the average dose-response-function, defined as $\mu(t) = E[Y_i(t)]$, for a given level t of treatment (travel time) of interest.

The definition of the generalized propensity score (GPS) is based on the conditional density of the treatment given the covariates. Thus, we let

$$r(t, x) = f_{T|X}(t | x) \tag{1}$$

Now, the generalized propensity score is defined by $R(T, X) = r(T, X)$. In this paper we will, as is standard, use a normal distribution for the treatment (travel

time) given the covariates, that is

$$\log T_i | X_i \sim N(\beta' X_i, \sigma^2) \quad (2)$$

where $\beta \in \mathbb{R}^k$ is a k -dimensional vector of parameters to be estimated, and $X_i \in \mathbb{R}^N \times \mathbb{R}^k$ is the data matrix. The parameters are estimated by standard OLS. Hence, the estimated GPS is given by

$$\hat{R}_i = \frac{1}{\sqrt{2\pi\hat{\sigma}^2}} \exp(\log T_i - \beta' X_i) \quad (3)$$

Next, we turn to the outcome variable. We will use a binary representation of the outcome variable, for instance $Y_i = 1$ if individual i is on sick leave, and zero otherwise. Given the thus estimated GPS, we estimate a binary logit model with Y_i as dependent variable, and the GPS R_i and commuting travel time (treatment) T_i as regressors. Thus, we specify

$$V_i(T_i, R_i) = \alpha_0 + \alpha_1 T_i + \alpha_2 R_i + \alpha_3 R_i^2 + \alpha_4 T_i^2 + \alpha_5 T_i \cdot R_i \quad (4)$$

In practice, one would like to use a flexible specification of V_i . Now, the logit model is defined by the probability that an individual will be on sick leave as given by

$$Pr(Y_i = 1) = \frac{e^{V_i}}{1 + e^{V_i}} \quad (5)$$

The parameters of the estimated model in (4) - (5) are not easily interpretable. In fact, it is not important that the estimated parameters are statistically significant. Instead, what we are really interested in is the average dose-response function, which is calculated from the logit model (5) - (4), where we insert a given treatment level we are interested in, for each individual i . In other words, for each individual i we calculate

$$\mu_i(t) = \frac{e^{V_i(t,r(t),X_i)}}{1 + e^{V_i(t,r(t),X_i)}} \quad (6)$$

Finally, the dose-response function is obtained by taking the average across the sample, i.e.

$$\mu(t) = \frac{\sum_i \mu_i(t)}{N} \quad (7)$$

We will also be interested in the derivative of the dose-response function, which is easily found by taking the derivative of (7).

To find the confidence levels of the dose-response function, we use a bootstrap procedure. In the results to be presented below, we have used 100 simulations, and each simulated sample was randomly drawn, with replacement. The sample size of each simulated sample size was taken to be 80% of the nominal size.

4 Results

4.1 Partial Sick Leave

4.1.1 Balancing

As outlined in Section 3 we need to test how the adjustment of the GPS works for balancing the covariates. If the treatment was binary, we would simply compare the covariate means for treated and untreated individuals before and after matching. In our case we have continuous treatment, and testing for balancing is somewhat more complicated. We will here outline the method in more detail.

We first estimate the propensity score; that is, we regress travel time on a set of covariates. The covariates used here are number of children 0-3 years of age, number of children 4-6 years of age, number of children 7-10 years of age, the individual's income, age of the individual, his/her educational level, a set of dummy variables for county of residence with the county of Stockholm being the reference county. Estimation results together with descriptive statistics (for both men and women) are found in Table 1.

Then, we divide the sample with respect to treatment (i.e. commuting distance). We have tested a number of different partitions. Note that the sample size is rather large, and we can therefore afford to have many partitions. Let us divide the sample into 10 treatment groups with respect to commuting distance, each of equal size. Here, group 1 includes individuals with the shortest travel times, group 2 includes those with the next-to-shortest travel times etc. For the data set of only women, each treatment group has 21160 observations. In the data set, we

coeff	Women						Men					
	mean	std dev	min	max	estimate	t-value	mean	std dev	min	max	estimate	t-value
const	1.00	0.00	1.00	1.00	1.93649	107.27	1.00	0.00	1.00	1.00	2.09882	95.20
children 0-3	0.15	0.42	0.00	4.00	0.09059	14.81	0.11	0.36	0.00	3.00	0.04610	5.42
children 4-6	0.10	0.33	0.00	4.00	0.00233	0.33	0.09	0.31	0.00	3.00	0.04481	4.55
children 7-10	0.18	0.46	0.00	4.00	0.01877	3.60	0.15	0.43	0.00	4.00	0.05547	8.00
income	1637.80	782.86	0.00	31093.00	0.00006	17.63	2118.06	997.57	0.00	32767.00	0.00005	16.49
age	43.75	11.57	16.00	77.00	-0.00329	-14.54	43.94	11.98	16.00	77.00	0.00130	5.07
edu	3.35	1.17	1.00	9.00	0.02242	10.83	2.94	1.12	1.00	9.00	-0.00510	-1.88
uppsala	0.05	0.22	0.00	1.00	0.38804	24.09	0.04	0.21	0.00	1.00	0.45998	21.86
sodermanland	0.04	0.19	0.00	1.00	0.16639	9.66	0.04	0.19	0.00	1.00	0.11741	5.35
ostergotland	0.07	0.25	0.00	1.00	0.36495	24.20	0.07	0.25	0.00	1.00	0.16157	8.29
jonkoping	0.04	0.20	0.00	1.00	0.05900	3.55	0.05	0.21	0.00	1.00	-0.08145	-3.90
kronoberg	0.02	0.15	0.00	1.00	0.18269	9.21	0.02	0.15	0.00	1.00	0.09630	3.89
kalmar	0.03	0.16	0.00	1.00	0.12746	6.89	0.03	0.17	0.00	1.00	0.01519	0.65
gotland	0.01	0.09	0.00	1.00	0.04812	1.71	0.01	0.09	0.00	1.00	-0.06592	-1.78
blekinge	0.02	0.14	0.00	1.00	0.16278	8.10	0.02	0.15	0.00	1.00	0.03615	1.43
skane	0.13	0.34	0.00	1.00	0.26006	18.79	0.13	0.34	0.00	1.00	0.20360	11.37
halland	0.04	0.20	0.00	1.00	0.31678	18.81	0.04	0.20	0.00	1.00	0.22422	10.40
vastra gotaland	0.24	0.43	0.00	1.00	0.20720	15.73	0.24	0.43	0.00	1.00	0.18770	11.01
varmland	0.03	0.17	0.00	1.00	0.11768	6.56	0.03	0.18	0.00	1.00	0.01499	0.66
orebro	0.04	0.20	0.00	1.00	0.02488	1.48	0.04	0.19	0.00	1.00	0.01905	0.87
vastmanland	0.04	0.19	0.00	1.00	-0.02227	-1.31	0.04	0.20	0.00	1.00	-0.04586	-2.13
dalarna	0.04	0.19	0.00	1.00	0.10248	5.99	0.04	0.20	0.00	1.00	-0.02657	-1.24
gavelborg	0.04	0.20	0.00	1.00	0.30960	18.58	0.04	0.20	0.00	1.00	0.17714	8.24
vasternorrland	0.04	0.19	0.00	1.00	0.49774	29.12	0.03	0.18	0.00	1.00	0.34540	15.46
jamtland	0.02	0.13	0.00	1.00	0.13054	6.04	0.02	0.12	0.00	1.00	0.10295	3.63
vasterbotten	0.04	0.19	0.00	1.00	0.63894	37.64	0.04	0.20	0.00	1.00	0.48120	22.27
nobs	158679						103575					

Table 1: Summary statistics and parameter estimates of generalized propensity score. Dependent variable: Commuting travel time. In this sample, only individuals that are absent due to sick leave (according to the definition) are included.

have 26 covariates (20 of these are county dummy variables). For each of these, we test whether the mean of this covariate is different in one treatment group, as compared to the the other 9 treatment groups. This is shown in the left panel of Table 2 where we see that the covariates are clearly not balanced. In other words, commuting times depend on the covariates.

In the next step, we do the same kind of balancing test, now adjusted by the GPS. To explain the balancing test in more detail, let us continue to consider the dataset with women only, and consider the last treatment group, with the longest commuting travel times (in the range [34.7,120] minutes); that is, group 10. The median travel time in this group is 45.7 minutes. We insert this value of travel time (treatment) $T = 45.7$ to calculate the propensity score $R(\log 45.7, X_i)$ in group 10, and calculate the corresponding quintiles. Based on the quintiles we obtain five subgroups within group 10. They are, more specifically, defined by the propensity score lying in the intervals [0.0008,0.02554], [0.02554,0.0529], [0.0529,0.0799], [0.0799,0.1122], and [0.1122,0.2646], respectively. We also calculate the propensity score $R(\log 45.7, X_i)$ for all observations outside the treatment group, in this case with $T_i < 34.7$ (groups 1-9). Among these we can identify groups of individuals having a value lying in each of the five intervals defined by the quintiles of the propensity score $R(\log 45.7, X_i)$ in group 10. Then to test for balance of the age covariate, for example, we use a t-test to see whether mean age in the treatment group of $T > 34.7$ (group 10) in the first quintile is equal to the mean age in the group with treatments $T < 34.7$ (groups 1-9) with a propensity score $R(\log 45.7, X_i)$ in the corresponding interval. We then proceed and apply a t-test to the corresponding mean age differences in quintiles 2-5. These five distinct t-tests are subsequently weighed together, using the sample sizes as weights, to produce a single value of the t-test. Then we check whether this t-test rejects the null hypothesis of no difference in the age covariate. In this treatment group (group 10), the t-statistics for age turns out to be -1.08, and we conclude that the balance property holds for this treatment group and this covariate, age. We proceed by undertaking the same calculations for the 9 remaining treatment groups and for each of the remaining covariates.

The t-statistics for each covariate and each treatment group are reported in the right panel of Table 2. It is clear that the GPS adjustment improves the balancing. However, it is also clear that the dummy variable related to the county of Stockholm is unbalanced. Indeed, Stockholm is the largest city in Sweden, and is in many aspects different from the rest of Sweden. Income, sickness insurance utilization, and (not least) commuting patterns are rather different. Thus, it may not be surprising that the Stockholm county singles out in an investigation of commuting distances and sickness insurance utilization. Since the balancing property is not fulfilled, it seems that we need to take care of the Stockholm county separately. If we exclude observations from Stockholm, it turns out that balancing is improved, see Table 3.

There are no clear guidelines regarding how to choose the number of treatment groups, nor the number of subgroups with respect to GPS. Typically, the number of treatment groups and subgroups are of equal or similar size. We have tested different combinations of 10 and 15 treatment groups, together with 5 or 15 subgroups, in different combinations. All results can not be shown here, due to space limitations, but we report the case with 15 treatment groups, and with 5 subgroups with respect to GPS (as before) in the Appendix. Generally, increasing the number of subgroups makes the balancing look better, but one has to be careful so that there are enough observations in each group. The sample size is quite large, however; if we have 10 treatment groups, and 15 subgroups, there will still be 782 observations in the smallest subgroup, which is still quite a large subsample compared to many other applications where the GPS method has been applied.

4.1.2 Dose-response

Having tested the balancing of covariates, we now turn to the estimation of the dose-response-functions. Recall that we have two data sets, one with men and one with women, and that we are interested in the probability of being on part time sick leave, instead of full-time sick leave, given that the individual uses sickness insurance as defined above.

The logit model estimation results are shown in Table 5, both for women and

	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
children 0-3	-15.08	-10.32	-4.90	-5.00	-1.63	2.13	3.97	5.17	9.85	12.46	-2.60	-2.61	-1.81	-2.53	-1.01	-0.14	0.70	1.43	2.61	3.68
children 4-6	-5.83	-3.22	0.26	0.36	2.33	2.18	2.17	1.61	1.12	-1.39	-0.41	-0.87	-0.09	-0.24	0.49	0.44	0.46	0.41	0.36	0.12
children 7-10	-4.61	-2.49	-0.35	1.61	3.85	2.53	3.09	1.12	-1.93	-3.19	-0.29	-0.67	-0.16	0.20	1.02	0.61	0.72	0.29	-0.45	-0.48
income	-13.46	-11.95	-9.13	-7.08	-6.24	-2.20	2.00	8.02	15.62	18.78	-2.36	-2.92	-2.86	-3.31	-2.61	-1.03	0.26	2.33	4.12	4.88
age	13.44	10.96	6.98	4.34	1.26	-1.08	-4.08	-6.94	-10.41	-14.57	2.59	2.46	2.20	2.34	0.70	-0.11	-1.01	-2.12	-2.99	-3.98
edu	-13.17	-9.87	-3.31	-4.62	-2.49	-0.42	5.20	7.16	12.54	9.02	-2.90	-2.18	-1.13	-2.49	-1.29	-0.47	1.27	2.08	3.53	2.69
stockholm	-94.07	-91.20	-23.23	-2.70	-7.88	1.91	14.65	31.49	53.63	58.74	-18.02	-38.53	-17.69	-9.54	-12.26	-1.82	3.03	18.84	27.50	37.58
uppsala	6.73	2.95	1.93	2.27	-3.37	-6.54	-9.37	-6.71	-4.80	12.73	-2.27	1.01	1.15	0.86	0.63	-1.19	-1.91	-1.68	-1.77	1.50
sodermanland	15.76	7.90	2.17	-1.86	-0.56	-2.07	-12.07	-10.89	-10.12	3.81	0.32	2.68	1.17	0.71	0.75	0.07	-3.23	-3.04	-3.60	-0.23
ostergotland	-13.32	10.46	-1.62	5.50	9.70	2.43	4.23	-3.68	-5.46	-13.38	-2.07	3.07	-0.41	0.31	3.13	0.52	1.11	-1.40	-1.26	-2.86
jonkoping	14.86	10.57	-0.71	-2.89	5.55	-1.95	-1.44	-4.93	-10.68	-16.46	2.66	2.48	-0.02	0.71	2.08	-0.86	-0.30	-1.38	-3.69	-5.53
kronoberg	1.65	8.35	8.85	-3.42	-4.91	1.24	-0.83	0.11	-7.06	-8.63	0.15	1.90	2.35	0.21	-0.51	0.50	0.02	0.09	-2.19	-2.62
kalmar	9.78	6.07	2.47	0.20	0.53	-4.07	-1.38	-2.50	-4.76	-10.09	1.18	1.61	1.08	1.19	0.68	-0.86	0.04	-0.71	-1.49	-3.72
gotland	4.57	8.81	-0.60	-1.91	-1.17	-0.88	-1.39	-2.84	-2.68	-5.83	0.26	1.96	0.00	0.37	0.23	-0.18	-0.48	-0.73	-0.93	-2.23
blekinge	3.92	6.96	2.78	0.97	1.85	-1.75	-1.84	-0.72	-5.13	-10.16	0.83	1.84	1.09	0.88	0.87	-0.20	-0.39	-0.17	-1.53	-3.23
skane	10.24	10.94	3.88	0.50	1.07	-0.17	-0.97	-5.44	-11.66	-11.19	0.84	3.45	1.82	1.30	2.10	1.13	0.60	-1.11	-3.61	-3.85
halland	-4.83	8.53	0.86	4.31	3.78	-0.24	-1.40	-2.33	-2.26	-8.77	-0.84	2.44	0.49	0.95	1.63	0.04	-0.20	-0.61	-0.55	-2.10
vastra gotaland	23.52	8.21	0.55	-1.40	1.95	10.45	4.30	-7.25	-19.33	-27.42	4.28	3.05	1.06	1.93	2.66	4.31	2.24	-1.41	-6.13	-9.87
varmland	9.92	5.75	5.24	-0.30	0.77	2.16	-3.54	-4.17	-9.78	-11.06	1.64	1.62	1.53	0.95	0.50	0.49	-0.87	-1.13	-3.29	-3.59
orebro	11.97	10.67	5.94	6.82	0.38	-5.54	-3.66	-9.74	-10.17	-15.19	1.89	2.75	1.61	2.72	-0.28	-2.22	-1.35	-3.11	-3.31	-5.03
vastmanland	18.33	10.94	7.26	3.83	-6.07	-6.86	-9.04	-8.57	-13.20	-7.63	1.88	2.65	2.16	1.63	-2.02	-1.97	-2.74	-2.81	-4.64	-3.11
dalarna	9.24	12.63	6.02	3.09	-3.69	-3.93	-3.72	-4.26	-11.64	-10.33	1.14	3.05	1.92	2.07	-0.71	-1.06	-1.06	-1.21	-3.77	-3.08
gavelborg	0.83	3.29	2.18	-2.32	6.93	2.94	1.82	1.16	-9.28	-10.40	0.54	1.12	0.77	-0.86	2.53	1.16	0.52	0.35	-2.39	-3.00
vasternorrland	-4.19	3.51	-3.66	-4.30	3.60	-1.58	-4.05	2.44	5.20	1.59	-1.72	0.51	-0.85	-1.75	1.80	-0.36	-1.02	0.44	1.08	-0.37
jamtland	6.88	2.56	4.17	2.47	0.58	-0.88	-2.37	-5.43	-6.51	-4.45	0.67	1.01	1.38	1.35	0.43	-0.19	-0.61	-1.44	-2.13	-1.54
vasterbotten	-3.88	-4.95	-2.09	-9.94	-4.91	0.21	-1.76	2.28	10.88	9.87	-2.00	-2.38	-0.47	-3.41	-1.03	0.24	-0.45	0.27	2.41	1.23

Table 2: Balancing test for the partial sick leave model for women, including observations from Stockholm county. Each of the 10 treatment groups are divided into 5 subgroups with respect to propensity score. The table shows t-statistics for equality of means.

	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
children 0-3	-9.86	-5.69	-3.64	-1.57	-0.92	0.72	2.96	4.07	5.47	6.90	-1.82	-1.56	-1.28	-1.23	-1.76	0.30	0.28	0.88	1.42	1.94
children 4-6	-5.05	-3.79	-0.71	-0.27	0.49	2.29	2.73	2.37	2.69	-1.27	-0.11	-0.94	-0.26	-0.45	-0.59	0.55	0.48	0.65	0.92	0.26
children 7-10	-5.09	-3.81	-1.87	-1.48	0.56	3.30	3.53	4.27	2.10	-2.05	0.05	-0.71	-0.56	-0.86	-0.69	0.76	0.70	1.28	0.91	0.17
income	-4.61	-2.91	-2.10	-0.55	-2.33	-2.15	-0.90	-1.32	3.38	12.18	-1.95	-0.98	-0.28	-0.08	-0.91	0.26	0.11	-0.06	0.85	2.37
age	8.54	5.71	4.69	2.80	-0.15	-1.08	-1.38	-3.89	-4.52	-10.85	2.30	1.35	1.11	1.19	1.17	-0.99	-0.52	-1.60	-1.59	-2.50
edu	-9.78	-4.64	-2.65	0.44	-2.14	-1.37	0.45	2.07	5.52	12.27	-2.81	-1.23	-0.66	-0.06	-1.51	0.41	0.24	0.79	1.58	2.74
upsala	-2.47	-1.72	-2.72	0.93	1.19	-4.08	-7.18	-7.65	-3.42	21.32	-3.55	-1.06	-0.47	0.46	-0.46	-0.03	-1.61	-1.75	-1.24	3.41
sodermanland	7.44	3.31	2.44	-0.47	-2.29	-1.32	-3.07	-9.70	-9.58	9.26	-0.80	1.40	1.54	0.48	0.77	0.12	-0.33	-2.32	-2.64	1.26
ostergotland	-18.29	-5.94	0.07	-3.92	7.08	7.92	2.62	6.81	2.50	-3.12	-2.05	-1.38	-0.35	-2.25	-1.54	1.55	0.15	1.63	0.83	1.49
jonkoping	8.61	2.03	3.41	-4.10	-0.91	3.15	-1.64	-0.31	-1.70	-11.01	2.32	0.16	0.66	-1.18	1.26	0.69	-0.94	-0.49	-0.76	-3.04
kronoberg	-4.09	5.17	2.09	4.32	-3.85	-5.38	1.98	1.86	0.07	-4.14	-0.46	1.28	0.33	1.44	0.49	-0.85	0.51	0.29	-0.24	-0.37
kalmar	4.54	4.74	-1.90	-1.94	-0.07	-0.34	-3.21	1.06	-0.26	-3.58	0.84	1.08	-0.31	-0.22	1.32	-0.08	-0.64	0.48	-0.41	-1.32
gotland	1.99	4.41	2.55	-1.84	-2.07	-2.30	-0.67	0.03	-0.89	-2.45	0.21	0.76	0.36	-0.23	0.43	-0.35	-0.14	-0.71	-0.62	-0.90
blekinge	-2.45	2.30	2.06	1.19	0.68	1.10	-2.03	-1.12	3.38	-6.19	0.10	0.46	0.72	0.57	0.73	0.18	-0.41	-0.22	0.92	-1.10
skane	-4.00	2.26	-3.24	1.48	-1.16	-0.53	0.58	1.06	2.06	1.28	-0.82	0.89	-0.52	0.79	0.41	0.71	0.81	0.99	1.05	0.66
halland	-11.24	-0.76	-0.98	2.10	3.72	1.89	1.27	-0.50	3.51	-0.70	-1.44	-0.01	-0.26	0.22	-0.04	0.46	0.22	-0.10	1.05	1.20
vastra gotaland	7.17	-4.78	-9.18	-5.01	-0.41	1.52	11.67	7.04	1.42	-10.80	3.06	-0.33	-2.13	-1.12	2.16	1.19	4.08	3.14	1.81	-3.12
varmland	1.13	4.07	-0.74	3.18	-0.41	0.53	2.44	-2.46	-2.73	-6.03	0.54	1.25	-0.04	0.86	0.91	-0.25	0.43	-0.70	-0.93	-1.19
orebro	5.42	0.00	7.22	4.73	3.09	0.13	-6.14	-2.66	-5.03	-9.63	1.38	0.11	1.84	0.89	0.64	-1.43	-2.76	-1.07	-1.41	-2.47
vastmanland	9.75	6.54	2.67	5.74	3.64	-7.28	-7.63	-7.70	-7.32	-3.00	0.82	1.19	0.65	1.70	0.33	-3.46	-2.52	-2.67	-2.65	-1.03
dalarna	3.51	2.27	3.99	6.55	1.07	-4.71	-4.03	-0.40	-4.64	-5.41	0.70	0.46	1.03	2.09	1.40	-1.81	-1.24	-0.63	-1.40	-0.84
gavelborg	-3.43	-7.05	0.71	-1.59	-2.34	5.99	3.43	6.56	0.56	-4.72	0.28	-1.38	0.00	-0.74	-1.76	1.79	1.00	1.78	0.88	-0.63
vasternorrland	-7.12	-6.36	-2.30	-7.01	-2.97	2.36	-1.42	-1.82	8.01	13.95	-1.46	-3.01	-1.17	-2.47	-2.80	1.19	-0.55	-1.24	0.88	2.87
jamtland	1.75	0.49	2.88	0.77	-0.63	0.54	0.05	-1.54	-3.45	-1.34	0.09	0.59	0.81	0.36	0.44	0.11	-0.07	-0.43	-0.63	-0.42
vasterbotten	-11.02	-7.39	-6.29	-6.63	-9.70	-4.76	0.85	-0.50	13.93	20.67	-3.25	-3.29	-2.76	-2.25	-4.29	-1.40	-0.03	-1.41	2.12	3.67

Table 3: Balancing test for the partial sick leave model for women with observations pertaining to Stockholm county excluded. Each of the 10 treatment groups are divided into 5 subgroups with respect to propensity score.

	1	2	3	4	5	6	7	8	9	10	1	2	3	4	5	6	7	8	9	10
children 0-3	-3.46	-4.35	-0.66	0.22	-0.04	1.26	2.43	2.67	2.12	-0.61	0.01	-0.94	-0.47	-0.32	-0.85	0.20	0.43	0.39	0.76	0.24
children 4-6	-5.15	-2.41	-1.24	-0.54	1.34	0.46	2.44	2.63	2.68	-0.72	-0.24	-0.57	-0.60	-0.50	-0.51	-0.09	0.52	0.36	0.72	0.37
children 7-10	-6.46	-2.19	-1.84	-1.69	0.65	1.34	2.12	3.60	3.53	0.32	-0.53	-0.61	-0.82	-0.87	-0.88	0.31	0.33	0.66	0.89	0.59
income	-4.88	-3.74	-3.18	-2.53	-4.24	-1.95	-0.06	1.92	5.99	11.20	-1.76	-1.18	-1.15	-0.75	-2.01	0.35	0.05	0.41	1.61	1.98
age	-0.26	-0.14	-1.65	-0.61	-2.28	0.73	-1.64	1.87	0.77	3.28	-0.47	-0.18	-0.49	-0.11	-0.70	0.52	-0.36	0.72	0.21	0.53
edu	-0.05	0.72	0.85	-2.03	-1.76	-4.09	-1.20	-1.48	2.28	6.65	-1.11	-0.31	0.08	-0.20	-0.14	-0.45	-0.02	-0.60	0.20	0.98
upsala	-3.40	-3.04	-2.80	-0.02	-5.97	-7.39	-7.16	-3.08	5.08	20.20	-3.02	-2.27	-1.68	0.05	-1.59	-0.44	-1.81	-1.86	0.08	3.04
sodermanland	7.45	1.58	2.70	1.10	-3.26	-3.35	-10.05	-9.09	-4.16	11.41	-1.08	0.62	1.65	1.37	0.48	-0.15	-2.25	-2.06	-1.17	1.43
ostergotland	-10.29	2.84	-1.51	5.21	5.97	0.01	2.78	-0.29	-0.23	-6.70	-0.77	1.37	-0.07	1.15	1.70	-0.50	0.58	0.58	0.26	0.06
jonkoping	8.08	4.61	0.21	-0.56	4.08	-0.08	-0.71	-2.39	-7.35	-8.75	1.90	0.65	-0.50	-0.26	0.81	-1.16	-0.89	-1.65	-2.67	-2.38
kronoberg	-4.78	7.49	3.90	-3.02	-4.72	0.20	0.90	2.34	-1.15	-3.77	-0.67	1.72	0.83	-0.58	0.15	0.79	0.32	0.53	-0.94	0.02
kalmar	5.04	2.80	1.64	-0.72	-0.96	-3.17	-1.24	-1.73	-0.77	-1.77	0.46	0.31	0.68	0.17	1.05	-0.95	-0.30	-0.38	-0.88	-0.73
gotland	4.07	3.64	-1.64	-2.57	-3.00	0.14	0.49	0.05	0.32	-3.44	0.76	0.27	-0.71	-0.42	-0.26	0.30	0.08	-0.42	-0.56	-1.21
blekinge	-1.29	3.07	1.05	2.92	0.22	-0.69	0.43	2.00	-4.29	-4.60	0.09	0.89	0.16	0.99	0.82	-0.42	-0.08	0.22	-1.45	-0.61
skane	-4.12	-2.58	-2.58	-0.45	0.61	2.64	1.81	1.99	2.75	-0.40	-0.13	-0.38	-0.53	-0.03	-0.34	1.16	1.17	1.09	1.68	0.18
halland	-6.40	2.08	-1.14	2.38	0.37	-1.80	0.60	-0.78	0.99	2.86	-1.25	0.56	-0.20	0.48	-0.10	-0.22	0.30	0.00	0.24	1.24
vastra gotaland	0.32	-11.01	-7.07	-4.22	1.79	9.65	7.53	5.05	1.77	-5.18	1.69	-1.78	-1.34	-1.51	-0.58	2.67	2.94	2.66	2.49	-1.28
varmland	4.46	0.83	3.17	-2.10	1.84	-0.12	-2.37	0.91	-4.45	-3.28	0.75	0.03	1.09	-0.47	1.49	-0.30	-1.05	0.27	-1.58	-0.81
orebro	0.99	1.65	3.02	4.95	0.03	-2.35	0.44	-0.29	-2.95	-6.80	0.88	0.45	0.67	1.43	0.55	-1.30	-0.07	-0.64	-0.88	-1.26
vastmanland	5.94	6.51	6.87	2.30	-3.50	-4.45	-5.39	-4.68	-7.15	0.14	0.24	1.45	1.66	0.81	-0.41	-1.52	-2.07	-1.74	-2.56	-0.16
dalarna	5.02	5.90	4.53	1.11	-2.17	-4.03	-3.04	-1.72	-4.46	-3.00	0.57	1.27	0.83	0.63	0.32	-1.38	-1.36	-0.98	-1.76	-0.94
gavelborg	-2.67	-4.43	-0.43	1.76	4.02	2.69	1.69	0.55	-0.67	-3.39	-0.01	-0.57	-0.06	0.25	0.85	0.51	0.57	0.61	0.48	-0.37
vasternorrland	-5.58	-4.79	-1.94	-3.08	-0.15	-1.15	0.81	4.36	8.25	1.02	-0.49	-1.80	-1.05	-1.57	-1.09	-0.13	-0.31	0.70	1.77	0.32
jamtland	1.07	-2.78	2.69	2.80	0.03	-0.23	0.03	-2.57	-2.08	0.27	-0.05	-0.39	0.98	0.71	0.65	-0.26	0.01	-0.62	-0.17	0.06
vasterbotten	-6.07	-9.20	-4.56	-8.24	-1.92	0.42	2.74	3.50	10.03	8.09	-1.22	-3.03	-2.07	-3.47	-2.73	-0.06	-0.32	0.04	1.79	1.64

Table 4: Balancing test for the partial sick leave model for men. Each of the 10 treatment groups are divided into 5 subgroups with respect to propensity score.

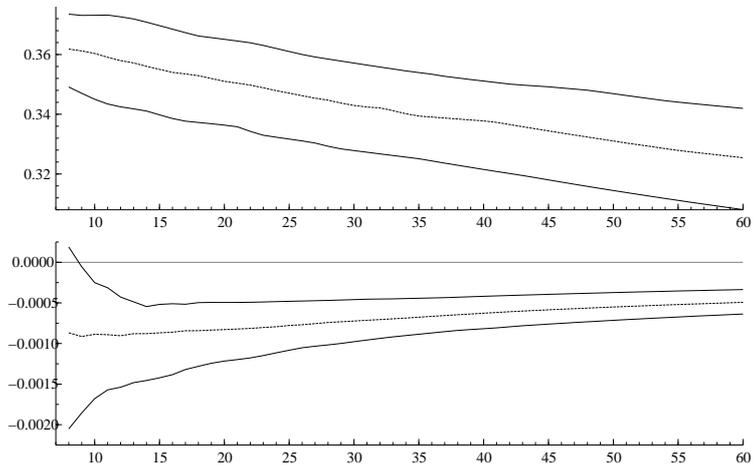
coeff	women		men	
	value	std err	value	std err
constant (part time)	-0.566	0.03	-0.978	0.04661
time	-0.060	0.06	-0.040	0.09202
time^2	-0.002	0.01	-0.013	0.01919
R	0.465	0.38	0.541	0.55784
R^2	-1.958	0.59	-1.358	0.83096
R*time	0.263	0.05	0.141	0.07398
Log of likelihood	-103213.08		-59395.14	
nobs	158679.00		103575.00	

Table 5: Estimation results for the logit model for partial sick leave.

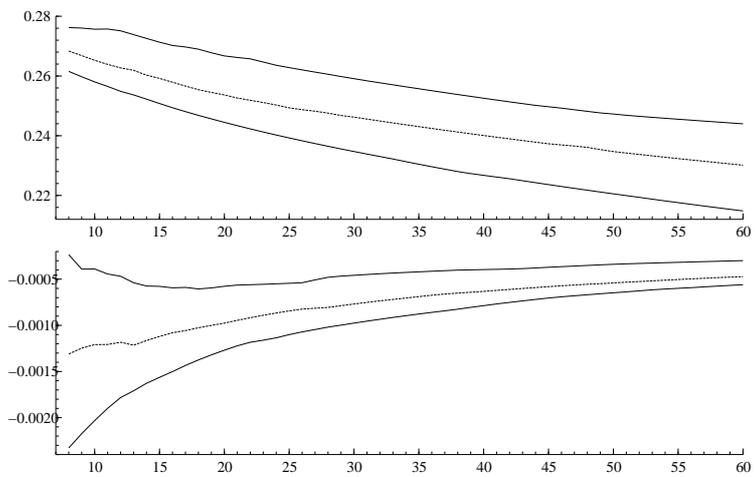
men. It should be noted that the coefficients cannot be directly interpreted. Instead, the main results are reported in Figure 1. In each figure a)-b), the upper panel shows the dose-response-function with commuting distance on the horizontal axis, and the probability of being part-time on the vertical axis. The 90 % confidence band is also indicated. The lower panel shows the derivative of the dose-response-function, i.e. the marginal propensity of increased partial sick leave as commuting distance increases. Here we see that the probability of part-time sickness decreases as commuting distance increases.

The proportion of part-time sickness is significantly different for women and men (see Eklund et al., 2004). Women has more part-time sickness than men, but they also have shorter commuting distances. One hypothesis is that the difference in part-time sickness is due to differences in commuting distances. This is, however, rejected by the model. There are 9 percentage points more women than men who are on part-time sickness, even after controlling for commuting distance. Interestingly, however, the part-time sickness as a response to commuting distances are rather similar for men and women. In other words, the level of part-time sickness differs between men and women, but the response to increased (decreased) commuting time is similar.

Hence, we have shown that part-time sickness decreases as commuting distance to work place increases. More specifically, if commuting time increases by an hour the probability of being on full-time sick leave increases by some 3 percentage points. From the perspective of transport infrastructure planning, the



(a) Women



(b) Men

Figure 1: Dose-response functions for partial sick leave.

effect thus appears rather weak when compared to the value of time used in cost-benefit analyses regarding investments in the transport infrastructure, which is currently some 40 SEK (around 4 euros) per hour for work trips in Sweden. To see this, assume that the hourly wage compensation equals the social value that an individual works an hour. This may be reasonable if wages reflect marginal products. Assume also, for the sake of this example, that an individual works 4 hours per working day if being on part-time sick leave and zero hours if being on full-time sick leave and that the employer does not hire an extra employee to do the work of the sick absent employee. As noted in the introduction, in 2002 some 7 percent of the employed individuals were on sick leave in Sweden and out of these some 70 percent were on full time sick leave. Hence, we should add some 0.6 percent of the average gross hourly wage rate per day of commuting to the current value of time (this is obtained from the following simple calculation: $0.03*0.07*0.70*4 = 0.006$).

4.2 Sick leave

We now turn to utilization of sickness insurance more generally. The outcome variable now is whether sickness insurance has been used at all. That is, we make no distinction between part time sick absence and full time sick absence, but we now include the outcome of not being on sick leave at all. The outcome variable is still binary, with the two outcomes being on sick leave, or not being on sick leave, respectively, during the year under study. Remember that an individual is defined to be on sick leave if he/she has been on sick leave for at least 15 days for at least one sickness episode (spell).

The sample is now much larger. The full sample includes about 1.7 million observations. Since we use a bootstrap procedure to calculate our dose-response-functions, their derivatives and the corresponding confidence intervals, we can draw from the full sample and do each estimation on a much smaller data set.

First we check whether the balancing property is fulfilled. The results for testing the balancing property are reported in Table 6, where we have 15 treatment groups, and also 15 propensity score subgroups. Although we are able to use the

	Unadjusted															Women															Adjusted																																																											
	Commuting travel time group															Commuting travel time group															Commuting travel time group																																																											
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15																																													
children 0-3	-6.09	-6.20	-4.36	-1.94	-0.45	-0.75	0.50	1.29	2.03	0.95	2.99	3.81	4.15	5.38	-2.69	-0.12	-0.47	-0.42	-0.25	-0.15	-0.21	-0.21	-0.07	0.08	-0.04	0.16	0.29	0.36	0.59	-0.03	-5.84	-3.68	-3.32	-1.48	-0.96	0.88	0.89	2.20	2.35	3.18	2.94	3.65	4.42	-0.50	-6.00	0.04	-0.08	-0.28	-0.19	-0.23	-0.10	-0.18	0.00	0.02	0.12	0.14	0.30	0.46	0.15	-0.15	-6.54	-3.70	-3.24	-1.78	-0.77	-0.43	2.31	2.65	1.85	2.64	2.94	3.42	5.23	0.60	-6.31	0.07	-0.13	-0.28	-0.21	-0.19	-0.21	-0.04	0.01	-0.01	0.09	0.15	0.27	0.50	0.21	-0.17
children 4-6	-5.84	-3.68	-3.32	-1.48	-0.96	0.88	0.89	2.20	2.35	3.18	2.94	3.65	4.42	-0.50	-6.00	0.04	-0.08	-0.28	-0.19	-0.23	-0.10	-0.18	0.00	0.02	0.12	0.14	0.30	0.46	0.15	-0.15	-6.54	-3.70	-3.24	-1.78	-0.77	-0.43	2.31	2.65	1.85	2.64	2.94	3.42	5.23	0.60	-6.31	0.07	-0.13	-0.28	-0.21	-0.19	-0.21	-0.04	0.01	-0.01	0.09	0.15	0.27	0.50	0.21	-0.17																														
children 7-10	-6.54	-3.70	-3.24	-1.78	-0.77	-0.43	2.31	2.65	1.85	2.64	2.94	3.42	5.23	0.60	-6.31	0.07	-0.13	-0.28	-0.21	-0.19	-0.21	-0.04	0.01	-0.01	0.09	0.15	0.27	0.50	0.21	-0.17	-3.10	-2.80	-2.61	-0.92	0.55	0.33	-2.54	0.42	-1.25	1.85	0.99	1.19	3.78	7.85	-3.86	0.18	-0.47	-0.42	-0.16	-0.01	-0.01	-0.23	0.18	-0.05	0.17	0.08	0.08	0.27	0.64	-0.14																														
income	-3.10	-2.80	-2.61	-0.92	0.55	0.33	-2.54	0.42	-1.25	1.85	0.99	1.19	3.78	7.85	-3.86	0.18	-0.47	-0.42	-0.16	-0.01	-0.01	-0.23	0.18	-0.05	0.17	0.08	0.08	0.27	0.64	-0.14	3.40	3.98	4.36	1.45	-0.30	-1.14	-2.00	-0.35	0.32	2.50	1.74	1.35	0.25	-1.22	-13.95	0.92	0.15	0.17	-0.04	-0.15	-0.17	-0.03	-0.10	-0.02	0.16	0.10	-0.04	-0.20	-0.24	-0.83																														
age	3.40	3.98	4.36	1.45	-0.30	-1.14	-2.00	-0.35	0.32	2.50	1.74	1.35	0.25	-1.22	-13.95	0.92	0.15	0.17	-0.04	-0.15	-0.17	-0.03	-0.10	-0.02	0.16	0.10	-0.04	-0.20	-0.24	-0.83	4.80	-4.55	-6.04	-0.57	-0.11	2.58	-1.32	-1.33	-1.60	-1.01	-0.40	-0.40	3.96	6.07	9.43	-0.76	-0.38	-0.55	0.00	0.00	0.27	-0.20	0.06	-0.01	-0.08	-0.02	0.01	0.41	0.59	0.51																														
edu	4.80	-4.55	-6.04	-0.57	-0.11	2.58	-1.32	-1.33	-1.60	-1.01	-0.40	-0.40	3.96	6.07	9.43	-0.76	-0.38	-0.55	0.00	0.00	0.27	-0.20	0.06	-0.01	-0.08	-0.02	0.01	0.41	0.59	0.51	upsala	-0.51	-0.12	-4.08	1.84	-1.91	3.99	1.15	-0.12	-6.32	-6.38	-9.30	-7.32	-5.77	4.35	21.90	-1.37	-0.37	-0.39	0.42	0.06	0.60	0.23	0.37	-0.35	-0.38	-0.69	-0.48	-0.49	0.19	1.07																													
upsala	-0.51	-0.12	-4.08	1.84	-1.91	3.99	1.15	-0.12	-6.32	-6.38	-9.30	-7.32	-5.77	4.35	21.90	-1.37	-0.37	-0.39	0.42	0.06	0.60	0.23	0.37	-0.35	-0.38	-0.69	-0.48	-0.49	0.19	1.07	sodermanland	4.66	9.23	-0.65	3.47	0.98	-0.57	-2.16	-2.49	-1.57	-2.67	-12.38	-6.57	-9.73	-2.94	14.82	-0.60	0.82	0.24	0.66	0.44	0.20	0.08	0.13	0.08	-0.01	-1.02	-0.35	-0.73	-0.41	0.68																													
sodermanland	4.66	9.23	-0.65	3.47	0.98	-0.57	-2.16	-2.49	-1.57	-2.67	-12.38	-6.57	-9.73	-2.94	14.82	-0.60	0.82	0.24	0.66	0.44	0.20	0.08	0.13	0.08	-0.01	-1.02	-0.35	-0.73	-0.41	0.68	ostergotland	-16.35	-15.97	-0.36	2.62	-1.56	-5.91	5.66	11.15	2.67	1.50	5.14	4.65	4.35	0.32	-4.91	-0.44	-1.31	-0.11	0.21	-0.25	-0.93	-0.23	0.47	-0.20	-0.15	0.37	0.40	0.34	0.30	0.55																													
ostergotland	-16.35	-15.97	-0.36	2.62	-1.56	-5.91	5.66	11.15	2.67	1.50	5.14	4.65	4.35	0.32	-4.91	-0.44	-1.31	-0.11	0.21	-0.25	-0.93	-0.23	0.47	-0.20	-0.15	0.37	0.40	0.34	0.30	0.55	jonkopning	8.02	6.77	-0.01	1.85	-0.14	-3.41	-3.51	3.66	3.83	0.58	0.55	-2.55	-3.21	-7.30	-8.66	0.87	0.28	-0.11	0.05	-0.15	-0.47	-0.12	0.27	0.27	-0.13	-0.14	-0.44	-0.41	-1.04	-0.49																													
jonkopning	8.02	6.77	-0.01	1.85	-0.14	-3.41	-3.51	3.66	3.83	0.58	0.55	-2.55	-3.21	-7.30	-8.66	0.87	0.28	-0.11	0.05	-0.15	-0.47	-0.12	0.27	0.27	-0.13	-0.14	-0.44	-0.41	-1.04	-0.49	kronoberg	-2.51	-2.08	6.93	0.40	5.55	2.96	-2.71	-6.09	-4.48	-1.84	4.03	1.22	-1.79	-2.56	-0.36	-0.13	-0.07	0.57	-0.13	0.44	0.37	0.12	-0.10	-0.17	-0.15	0.29	-0.03	-0.34	-0.13	0.23																													
kronoberg	-2.51	-2.08	6.93	0.40	5.55	2.96	-2.71	-6.09	-4.48	-1.84	4.03	1.22	-1.79	-2.56	-0.36	-0.13	-0.07	0.57	-0.13	0.44	0.37	0.12	-0.10	-0.17	-0.15	0.29	-0.03	-0.34	-0.13	0.23	kalmar	6.49	0.78	3.20	-5.24	2.56	-2.95	2.12	-2.36	1.98	-1.82	0.09	-0.30	-1.45	-1.25	-3.81	0.54	-0.08	0.32	-0.48	0.34	-0.26	0.43	-0.23	0.22	-0.18	0.07	0.03	-0.20	-0.21	-0.45																													
kalmar	6.49	0.78	3.20	-5.24	2.56	-2.95	2.12	-2.36	1.98	-1.82	0.09	-0.30	-1.45	-1.25	-3.81	0.54	-0.08	0.32	-0.48	0.34	-0.26	0.43	-0.23	0.22	-0.18	0.07	0.03	-0.20	-0.21	-0.45	gotland	4.08	-0.25	6.96	1.62	1.89	-5.63	-3.28	-1.38	-2.18	0.19	-2.26	1.22	-1.38	-0.62	-3.02	0.23	-0.11	0.43	-0.10	0.03	-0.51	0.01	0.05	-0.07	0.02	-0.40	-0.18	-0.30	-0.12	-0.42																													
gotland	4.08	-0.25	6.96	1.62	1.89	-5.63	-3.28	-1.38	-2.18	0.19	-2.26	1.22	-1.38	-0.62	-3.02	0.23	-0.11	0.43	-0.10	0.03	-0.51	0.01	0.05	-0.07	0.02	-0.40	-0.18	-0.30	-0.12	-0.42	blekinge	0.31	-1.44	3.97	1.06	1.67	-0.23	0.93	0.67	1.37	-3.83	-1.54	0.98	2.68	-2.26	-5.88	0.33	-0.05	0.25	0.01	0.25	0.02	0.14	0.00	0.10	-0.32	-0.08	-0.01	0.12	-0.11	-0.45																													
blekinge	0.31	-1.44	3.97	1.06	1.67	-0.23	0.93	0.67	1.37	-3.83	-1.54	0.98	2.68	-2.26	-5.88	0.33	-0.05	0.25	0.01	0.25	0.02	0.14	0.00	0.10	-0.32	-0.08	-0.01	0.12	-0.11	-0.45	skane	-7.40	0.96	-0.80	-4.19	-1.69	2.54	-1.92	-0.22	0.40	-1.59	2.62	0.18	6.65	1.82	1.82	-0.58	0.17	0.04	-0.25	-0.03	0.44	-0.15	0.55	0.27	0.01	0.44	0.22	0.81	0.24	0.30																													
skane	-7.40	0.96	-0.80	-4.19	-1.69	2.54	-1.92	-0.22	0.40	-1.59	2.62	0.18	6.65	1.82	1.82	-0.58	0.17	0.04	-0.25	-0.03	0.44	-0.15	0.55	0.27	0.01	0.44	0.22	0.81	0.24	0.30	halland	-6.91	-9.71	-0.36	1.87	0.26	2.79	2.15	2.61	-0.26	1.30	0.00	1.08	2.02	3.36	-2.40	-0.11	-0.77	-0.07	0.23	0.04	0.24	-0.01	0.26	-0.15	0.07	0.00	0.16	0.20	0.47	0.10																													
halland	-6.91	-9.71	-0.36	1.87	0.26	2.79	2.15	2.61	-0.26	1.30	0.00	1.08	2.02	3.36	-2.40	-0.11	-0.77	-0.07	0.23	0.04	0.24	-0.01	0.26	-0.15	0.07	0.00	0.16	0.20	0.47	0.10	vastra gotaland	4.60	-1.58	-5.91	-6.76	-6.18	-1.41	-0.79	0.82	5.46	10.93	9.79	3.43	1.23	-5.42	-9.92	0.93	0.42	-0.06	-0.41	-0.61	-0.13	0.02	0.82	0.65	1.25	1.19	0.71	0.71	0.01	-0.95																													
vastra gotaland	4.60	-1.58	-5.91	-6.76	-6.18	-1.41	-0.79	0.82	5.46	10.93	9.79	3.43	1.23	-5.42	-9.92	0.93	0.42	-0.06	-0.41	-0.61	-0.13	0.02	0.82	0.65	1.25	1.19	0.71	0.71	0.01	-0.95	orebro	1.55	4.21	1.26	-2.29	-0.47	5.28	1.04	-2.70	0.10	5.21	-1.01	-0.43	-3.62	-6.44	-4.04	0.27	0.52	0.09	-0.21	-0.09	0.37	0.19	-0.26	-0.11	0.34	-0.16	-0.04	-0.40	-0.50	-0.16																													
orebro	1.55	4.21	1.26	-2.29	-0.47	5.28	1.04	-2.70	0.10	5.21	-1.01	-0.43	-3.62	-6.44	-4.04	0.27	0.52	0.09	-0.21	-0.09	0.37	0.19	-0.26	-0.11	0.34	-0.16	-0.04	-0.40	-0.50	-0.16	vastmanland	5.35	4.97	0.11	7.31	4.28	4.03	4.40	-1.67	-3.03	-5.15	-2.16	-2.81	-4.73	-5.26	-10.15	0.59	0.31	-0.09	0.55	0.24	0.15	0.46	-0.77	-0.62	-0.83	-0.51	-0.43	-0.62	-0.60	-0.85																													
vastmanland	5.35	4.97	0.11	7.31	4.28	4.03	4.40	-1.67	-3.03	-5.15	-2.16	-2.81	-4.73	-5.26	-10.15	0.59	0.31	-0.09	0.55	0.24	0.15	0.46	-0.77	-0.62	-0.83	-0.51	-0.43	-0.62	-0.60	-0.85	dalarna	8.89	10.08	3.51	1.24	5.56	3.19	3.89	-3.61	-7.21	-6.37	-6.08	-7.46	-6.99	-6.66	0.94	0.35	0.64	0.16	0.10	0.55	0.27	0.36	-0.95	-1.07	-0.67	-0.61	-0.83	-0.88	-0.21																														
dalarna	8.89	10.08	3.51	1.24	5.56	3.19	3.89	-3.61	-7.21	-6.37	-6.08	-7.46	-6.99	-6.66	0.94	0.35	0.64	0.16	0.10	0.55	0.27	0.36	-0.95	-1.07	-0.67	-0.61	-0.83	-0.88	-0.21	gavleborg	0.53	3.26	5.14	4.99	4.13	3.07	1.97	-5.05	-3.57	-3.45	-3.96	2.97	-5.05	-4.92	-3.07	0.11	0.31	0.37	0.23	0.38	0.32	0.36	-0.61	-0.38	-0.34	-0.42	0.01	-0.64	-0.45	0.23																														
gavleborg	0.53	3.26	5.14	4.99	4.13	3.07	1.97	-5.05	-3.57	-3.45	-3.96	2.97	-5.05	-4.92	-3.07	0.11	0.31	0.37	0.23	0.38	0.32	0.36	-0.61	-0.38	-0.34	-0.42	0.01	-0.64	-0.45	0.23	vasternorrland	-1.84	-5.10	-2.50	0.11	-4.82	-0.48	-1.44	2.78	4.29	2.87	2.03	5.37	2.22	-2																																													

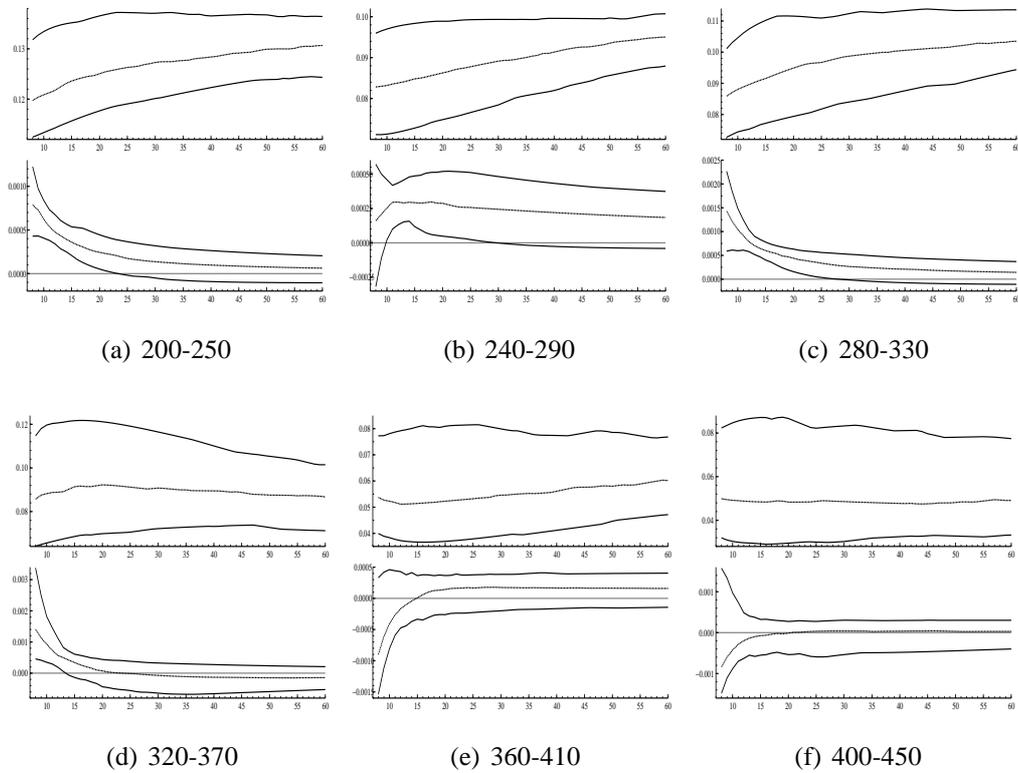


Figure 2: Dose-response functions for women, decomposed into segments by income (as indicated in thousand SEK).

full sample size for the dose-response-functions, it turned out to be difficult to have the full sample when testing the balancing property, and the reported values are from 200 000 randomly drawn observations. Thus, the subgroups are of similar size to what we had in the case of partial sick leave, in Section 4.1.1. The pattern of balance is also quite similar to the data on partial sick leave; observations for Stockholm county are not balanced (not reported here) and the pattern for the rest of the counties is also similar.

Since income is highly correlated both with commuting travel time and sick leave variables, it makes sense to use the large sample to control for income. Therefore we decompose the data set into income segments and estimate separate

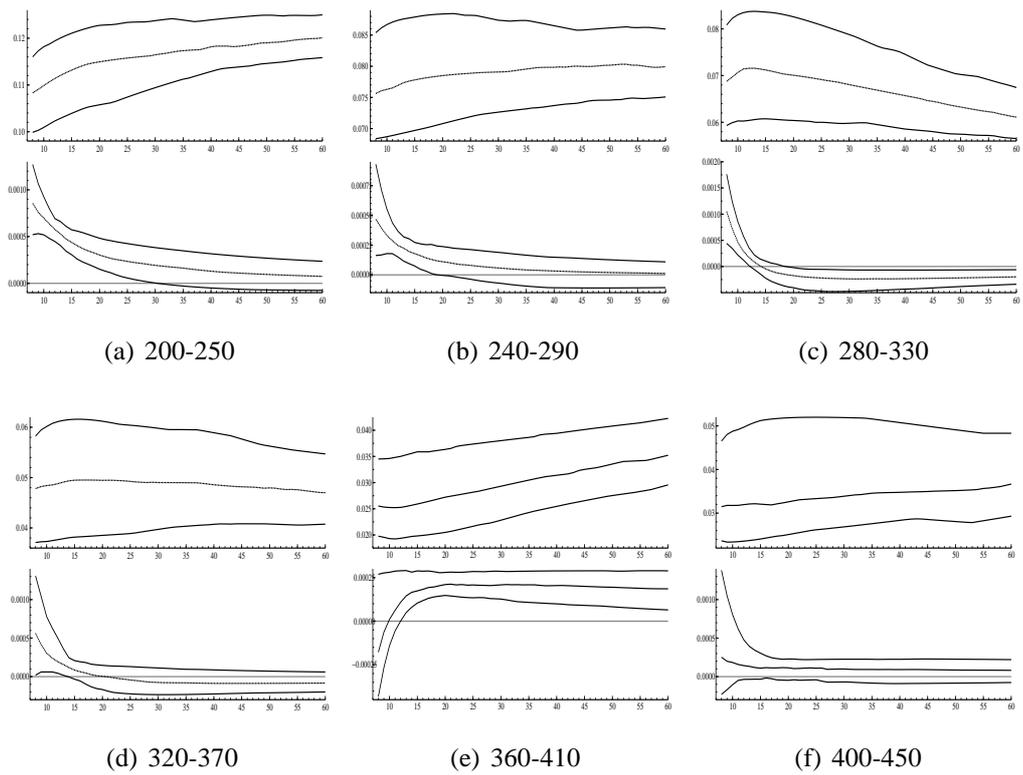


Figure 3: Dose-response functions for men, decomposed into segments by income (as indicated in thousand SEK).

dose-response functions for each segment. The results for women are reported in Figure 2. First note that for the lower income segments there is, for the most part, a positive relationship between commuting travel time and sickness insurance utilization. On the other hand, in the higher income segments we find no significant relationship. Now, consider the results for men reported in Figure 3. Again, there seems to be a fairly stable significant relationship for the lower income segments, while there is no or ambiguous relationships in the higher income segments. Also, note that although the level of absenteeism is different between men and women, there is no clear pattern as to how sick leave is changing as travel time increase.

To summarize, among lower income people there seems to be a positive relationship between the probability of being on sick leave and commuting travel time, and this applies both to men and women. For higher incomes, we find no or only weak support for the hypothesis that sick leave increases as commuting travel time increases.

5 Concluding Remarks

The purpose of this paper is to investigate the relationship between sick leave absence and commuting travel time. Many previous studies suggest both that travel time increase stress levels of commuters and that there may be a positive and significant relationship between sick absence and commuting travel time. Many (most or all) of these studies rely, however, on fairly small data sets, often based on a single workplace or employer. In this paper we have investigated the hypothesis that the risk of longer term (longer than 14 days) sick leave increases as commuting time increases using a large data set with 1.7 million observations. However, we do acknowledge that there are missing data, primarily for individuals for which the work place could not be geographically associated.

Our first result shows that part-time sick leave decreases as commuting travel time increases. Part time sick leave is 3 percentage points higher for those with very short commuting travel time, as compared with those having an hour of one-way commuting. From the perspective of cost-benefit analyses regarding invest-

ments in the transport infrastructure we conclude that this effect is rather small in comparison to the value of travel time savings pertaining to work trips. A simple calculation of the value of reducing travel time by one hour to move sick absent employees from full-time to part-time sickness absence suggests that we should add some 0.6 percent of the average gross hourly wage to the current value of time used in cost benefit analyses of investments in the transport infrastructure. This would, hence, be nothing but a minor change of the current value of travel time savings used by the Swedish National Rail and Road administrations.

Nevertheless, from a policy perspective, part-time sick leave is an instrument that was suggested by the Swedish government in 2002 as a measure to decrease sickness insurance utilization. Our results clearly suggest that part-time sick leave is more difficult to implement for people with longer commuting distances. Obviously, a part-time sick leave implemented as working during part of the day, and part of the week is very different from a commuting perspective.

One hypothesis is that health and well-being suffers when commuting travel time is long. This is supported by other studies, showing that stress is related to commuting distance, congestion etc. Studies have also shown commuting to be related to absenteeism. However, we are not able to find any general support for the hypothesis that (longer term) sick leave as such is related to commuting travel time. To the extent that we did find a significant relationship it appeared to be restricted to lower income groups, in particular among women. In Isacson et al (2008) we were also not able to find any statistically significant effects of commuting on objective measures of health, such as high blood pressure and other symptoms, although we did find a negative effect of commuting times on life satisfaction and job satisfaction. Given this evidence, we believe that the lower utilization of part-time sick leave for individuals with a longer commute is not directly related to health. In addition, the results pertaining to lower income groups might be related to results suggesting relatively high labour force participation elasticities among low income groups (see for example Meyer and Rosenbaum, 2001). This may, in turn, be relevant for assessing the marginal cost of public funds for investments that affect travel times among lower income groups (cf.

Kleven and Kreiner, 2006, who presents estimates of the marginal costs of public funds across various deciles of the earnings distributions in a set of European countries).

Finally, we also found that although there are clear gender differences in terms of the level sickness insurance utilization and commuting times, the effect of commuting distance on part time sickness absence seemed similar for men and women. This may be in line with the results reported by Evans and Wener (2006) who report that gender does not moderate the effect of rail commuting duration on stress.

References

- Algers, S. and Beser, M., 2000, SAMPERS - The New Swedish National Travel Demand Forecasting Tool, Proceedings of the IATBR Conference.
- Blundell, R., and MaCurdy, T., 1999, Labor Supply: A Review of Alternative Approaches, in Ashenfelter, O. and Card, D. (eds.), *Handbook of Labor Economics*, vol 3A, North-Holland, Amsterdam.
- Cogan, J.F., 1981, Fixed costs and labor supply, *Econometrica*, 49, pp. 945-964.
- Costa, Giovanni, Pickup, Laurie, and di Martino, Vittorio, 1988, Commuting - a further stress factor for working people: evidence from the European Community, *International Archives of Occupational and Environmental Health*, 60, 5, pp. 371-376. 20.
- Eklund, M., von Granitz, H., and Marklund, S., 2004, Deltidssjukskrivning – individ, arbetsplats och hälsa, in *Den höga sjukfrånvaron - sanning och konsekvens*, C. Hogstedt, M. Bjurvald, S. Marklund, E. Palmer och T. Theorell (eds.) Statens folkhälsoinstitut. In Swedish.
- Evans, G.W., 1994, Working on the hot seat: urban bus drivers, *Accident Analysis and Prevention*, 26, pp. 181-193
- Evans, G.W. and Wener, 2006, Rail Commuting Duration and Passenger Stress, *Health Psychology*, 25(3) pp. 408
- Heckman, J., Ichimura, H., and Todd, P., 1998, Matching as an econometric evaluations estimator, *Review of Economic Studies*, 65, pp. 261–294.

- Hennessy, D.A., and Wiesenthal, D.L., 2004, Traffic Congestion, Driver Stress, and Driver Aggression, *Aggressive Behavior*, 25, pp. 409–423.
- Hirano, K., and Imbens, G.W., 2004, The Propensity Score with Continuous Treatments, in *Applied Bayesian Modeling and Causal Inference from Incomplete Data Perspectives*, Gelman A., and Meng, X.-L. (eds) John Wiley & Sons.
- Imai, K. and van Dyk, D.A., 2004, Causal Inference With General Treatment Regimes: Generalizing the Propensity Score, *Journal of the American Statistical Association*, 99(467), pp. 854–866.
- Imbens, G.W., 2000, The role of the propensity score in estimating dose-response functions, *Biometrika*, 83, pp. 706–710.
- Isacsson, G. and Swärdh, J.-E., 2007, An Empirical on-the-job Search Model with Preferences for Relative Earnings: How High is the Value of Commuting Time?, Swopec working paper, VTI series, 2007:12.
- Isacsson, G., Karlström, A., and Swärdh, J.-E., 2008, The value of time from subjective data on life satisfaction and job satisfaction: An empirical assessment, Swopec working paper, VTI series, 2008:2.
- Kleven H.J., and Kreiner, C.T., 2006, The marginal cost of public funds: Hours of work versus labor force participation, *Journal of Public Economics*, 90, pp. 1955–1973.
- Kosolowsky, M., Kluger, A., and Reich, M., 1995, *Commuting Stress: Causes, Effects, and Methods of Coping.*, Plenum Press, New York.
- Lucas, J., and Heady, R. B., 2002, Flextime Commuters and Their Driver Stress, Feelings of Time Urgency, and Commute Satisfaction, *Journal of Business and Psychology*, 16(4), pp. 565–571.
- Meyer, B.D., and Rosenbaum, D. T., 2001, Welfare, the Earned Income Tax Credit, and the Labor Supply of Single Mothers, *Quarterly Journal of Economics*, 66, pp. 1063–1114.
- Moczulski, V., McMahan, S., Weiss, J., Beam, W., and Chandler, L., 2007, Commuting Behaviors, Obesity Risk and the Built Environment, *American Journal of Health Studies*, 22(1), pp. 26-32.

- Novaco, Raymond W., Collier, Cheryl, 1994, Commuting Stress, ridesharing, and Gender: Analyses from the 1993 State of the Commute Study in Southern California.
- Novaco, R., Stokols, D., and Milanese, L., 1990, Objective and subjective dimensions of travel impedance as determinants of commuting stress, *American Journal of Community Psychology*, 18, 1990, pp. 231-257.
- RFV (2003c), Regionala skillnader i sjukskrivningar . kommun och bransch, RFV Analyserar 2003:4. In Swedish.
- Rosenbaum, P.R., 2002, *Observational Studies*, second edition, Springer New York.
- Rosenbaum, P.R., and Rubin, D.B., 1983, The central role of the propensity score in observational studies for causal effects, *Biometrika*, 70, pp. 41–55.
- Rouwendal, J., 2004, Search theory and commuting behavior, *Growth and Change*, 35(3), pp. 391–418.
- Stutzer, A., and Frey, B., 2004, Stress that doesn't Pay: The commuting paradox. IZA working paper DP No 1278.
- Taylor och Pocock, 1972, Commuter travel and sickness: absence of London office workers, *British Journal of Preventive and Social Medicine* 26, pp 165-172.
- van Ommeren, J., 1998, On-the-job Search behavior: The importance of commuting time, *Land Economics*, 74(4), pp. 526-540
- van Ommeren, J., van den Berg, G. J., and Gorter, C., 2000, Estimating the Marginal Willingness to Pay for Commuting *Journal of Regional Science* 40(3), pp. 541-563.
- Wener, R.E., Evans, G.W., Phillips, D., and Nadler, N., 2003, Running for the 7:45: The effects of public transit improvements on commuter stress *Transportation*, 30(2), 203–220

Appendix

	Unadjusted															Adjusted														
	Commuting travel time group															Commuting travel time group														
	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15
children 0-3	-8.57	-5.73	-4.13	-3.57	-1.68	-0.92	-0.96	-0.42	1.14	1.35	3.60	3.32	3.16	6.37	5.02	-1.63	-1.44	-1.19	-1.15	-0.76	-0.89	-1.19	-0.30	0.12	-0.01	0.75	0.83	0.80	1.86	1.57
children 4-6	-4.99	-2.51	-2.99	-0.51	-0.97	0.31	0.38	1.10	1.81	2.35	2.08	1.58	2.65	1.20	-2.21	-0.15	-0.22	-0.78	-0.18	-0.46	-0.21	-0.43	0.18	0.32	0.39	0.41	0.50	0.81	0.66	0.03
children 7-10	-5.19	-2.20	-3.16	-1.14	-2.48	-0.36	-0.12	2.81	1.86	2.79	2.99	3.43	2.76	-0.13	-2.63	-0.05	-0.15	-0.65	-0.34	-0.92	-0.50	-0.70	0.56	0.29	0.49	0.66	1.04	0.99	0.35	-0.11
income	-3.41	-3.08	-2.40	-2.12	0.02	-1.04	-2.33	-1.31	-1.66	-0.63	-0.99	-0.99	1.95	6.04	10.28	-1.52	-1.30	-0.80	-0.44	0.18	-0.19	-0.78	0.24	-0.04	0.06	-0.04	-0.08	0.57	1.42	1.92
age	6.91	5.26	4.64	4.26	3.03	1.55	-0.54	0.09	-1.01	-0.97	-1.54	-3.72	-3.53	-5.02	-9.60	2.23	1.07	1.18	1.02	0.83	0.81	0.65	-0.46	-0.42	-0.30	-0.58	-1.48	-1.17	-1.69	-2.11
edu	-7.47	-5.03	-4.53	-2.93	-0.41	0.73	-1.72	-1.38	-1.05	-0.02	1.72	1.27	2.68	8.60	9.74	-2.27	-1.57	-1.33	-0.79	-0.15	0.05	-1.07	0.05	-0.02	0.07	0.55	0.47	0.85	2.29	2.07
upsala	-1.72	0.67	-4.04	-1.09	-3.22	2.09	1.07	-0.77	-3.70	-4.12	-7.50	-6.03	-2.12	2.92	20.22	-3.41	-1.26	-1.42	-0.16	-0.57	0.71	0.05	0.39	-0.52	-0.85	-1.73	-1.50	-0.61	-0.09	3.38
sodermanland	4.75	8.29	-0.86	1.52	0.56	0.29	-1.97	-1.51	-0.78	0.09	-9.46	-6.20	-7.61	-3.64	10.49	-1.58	2.02	0.26	1.04	0.56	0.55	0.19	0.14	0.18	0.36	-2.74	-1.31	-1.95	-1.50	1.70
ostergotland	-15.06	-14.22	-0.29	1.29	-0.91	-5.07	5.49	8.96	3.06	1.15	6.22	3.71	0.72	2.65	-4.21	-1.57	-3.52	-0.14	0.22	-0.68	-2.49	-0.73	1.53	-0.03	-0.19	1.50	0.88	0.15	1.55	1.00
jonkoping	5.92	5.06	1.68	2.75	0.72	-4.31	-4.72	4.02	2.85	-0.44	-0.66	-1.19	-0.59	-4.64	-9.90	1.98	0.83	0.26	0.48	0.04	-1.16	-0.41	1.34	0.77	-0.47	-0.56	-0.73	-0.44	-1.95	-2.41
kronoberg	-2.65	-2.20	5.94	-0.87	5.29	2.82	-2.65	-4.15	-4.15	0.95	2.00	1.57	1.29	-2.59	-3.62	-0.07	-0.28	1.27	-0.61	1.37	1.11	0.21	-0.29	-0.72	0.28	0.36	0.17	-0.01	-0.36	-0.31
kalmar	4.54	1.54	4.74	-4.46	0.67	-1.00	2.13	-3.84	0.89	-1.66	-0.58	-0.17	-0.91	0.45	-4.20	1.00	0.03	1.13	-1.28	0.58	-0.06	1.35	-1.04	0.39	-0.35	0.11	-0.10	-0.58	-0.04	-1.33
gotland	2.49	-0.22	4.94	3.11	-0.14	-2.34	-3.32	0.26	-2.34	0.34	-2.73	1.34	-1.42	0.18	-2.82	0.56	-0.31	0.97	0.47	-0.12	-0.39	-0.22	0.42	-0.41	0.11	-1.08	-0.14	-0.69	-0.12	-1.17
blekinge	0.23	-1.24	0.98	2.42	0.88	0.48	0.58	1.86	-0.39	-1.62	-1.79	-0.34	3.57	-1.51	-5.36	0.76	-0.14	0.20	0.70	0.44	0.22	0.33	0.52	-0.20	-0.37	-0.40	-0.12	0.95	-0.35	-1.12
skane	-5.49	2.00	1.32	-2.49	-1.28	1.70	-2.51	-0.07	0.56	0.28	1.55	0.10	1.81	0.25	1.87	-1.08	0.78	0.70	-0.38	-0.04	0.76	-0.55	1.28	0.64	0.48	0.92	0.54	0.86	0.27	0.97
halland	-7.14	-9.20	1.82	1.85	-1.83	1.24	2.80	3.22	0.54	1.46	-0.89	0.32	1.10	3.94	-1.83	-0.50	-2.47	0.55	0.56	-0.55	0.01	-0.03	1.01	-0.06	0.22	-0.14	0.12	0.39	1.34	0.62
vastra gotaland	6.30	1.28	-4.75	-6.86	-6.68	-3.23	-0.58	-0.81	2.68	8.57	9.40	4.09	1.82	-3.18	-9.72	3.09	1.24	-0.48	-1.62	-1.78	-0.63	0.69	1.16	1.30	2.96	3.18	1.96	1.56	-0.03	-3.04
varmland	1.83	3.08	1.26	-0.42	-0.38	3.62	0.76	-2.71	1.90	3.20	-2.11	-1.21	-0.90	-4.63	-4.93	0.68	1.01	0.29	0.06	-0.08	0.99	0.76	-0.81	0.34	0.68	-0.75	-0.29	0.39	-1.35	-1.08
orebro	4.55	2.69	-0.88	6.04	2.48	5.50	3.55	1.42	-1.26	-4.21	-2.85	-3.29	-4.98	-3.92	-8.52	1.45	0.86	-0.18	1.59	0.35	1.26	1.06	-0.99	-1.18	-1.94	-1.43	-1.12	-1.42	-1.04	-2.32
vastmanland	7.37	8.64	2.99	3.45	4.42	2.06	4.45	-3.44	-5.33	-6.24	-5.83	-6.11	-4.92	-6.62	-0.82	0.22	1.77	0.40	0.98	1.16	0.60	1.19	-2.37	-2.31	-1.95	-1.90	-2.05	-1.85	-2.47	-0.79
dalarna	1.59	1.44	3.74	4.91	5.31	2.14	1.59	-2.92	-2.96	-4.93	-0.99	0.53	-3.39	-4.88	-3.65	0.34	0.47	0.89	1.22	1.50	0.71	1.05	-1.15	-1.04	-1.55	-0.37	-0.31	-1.24	-1.31	-0.17
gavleborg	-1.79	-6.15	-4.52	-0.72	-1.83	1.47	-2.18	1.82	4.75	2.58	1.18	7.76	2.03	-3.82	-3.25	0.31	-0.70	-1.00	-0.46	-0.76	0.08	-1.45	0.44	1.14	0.65	0.24	2.03	0.97	0.08	-0.40
vasternorrland	-7.51	-6.41	-2.30	-4.58	-2.51	-3.83	-2.21	-0.09	1.66	-1.80	-2.55	0.45	6.86	11.24	7.78	-1.86	-2.86	-1.57	-1.76	-0.93	-1.42	-1.69	-0.86	0.60	-0.53	-0.94	-0.39	1.06	2.13	1.52
jamtland	1.25	2.47	-1.22	-1.04	4.78	0.20	0.59	0.98	-1.77	-1.59	1.79	-2.15	-3.80	-1.71	-0.27	-0.04	0.80	-0.03	-0.22	1.33	0.15	0.48	0.15	-0.54	-0.46	0.40	-0.61	-0.87	-0.47	-0.05
vasterbotten	-7.28	-6.86	-7.62	-7.09	-3.34	-4.99	-6.48	-8.54	-2.27	-0.90	1.81	-0.55	7.81	16.09	16.38	-2.24	-2.88	-3.24	-2.77	-1.27	-1.61	-2.87	-3.55	-0.32	-0.14	0.02	-0.99	1.15	3.36	2.93

Table 7: Balancing test for the model on partial sick leave for women, with 15 treatment groups and 5 GPS subgroups.