Road Injuries and Long-Run Effects on Disposable Income, Wages, and Employment*

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Abstract

In this paper we seek to establish whether road injuries 'causes' a permanent reduction in disposable income, wages and employment. Our data are drawn from a longitudinal sample of Danish citizens for the years 1981-1998. In practice, we work with a 10 per cent sample of the adult population. In particular, we have very full records for each person throughout the sample period. We can identify all persons who have been involved in a traffic accident in the data period if they were hospitalised subsequently, and related diagnoses due to the injury. We decompose earnings into working hours and an hourly wage rate, and use the method of 'matching on observables' to estimate the counter-factual of what the disposable income, the hourly wage rate, and the number of working hours would have been of a particular group of persons injured by road accidents if they had not in fact been injured. We find that road injuries have no significant overall effect on disposable income or the hourly wage rate (for persons with a positive employment rate before and after injury), but we find significant effects on employment rates. In the long run (after five years) the employment rates for the injured are 8 and 6 percentage points lower for men and women, respectively. Thus, reductions in earnings due to road injuries seem only to be explained by reductions in working hours.

Keywords: Traffic injuries, Earnings, Time allocation, 'Matching on observables'

JEL-Code: I18, J28, J22, J23, C23, C52

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1. Introduction

Road accidents induce costs in terms of both human costs and socio-economic costs. Socio-economic costs include, for example, hospitalisation, long term customer care, material damage, police and rescue service, production loss, and welfare loss. In 2000, road accidents killed over 40,000 people in the European Union, and more than 1.3 million road accidents involved personal injury[1].

From a welfare point of view, investigating loss in disposable income due to road injuries is of interest. We suppose that disposable income will fall in the short run, but in the long run, will it reach the level had the person not been injured or will it stay at a constant lower level? Disposable income may be broken down into various components to determine those aspects in which the impact of the road injury is greatest. Injuries may lead to changes in income for different reasons; for example, due to retirement benefits instead of wage income, payments from accident insurances, or because earnings are reduced due to shorter working hours and/or lower wages.

In this study we seek to establish whether road injuries 'causes' permanent reductions in annual disposable income. Further, we decompose annual earnings into an hourly wage rate and the number of working hours to investigate whether these components of the disposable income are reduced in both the short and the long run. If income losses are permanent then it is important to include these costs in evaluating socio-economic costs. Young men, for example, are to a higher degree involved in road accidents; and if their income losses are permanent, then the lifetime impact on earnings could be enormous. To our knowledge no studies have so far investigated long term causal effects of road injuries on disposable income, wage rates and working hours.

A number of studies indicate that there is a positive relationship between health and earnings; see for instance Currie and Madrian (1999) who give a review of the effects of health on wages, earnings, and hours of work in the United States. One common finding in this review

1 European Commission (2001).

is that health has a greater impact on hours of work than on wages; see for instance studies by Chirikos and Nestel (1985) and Mitchell and Burkhauser (1990).

The problem is to find out whether this relationship reflects the effects of health on earnings/employment or whether it reflects the effect of earnings/employment on health, or the effects of other variables in both health and earnings/employment. Only few studies investigate a causal relation from health to earnings/working hours. With respect to effects on earnings, Reville and Schoeni (2001) estimate the earnings losses associated with workplace injuries that lead to permanent partial disability. Injured workers are matched to workers with similar pre-injury earnings. They estimate earnings losses as the difference in earnings between the two groups following injury. They find large earnings losses, especially in the short run, but also 4-5 years after injury. However, investigating workplace injuries as a health shock may be problematic, for example if it is lower back, or mental and psychiatric stress injuries, since they most often do not show up from one day to another. In these cases earnings reductions may show up before the individuals are categorised as injured, making it problematic to investigate causal effects.

In another study, Riphahn (1999) investigate health shocks and their effects on the employment and income position of older workers. Health shocks are here defined as sudden deteriorations in a person's health that might be brought about by accidents or by diseases. The central findings which are based on estimations of logit models are that health shocks have a clear impact on subsequent labour force participation. Effects on household income and individual earnings are visible, especially in the short run. In the study by Wu (2003), health events are used as an exogenous measure of health changes; these include heart conditions, strokes, cancer, lung diseases, and diabetes. The results from this study, which are based on quantile regressions with the change in assets between two periods as dependent variable, indicate that health shocks lead to significant declines in household wealth through lower earnings, but that the effect is larger for women than for men.

Investigating road injuries as a measure of health shocks has the advantage that road injuries may be perceived as exogenous health shocks, since in most cases individuals do not ex-

pect to be involved in an accident. But, to address the causal link between injuries and income (wages, employment) we cannot simply compare injured persons with non-injured persons. This is because 'selection' into being injured is correlated with a number of individual characteristics. As an example young men have a higher risk of being involved in a road accident and lower earnings than older men. Ignoring this would lead to spurious negative correlation between being injured and subsequent earnings.

We use the method of 'matching on observables' to overcome these problems, and estimate the counter-factual of what the levels of disposable income, wages and the number of working hours would have been of a particular group of persons injured by road accidents if they had not in fact been injured. We match each injured person with a non-injured person who has the same individual characteristics such as age, gender, marital status, wages, and education. The identifying assumption is that the conditional expected outcome is the same for both the injured persons and their match, given that neither of them experience involvement in a road accident. In our empirical sample we consider men and women separately.

Since selection may not only be driven by observable characteristics, we exploit the panel structure of data to eliminate selection bias due to time invariant unobservables. First, we estimate the propensity score for being injured due to a road accident. Next, we match each injured person with that control person who has the closest propensity score. In addition, we match on the year of the injury, and on disposable income (employment, wages) the year before the injury. Matching on e.g. the disposable income the year before the injury removes the difference between the disposable income the year before the injury for the injured and their match controls, and thereby also time invariant unobservables.

We have the fortune to have very good data, which are based on a random 10 per cent sample of Danish citizens for the period 1981 to 1998. In particular, we have very full records for each person throughout the sample period. We can identify all persons who have been involved in a road accident in the data period if they were hospitalised subsequently, and related diagnoses due to the injury. Similarly, we can identify control persons who have not been hospitalised due to a road accident in the sample period.

The central findings are that a road injury has no significant overall effect on the disposable income, but has a clear impact on subsequent employment. This indicates that people suffering from road injuries, on average, are compensated in terms of either the same wages during illness, or from other components of the disposable income. We find no significant effect on the hourly wage rate (for those who remain in employment), which indicates that reductions in earnings due to road injuries seem only to be explained by reductions in working hours.

Section 2 contains a presentation of the econometric method. In section 3 a description of the data is given. Section 4 presents the estimation results, and section 5 contains conclusions.

2. Econometric methodology

The aim of this paper is to analyse whether there is a causal effect of road injuries on disposable income, wages, and employment. Investigating this, we use a recently developed methodology specially designed to identify causal treatment effects on the treated; see papers by Heckman, LaLonde and Smith (1999), and Angrist and Krueger (1999) for an overview about available identification strategies.

Suppose that a person can be in either a treated state denoted state "1" or an untreated state, denoted state "0", and that there are outcomes given by Y_1 and Y_0 associated with each state. If we let D=1 indicate treatment and D=0 indicate non-treatment then the observed outcome for an individual is given by $Y = DY_1 + (1-D)Y_0$. The fundamental evaluation problem is that we do not observe both Y_1 and Y_0 for anyone. This missing data problem can not be solved at the individual level. Instead, we focus on average effects. The usual parameter of interest in the literature is the average treatment effect on the treated (ATET), defined as:

$$ATET = E(Y_1-Y_0| D=1) = E(Y_1|D=1)-E(Y_0|D=1) \quad (1)$$

ATET cannot be identified without further assumptions, because $E(Y_0 \mid D=1)$ is unobserved. The assumption of random selection is not satisfied in this study since there are a number of

characteristics which may influence both the risk of a road injury and disposable income (and wages, and employment). Therefore, we cannot simply assume that $E(Y_0 \mid D=1) = E(Y_0 \mid D=0)$. Conditioning on a vector of covariates, X, the average treatment effect on the treated is given by

$$E(Y_1 - Y_0 \mid D=1, X) = E(Y_1 \mid D=1, X) - E(Y_0 \mid D=1, X) \tag{2}$$

where X is a vector of characteristics not affected by the treatment.

In this paper we consider 'matching on observables' to identify a causal treatment effect on the treated, i.e. to estimate the counter-factual of what would have happened to the disposable income of a particular group of treated individuals if they had not in fact been treated. A number of previous studies have applied matching methods; see for instance papers by Heckman *et al*. (1997), Heckman *et al*. (1998), Angrist (1998), Deheija and Wahba (1999), and Lechner (2000).

The basic idea of the 'matching on observables' approach is to select a control group which is as similar as possible to the group of treated with respect to observed characteristics. To be more precise, the average causal treatment effect may be identified by introducing the conditional independence assumption (CIA) (Rubin, 1977):

$$(Y_0, Y_1) \perp\!\!\!\perp D \mid X \tag{3}$$

where $\perp\!\!\!\perp$ is the notation for statistical independence. This assumption ensures that conditional on the observed X's, potential non-treatment (and treatment) outcomes are independent of treatment status. For the average treatment effect on the treated, a weaker version of the CIA is sufficient:

$$E(Y_0 \mid D=1, X) = E(Y_0 \mid D=0, X) \tag{4}$$

This assumption implies that conditioning on X, the expected potential outcome in case of non-treatment is the same for the two groups of treated and non-treated persons, respectively. Thus, observed income (employment, wages) of non-injured may be used to measure potential income (employment, wages) for injured had they not been injured, conditional on the characteristics X. When the set of observed characteristics is large and informative enough, matching enables us to consistently estimate the causal effect of being injured due to a road accident on subsequent disposable income, employment, and wages.

Rosenbaum and Rubin (1983) showed that instead of conditioning on a possibly high-dimensional vector X, control for covariates can be obtained by controlling solely for a function of X, *P(X)*, called the propensity score, which is the treatment probability given the vector X. This implies that

$$E(Y_0|D=1, P(X)) = E(Y_0|D=0, P(X)) \tag{5}$$

To ensure that (5) has empirical content, we must also assume that there are controls and injured individuals for each X for which we want to make a comparison. This means that

$$0 < P(X) < 1 \tag{6}$$

The problem is of course that the propensity score is not known, but has to be estimated. For matching on an estimated propensity score to be reliable it is essential to check the balancing properties of the estimated score carefully (cf. Rosenbaum and Rubin, 1985). In this paper we estimate propensity score functions specified as probit models.

It is important to note that even though matching is done using estimated parametric propensity scores, the method of matching still has the virtue of not relying on distributional assumptions or functional form restrictions in the outcome equation, and the method does not put any restrictions on heterogeneity of individual treatment effects. In this paper the one-to-

one matching algorithm is applied, where each treated person is matched to that non-treated person who has the closest propensity score. In our case matching is not directly on the propensity score, but on its linear index, since the linear index generates better matches in regions where probabilities are very close to zero or one; See Lechner (2000). One-to-one matching may be done with or without replacement. Matching with replacement allows each non-treated person to be matched to more than one person in the treatment group. There is a trade off between matching quality and variance when taking into account the possibility of replacement. Matching without replacement seeks to reduce variance, but at the possible cost of increased bias. Since our control groups are very large compared to the treatment groups, matching without replacement is chosen.

Since selection may not only be driven by observable characteristics, we exploit the advantage of the panel structure of data to eliminate selection bias due to time invariant unobserved characteristics. The strategy follows Heckman, Ichimura, and Todd (1997) Difference-in-difference matching methods, which use both comparisons between treated and non-treated, and differencing over time. In this paper the strategy diverges a bit since we both match on the propensity score, on the year of the injury, and on disposable income (employment, wages) the year before the injury. The reason for matching on the year of the injury is to take account of a falling trend in road injuries, and to ensure a representative control sample. Matching on e.g. the disposable income the year before the injury is similar to Difference-in-difference matching, since matching removes the difference between the disposable income the year before the injury for the treated and non-treated, and thereby time invariant unobservables.

3. Data

The data from this study contains a 10 per cent random sample of the Danish Population and is constructed by merging data from several administrative registers in Statistics Denmark. It is a panel data set which covers the period 1981-1998. The data set contains information on a large number of demographic, educational, labour market variables, annual earnings, hourly

wages, disposable income, as well as information about admission to somatic hospitals which are both due to traffic accidents and other health problems. The main advantages of these data based on administrative registers as compared to case studies or surveys, are that it is possible to follow a large and representative sample of the population over a long period of time, that information is registered with very high reliability, and that there are no problems of attrition (except for death and emigration).

We investigate persons between 20-54 years of age. We exclude persons above the age of 54 since they may be eligible for retirement programmes. We use three different outcome measures: the disposable income, the hourly wage rate, and the individual employment rate. Disposable income is formed using total gross taxable income minus payments of taxes[2]. The hourly wage rate is constructed from annual earnings and the number of employed hours[3]. Employed hours are based on information from the register on supplementary pension payments (ATP) which contains information on annual ATP-payments calculated on the basis of a stepwise function of the weekly hours of employment. The individual degree of employment is derived from observed annual ATP-payments and the maximum annual ATP-payment (corresponding to being in full-time employment throughout the whole year). A degree of employment on one, means that the person is working full time within a given year. If the person is not working at all during the year due to e.g. disability, unemployment, or education, a degree of employment of zero is registered.

Our data have several advantages. First, we are able to observe the annual disposable income, hourly wage rate, and the annual individual employment rate over a long period of time, from 1981-1998 (disposable income from 1984), which allows us to distinguish short-term from long-term effects of road injuries. Second, we have a very large sample of workers not being injured from road accidents from which control groups are constructed. Third, since

2 Total gross taxable income includes wage income, social welfare, unemployment insurance benefits, public pensions, capital income, insurance payments, accident compensation payments and payments from capital pensions.

3 Disposable income and the hourly wage is deflated to 1980 prices using the consumer price index.

diagnoses are registered for persons being injured from road accidents, we may distinguish between different diagnoses with respect to severity and the duration of health effects.

3.1 Identification of road injuries and control groups

We can identify road accidents from data which are based on admissions to somatic hospitals[4]. Information on hospital admissions is obtained from the Danish national register of patients which includes detailed information on diagnoses, dates of admission, discharge, and whether the hospitalisation is due to a road accident. This is observed for all admissions to somatic hospitals in Denmark.

In our data set we have information on a road accident if the person is hospitalised subsequently. Less severe sores or scrapes which are treated at the casualty department without admission to the hospital, and small cuts which do not require medical treatment are not registered in our data.

If a person is involved in a road accident more than once, only the first road accident in the sample period is used in the analysis. We identify road injuries and control groups for each base year 1984-1994. By choosing 1984 to be the first base year, we are able to control for a number of different characteristics such as previous health, wages, and employment up to three years prior to a possible road injury. To avoid that some persons would be included in the control group in one year and in the treatment group in later years, we restrict the controls to only include persons who have not been hospitalised due to a road accident in any year in the sample period.

We construct three different samples depending on which outcome measure to be considered. The sample investigating the disposable income as outcome measure includes both persons in jobs, unemployed and persons being out of the labour force, but we exclude persons who are self-employed for whom register information on income is less reliable. Considering the employment rate as outcome, persons in employment and in unemployment are included

4 The Danish Public Health Insurance scheme (of which all Danish citizens are members) meets the cost of admission to hospitals implying that economic considerations have no influence on admission decisions.

in the sample, but we exclude persons who are self-employed or outside the labour force the year before the base year. Persons outside the labour force are not included because we are only interested in analysing employment effects for persons who have some attachment to the labour market. Focussing on the hourly wage rate as outcome, we require that every person receives some wage income each year from three years before the base year to five years after.

For all three samples all base years are pooled when estimating the propensity score functions, due to relatively few observations on injuries in each single year. To reduce the computational burden in the estimations, the size of the control groups is reduced. A 10 per cent sample of the controls was randomly chosen from the full sample of controls. Table 1 reports the numbers of injured and controls in the period 1984-1994 for the three samples. Since disposable income is only observed from 1984, and we want to control for disposable income three years prior to a possible road injury, the number of injured and controls in the disposable income sample is based on the period 1987-1994.

Table 1. Numbers of injured and controls in the three different samples, 1984-1994. (Disposable income sample from 1987-1994)

	Men		Women	
	Injured	Controls	Injured	Controls
Disposable inc. sample	1,601	94,924	914	96,614
Employment sample	2,068	113,524	1,070	106,904
Wage sample	710	62,027	328	43,266

The disposable income sample includes 2,500 road injured and 190,000 controls, and the employment sample consists of 3,100 road injuries and 220,000 controls. The wage sample is smaller, and includes around 1,000 injured and 105,000 controls. We have fewer observations in the disposable income sample than in the employment sample due to the fact that data on disposable income only is available from 1984.

3.2 Descriptive statistics

Summary statistics of variables included in the estimation of the propensity score for the three samples for treatment and control groups are shown in the appendix, tables A.1, A.2, and A.3,

respectively, for men and women separately. The individual characteristics include dummy variables for age, living as a couple, living outside the Copenhagen metropolitan area, the number of children 3-6 or 7-14 years of age, labour market experience in years, educational dummies, dummy variables for industry of employment, the annual individual unemployment rate, the individual annual employment rate, the hourly wage rate, and the disposable income. Indicators of previous health is included in terms of the number and duration of previous admissions to hospitals, 1-4 years prior the base year (for any diagnosis except birth and a few other diagnoses not related to illness), and the duration of previous sickness benefits.[5] All explanatory variables are lagged one year prior to the base year to ensure that the controls are not affected by whether the individuals are treated or not.

From these statistics it is obvious that there is heterogeneity with respect to a number of individual characteristics. Especially, young men, singles, individuals with no children, uneducated, individuals with many sick days, and unemployed have on average a higher risk of being injured in all three samples. Most of these differences hinges on the fact that especially young persons are in a higher risk of being involved in a road accident.

In the following pages we present figures of the profiles of the three different outcome measures. All base years are pooled, such that the time of the road accident is time "0". The disposable income, the employment rate, and the hourly wage rate are measured one to three years before time "0", and one to four years after.[6] Both treatment and the different outcomes are based on annual observations, which mean that we do not measure whether the road injury occurred at the beginning or at the end of the year. The same applies to the three outcome measures. Therefore, short-run effects could be both at time "0" and "1".

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5 Employees are entitled to sickness benefits if they have been attached to the labour market for the last 13 weeks prior to the start of the sickness. Employees who do not receive full pay during sickness are entitled to benefits from their employer during the first two weeks of absence. If the employer pays the full wage during sickness or is paying sickness benefits beyond the first two weeks, the employer will be entitled to reimbursement of the amount of the benefit from the municipal authorities. Sickness benefits will lapse when benefits or wage during illness have been paid for more than 52 weeks during the preceding 18 months. There are, however, a number of possibilities for extending the benefit period; e.g. if there is a strong probability that rehabilitation measures will be initiated, or if the person is undergoing or waiting for medical treatment which is expected to restore the working capacity within a short period of time.

6 Disposable income and the hourly wage is in Danish kroner and is deflated to 1980 prices.

In figure 1 and 2, the disposable income profiles for the injured and non-injured are shown for men and women, respectively. For both men and women the disposable income profile for the injured is at a lower level than for the non-injured, but the difference is most pronounced for men. The income profiles for men both increase until time "0" after which the profile for the injured stops increasing. After time "1" it increases again. With respect to women, the income profiles are relatively close and the gap does not increase after time "0" indicating no significant difference.

Figure1. Disposable income profiles for both injured and non-injured men

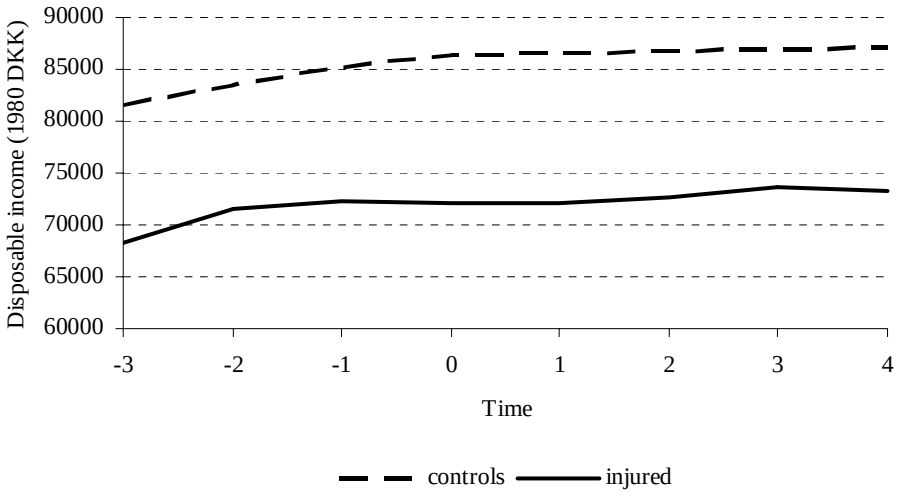
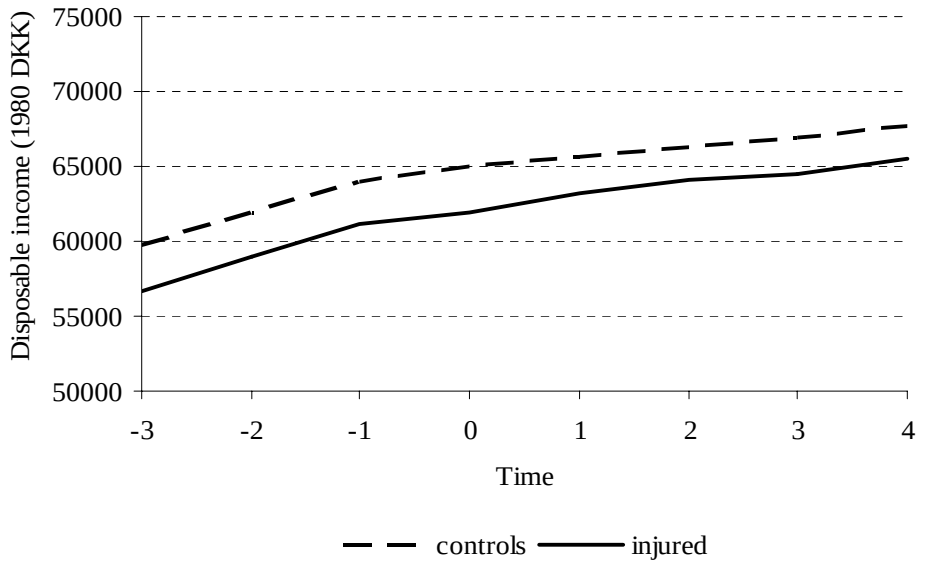


Figure2. Disposable income profiles for both injured and non-injured women



In figure 3 and 4 we present figures of the employment rate for treatments and controls, for men and women, respectively. For both men and women the degree of employment is lower on average for persons being injured, both before and after the accident. This hinges on the fact that especially young persons are involved in road accidents, and they are to a higher degree in the education system instead of working. It is interesting what happens to the employment rate around time "0". For injured men, the employment rate decreases significantly in the first two years after the injury, after which it stays at a low level. For women, the employment rate decreases after the injury, and the gap between injured and controls increases in the four-year period after the accident. Whether there is a significant difference between injured and controls is investigated in the next section where the matching results are presented.

Figure 3. Degree of employment profiles for both injured and non-injured men

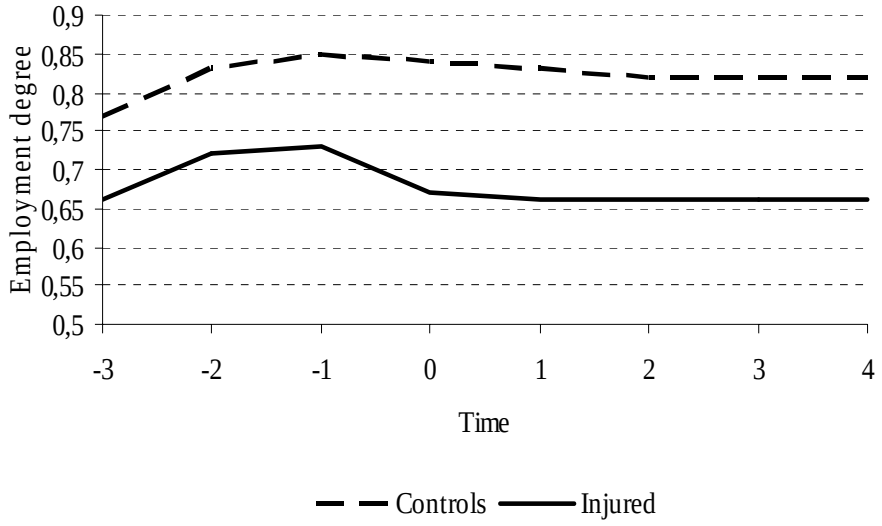
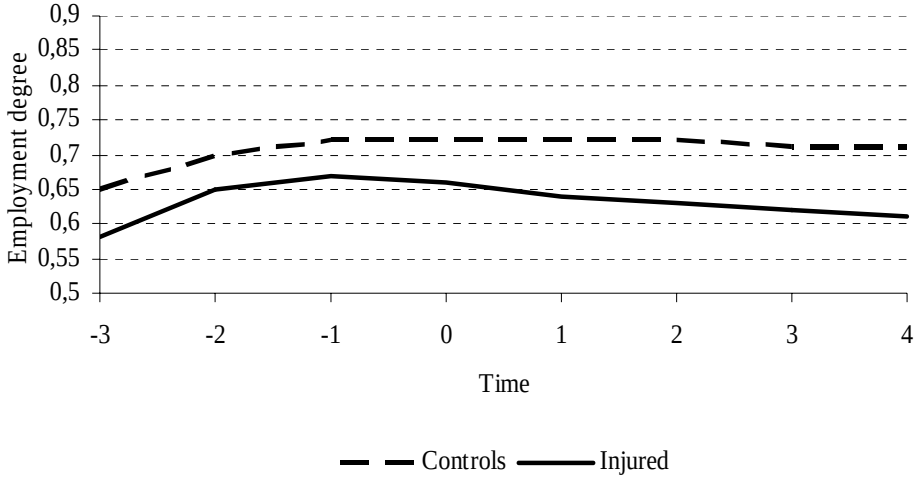


Figure 4. Degree of employment profiles for both injured and non-injured women



In Figure 5 and 6, we present profiles for hourly wage rates for injured and non-injured men and women. As discussed above, the wage profiles are calculated for persons having some wage income in each year in the period from three years before the base year to four years after. For men, the wage profiles are increasing over time. On average, injured persons have lower wages both before and after an accident. The first year after the accident, the wages stop increasing, but increase again after that. With respect to women, there is no evidence of a difference between the two wage profiles, indicating that a road accident does influence the hourly wage rate.

Figure 5. Wage profiles for injured and non-injured men

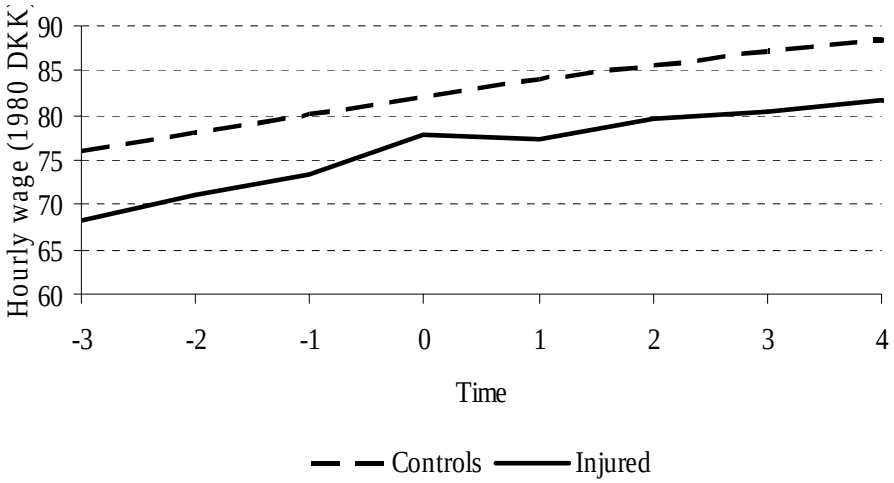
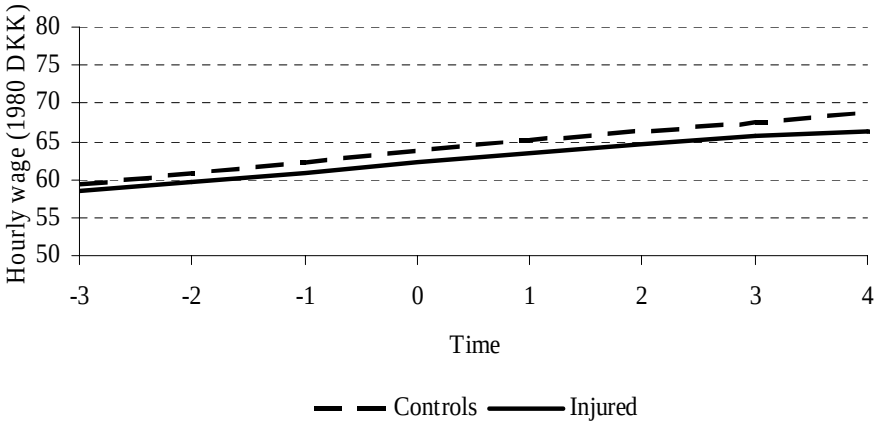


Figure 6. Wage profiles for injured and non-injured women



4. Estimation results

In this section results from estimation of the propensity scores of the three samples are presented, for men and women, respectively. Probit models for being injured are estimated. The explanatory variables included in the estimations are described in section 3. Further, base year indicator variables and a number of interaction terms are included. Table 2 shows results for the disposable income samples for men and women, separately. The results suggest that young men and persons living as singles without children have a higher risk of being injured. If they have no education beyond compulsory school or have a low disposable income, they

also have a higher risk of being involved in a road accident. The estimation results from the employment and the wage samples are based on almost the same set of explanatory variables except for an individual unemployment rate and a log hourly wage rate in the wage sample, and an individual employment rate in the employment sample. Further, the number of interaction terms differs. The results from these estimations are shown for men and women in the appendix, table A.4-A.5. Very similar effects on the propensity score of being injured are found in these estimations.

The validity of the specification of the probit model for being injured is tested by setting up a normality test and a heteroskedasticity test[7]. For both men and women in all three models, we cannot reject the normality test and for most of the included explanatory variables, homoskedasticity is not rejected.

In the appendix in figure A.1-A.6 kernel density estimates of the distribution of the propensity score are presented for the disposable income, the employment rate, and the wage samples, for men and women, respectively. The treatment and control groups are very close to having a common support. It emerges from the figures that, especially for men, the shape of the distribution differs.

7 The score test against heteroskedasticity is based on (expected Hessian)-1*(outer product of the gradient)* (expected Hessian)-1. See Lechner (2000).

Table 2. Estimation of the propensity score (probit model for being injured), for men and women for the disposable income sample

	Men			Women		
	Estimation		Heteroske-dasticity test	Estimation		Heteroske-dasticity test
Variable	Coef.	Std. err.	$\chi^2(1)$	Coef.	Std. err.	$\chi^2(1)$
Const	-3.963	0.551	-	-2.573	0.133	-
Age 30-39	-0.034	0.031	2.8	-0.066	0.039	6.8
Age 40-49	-0.051	0.044	10.8	-0.072	0.039	3.2
Age 50-59	-0.329	0.114	0.1	-0.105	0.053	6.1
Couple	-0.267	0.029	7.5	-0.065	0.030	1.1
#Children 0-6 years	-0.065	0.033	0.5	-0.148	0.035	2.1
#Children 7-14 years	-0.082	0.070	5.4	-0.031	0.033	0.2
Province	0.140	0.023	10.6	0.129	0.028	0.4
Exp. (years/100)	-1.787	0.512	6.0	-0.333	0.718	0.1
Exp. sq (years/100)	-	-	-	-0.217	2.877	0.1
Log(disp.inc)	0.194	0.051	0.6	0.023	0.012	0.6
Vocational education	-0.110	0.023	0.8	-0.052	0.031	4.5
College education	-0.067	0.053	0.1	0.033	0.052	1.2
Bachelor degree	-0.279	0.052	0.3	-0.067	0.051	3.2
Master's degree	-0.329	0.062	4.5	0.019	0.065	1.7
No unempl. insurance	-0.025	0.030	3.0	0.051	0.035	0.2
Manufacturing	0.121	0.038	0.8	0.114	0.058	3.8
Construction	0.077	0.046	0.0	0.031	0.144	1.4
Infrastructure	0.013	0.051	6.3	0.132	0.085	0.0
Financial services	-0.059	0.056	0.1	-0.008	0.068	0.1
Other industries	0.063	0.042	0.3	0.150	0.055	0.1
Public sector	0.074	0.040	0.8	0.121	0.048	0.7
#of prev. hosp. admiss	7.539	1.819	1.0	5.176	1.382	1.6
Dur. prev admissions	0.593	0.121	0.2	0.024	0.155	3.4
Sick. benefits (days)	0.221	0.029	0.1	0.082	0.029	2.6
Year88	1.999	0.638	0.8	-0.019	0.047	0.4
Year89	2.213	0.602	2.5	-0.100	0.049	0.3
Year90	0.979	0.654	0.8	-0.142	0.050	0.2
Year91	1.557	0.696	0.2	-0.073	0.048	0.0
Year92	1.726	0.665	1.9	-0.108	0.050	0.0
Year93	0.911	0.713	0.2	-0.047	0.049	0.0
Year94	0.970	0.642	0.2	-0.009	0.064	0.0
Log likelihood		7,785			5,071	
Normality test $\chi^2(2)$		5.3			1.2	
Observations		96,525			95,528	

Note: All explanatory variables are lagged at least 1 year relative to the base year, see section 3.2 for details. The reference person is less than 30 years of age, without formal educational qualifications (or of unknown educational status), single, working in the service sector. A number of interaction terms are included in the estimation for men, but not shown.

It is important to check the balancing properties of the propensity scores for the treated and their matched controls. Two-sample t-statistics and absolute standardised biases are presented in tables A.6-A.8 in the appendix. The two-sample t-statistics indicate whether the two samples come from distributions with the same mean, and the standardised bias is the difference

of the sample means between treated and their matched controls as a percentage of the square root of the sample variances in the two groups (see Rosenbaum and Rubin, 1985). Table A.6-A.8 show that matching removes almost all differences for the variables included in the estimations of the propensity score. We cannot reject the hypothesis of no difference in the mean, indicating that the conditional independence assumption is not rejected.

4.1 Matching results

Having estimated the propensity score for being injured, we match each injured person with the control person who has the closest propensity score. For the employment rate sample, we also match on intervals of the employment rate the year before the road injury to make sure that we e.g. do not match an injured person with a low employment rate with a control person working full time. The same applies for the wage sample and the disposable income sample, where we match on wages and disposable income, respectively, the year before the base year. Since the estimation results of the propensity score showed a falling trend in road injuries over time, and to not get biased matching results due to pooling of data, we further match on the base year in all three samples.

The average treatment effect on the treated with respect to annual disposable income is shown in table 3. For neither men nor women we find any significant difference (although for men the point estimate is negative for all five years). This is very clear considering figure 7 and 8, where the average disposable income is drawn for the injured and their matched controls, for men and women, respectively. The lines are almost identical, except for a minor difference in the men's case. Overall, the average level of the disposable income does not change, which may be explained by the fact that Danish citizens are compensated in terms of either the same wages during illness, and/or by accident insurance payments, or by different public transfer incomes. In this paper we only consider effects on wages and employment, but in the future we plan to investigate this more closely, by investigating other separate components of disposable income. Another explanation for finding no significant effects, may be that we do not distinguish between different diagnoses and severity of illness, since it is plau-

sible that more severe illnesses may have larger effects. In the future we also plan to investigate this by looking at specific injuries.

Table 3. Average treatment effect on the treated with respect to the annual disposable income

Years since injury	Men		Women	
	ATET	Std.dev.	ATET	Std.dev.
0	-1210.7	3041.8	-529.1	2599.5
1	-1057.7	3163.4	-527.5	2628.0
2	-1359.1	3463.5	1099.1	2861.3
3	-1315.0	5229.7	134.9	2672.0
4	-2735.8	4034.2	791.6	2761.5

Figure 7. Average treatment effect on the treated with respect to the annual disposable income, men

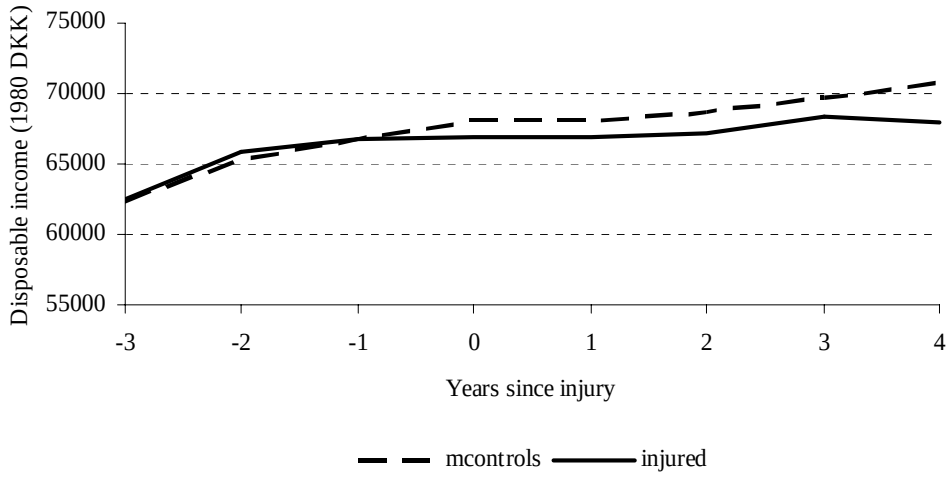
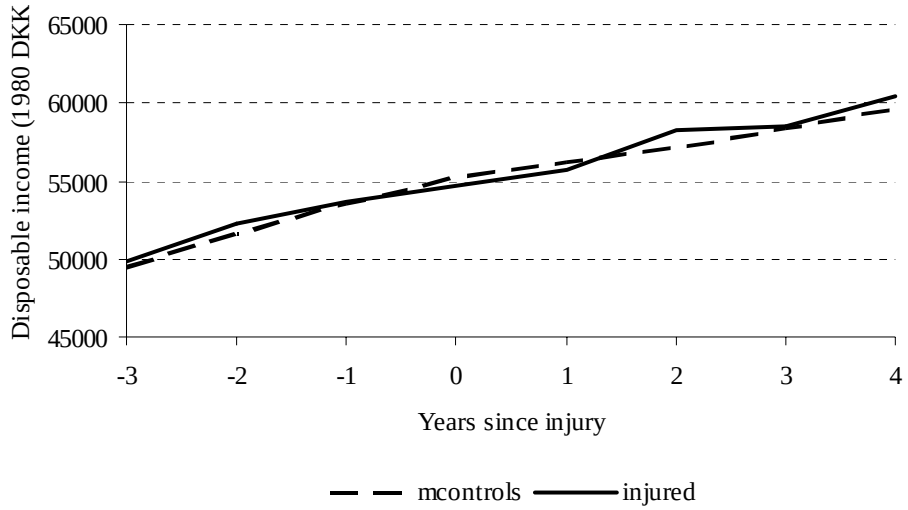


Figure 8. Average treatment effect on the treated with respect to the annual disposable income, women



If we focus on the average treatment effect of the treated for the employment rate sample, which is shown for men and women in table 4, we find significant average treatment effects for men in both the short run and in the long run. The average treatment effects of the treated between the two groups vary between 7 and 8.4 percentage points. In figure 9, the average employment rate for the injured and the matched control is shown for both the years before the injury and one to four years after the injury. There is a clear effect. The employment rate declines sharply the year of the road accident for the injured, and most interestingly, it does not approach the level of the counterfactual within the four-year period, indicating a clear effect also in the long run.

The picture for women is a bit different since we only find significant effects 3-4 years after the injury. In figure 10 we see that at time "0" the employment rate for the injured does not decrease as much as was the case for men. The difference between the group of injured and the matched controls is still there, though, and this difference is increasing over years. So for women, we also find that in the long run the injured persons have a significantly lower employment rate than the matched controls.

Table 4. Average treatment effect on the treated with respect to the employment rate

Years since injury	Men		Women	
	ATET	Std.dev.	ATET	Std.dev.
0	-0.0728**	0.0196	-0.0146	0.0276
1	-0.0841**	0.0199	-0.0271	0.0278
2	-0.0738**	0.0200	-0.0397	0.0279
3	-0.0695**	0.0201	-0.0536*	0.0281
4	-0.0773**	0.0202	-0.0594**	0.0283

Note: ** indicates statistically significant at the 5 per cent level, and * at the 10 per cent level

Figure 9. Average treatment effect on the treated with respect to the employment rate, men

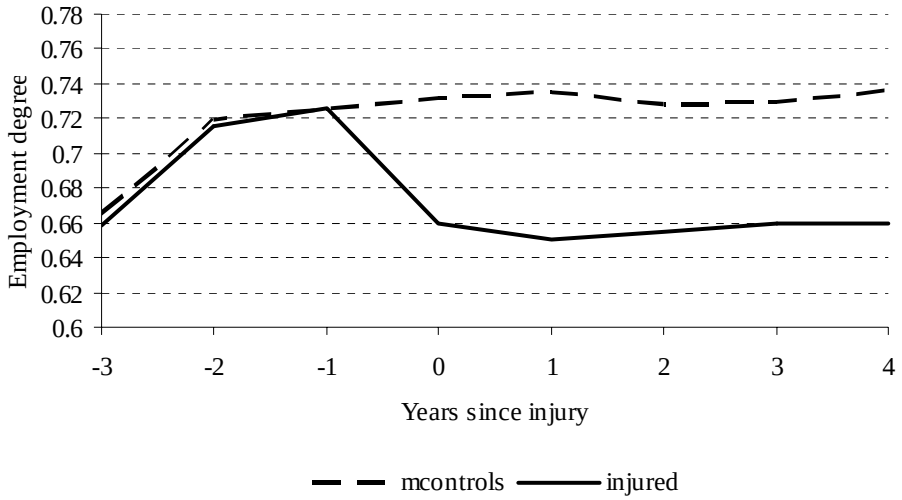
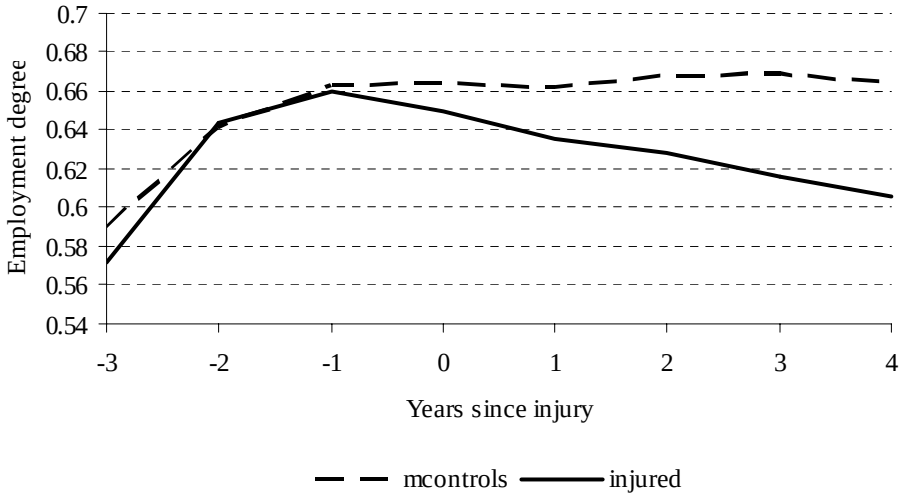


Figure 10. Average treatment effect on the treated with respect to the employment rate, women



We now turn to investigating whether a road injury has an influence on the hourly wage rate. Unlike the analysis of effects on the employment rate, we now only consider those persons who actually have a job and who receive some wage earnings both before and after the injury.

The average treatment effects for the wage sample in table 5, and the curves in figure 11 and 12 for men and women, respectively, clearly show no significant difference between injured and their matched controls; in neither the short run or 1-4 years after the injury. We should note that the hourly wage rate in the first year after the injury may be difficult to analyse, since many of the injured persons receive normal wages during absence from work. So in the short run we are not able to see if there should be any difference.

Table 5. Average treatment effect on the treated with respect to the hourly wage rate

Years since injury	Men		Women	
	ATET	Std.dev.	ATET	Std.dev.
0	1.3796	1.5272	0.6382	1.2385
1	-1.5163	1.5317	0.3415	1.2286
2	-0.6023	1.5898	0.2268	1.2114
3	-1.7205	1.6235	-0.3895	1.2577
4	-2.1820	1.6557	-0.9192	1.2593

Figure 11. Average treatment effect on the treated with respect to the hourly wage rate, men

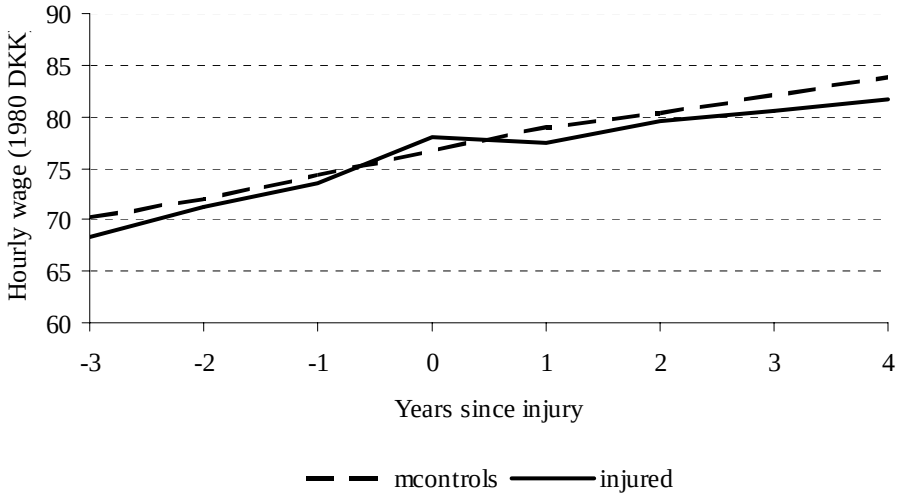
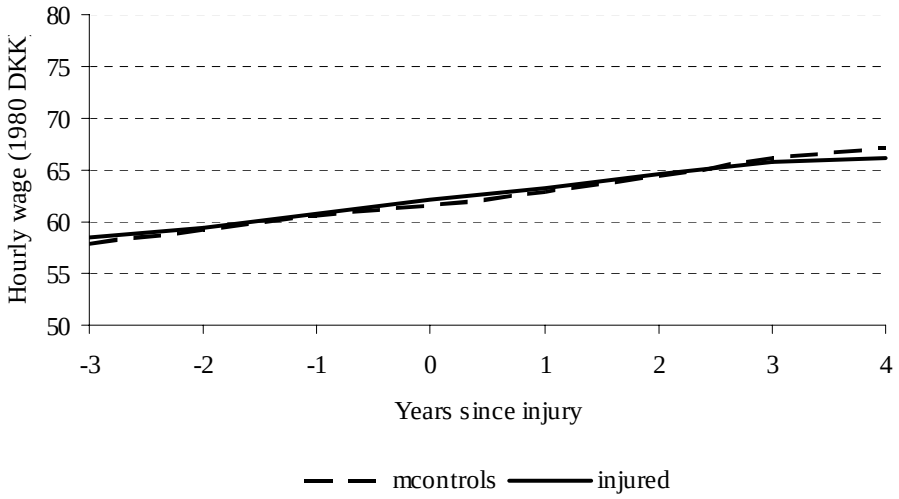


Figure 12. Average treatment effect on the treated with respect to the hourly wage rate, women



5. Summary and conclusion

This study investigates short- and long-run causal effects of road injuries on disposable income, hourly wage rate, and employment.

Focussing on the disposable income, we do not find any significant causal effects for neither men nor women. This result indicates that people suffering from road injuries are on average compensated in terms of either the same wages during illness, by accident insurances payments, or by different public transfer incomes. In this paper we only consider effects on wages and employment, but in the future we plan to investigate this more closely, by investigating other separate components of the disposable income.

Even though we do not find any overall decrease in the disposable income for road injured persons, we find significant differences in the labour market conditions. The average employment rate declines sharply for men in the year of the road accident for the injured, and most interestingly, it does not approach the level of the counterfactual within a four-year period, indicating a clear effect also in the long run. The employment rate for the injured is on a constant lower level. Four years after the injury, the employment rate is around 8 percentage points lower for the injured than their matched controls. With respect to women, the picture is a bit different since we only find significant effects 3-4 years after the injury. The difference between the injured and their matched controls is around 6 percentage points four years after the injury. These large and persistent effects represent a significant loss of production from road accidents.

The other component of earnings is the hourly wage rate (for persons earning wage income both before and after the base year), and for this outcome we find no significant effects at all, so reductions in earnings due to road injuries are only explained by reductions in working hours.

In the future we want to go more closely into analysing effects for specific injuries, because we expect that illness related to more severe diagnoses affects both the disposable income and labour market conditions to a particularly large degree.

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Appendix

Table A.1 Summary statistics for sample based on annual disposable income as outcome

	Men				Women			
	Injured		Controls		Injured		Controls	
	mean	std.dev	mean	std.dev	mean	std.dev	mean	std.dev
Age 20-29	0.49	0.50	0.36	0.48	0.41	0.49	0.35	0.48
Age 30-39	0.25	0.43	0.29	0.45	0.25	0.43	0.29	0.45
Age 40-49	0.20	0.40	0.27	0.44	0.26	0.44	0.27	0.45
Age 50-59	0.05	0.22	0.08	0.27	0.08	0.27	0.09	0.28
Couple	0.38	0.49	0.60	0.49	0.61	0.49	0.68	0.47
#Children 0-6 years	0.13	0.33	0.20	0.40	0.18	0.39	0.24	0.43
#Children 7-14 years	0.15	0.35	0.22	0.42	0.24	0.43	0.27	0.45
Province	0.73	0.44	0.65	0.48	0.72	0.45	0.65	0.48
Exp. (years/100)	0.10	0.08	0.12	0.08	0.08	0.07	0.09	0.07
Exp. sq (years/100)	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.02
No further education	0.48	0.50	0.35	0.48	0.50	0.50	0.43	0.50
Vocational education	0.37	0.48	0.43	0.49	0.28	0.45	0.33	0.47
College education	0.04	0.20	0.05	0.21	0.07	0.26	0.07	0.26
Bachelor degree	0.04	0.19	0.08	0.27	0.07	0.26	0.09	0.28
Master's degree	0.02	0.15	0.06	0.23	0.04	0.20	0.04	0.19
Manufacturing	0.23	0.42	0.20	0.40	0.11	0.31	0.10	0.30
Services	0.10	0.31	0.12	0.33	0.08	0.27	0.10	0.29
Construction	0.09	0.29	0.09	0.28	0.01	0.09	0.01	0.10
Infrastructure	0.06	0.24	0.07	0.26	0.03	0.17	0.03	0.16
Financial services	0.04	0.20	0.07	0.26	0.05	0.22	0.08	0.27
Other industries	0.20	0.40	0.14	0.35	0.24	0.43	0.18	0.38
Public sector	0.16	0.36	0.18	0.38	0.38	0.48	0.38	0.48
#of prev. hosp. admiss	0.01	0.02	0.00	0.01	0.01	0.02	0.00	0.01
Dur. prev admissions	0.04	0.15	0.02	0.08	0.04	0.15	0.02	0.09
Sick. benefits (days)	0.11	0.42	0.04	0.26	0.10	0.43	0.05	0.32
No unempl. Insurance	0.23	0.42	0.21	0.41	0.25	0.44	0.21	0.40
Disposable income (DKK)	66759	31217	78570	61291	53612	23789	56459	50048
Year87	0.14	0.35	0.12	0.33	0.15	0.36	0.12	0.33
Year88	0.13	0.34	0.12	0.33	0.14	0.35	0.12	0.33
Year89	0.13	0.34	0.12	0.33	0.12	0.32	0.12	0.33
Year90	0.12	0.32	0.13	0.33	0.11	0.31	0.12	0.33
Year91	0.12	0.32	0.13	0.33	0.13	0.33	0.13	0.33
Year92	0.13	0.34	0.13	0.33	0.11	0.32	0.13	0.33
Year93	0.12	0.33	0.13	0.33	0.13	0.34	0.13	0.33
Year94	0.11	0.31	0.13	0.33	0.11	0.31	0.13	0.33
# obs.	1,601		94,924		914		96,614	

Table A.2 Summary statistics for sample based on degree of employment as outcome

	Men				Women			
	Injured		Controls		Injured		Controls	
	mean	std.dev	mean	std.dev	mean	std.dev	mean	std.dev
Age 20-29	0.53	0.50	0.34	0.47	0.41	0.49	0.34	0.47
Age 30-39	0.25	0.43	0.31	0.46	0.27	0.44	0.32	0.46
Age 40-49	0.18	0.38	0.27	0.45	0.25	0.44	0.27	0.44
Age 50-59	0.04	0.20	0.08	0.27	0.07	0.26	0.07	0.26
Couple	0.42	0.49	0.66	0.47	0.63	0.48	0.72	0.45
#Children 0-6 years	0.15	0.36	0.22	0.41	0.20	0.40	0.26	0.44
#Children 7-14 years	0.16	0.36	0.26	0.44	0.26	0.44	0.30	0.46
Province	0.71	0.45	0.65	0.48	0.69	0.46	0.65	0.48
Exp. (years/100)	0.10	0.07	0.13	0.08	0.08	0.06	0.10	0.06
Exp. sq (years/100)	0.01	0.02	0.02	0.02	0.01	0.01	0.01	0.02
No further education	0.46	0.50	0.33	0.47	0.48	0.50	0.41	0.49
Vocational education	0.41	0.49	0.46	0.50	0.30	0.46	0.36	0.48
College education	0.04	0.20	0.05	0.21	0.08	0.27	0.08	0.27
Bachelor degree	0.04	0.19	0.09	0.28	0.08	0.28	0.10	0.30
Master's degree	0.03	0.16	0.06	0.23	0.03	0.18	0.04	0.19
Manufacturing	0.26	0.44	0.23	0.42	0.13	0.34	0.12	0.32
Services	0.12	0.33	0.14	0.34	0.10	0.30	0.11	0.32
Construction	0.11	0.32	0.10	0.30	0.01	0.09	0.01	0.11
Infrastructure	0.07	0.26	0.08	0.27	0.03	0.16	0.03	0.16
Financial services	0.04	0.20	0.08	0.27	0.06	0.24	0.09	0.29
Other industries	0.13	0.33	0.09	0.28	0.12	0.32	0.09	0.28
Public sector	0.19	0.39	0.20	0.40	0.47	0.50	0.46	0.50
#of prev. hosp. admiss	0.00	0.01	0.00	0.01	0.01	0.01	0.00	0.01
Dur. prev admissions	0.03	0.14	0.01	0.06	0.04	0.14	0.02	0.07
Sick. benefits (days)	0.09	0.36	0.04	0.23	0.09	0.40	0.05	0.28
No unempl. insurance	0.18	0.39	0.18	0.38	0.17	0.38	0.15	0.36
Employment rate	0.66	0.36	0.71	0.34	0.73	0.34	0.84	0.29
Year84	0.11	0.31	0.09	0.28	0.11	0.32	0.08	0.27
Year85	0.11	0.31	0.09	0.28	0.11	0.32	0.09	0.28
Year86	0.11	0.32	0.09	0.29	0.09	0.29	0.09	0.28
Year87	0.10	0.30	0.09	0.29	0.11	0.31	0.09	0.29
Year88	0.09	0.28	0.09	0.29	0.10	0.30	0.09	0.29
Year89	0.09	0.28	0.09	0.29	0.08	0.27	0.09	0.29
Year90	0.08	0.26	0.09	0.29	0.06	0.25	0.09	0.29
Year91	0.08	0.27	0.09	0.29	0.09	0.29	0.09	0.29
Year92	0.09	0.28	0.09	0.29	0.08	0.27	0.09	0.29
Year93	0.08	0.27	0.09	0.29	0.09	0.28	0.09	0.29
Year94	0.07	0.26	0.09	0.29	0.08	0.27	0.10	0.29
# obs.	2,068		113,524		1,070		106,904	

Table A.3 Summary statistics for sample based on hourly wage as outcome

	Men				Women			
	Injured		Controls		Injured		Controls	
	mean	std.dev	mean	std.dev	mean	std.dev	mean	std.dev
Age 20-29	0.42	0.49	0.24	0.43	0.26	0.44	0.23	0.42
Age 30-39	0.28	0.45	0.35	0.48	0.31	0.46	0.36	0.48
Age 40-49	0.24	0.43	0.33	0.47	0.34	0.47	0.33	0.47
Age 50-59	0.06	0.23	0.09	0.28	0.09	0.29	0.08	0.26
Couple	0.57	0.49	0.77	0.42	0.70	0.46	0.77	0.42
#Children 0-6 years	0.19	0.39	0.24	0.43	0.17	0.37	0.23	0.42
#Children 7-14 years	0.22	0.42	0.32	0.47	0.29	0.45	0.34	0.47
Province	0.69	0.46	0.65	0.48	0.64	0.48	0.61	0.49
Exp. (years/100)	0.13	0.07	0.16	0.07	0.13	0.06	0.13	0.06
Exp. sq (years/100)	0.02	0.02	0.03	0.02	0.02	0.02	0.02	0.02
No further education	0.34	0.47	0.27	0.45	0.35	0.48	0.30	0.46
Vocational education	0.47	0.50	0.49	0.50	0.34	0.47	0.41	0.49
College education	0.08	0.27	0.06	0.23	0.12	0.32	0.09	0.29
Bachelor degree	0.07	0.25	0.10	0.31	0.15	0.36	0.15	0.35
Master's degree	0.03	0.18	0.06	0.23	0.03	0.17	0.04	0.18
Manufacturing	0.26	0.44	0.24	0.43	0.11	0.31	0.11	0.31
Services	0.14	0.35	0.14	0.35	0.09	0.29	0.09	0.29
Construction	0.09	0.28	0.08	0.27	0.01	0.10	0.01	0.11
Infrastructure	0.08	0.27	0.08	0.27	0.03	0.17	0.03	0.18
Financial services	0.05	0.22	0.10	0.30	0.10	0.31	0.12	0.32
Other industries	0.06	0.23	0.05	0.22	0.02	0.14	0.02	0.14
Public sector	0.25	0.43	0.22	0.41	0.54	0.50	0.53	0.50
#of prev. hosp. admiss	0.00	0.01	0.00	0.01	0.00	0.01	0.00	0.01
Dur. prev admissions	0.01	0.06	0.01	0.05	0.03	0.13	0.02	0.05
Sick. benefits (days)	0.02	0.10	0.01	0.09	0.01	0.07	0.01	0.10
Unemployment rate	0.02	0.07	0.01	0.05	0.01	0.06	0.01	0.05
No unempl. insurance	0.17	0.38	0.17	0.38	0.16	0.36	0.14	0.35
Hourly wage (DKK)	73.5	24.7	80.2	30.4	60.8	16.6	62.2	16.5
Year84	0.11	0.32	0.09	0.29	0.13	0.33	0.09	0.28
Year85	0.11	0.31	0.09	0.29	0.13	0.33	0.09	0.28
Year86	0.12	0.33	0.09	0.29	0.09	0.28	0.09	0.29
Year87	0.09	0.29	0.09	0.29	0.09	0.29	0.09	0.29
Year88	0.09	0.29	0.09	0.29	0.10	0.30	0.10	0.29
Year89	0.08	0.27	0.09	0.29	0.09	0.29	0.10	0.30
Year90	0.07	0.26	0.09	0.29	0.07	0.25	0.09	0.29
Year91	0.06	0.25	0.09	0.29	0.06	0.24	0.09	0.29
Year92	0.10	0.30	0.09	0.28	0.10	0.30	0.09	0.29
Year93	0.08	0.27	0.09	0.28	0.05	0.22	0.09	0.28
Year94	0.07	0.26	0.09	0.29	0.09	0.29	0.09	0.28
# obs.	710		62,027		328		43,266	

Table A.4 Estimation of the propensity score (probit model for being injured), for men and women for the employment sample

	Men			Women		
	Estimation		Heteroske-dasticity test	Estimation		Heteroske-da-sticity test
Variable	Coef.	Std. err.	$\chi^2(1)$	Coef.	Std. err.	$X^2(1)$
Const	-1.714	0.093	---	-2.085	0.066	---
Age 30-39	-0.047	0.082	2.3	-0.067	0.036	3.9
Age 40-49	-0.096	0.111	7.4	-0.060	0.038	4.2
Age 50-59	-0.180	0.153	0.7	-0.079	0.052	2.9
Couple	-0.232	0.024	1.4	-0.115	0.027	2.8
#Children 0-6 years	-0.045	0.028	0.7	-0.145	0.032	1.5
#Children 7-14 years	-0.054	0.027	3.4	-0.028	0.030	0.7
Province	0.095	0.020	4.5	0.080	0.025	4.0
Exp. (years/100)	-0.570	0.816	2.0	-0.316	0.704	1.8
Exp. sq (years/100)	---	---	---	0.377	2.780	1.3
Vocational education	-0.093	0.020	0.1	-0.074	0.028	1.4
College education	-0.035	0.046	4.3	-0.002	0.047	0.0
Bachelor degree	-0.266	0.046	1.1	-0.057	0.044	1.0
Master's degree	-0.261	0.055	3.0	-0.054	0.067	0.4
No unempl. insurance	0.007	0.026	0.8	0.019	0.033	1.1
Manufacturing	0.090	0.032	1.4	0.089	0.049	4.5
Construction	0.051	0.038	0.1	-0.076	0.132	2.6
Infrastructure	0.028	0.042	2.7	0.070	0.079	1.6
Financial services	-0.087	0.049	3.5	-0.041	0.057	0.0
Other industries	0.031	0.042	0.5	0.067	0.055	0.1
Public sector	0.055	0.034	0.0	0.084	0.041	1.6
#of prev. hosp. admiss	4.324	1.977	3.1	5.571	1.392	0.2
Dur. prev admissions	0.661	0.150	0.1	0.169	0.178	0.0
Sick. benefits (days)	0.183	0.032	0.3	0.086	0.031	5.4
Employment rate	0.353	0.171	0.0	-0.072	0.043	0.0
Employ. degree sq.	-0.467	0.122	0.1	---	---	---
Year85	0.079	0.106	0.2	-0.036	0.050	0.0
Year86	-0.029	0.113	0.5	-0.129	0.052	1.8
Year87	-0.026	0.112	0.9	-0.077	0.051	1.5
Year88	0.021	0.114	0.3	-0.105	0.052	2.2
Year89	-0.047	0.112	2.7	-0.192	0.054	1.0
Year90	-0.217	0.117	0.9	-0.266	0.056	1.3
Year91	-0.205	0.113	0.0	-0.133	0.052	0.0
Year92	-0.320	0.115	1.0	-0.199	0.055	0.1
Year93	-0.313	0.110	0.8	-0.164	0.054	0.1
Year94	-0.233	0.120	0.2	-0.129	0.064	0.2
Log likelihood	9,825			5,886		
Normality test $\chi^2(2)$	5.08			1.51		
Observations	115,592			107,974		

Note: All explanatory variables are lagged at least 1 year relative to the base year, see section 3.2 for details. A number of interaction terms are included in the estimation for men, but not shown. The reference person is less than 30 years of age, without formal educational qualifications (or of unknown educational status), single, working in the service sector.

Table A.5. Estimation of the propensity score (probit model for being injured), for men and women for the wage sample

	Men			Women		
	Estimation		Heteroske-dasticity test	Estimation		Heteroske-dasticity test
Variable	Coef.	Std. err.	$\chi^2(1)$	Coef.	Std. err.	$\chi^2(1)$
Const	-1.769	0.220		-1.893	0.435	
Age 30-39	-0.137	0.049	0.7	-0.080	0.069	1.1
Age 40-49	-0.166	0.066	1.6	-0.062	0.075	0.1
Age 50-59	-0.238	0.090	1.8	-0.036	0.090	0.2
Couple	-0.242	0.039	0.0	-0.111	0.048	0.8
#Children 0-6 years	-0.051	0.042	0.0	-0.137	0.061	0.7
#Children 7-14 years	-0.032	0.038	1.4	-0.061	0.049	3.8
Province	0.075	0.033	0.0	0.071	0.043	1.2
Exp. (years/100)	-2.480	1.127	0.2	1.449	1.588	0.1
Exp. sq (years/100)	7.145	3.654	0.2	-4.118	5.113	0.0
Log(wage)	0.002	0.053	0.2	-0.083	0.111	0.1
Vocational education	-0.062	0.033	3.8	-0.121	0.049	1.5
College education	0.106	0.060	5.8	0.050	0.072	0.5
Bachelor degree	-0.159	0.062	2.3	-0.026	0.071	0.0
Master's degree	-0.185	0.088	3.5	-0.031	0.132	1.8
No unempl. insurance	0.015	0.043	1.7	0.053	0.061	3.5
Manufacturing	0.050	0.049	0.3	-0.013	0.091	0.4
Construction	0.031	0.065	3.0	-0.081	0.216	2.5
Infrastructure	0.042	0.064	0.3	-0.016	0.133	0.3
Financial services	-0.152	0.073	6.6	-0.007	0.094	0.0
Other industries	0.030	0.074	0.9	-0.024	0.156	2.1
Public sector	0.116	0.051	0.2	-0.018	0.075	0.1
#of prev. hosp. admiss	-0.375	2.670	2.9	1.746	3.822	0.3
Dur. prev admissions	0.617	0.344	0.2	0.444	0.583	2.0
Sick. benefits (days)	0.085	0.104	0.1	0.045	0.127	3.3
Unemployment	0.396	0.230	3.0	0.123	0.393	0.0
Year85	-0.044	0.063	6.7	-0.008	0.084	0.2
Year86	0.004	0.062	1.7	-0.141	0.090	0.0
Year87	-0.111	0.066	0.4	-0.145	0.089	0.1
Year88	-0.110	0.066	1.2	-0.113	0.088	0.0
Year89	-0.172	0.067	4.9	-0.136	0.089	2.6
Year90	-0.187	0.069	0.0	-0.252	0.095	0.4
Year91	-0.220	0.072	0.7	-0.267	0.101	2.1
Year92	-0.041	0.066	5.2	-0.075	0.092	0.4
Year93	-0.153	0.071	0.0	-0.305	0.106	0.0
Year94	-0.142	0.081	1.0	-0.109	0.110	1.0
Log likelihood	3,749			1900		
Normality test $\chi^2(2)$	1.3			4.2		
Observations	62,737			43,594		

Note: All explanatory variables are lagged at least 1 year relative to the base year, see section 3.2 for details. A number of interaction terms are included in the estimation for men, but not shown. The reference person is less than 30 years of age, without formal educational qualifications (or of unknown educational status), single, working in the service sector.

Table A.6. Matching quality in terms of imbalance of individual characteristics, for the disposable income sample for men and women (matching is conditioned on the propensity score, year of the injury, and disposable income intervals). Two-sample t-tests and standardised differences (% bias) are given

	Men				Women			
	Matched controls	Injured			Matched controls	Injured		
	Mean	Mean	Two-sample t-test	%bias	Mean	Mean	Two-sample t-test	%bias
Age 30-39	0.24	0.25	0.4	1.3	0.23	0.25	-1.1	5.4
Age 40-49	0.20	0.20	0.1	0.5	0.25	0.26	-0.4	2.0
Age 50-59	0.04	0.05	1.2	4.4	0.09	0.08	0.6	-2.8
Couple	0.39	0.38	-0.4	-1.3	0.59	0.61	-0.5	2.5
#Children 0-6 years	0.12	0.13	0.9	3.0	0.19	0.18	0.2	-0.8
#Children 7-14 years	0.16	0.15	-0.7	-2.4	0.20	0.24	-2.2	10.1
Province	0.73	0.73	0.2	0.7	0.69	0.72	-1.3	6.0
Exp. (years/100)	0.09	0.10	0.7	2.5	0.08	0.08	0.1	-0.6
Exp. sq (years/100)	0.01	0.01	0.4	1.5	0.01	0.01	0.3	-1.3
Log(disp.inc)	10.96	10.96	-0.2	-0.9	10.65	10.67	-0.4	1.7
Vocational education	0.36	0.37	0.7	2.6	0.26	0.28	-0.8	3.9
College education	0.04	0.04	0.4	1.3	0.07	0.07	-0.2	0.9
Bachelor degree	0.04	0.04	-0.5	-1.9	0.06	0.07	-0.8	4.0
Master's degree	0.03	0.02	-1.0	-3.5	0.04	0.04	-0.4	1.7
No Unempl. Insurance	0.25	0.23	-0.9	-3.2	0.27	0.25	0.8	-4.0
Manufacturing	0.22	0.23	0.5	1.8	0.10	0.11	-0.6	2.9
Construction	0.09	0.09	-0.1	-0.2	0.01	0.01	-0.3	1.3
Infrastructure	0.06	0.06	0.1	0.3	0.02	0.03	-0.9	4.1
Financial services	0.04	0.04	0.9	3.2	0.05	0.05	0.2	-1.0
Other industries	0.20	0.20	0.1	0.3	0.26	0.24	1.1	-5.3
Public sector	0.01	0.01	0.4	1.1	0.37	0.38	-0.5	2.3
#of prev. hosp. admiss	0.03	0.04	0.4	1.5	0.01	0.01	-0.7	2.8
Dur. prev admissions	0.12	0.11	-0.4	-1.4	0.05	0.04	0.3	-1.5
Sick. benefits (days)	0.11	0.14	2.9	10.3	0.09	0.10	-0.5	2.3
Year88	0.13	0.13	0.0	0.0	0.14	0.14	0.0	0.0
Year89	0.13	0.13	0.0	0.0	0.12	0.12	0.0	0.0
Year90	0.12	0.12	0.0	0.0	0.11	0.11	0.0	0.0
Year91	0.12	0.12	0.0	0.0	0.13	0.13	0.0	0.0
Year92	0.13	0.13	0.0	0.0	0.11	0.11	0.0	0.0
Year93	0.12	0.12	0.0	0.0	0.13	0.13	0.0	0.0
Year94	0.11	0.11	0.0	0.0	0.11	0.11	0.0	0.0
Propensity score	-2.03	-2.02	0.1	0.0	-2.30	-2.30	-0.2	0.0
# of observations	1,601	1,601			914	914		

Note: The standardised difference in per cent is:

$$100(\overline{x}_{treated} - \overline{x}_{mcontrols}) / [(s^2_{treated} + s^2_{mcontrols}) / 2]^{½}$$

Table A.7. Matching quality in terms of imbalance of individual characteristics, for the employment sample for men and women (matching is conditioned on the propensity score, year of the injury, and employment intervals). Two-sample t-tests and standardised differences (% bias) are given

	Men				Women			
	Matched controls	Injured			Matched controls	Injured		
	Mean	Mean	Two-sample t-test	%bias	Mean	Mean	Two-sample t-test	%bias
Age 30-39	0.26	0.25	-0.3	-0.9	0.25	0.27	0.9	3.8
Age 40-49	0.20	0.18	-1.4	-4.3	0.25	0.25	0.1	0.2
Age 50-59	0.04	0.04	0.5	1.5	0.07	0.07	0.6	2.6
Couple	0.41	0.42	0.7	2.2	0.64	0.63	-0.7	-3.1
#Children 0-6 years	0.15	0.15	0.0	0.1	0.21	0.20	-0.5	-2.3
#Children 7-14 years	0.17	0.16	-1.3	-4.0	0.26	0.26	-0.2	-0.6
Province	0.71	0.71	0.3	1.1	0.69	0.69	0.1	0.4
Exp. (years/100)	0.10	0.10	-0.7	-2.1	0.08	0.08	1.2	5.3
Exp. sq (years/100)	---	---	---	---	0.01	0.01	0.7	3.2
Vocational education	0.40	0.41	0.1	0.3	0.29	0.30	0.2	1.0
College education	0.04	0.04	-0.5	-1.7	0.08	0.08	-0.4	-1.7
Bachelor degree	0.04	0.04	-0.6	-2.0	0.08	0.08	0.4	1.7
Master's degree	0.02	0.03	0.5	1.6	0.03	0.03	0.5	2.2
No Unempl. Insurance	0.20	0.18	-1.3	-4.0	0.18	0.17	-0.3	-1.2
Manufacturing	0.25	0.26	0.4	1.2	0.14	0.13	-0.4	-1.6
Construction	0.11	0.11	-0.2	-0.5	0.01	0.01	0.5	2.3
Infrastructure	0.08	0.07	-0.7	-2.2	0.03	0.03	-0.3	-1.1
Financial services	0.04	0.04	0.3	1.0	0.05	0.06	0.9	4.0
Other industries	0.14	0.13	-1.2	-3.7	0.12	0.12	0.1	0.6
Public sector	0.19	0.19	-0.2	-0.6	0.48	0.47	-0.3	-1.1
#of prev. hosp. admiss	0.00	0.00	0.3	0.8	0.01	0.01	0.7	2.8
Dur. prev admissions	0.03	0.03	0.9	2.7	0.04	0.04	0.4	1.8
Sick. benefits (days)	0.11	0.09	-1.4	-4.3	0.09	0.09	0.4	1.7
Employment rate	0.73	0.73	-0.1	-0.2	6.99	6.99	0.0	0.0
Employ. degree sq.	0.64	0.64	-0.1	-0.2	---	---	---	---
Year85	0.11	0.11	0.0	0.0	0.11	0.11	0.0	0.0
Year86	0.11	0.11	0.0	0.0	0.09	0.09	0.0	0.0
Year87	0.10	0.10	0.0	0.0	0.11	0.11	0.0	0.0
Year88	0.09	0.09	0.0	0.0	0.10	0.10	0.0	0.0
Year89	0.09	0.09	0.0	0.0	0.08	0.08	0.0	0.0
Year90	0.08	0.08	0.0	0.0	0.06	0.06	0.0	0.0
Year91	0.08	0.08	0.0	0.0	0.09	0.09	0.0	0.0
Year92	0.09	0.09	0.0	0.0	0.08	0.08	0.0	0.0
Year93	0.08	0.08	0.0	0.0	0.09	0.09	0.0	0.0
Year94	0.07	0.07	0.0	0.0	0.08	0.08	0.0	0.0
Propensity score	-1.98	-1.98	0.1	0.0	-2.28	-2.29	0.2	0.0
# of observations	2,068	2,068			1,070	1,070		

Note: The standardised difference in per cent is:

$$100(\overline{x}_{treated} - \overline{x}_{mcontrols}) / [(s^2_{treated} + s^2_{mcontrols}) / 2]^{½}$$

Table A.8. Matching quality in terms of imbalance of individual characteristics, for the wage sample for men and women (matching is conditioned on the propensity score, year of the injury, and wages intervals). Two-sample t-tests and standardised differences (% bias) are given

	Men				Women			
	Matched controls	Injured			Matched controls	Injured		
	Mean	Mean	Two-sample t-test	%bias	Mean	Mean	Two-sample t-test	%bias
Age 30-39	0.28	0.28	0.1	0.6	0.35	0.31	-1.0	-7.8
Age 40-49	0.25	0.24	-0.1	-0.7	0.31	0.34	0.7	5.9
Age 50-59	0.05	0.06	0.8	4.4	0.07	0.09	0.9	6.6
Couple	0.58	0.57	-0.1	-0.6	0.65	0.70	1.6	12.4
#Children 0-6 years	0.20	0.19	-0.5	-2.5	0.18	0.17	-0.5	-4.0
#Children 7-14 years	0.23	0.22	-0.4	-2.3	0.28	0.29	0.1	0.7
Province	0.68	0.69	0.7	3.6	0.60	0.64	1.1	8.8
Exp. (years/100)	0.13	0.13	0.1	0.4	0.13	0.13	0.0	0.1
Exp. sq (years/100)	0.02	0.02	0.0	-0.2	0.02	0.02	0.1	0.4
Log(wages)	4.26	4.25	-0.3	-1.6	4.07	4.07	0.2	1.3
Vocational education	0.46	0.47	0.2	1.1	0.34	0.34	-0.2	-1.3
College education	0.09	0.08	-0.8	-4.1	0.12	0.12	0.0	0.0
Bachelor degree	0.07	0.07	-0.1	-0.6	0.15	0.15	0.1	0.9
Master's degree	0.04	0.03	-0.6	-3.1	0.02	0.03	0.5	3.7
No Unempl. Insurance	0.17	0.17	0.1	0.8	0.17	0.16	-0.6	-4.9
Manufacturing	0.28	0.26	-0.7	-3.5	0.08	0.11	1.5	11.5
Construction	0.08	0.09	0.3	1.5	0.01	0.01	0.0	0.0
Infrastructure	0.07	0.08	0.9	4.8	0.03	0.03	0.2	1.8
Financial services	0.05	0.05	-0.2	-1.3	0.09	0.10	0.5	4.1
Other industries	0.05	0.06	0.5	2.5	0.02	0.02	-0.3	-2.0
Public sector	0.25	0.25	0.0	0.0	0.59	0.54	-1.2	-9.2
#of prev. hosp. admiss	0.00	0.00	-0.2	-1.1	0.00	0.00	0.7	5.9
Dur. prev admissions	0.01	0.01	0.5	2.6	0.02	0.03	0.7	5.4
Sick. benefits (days)	0.02	0.02	0.6	3.0	0.02	0.01	-0.5	-3.8
Unemployment rate	0.01	0.02	0.4	1.9	0.01	0.01	0.3	2.5
Year85	0.11	0.11	0.0	0.0	0.13	0.13	0.0	0.0
Year86	0.12	0.12	0.0	0.0	0.09	0.09	0.0	0.0
Year87	0.09	0.09	0.0	0.0	0.09	0.09	0.0	0.0
Year88	0.09	0.09	0.0	0.0	0.10	0.10	0.0	0.0
Year89	0.08	0.08	0.0	0.0	0.09	0.09	0.0	0.0
Year90	0.07	0.07	0.0	0.0	0.07	0.07	0.0	0.0
Year91	0.06	0.06	0.0	0.0	0.06	0.06	0.0	0.0
Year92	0.10	0.10	0.0	0.0	0.10	0.10	0.0	0.0
Year93	0.08	0.08	0.0	0.0	0.05	0.05	0.0	0.0
Year94	0.07	0.07	0.0	0.0	0.09	0.09	0.0	0.0
Propensity score	-2.20	-2.19	0.1	0.0	-2.40	-2.39	-0.1	0.0
# of observations	710	710			328	328		

Note: The standardised difference in per cent is:

$$100(\overline{x}_{treated} - \overline{x}_{mcontrols}) / [(s^2_{treated} + s^2_{mcontrols}) / 2]^{½}$$

Figure A.1 Density of the linear predictor of road injury risk, 1987-94, men, disposable income sample

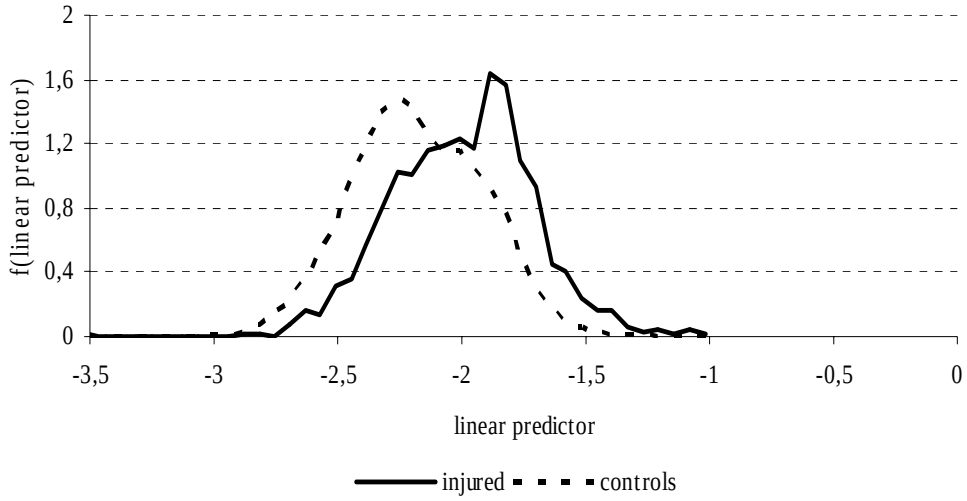

Figure A.2 Density of the linear predictor of road injury risk, 1987-94, women, disposable income sample

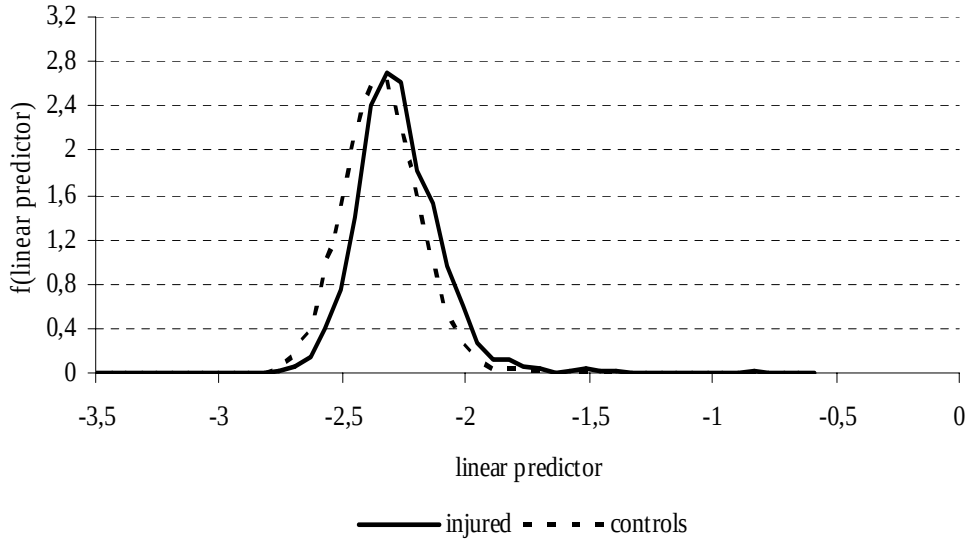

Figure A.3 Density of the linear predictor of road injury risk, 1984-94, men, employment sample

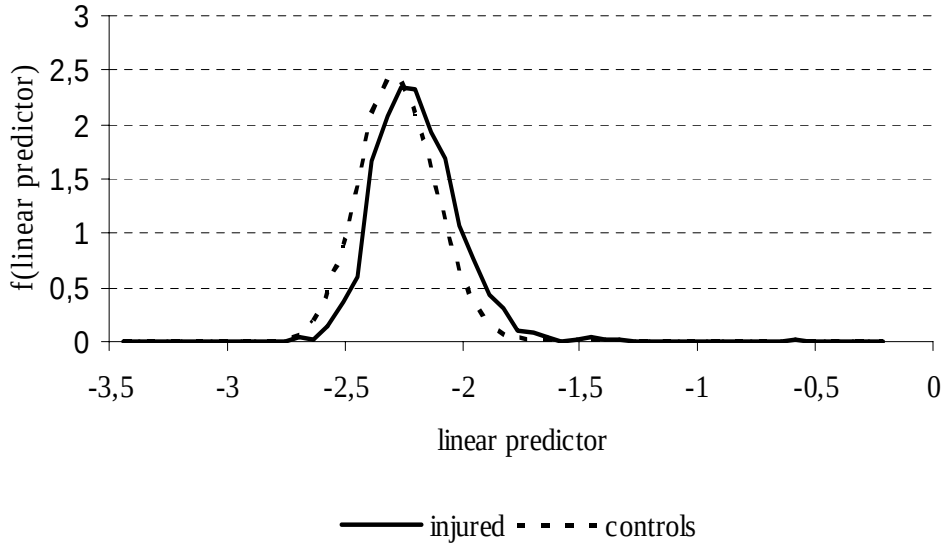

Figure A.4 Density of the linear predictor of road injury risk, 1984-94, women, employment sample

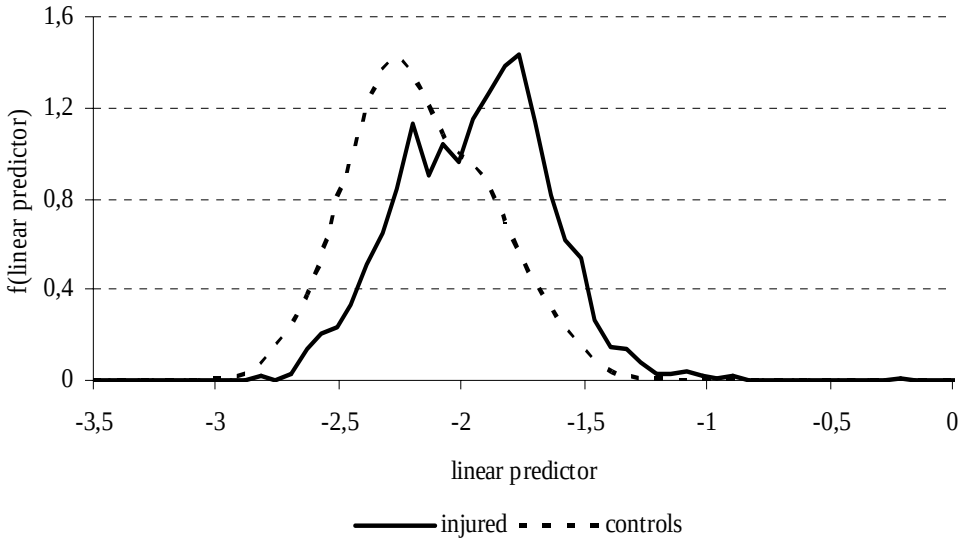

Figure A.5 Density of the linear predictor of road injury risk, 1984-94, men, wage sample

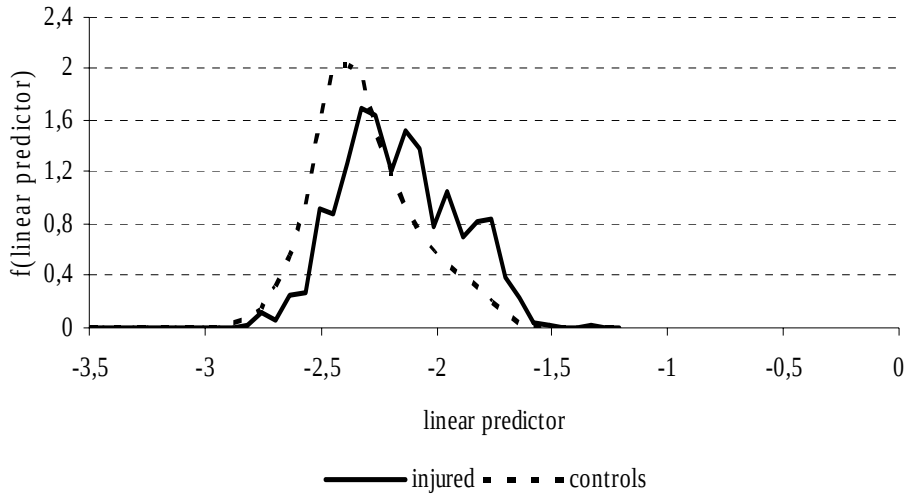

Figure A.6 Density of the linear predictor of road injury risk, 1984-94, women, wage sample