The Short-run Health Costs of Unemployment

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May 2006
VERY PRELIMINARY

Abstract

This paper studies how the (short-run) monetary costs associated with take-up of health care benefits is affected by unemployment. We use individual social security register data matched to health insurance records from a large region in Austria. These data provide high-quality information on the type of health care benefits (including diagnoses) that an unemployed workers causes to the health insurance fund. We use instrumental variable techniques to tackle the issue of reverse causality using job loss due to plant closure as an instrument. Plant closure strongly disruptes workers' employment careers but workers' health is unlikely to cause a plant closure.

We find that one additional day in unemployment (during the year that follows a job loss) increases the costs to the health insurance agency (during that same year) by 7.70 Euros (9.30 USD) for men and 5.30 Euros (6.40 USD) for women. This is on the order of 10 percent of both the male and the female daily wage. Most of these costs are due to higher sickness transfer payments that are paid to unemployed workers not capable of searching for a new job and to employed workers not capable of working. We also find that higher unemployment decreases doctor consultations, does affect hospitalization costs that are caused by mental health problems for males and overall hospitalization costs for women. Except for psychotropic drugs for males, drug prescriptions are not significantly affected by unemployment.

JEL classification: I12, I19, J28, J65

Keywords: Social cost of unemployment, health, non-employment, plant closure

*We thank Dr. med. Ruth Lalive d'Epinay for helpful discussions regarding the classification of the drugs. Financial support by the Austrian National Bank under the grant No. 10643 is gratefully acknowledged. Address: Andreas Kuhn, IEW, Bluemlisalpstrasse 10, CH-8006 Zurich, Switzerland, email: akuhn@access.unizh.ch. Rafael Lalive, IEW, Bluemlisalpstrasse 10, CH-8006 Zurich, Switzerland, e-mail: rlalive@iew.unizh.ch. Josef Zweimüller, IEW, Bluemlisalpstrasse 10, CH-8006 Zurich, Switzerland, e-mail: zweim@iew.unizh.ch.

1 Introduction

What are the costs of unemployment? While economists typically emphasize the loss of income (for the individual and in the aggregate)[1], researcher from other discipline such as social psychology, sociology, and social medicine have been arguing since a long time that unemployment may have a strong impact on an individual's health. A common hypothesis is that unemployment leads to emotional distress. Such distress is either due to the financial strain associated with the loss in income or, more importantly, due to the emotional damage that unemployment does to an individual's self-esteem. When such strains are long-lasting, a worker's resistance to (psycho-somatic and mental) illnesses may be seriously weakened.

One major difficulty in assessing the impact of unemployment on costs associated with workers' deteriorating health is reverse causality. While there are many good reasons why unemployment may indeed have negative health consequences, empirical work has to tackle the main difficulty of establishing a causal effect beyond mere statistical association. As long as we cannot rule out that bad health may be a reason that pushes people into unemployment, we cannot separate the effect of unemployment on health from compositional effects.

The present analysis sheds new light on the health-unemployment relationship by studying the causal effect of unemployment on the short-run costs (incured by health insurance funds) associated with take-up of health care benefits. Our study is innovative in at least three important respects. *First*, it tackles the causality issue by applying modern econometric techniques that have been recently developed to study causal relationships in economics. We apply IV-estimation techniques using plant closure as an instrument for unemployment. This instrument is strongly correlated with subsequent unemployment but unlikely to be correlated with workers' health situation. Moreover, chronic strains (psychological and financial distress) following a job loss are most likely due to the subsequent unemployment experience rather than to the job-loss as such.

The *second* innovative feature of our study concerns the health indicator we use to measure emotional distress. Our data set is informative on individuals' take-up of health benefits provided by mandatory health insurance in the short run. It contains information on all costs incured by the health insurance fund. In order to measure the impact of involuntary unemployment on these health costs we focus on the following health care benefits: sick leave benefits, doctor consultations, hospitalizations, and drug prescriptions. For hospitalizations and drug prescription we know the detailed cost types (diagnoses and types of drugs, respectively). Hence this is the first study that provides a comprehensive picture on the short-run health costs caused by unemployment.

A further dimension where our paper differs from much of the previous literature relates to the coverage and quality of our data set. Our data are taken from a large regional health insurance fund in Austria, ("Gebietskrankenkasse Oberösterreich") which covers about one sixth of the Austrian population and work force. The data are informative on both a worker's health and his or her employment and earnings history. The data are exhaustive in the sense that all private sector worker in this region

[1]Despite the potentially high costs that unemployment imposes on individuals, economists have almost exclusively concentrated on macroeconomic costs, such as the loss of aggregate output and the fiscal burden associated with joblessness. Only recently have economists begun to study how the subjective well-being of individuals is affected when they experience unemployment (see e.g. Oswald 1997 or Frey and Stutzer 2002 for recent overviews).

are covered. The data are very unlikely to suffer measurement error and/or underreporting.

Our paper is related to an old literature that has been emphasizing the negative consequences of the experiences of unemployment on well-being of workers. This literature, starting with Jahoda et al. (1975), sociologists and social psychologists have argued that unemployment has strong effects on individuals' emotional health, such as loss of self-confidence and self-esteem, depression, anxiety, and strained personal relations. Subsequently, researchers in these disciplines have developed various theories that emphasize particular channels by which unemployment may affect health and, more generally, the well-being of individuals.

Unemployment is associated with loss of self-esteem and feelings of personal failure. Jahoda (1981) mentions that individuals suffer form unemployment because it deprives them from basic needs. Having a job imposes a time structure on individuals; it implies regular contact and shared experiences with co-workers; it links individuals to others' goals; having a job defines the status of an individual and is part of one's identity. As a result, people suffer from unemployment even after having lost a job that was consciously experienced as bad. A related point concerns the observation that most people would continue working, even if it would not be necessary in order to earn one's living (see e.g. the classical study by Morse and Weiss 1955).

Sen (1997) mentions the importance of loss of freedom that is experienced by the unemployed that goes beyond the loss in income. Unemployment can be a major factor in predisposing people to social exclusion, depriving them not only of economic opportunities but also from social activities such as participation in the life of the community, which may have several consequences for emotional health of individuals (see also Solow 1990). Other channels through which unemployment may feed back to health (e.g. increase alcohol use, loss the loss of time structure in everyday life) are results of distress resulting from role loss or severe role threatening caused by unemployment.

Many recent approaches to link unemployment to a worker's health rely on stress theory (see e.g. Pearlin 1989 for an overview of sociological stress theory). Unemployment is considered as a major stressor. One domain where stresses occur is on the financial side. Often the reduction in disposable income requires substantial adjustment by the individual and involved families. This exposes individuals not only to economic hardship, but in addition to the income losses to serious psychological distress. Many studies have found that financial strain causes substantial psychological harm (e.g. Kessler et al. 1987, Turner 1995). The second domain rests on the damage that unemployment does to an individual's self-concept. Unemployment implies loss of social status associated with the previous job and deprives the individual from a socially accepted role. Furthermore, unemployment also implies a status that is often seen as deviant and shameful by the social environment. Marsh and Alvaro (1990), for example, interpret their finding of different distress symptoms of unemployed individuals in Spain and the UK as resulting partly from differences in work ethics.

When such distress persists for prolonged periods of time individuals' resistance to illnesses may be seriously affected and unemployed workers may end up with severe health problems (see Dooley et al. 1996). Such health responses to unemployment range from physical illnesses (Kessler et al. 1987) to mortality (Brenner 1973, 1979), especially suicide. However, the most frequently observed response of health to unemployment relates to suspected mental health effects. Studies that have empirically addressed this issue predominantly work with self-reported measures of mental health problems (e.g. Björklund 1985) or admissions to mental hospitals (e.g. Agerbo et al. 1998 and Westergaard-Nielsen et al. 2003).

A second strand of literature which is of importance here are studies discussing differential exposure and differential vulnerability to distressing events like unemployment. It is argued here that there are mainly differences in coping strategies (Pearlin and Schooler 1978) and different subjective meanings attached to various (undesirable) life events which are threatening a specific role (see e.g. Turner 1995).

Many previous studies, especially in economics, have been concerned with the effect of unemployment on subjective well-being. These studies confirm the hypothesis that unemployment may have strongly detrimental effects on an individuals psychological health. Flatau et al. (1998), using data on mental health and on subjective well-being from Australia, conclude that unemployment and some measures of well-being are consistently and strongly correlated. For the UK, Clark and Oswald (1994) also find a negative effect of unemployment on subjective well-being. In fact, they conclude that the negative impact of job loss may be larger than for separations or divorces. Winkelmann and Winkelmann essentially find the same negative effect on subjective wellbeing for Germany and Agerbo et al. (1998) reach similar conclusions for Danish data. Other studies focus on youth workers and they also find detrimental effects of unemployment on well-being, as Goldsmith et al. (1996) for the United States and Korpi (1997) for Sweden. Suggestive of the existence of contextual effects are the studies by Shields and Price (2001) or Stutzer and Lalive (2004), for example.

The paper is organized as follows: Section 2 discusses our identification strategy which implements an instrumental variable estimator to assess the effects of unemployment on short-run health costs. Section 3 presents the data sources, discusses the definition of the interesting variables, and provides first descriptive evidence on the relationship between unemployment and health costs. In Section 4 we present our results. We first look at the cross-sectional relationship between unemployment and health costs before we show the results from the instrumental variable estimation. Section 5 concludes.

2 Estimating the causal impact of unemployment on health

Define Y_i as the health costs attibutable to individual i (i.e. payments incurred by the health insurance fund that are associated with take-up of health insurance provisions of a particular individual) and by D_i the number of days that the individual spent in unemployment. Both Y_i and D_i are measured within one particular year. (Note that D_i is not a binary but a multi-valued treatment.) Suppose D_i and Y_i are related by the following linear relationship

$$Y_i = \beta_0 + \beta_1 D_i + X_i \gamma + u_i$$

where X_i is a vector of control variables and u_i is an error term capturing the effect of ommitted variables affecting health costs, and β_0, β_1, and γ are coefficients to be estimated, the parameter of our main interest being β_1. The OLS estimate of β_1 is potentially bias because of endogeneity of the unemployment variable D_i. Days spent in unemployment D_i are likely correlated with u_i simply because a bad health status (that leads to high health costs) may also affect the duration that an individual spends in unemployment.

To tackle the problem of endogeneity we use an instrument variable approach. This approach utilizes exogenous variation in the treatment variable D_i which is generated by some exogenous factor. First of all one has to essentially think of a situation, where variation in unemployment is not driven by individuals' health status. Because these methods do not in general identify a causal effect, it is then essential to discuss the additional assumptions necessary to draw any plausible causal inference (Imbens and Angrist 1995 and Angrist et al. 1996).

We use employment in a plant closure firm as our instrument for the number of days in unemployment during the year that follows a job loss. We define Z_i as a binary variable, that equals 1 if a person is employed in a plant closure firm at the reference date and equals 0 if a person is employed in a firm that continues to exist after some reference date. Let Y_i be health costs caused by individual i during the year after the reference date and let D_i denote the number of days in unemployed during the year after the reference date. Neglecting control variables the instrumental variable estimator is equal to the simple Wald estimator

$$\beta_{IV} = \frac{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]}{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]}.$$

The Wald estimator measures the difference in health costs of plant closure and non-plant closure workers divided by the excess unemployment days for plant closure workers as compared to non-plant closure workers. To interpret the Wald estimator in a causal way in a situation with heterogeneous responses to treatment, one has to impose additional assumptions beyond the usual assumptions invoked when using IV methods.

In order to evaluate if plant closure is a valid instrument for the causal effect of nonemployment on drug usage, it has to satisfy several assumptions, the key assumptions will be discussed below (Imbens and Angrist 1995).

(i) The first assumption concerns the ignorability (the randomness) of the instrument. Stated in terms of potential outcomes

$$(Y_j, D_0, D_1) \quad \perp \quad Z$$

where Z is the (dichotomous) instrument, D_1 (D_0) are the potential treatment intensities for an individual working in a plant closure firm (non plant closure firm). Y_j is the potential outcome for a treatment intensity of j units. This first assumption thus essentially states that the instrument can be viewed as randomly assigned, so that both potential treatments and potential outcomes do not differ between the two sub-samples.

This is a strong assumption in our case, as we cannot plausibly assume a priori randomness of the instrument (see section 3 above), as there are both differences in the probability of plant closures between different firms and also between different individuals (because firms with different probability of shut-down have not necessarily the same composition of their work force). It is thus more realistic in our setting to assume ignorability of the instrument, conditional on observed (individual and firm) characteristics X

$$(Y_j, D_0, D_1) \quad \perp \quad Z \quad | \quad X.$$

We thus control for X parametrically using two stage least squares. As this assumption cannot be ultimately verified, it finally rests on arguments of plausibility.

Our first assumption also implies an exclusion restriction, i.e. the instrument must not have any direct effect on health costs. The assumption is that job-loss due to plant closure does not directly affect the health status of a worker. Essentially, we assume that a worker who finds a new job immediately does not suffer from health problems and hence does not take up additional health insurance provisions. Any effect on such health costs comes via days spent in unemployment.

(ii) The second assumption is that instrument must affect the treatment intensity. This assumption implies

$$E[D|Z = 1] > E[D|Z = 0].$$

Working in a plant closure firm at the reference date must increase unemployment duration during the year following the shut-down of the plant for at least some workers. As we will shown below, working in a plant closure firm has a huge impact on unemployment. Hence empirical evidence shows that the assumption is plausible.

(iii) The third assumption postulates that the instrument has to affect all individuals in the same way (monotonicity). That is, in our case required it is required that

$$D_1 \geq D_0 \quad \forall \quad i$$

This assumption states that, for each individual, the (potential) duration of unemployment during the year after the reference date is longer when the individual looses the job because the firm goes bankcrupt than when the individual does not loose the job due to plant closure. Although this assumption is not verifiable (because it involves potential and thus fundamentally unobserved outcomes), it has a testable implication in the case of a non-binary treatment, in that the empirical cumulative distribution functions of the treatment variable should not cross for the two sub-samples (see Angrist and Imbens 1995).

Angrist and Imbens (1995) show that – if all three of the above mentioned assumptions hold – the Wald estimator measures the following average causal response (ACR) parameter

$$\frac{E[Y_i|Z_i = 1] - E[Y_i|Z_i = 0]}{E[D_i|Z_i = 1] - E[D_i|Z_i = 0]} = \sum_j \omega_j E[Y_j - Y_{j-1}|D_1 \geq j > D_0].$$

The ACR is a weighted average of causal responses for individuals which are induced to change their treatment intensity with the weights ω_j being proportional to the share of individuals who change their treatment from less than j to j or more units on the treatment. That is, if the stated assumptions hold, we can estimate an average causal effect running from nonemployment to health for individuals which are induced an increase their duration of nonemployment due to the fact that they are working in a plant closure firm. The ACR depends on both the instrument used and and on the distribution of the treatment variable. This means that any estimated causal effect does not necessarily coincide with health effects of nonemployment resulting from other sources of job-loss.

3 Data and Descriptive Statistics

3.1 Data Sources

We draw on social security register data that are linked to expenditures data form the statutary health insurance fund from a large region in Austria ("Upper Austria").[2] This data set covers individuals that are employed in the private sector. Social security register data provide information, on a daily basis, on the workers' earnings and employment history (collected for the purpose of calculating a worker's old age social security benefits). Data from the statutory health insurance record all contacts between the worker and the health insurance fund that lead to payments by the health insurance fund for the the worker's take-up of health care benefits.

The data set is unique in the following respects. First, the data set links information on workers' labor market performance and workers' take-up of health insurance provisions. These problems. In Austria, health insurance is mandatory for all employees. A firm who hires a new employee is obliged to immediately register the worker with the regional health insurance fund. As contribution payments depend on wages, the health insurance fund collects information not only on employment histories of workers, but also on their labor earnings as well as a number of individual characteristics (such as age, broad occupation, and sex).

A second unique feature of the available data set is that it covers the universe of the Upper Austrian private sector employees (more than 80 % of the active state population). There is mandatory health insurance for these workers covers.[3] Each worker-observation can be linked to a firm via a firm-identifier. Because the data cover the universe of workers we can perfectly reconstruct firms. A "firm" is simply defined as the set of individuals that is observed under a given employer social security number ("firm identifier") at a given date. This is particularly helpful for our estimation strategy which relies on a firm characteristic: the date of shut-down of a firm. Firm information is further helpful in making plant-closure workers better comparable to employees in ongoing firms thus allowing to compare samples of workers with similar previous job situations.

A third unique feature is related to the measurement of a worker's health situation. Every employee has access to primary health care benefits provided by the regional health insurance fund.[4] Among others benefit, the fund covers all costs of associated with medical treatments of insured individuals and reports the associated payments incurred by the health insurance fund that are associated with take-up of the various health care provisions by insured individuals. These payments can be broadly divided into the following categories (see Table A1 for an exact definition of these categories and further subcategories used in the empirical analysis below):

(i) Sick leave transfers. These are payments to employed and unemployed workers during periods of sickness (when they are not capable of searching for a new job or not capable of working). This

[2]Health insurance administration is divided into regional units ("Gebietskrankenkassen", GBKK) and our data set comes from that GBKK of Upper Austria, which is one of totally nine Austrian states, located in the north–east of the country. This region covers about one sixth of the total Austrian population and work force.

[3]There are separate funds for the self-employed, the farmers, public sector workers, and employees of several public utility firms, so not the entire population is covered).

[4]Benefits covered by the Fund are comprehensive. It covers all costs associated with a primary health care such as treatment by physicians, drug prescriptions, and hospitalized care.

benefit is roughly equal to a worker's wage when employed and to the unemployment benefit when the worker is unemployment. Days of sick leave transfers do not reduce the number of (remaining) days during which an unemployed worker is eligible to regular unemployment benefits. Hence, by going on sick leave, a workers can, in principle, extend the duration of benefits. However, in order to claim sick leave benefits, a physician has to approve a workers impaired health situation.

(ii) Doctor consultations. Doctors have contracts with the health insurance fund and get paid for each consultation by insured workers.

(iii) Hospitalization (including diagnoses). The data record each hospitalization and details the particular reason for the hospitalization. In particular, it classifies the costs by the main diagnosis of the hospitalization accroding to the ICD-9 codes. We aggregate the diagnoses into the following reasons for hospitalization: cancer, heart desease, mental health problems, respiratory diseases, cerebrovascular diseases, and other diseases.

(iv) Drug prescriptions (including detailed types of prescribed drugs). The data record all payments to drug stores (or refund to individuals) for prescribed and self-medicated drugs. The data are extremely detailed concerning the type of drugs. We classify these drugs into a category that is "specific" to treat health problems associated with unemployment and a residual category of non-specific drugs. Among specific drugs we distinguish "psychosomatic" drugs (targeted at psychosomatic afflictions such as migrain therapeutics, antiinflammatory drugs, etc.) and "psychotropic" drugs (treating psychological distress such as sedatives, benzodiazepins, antidepressants, etc.).

Table A2 in the appendix reports the yearly health costs per individual. Overall health costs per year and per individual are 1112 Euros (1334 USD) for males and 1176 Euros (1411 USD) for females. A large fraction of these overall health costs is due to sick-leave transfer payments. For males, almost 50 percent of overall health costs are due to such transfers whereas for females sick leave transfer payments account for less than 30 percent. The reason for these unequal sick leave benefit payments for males and females, respectively, is that these payments are closely linked to previous earnings. Hence the higher payments for males are mainly due to the fact that males get a higher benefits per day on sick leave and to a smaller extent to more days on sick leave. Other health costs arise from medical treatments. For the remaining categories health costs caused by males amount of 183 Euro for doctor consultations, 250 Euros for hospitalizations, and 119 Euros for drug prescriptions. For females, health costs are considerably higher in each of these categories. Their yearly costs arising from doctor consultations are 345 Euros, from hospitalizations 330 Euros and from drug prescriptions 176 Euros. This is in line with the prejudice that females are more health-conscious than males.

The data of transfer payment from the health insurance fund cover the five-year period from January 1, 1998 to December 31, 2002. To get information on the previous work experience as well as on tenure with the current firm, we linked the data from the health insurance fund with the Austrian social security register data (ASSD) provided by the central social security agency ("Hauptverband der Sozialversicherungsträger"), which covers the individuals' earnings and employment histories from January 1, 1972 to December 31, 2002.[5]

[5]The Central Social Security Administration gets its data from the Funds and process this information for the purpose of calculating of old-age calculating of old-age social security benefits. So retrospective data from the Central Social Security Administration are collected in the same way as the recent data from the Fund.

To link the information of individual health costs and individual unemployment experiences we constructed a monthly panel of individuals' health and employment histories. Within the period 01.1998 and 12.2002, we measure the health costs of an individual by calculation overall health costs and disagregated these costs into the above categories and subcategories. To calculate the days in unemployment we make use of the daily information provided by the social security register data and aggregated unemployment days on a monthly basis. (Here "unemployment" does not necessarily mean that an individual is eligible to unemployment insurance benefits, nor does it means that the individual is counted as unemployment by the unemployment insurance office. However, most of the unemployment days captured in our data are covered by unemployment insurance).

3.2 Definition of plant closure

As mentioned above, in order to assess the causal impact of unemployment on health costs we use plant closure as an instrument for an individual's unemployment. The assumption is that workers in a plant-closing firm loose their job involuntarily, whereas for other job separations it is not clear whether such separation results from a quit or a layoff. Let us first make precise how we define a "plant closure" and how we define job-loss due to plant closure.

Definition of plant closure firms. To identify plant closure in our data it is particularly helpful that employer and employee information can be matched. In a first step, we use this information to identify, a "plant closure". A firm is considered as a plant closure firm if it fulfills the following criteria: (i) There has to be positive employment through at least 12 months up to some month t and zero employment from month $t+1$ through month $t+12$. (ii) If a firm disappears at date t no more than 50 percent of the employees swith to the same employer at date $t+1$. (This latter criterion is adopted to rule out misclassification of a take-over as a bankcrupcy). Whenever more than 50 percent of the employees are found under an identical new employer identifier these observations are excluded from the sample. Furthermore, we exclude "distressed" firms from the sample. To make the distinction between plant closure firms and non-plant closure firms as clean as possible all firms with large and long-lasting drops in employment (and thus all workers employed in theses firms) are excluded from the sample.

We consider all plant closures that take place between January 1999 and December 2001 (using the 10th of each month as the baseline date). In the final selection of plant-closure and non-plant closure firms we leave out the first and the last year (1999 and 2001) so that we have – for each individual – at least one year of information before and after the plant closure date.

Definition of plant closure and non-plant closure workers. Just like plant closure firms, we define plant closure workers in a narrow sense. Our plant closure sample (PC) consists of all workers, who are still employed in the month of plant closure of who were employed in one months during the year before plant closure (but left before the effective shut-down of the plant). Hence our sample of plant-closure worker also includes "early leavers".

Non-plant closure workers are sampled randomly of among all workers employed in non-plant closure firms and non-distressed firms. We take a 2.5 % random sample of from the universe of the control group of all small firms (3 or 4 employees) and a 0.25 % sample of all larger firms (more than 4 employees). All employees in firms with less than 3 employees are excluded from the data. (If such a firm disappears, it is likely that this is just a recoding of the employer identifier rather than a bankruptcy).

3.3 Descriptive statistics

It is interesting to take a first look at the characteristics of these two groups. (See Appendix Table A3). Applying the sample selection procedure described above leave us with 53,303 individuals of which 14,602 are plant-closure workers and 39,701 are non-plant closure workers. The majority of plant-closure workers are blue collar, male, relatively young (on average 34.9 years) and relatively low paid (on average 17,194 Euros during the year before the plant closure date). The sample of non-plant closure workers has a higher fraction of females and a lower fraction of blue collars, is somewhat older (on average 36.7 years) and better paid (on average 20,769 Euros during the year before the plant-closure).

Plant closure workers were somewhat more frequently unemployed during the year before the plant closure date, (on average 37 days) than non-plant closure workers (on average 15 days) during the same year. During the year after the plant-closure date, however, the difference is much bigger. Non-plant closure workers spent on average still only 17 days in unemployment, whereas for plant-closure workers the number of days in unemployment increases to an average of 84 days in unemployment, more than twice as much as before. This suggests that plant closure is strongly correlated with subsequent unemployment and hence satisfies one criterion for a meaningful instrumental variable.

Figure 1 depicts both the evolution of unemployment experiences for plant-closure and non-plant closure workers. The unemployment measure used in Figure 1 is the number of days in unemployment per individual during the last quarter. We see that plant closure workers spent about 9 days per quarter in unemployment throughout the year before the plant closure date. In contrast, non-plant closure workers spent about 4 days in unemployment per quarter during the last year before the reference date. After the plant closure, unemployment soars for plant closure workers. In particular during the first three months the unemployment rises to an average of 25 days and then is reduced again continuously reaching a still notedly higher level than before. In contrast, the evolution of unemployment for non-plant closure worker is very similar after the plant-closure date.

Figure 1

Figure 2 shows the corresponding graphs for the evolution of health costs. We see that plant closure workers cause slightly higher health costs before the plant closure date than non-plant closure workers. After the plant closure, health costs more than double during the first months after the plant closure and then fall again. Interestingly, also for non-plant closure workers we find an increase in health costs. One reason for this increase is that we select on workers that are employed (and hence in good health) at the date of plant closure (and most likely during the months before that date) but may become sick after that date. Therefore is not surprising that we see an asymmetric evolution of the health care costs before and after the reference date. Moreover, the periods under consideration health costs were strongly increasing in general (in particular, in the years 2000-2002) which is reflected in the upward trend of health costs of non-plant closure workers after the reference (plant-closure) dates.

Figure 2

4 Empirical results

4.1 The cross-sectional relation between unemployment and health costs

We start with presenting some descriptive analysis that shows how health costs and unemployment are correlated in a cross-section of individuals. Since men and women cause different levels of costs to the health insurance fund and since it is likely that men have different health reactions to changes in their employment situations, we report all our estimates separately for men and for women.

Table 1 shows results for males from a simple cross-sectional regression with yearly overall health costs as the dependent variable. Column 1 regresses this variable on the number of unemployment days per year without any further control variables. It turns out that there is a positive relation between these two variables but the regression coefficient is not statistically different from zero. In Column 2 age, tenure, and firm size (as well as their square) and industry dummies are included as additional control variables. This does not have any major impact on results. Unsurprisingly we find that age has a significant effect on the health costs. In columns 3 and 4 we include regional dummies, calendar year dummies and dummies for month of unemployment entry (to capture seasonal effects) into the regression. It turns out that all regression coefficients stay roughly constant. Finally, in column 5 we include a worker's wage (and its square) into the regression. It turns out that including the wage rate of the worker (which is a good proxy for skills and education) is important and improves the fit of this regression. Interestingly, we find that, holding the wage constant, unemployment and health costs are even significantly negatively related. We also see that including the wage has an important impact on the estimated age-profile of health costs. Moreover, tenure and firm size coefficients turn out significant when we include earnings into this regression.

Table 1

Table 2 repeats the same regression for females. Just like for males, we do not find any positive association between individuals health costs and days spent in unemployment. And just like for males, woman's earnings are significantly associated with health costs. Furthermore including this and other additional control variables improves the overall fit of the regression. In what follows, all our regression results are based on the full set of control variables.

Table 2

In Tables 3 and 4 we split the total costs into their various components: sick leave benefits, doctor consultations, hospitalizations, and drug prescriptions. For ease of comparison column 1 repeats the respective last columns of Tables 1 and 2. For males (Table 3), it turns out that the signficantly negative coefficient of the unemployment variable is driven by the effect on unemployment on sick leave benefits. (Interestingly, a larger number of days in unemployment are associated with a lower number of days for which sick leave benefits are drawn). We also see that health costs slightly increase with days in unemployment due to doctor visits. No correlation between days in unemployment and costs due to hospitalizations and drug prescriptions can be detected.

Tables 3 and 4

For females (Table 4), we do not observe an significant relationship between overall costs and days in unemployment. Nevertheless we could, in principle, have significant (positive and negative) relationship when we disaggregate these costs in various subcategories. Table 4 shows that this is not the case, with doctor consultations being the sole exception. Just like for males, it seems that unemployed females visit the doctor more frequently during unemployment episodes.

4.2 The causal effect of unemployment on health costs

Our aim is to study the health costs caused by unemployment based on a comparison of unemployment experiences of plant-closure and non-plant closure workers. This is reliable identification strategy if the two groups do not differ with respect to their health status ex ante. To get a first hint whether this is indeed the case, we run a simple OLS regression on health costs before the plant-closure date on all variables included in the basic model (with all control variables) and include the plant-closure status as an additional control variable.

Table 5 includes the treatment dummy (=1 for plant closure workers, =0 for non-plant closure workers) into this regression for males. We find a positive point estimate for overall health costs (column 1) suggesting that subsequent plant-closure workers cause indeed higher health costs than non-plant closure workers. However, the coefficient is not statistically different from zero. This suggests that our assumption of no differences in average health status between the two groups of workers cannot be rejected by the data. This conclusion conclusion remains unchanged if we look at different subcategories of health costs. In all cases the standard error is much larger than the point estimate indicating no significant differences between the two groups for health costs due to sick leave benefits, doctor consultations, hospitalizations and drug prescriptions.

Table 5

The situation is similar for women as far as overall health costs are concerned (Table 6). We find a positive point estimate which is not statistically different from zero. When we split up costs in subcategories for different types of health insurance provisions, we find no significant effect for sick leave benefits and drug prescriptions. However, women in plant-closure firms cause higher costs due to doctor consultations and due to hospitalizations. According to these dimensions it seems that plant-closure women are somewhat more sickness-prone than non-plant closure women. In sum, however, the ex-ante difference between plant-closure workers and non-plant closure workers is not dramatic and not signficant overall. Hence we conclude that plant-closure and non-plant closure workers are also of a similar health status ex ante.

Table 6

In what follows we present IV-estimates on the causal effects of unemployment on health costs. To get a first impression none of these estimates includes control variables and focuses solely on the effect of unemployment on health costs. In column 1 of Table 7 we present, for males, the first stage which regresses the instrument (plant-closure status) on days spent in unemployment during the year after the plant-closure date. We see that the instrument works quite well. The coefficient is highly significant (the coefficient being more than 75 times larger than the standard error) and the impact is quantitatively important. The average plant closure worker spends 67 days more in unemployment than the average non-plant closure worker. The remaining 5 columns in Table 7 present the Wald estimator described in the last section. As mentioned there the Wald-estimator is identical to the IV-estimator when the instrument is binary. In the present context, the Wald-estimator calculates the ratio between the difference in health costs of plant-closure and non-plant closure workers and the difference in unemployment days between these two groups of workers. As can be seen from columns 2 to 6 of Table 7, the Wald estimator indicates that more days spent in unemployment cause an increase in the health costs. This increase is non-negligible: per additional day in unemployment health costs increase by 6.4 Euros (or 7.7 USD). Column 3 of Table 7 suggests that the increase in overall costs is entirely due to the increase in sick leave payments (to which employed and unemployed workers are eligible). Clearly, the higher sick leave payments drawn by individuals that are longer unemployed could be either due to more days on sick leave during an unemployment spell (a contemporaneous effect of unemployment on health) but could also be due to more sickness leaves during a subsequent job (a lagged effect of unemployment on health). Columns 4 to 6 show the effects of unemployment on the remaining health cost categories. Interestingly higher unemployment does not cause increasing costs due to doctors visits. Consultations do even seem to decrease during period of unemployment. We note that this result does not support the hypothesis that unemployed individuals have more time available and lower opportunity costs of seeing a doctor and hence, for a given health problem, will be more likely to consult a doctor. More days unemployment cause increasing health costs due to hospitalizations. However, the effect is comparably small amounting to 0.37 Euros per additional day in unemployment. Obviously, this small effect comes is due to the fact that only a small number of hospitalizations (each of which being expensive) occur. Finally, we do not find evidence for an unemployment effects on drug prescription costs.

Table 7

Table 8 repeats the above exercise for woman with very similar results. Just like for males, plant-closure turns out to be a very good instrument. The quantitative effect of plant closure status on subsequent days in unemployment for females is almost identical to that of males and also highly significant. Column 2 of Table 8 shows the causal effect of unemployment on overall health costs for females as suggested by the Wald estimator. We see that an increase in unemployment after plant closure by one day increases overall health costs by about 4 Euros (or 4.8 USD), an effect which is only about two thirds of the effect estimated for males. In column 2, we see that, just like for males, this effect is almost entirely due to an increase in sick leave benefits, which increase by 3.8 Euros per additional day in unemployment. Does this means that women are better able to cope with unemployment? Not necessarily. The reason is that sick leave benefits are closely tied to an individual's earnings. Since average earnings of Austrian females are roughly two thirds of those of males, we are led to conclude that unemployment causes very similar effects for both sexes. This result is further supported in column 4 of Table 8 which shows the effect of unemployment on consultation costs. Just like for males, one additional day in unemployment reduces consultation costs by roughyl 0.40 Euros per additional unemployment day. Moreover, unemployment increases hospitalization costs also for females. This effect is twice as large for women than for men. Interestingly, higher unemployment leads to a significant reduction in drug prescriptions, although this effect turns out to be relatively small.

Table 8

The simple Wald estimator of Tables 7 and 8 may be misleading because it does not account for control variables and omitting these variables may cause a bias in the unemplyoment effect on health costs. In Tables 9 and 10 we present IV-estimates that control for the various individual and firm characteristics that are available in our data set. Again, the first column reports the results from the first stage regression, where we estimate the impact of the plant closure status on days in unemployment. The results turn out to be very similar to Tables 7 and 8. Both for men and for women we find a strong quantitative impact of plant-closure status on unemployment. The effect is somewhat smaller for men, but almost identical for women. Similarly, the effect of unemployment on overall health costs is slightly larger than for the simple Wald estimator. For men, one additional day in unemployment causes additional health costs of 7.70 Euros (9.20 USD), whereas the corresponding effect for women is 5.30 Euros (6.40 USD). Both for men and for women, additional costs are additional sick leave benefits payments, which amount to 7.40 Euros (8.90 USD) for men and 4.70 Euros (5.60 USD) for women. The health costs arising from other types of health insurance provisions account for only a minor part of overall costs. Just like before doctor consultations significantly decrease when an individual suffers longer from unemployment. Costs arising from hospitalization increase significantly for women but not for men and drug prescriptions are not significantly affected by unemployment for both sexes.

Tables 9 and 10

As our data allow a more detailed look behind specific categories of hospitalizations and drugs, we ran additional IV-regressions to check for unemployment-effects on specific types of health costs. For men, it turns out that overall hospitalization costs are not affected by unemployment, although we find a significant effect in one subcategory: hospitalization for mental health reasons (see column 4 of Table 11). This finding is line line with the hypothesis that short-run unemployment effects on health do not materialize in severe physical illness but do so in mental illnesses. This is further supported by the findings for effects of unemployment on drug prescriptions. (see column 4 of Table 13). For women, the significant increase in hospitalization costs is mainly due to the residual category ”other hospitalizations”. One reason could be that costs of giving birth to a child are counted as hospitalization costs. Lower opportunity costs (in terms of foregone earnings) due to childbearing could induce unemployed women to get a (further) child. Notice, however, that the effect is quantitatively not particularly high. One additional day in unemployment triggers 0.46 Euros (0.55 USD) additional hospitalization costs. Moreover, we find a signficant increase in hospitalization costs due to respiratory diseases (column 6 of Table 12), but no other significant effects for females. Female unemployment does not have significant effects on drug prescriptions costs.

Tables 11 - 14

5 Conclusions

In this paper we have analyzed the causal effect of (involuntary) unemployment on the short-run health costs caused by take-up of health insurance provisions. To assess this relationship we have exploited a unique data set that combines detailed information on a worker's earnings and employment history (and their firms) with detailed information on payments (such as sick leave transfers, hospitalization and associated diagnoses, doctor visits, and drug prescriptions). Our data set is extremely detailed on various types of health insurance provisions (diagnosis for hospitalizations, drug prescriptions) from which specific health consequences of unemployment can be inferred.

To tackle the problem of reverse causality – bad health may cause unemployment – we use job loss due to plant closure as an instrumental variable. Job loss due to plant closure is a meaningful instrument because such job losses are very closely associated with higher subsequent unemployment. Moreover it is very unlikely that job losses due to plant closure are caused by a worker's health.

It turns out that unemployment increases the (direct) health costs indicating that unemployment has negative health consequences. We find that one additional day in unemployment during the first year following the plant closure causes an increase in health costs of 7.70 Euros (9.20 USD) for males and 5.30 Euros (6.40 USD) for females during the first year following the plant closure. For both females and males, the bulk of this increase is due to an increase in sick leave transfer payments (to which both unemployed and employed workers are eligible). Sick leave transfer payments are closely linked to earnings which explains why unemployment-related health costs are lower for women than for men. For males, we find additional significant effects on hospitalizations due to mental illnesses and psychotropic drug prescriptions. This is line with the hypothesis that short-run health problems caused by unemployment are predominantely mental health problems. For females, we also find significant effects on hospitalizations (respiratory diseases and other health problems). No effects of female unemployment on costs due to drug prescriptions could be detected.

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6 Figures

Figure 1: Unemployment (mean days/quarter)

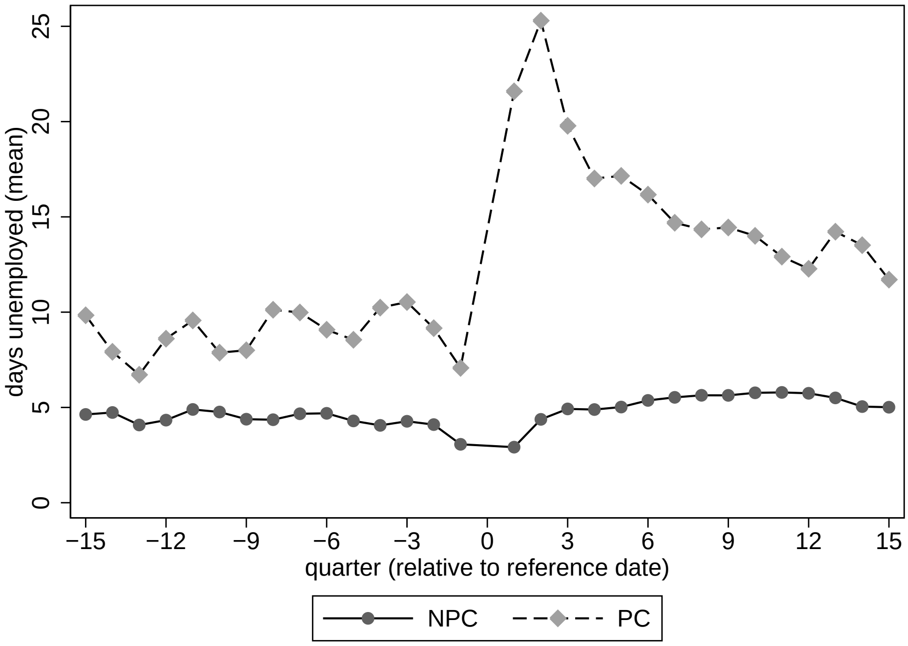
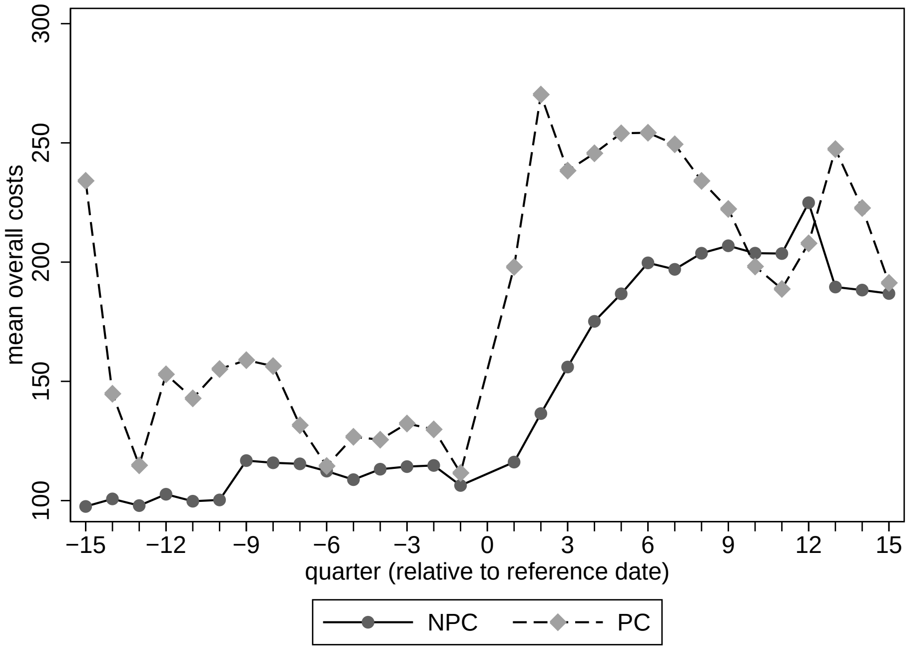


Figure 2: Overall costs (mean costs/quarter)



7 Tables

Table 1: Level regressions, one year before reference date (men)

dependent variable:			overall costs		
days unemployed (one year before ref. date)	0.345	0.191	0.264	0.271	-1.014***
	(0.249)	(0.281)	(0.281)	(0.282)	(0.286)
age (in years)		-35.129***	-24.087*	-23.382*	63.088***
		(10.341)	(10.431)	(10.441)	(11.110)
age/10 squared		68.504***	54.184***	53.483***	-45.828**
		(13.401)	(13.501)	(13.511)	(14.193)
tenure (in years)		-0.140	-0.166	-0.145	0.484***
		(0.123)	(0.123)	(0.123)	(0.127)
tenure/10 squared		0.006	0.005	0.004	-0.018**
		(0.006)	(0.006)	(0.006)	(0.006)
size of firm		0.063*	0.047	0.046	0.088**
		(0.026)	(0.027)	(0.028)	(0.028)
size of firm/10 squared		-0.000*	-0.000	-0.000	-0.001**
		(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)					-10.893***
					(0.714)
wage/10 squared					1.370***
					(0.143)
Industry dummies	no	yes	yes	yes	yes
Regionl dummies	no	no	yes	yes	yes
Time dummies (year, month)	no	no	no	yes	yes
N	33352	33352	33352	33352	33352
r2	0.000	0.005	0.008	0.009	0.023
p	0.167	0.000	0.000	0.000	0.000

Table 2: Level regressions, one year before reference date (women)

dependent variable:			overall costs		
days unemployed (one year before ref. date)	0.194	0.386	0.413	0.419	0.189
	(0.212)	(0.229)	(0.228)	(0.229)	(0.229)
age (in years)		-13.483	-8.933	-10.531	-0.655
		(8.000)	(8.032)	(8.099)	(8.146)
age/10 squared		37.110***	30.026**	31.982**	20.125
		(10.739)	(10.779)	(10.847)	(10.896)
tenure (in years)		-0.008	-0.048	-0.028	0.110
		(0.096)	(0.096)	(0.097)	(0.098)
tenure/10 squared		0.002	0.003	0.002	-0.001
		(0.005)	(0.005)	(0.005)	(0.005)
size of firm		0.030	0.016	0.019	0.034
		(0.017)	(0.019)	(0.020)	(0.020)
size of firm/10 squared		-0.000	-0.000	-0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)					-3.615***
					(0.527)
wage/10 squared					0.546***
					(0.130)
Industry dummies	no	yes	yes	yes	yes
Regionl dummies	no	no	yes	yes	yes
Time dummies (year, month)	no	no	no	yes	yes
N	19243	19243	19243	19243	19243
r2	0.000	0.011	0.016	0.017	0.022
p	0.360	0.000	0.000	0.000	0.000

Table 3: Level regression, one year before reference date (men)

dependent variable:	overall costs	sick leave	consultations	hospitalisation	drugs
days unemployed (one year before ref. date)	-1.014***	-1.033***	0.041***	-0.052	0.030
	(0.286)	(0.262)	(0.012)	(0.056)	(0.030)
age (in years)	63.088***	70.685***	-5.181***	1.800	-4.216***
	(11.110)	(10.164)	(0.448)	(2.195)	(1.166)
age/10 squared	-45.828**	-68.616***	9.579***	3.995	9.215***
	(14.193)	(12.985)	(0.573)	(2.805)	(1.489)
tenure (in years)	0.484***	0.448***	0.001	0.020	0.015
	(0.127)	(0.116)	(0.005)	(0.025)	(0.013)
tenure/10 squared	-0.018**	-0.018**	0.000	-0.001	-0.000
	(0.006)	(0.006)	(0.000)	(0.001)	(0.001)
size of firm	0.088**	0.067**	0.002	0.020***	-0.001
	(0.028)	(0.026)	(0.001)	(0.006)	(0.003)
size of firm/10 squared	-0.001**	-0.000*	-0.000	-0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-10.893***	-9.786***	0.144***	-1.112***	-0.138
	(0.714)	(0.653)	(0.029)	(0.141)	(0.075)
wage/10 squared	1.370***	1.261***	-0.027***	0.119***	0.016
	(0.143)	(0.131)	(0.006)	(0.028)	(0.015)
Industry dummies	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes
N	33352	33352	33352	33352	33352
r2	0.023	0.017	0.126	0.017	0.019
p	0.000	0.000	0.000	0.000	0.000

Table 4: Level regression, one year before reference date (women)

dependent variable:	overall costs	sick leave	consultations	hospitalisation	drugs
days unemployed (one year before ref. date)	0.189	0.086	0.057**	0.044	0.001
	(0.229)	(0.176)	(0.022)	(0.077)	(0.055)
age (in years)	-0.655	9.584	-0.532	-7.467**	-2.240
	(8.146)	(6.240)	(0.768)	(2.721)	(1.951)
age/10 squared	20.125	-6.065	4.630***	14.016***	7.544**
	(10.896)	(8.347)	(1.028)	(3.640)	(2.609)
tenure (in years)	0.110	0.115	-0.001	0.008	-0.012
	(0.098)	(0.075)	(0.009)	(0.033)	(0.023)
tenure/10 squared	-0.001	-0.004	0.001	0.001	0.001
	(0.005)	(0.004)	(0.000)	(0.002)	(0.001)
size of firm	0.034	0.013	0.003	0.016*	0.003
	(0.020)	(0.015)	(0.002)	(0.007)	(0.005)
size of firm/10 squared	-0.000	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-3.615***	-3.405***	0.177***	-0.349*	-0.038
	(0.527)	(0.404)	(0.050)	(0.176)	(0.126)
wage/10 squared	0.546***	0.582***	-0.057***	0.028	-0.008
	(0.130)	(0.099)	(0.012)	(0.043)	(0.031)
Industry dummies	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes
N	19243	19243	19243	19243	19243
r2	0.022	0.010	0.132	0.014	0.015
p	0.000	0.000	0.000	0.000	0.000

Table 5: Level regressions, one year before reference date (men)

dependent variable:	overall costs	sick leave	consultations	hospitalisation	drugs
treat	29.759	17.423	-1.413	12.226	1.522
	(40.526)	(37.077)	(1.635)	(8.009)	(4.252)
days unemployed (one year before ref. date)	-1.024***	-1.039***	0.041***	-0.056	0.030
	(0.286)	(0.262)	(0.012)	(0.057)	(0.030)
age (in years)	62.759***	70.492***	-5.166***	1.665	-4.232***
	(11.119)	(10.172)	(0.449)	(2.197)	(1.167)
age/10 squared	-45.465**	-68.404***	9.561***	4.144	9.233***
	(14.202)	(12.993)	(0.573)	(2.807)	(1.490)
tenure (in years)	0.488***	0.451***	0.001	0.021	0.015
	(0.127)	(0.116)	(0.005)	(0.025)	(0.013)
tenure/10 squared	-0.018**	-0.018**	0.000	-0.001	-0.000
	(0.006)	(0.006)	(0.000)	(0.001)	(0.001)
size of firm	0.090**	0.068**	0.001	0.021***	-0.001
	(0.028)	(0.026)	(0.001)	(0.006)	(0.003)
size of firm/10 squared	-0.001**	-0.000*	-0.000	-0.000***	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-10.841***	-9.756***	0.141***	-1.091***	-0.136
	(0.718)	(0.657)	(0.029)	(0.142)	(0.075)
wage/10 squared	1.358***	1.255***	-0.027***	0.115***	0.016
	(0.144)	(0.131)	(0.006)	(0.028)	(0.015)
Industry dummies	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes
N	33352	33352	33352	33352	33352
r2	0.023	0.017	0.126	0.017	0.019
p	0.000	0.000	0.000	0.000	0.000

Table 6: Level regressions, one year before reference date (women)

dependent variable:	overall costs	sick leave	consultations	hospitalisation	drugs
treat	49.733	19.322	8.535**	24.369*	-2.492
	(32.890)	(25.195)	(3.101)	(10.985)	(7.876)
days unemployed (one year before ref. date)	0.181	0.083	0.056**	0.040	0.002
	(0.229)	(0.176)	(0.022)	(0.077)	(0.055)
age (in years)	0.051	9.858	-0.410	-7.121**	-2.275
	(8.159)	(6.250)	(0.769)	(2.725)	(1.954)
age/10 squared	19.219	-6.417	4.474***	13.572***	7.589**
	(10.913)	(8.359)	(1.029)	(3.645)	(2.613)
tenure (in years)	0.108	0.114	-0.001	0.007	-0.012
	(0.098)	(0.075)	(0.009)	(0.033)	(0.023)
tenure/10 squared	-0.001	-0.004	0.001	0.001	0.001
	(0.005)	(0.004)	(0.000)	(0.002)	(0.001)
size of firm	0.038	0.014	0.003	0.017**	0.003
	(0.020)	(0.015)	(0.002)	(0.007)	(0.005)
size of firm/10 squared	-0.000	-0.000	-0.000	-0.000*	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-3.564***	-3.385***	0.186***	-0.325	-0.041
	(0.528)	(0.405)	(0.050)	(0.176)	(0.126)
wage/10 squared	0.534***	0.578***	-0.059***	0.022	-0.007
	(0.130)	(0.100)	(0.012)	(0.043)	(0.031)
Industry dummies	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes
N	19243	19243	19243	19243	19243
r2	0.022	0.010	0.133	0.014	0.015
p	0.000	0.000	0.000	0.000	0.000

Table 7: Wald–estiamtes (men)

dependent variable	days unemployed (after ref. date)	overall costs	sick leave	consultations	hospitalisation	drugs
treat	66.750***					
	(0.887)					
days unemployed (after ref. date)		6.378***	6.498***	-0.392***	0.371**	-0.100
		(0.871)	(0.805)	(0.029)	(0.130)	(0.069)
N	34677	34677	34677	34677	34677	34677
r2	0.140	.	.	.	.	.
p	0.000	0.000	0.000	0.000	0.004	0.151
F	5657.800	53.645	65.159	182.627	8.104	2.060

Table 8: Wald–estiamtes (women)

dependent variable	days unemployed (after ref. date)	overall costs	sick leave	consultations	hospitalisation	drugs
treat	65.745***					
	(1.247)					
days unemployed (after ref. date)		4.020***	3.830***	-0.376***	0.802***	-0.236*
		(0.940)	(0.851)	(0.054)	(0.200)	(0.098)
N	19626	19626	19626	19626	19626	19626
r2	0.124	.	.	.	.	.
p	0.000	0.000	0.000	0.000	0.000	0.016
F	2780.508	18.290	20.255	48.102	16.069	5.821

Table 9: IV–estimates (men)

dependent variable	days unemployed (after)	overall costs	sick leave	consultations	hospitalisation	drugs
treat	52.870***					
	(0.991)					
days unemployed (after)		7.683***	7.443***	-0.116**	0.231	0.124
		(1.276)	(1.184)	(0.040)	(0.190)	(0.104)
age (in years)	3.310***	-58.298**	-42.123*	-4.440***	-5.395	-6.341***
	(0.270)	(19.027)	(17.660)	(0.600)	(2.830)	(1.551)
age/10 squared	-3.336***	119.958***	83.601***	9.531***	14.170***	12.657***
	(0.345)	(24.046)	(22.319)	(0.758)	(3.577)	(1.960)
tenure (in years)	-0.042***	0.323	0.387	-0.023***	-0.055	0.013
	(0.003)	(0.215)	(0.200)	(0.007)	(0.032)	(0.018)
tenure/10 squared	0.001***	-0.011	-0.015	0.001***	0.003	-0.000
	(0.000)	(0.010)	(0.009)	(0.000)	(0.001)	(0.001)
size of firm	-0.000	0.001	-0.003	0.003	0.002	-0.001
	(0.001)	(0.047)	(0.044)	(0.001)	(0.007)	(0.004)
size of firm/10 squared	-0.000	0.000	0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-0.126***	0.161	0.584	0.091*	-0.408*	-0.106
	(0.017)	(1.210)	(1.123)	(0.038)	(0.180)	(0.099)
wage/10 squared	0.008*	-0.216	-0.234	-0.019*	0.024	0.012
	(0.003)	(0.239)	(0.222)	(0.008)	(0.036)	(0.020)
Industry dummies	yes	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes
N	33352	33352	33352	33352	33352	33352
r2	0.205	0.001	.	0.120	0.013	0.015
p	0.000	0.000	0.000	0.000	0.000	0.000
F	145.230	7.039	4.611	80.421	7.554	8.697

Table 10: IV–estimates (women)

dependent variable	days unemployed (after)	overall costs	sick leave	consultations	hospitalisation	drugs
treat	66.065***					
	(1.378)					
days unemployed (after)		5.319***	4.677***	-0.146*	0.888***	-0.100
		(1.076)	(0.975)	(0.058)	(0.230)	(0.112)
age (in years)	2.787***	-43.552*	-22.648	-3.034**	-15.175***	-2.694
	(0.341)	(17.692)	(16.029)	(0.950)	(3.780)	(1.842)
age/10 squared	-2.747***	90.537***	50.791*	8.338***	22.545***	8.863***
	(0.457)	(23.581)	(21.364)	(1.266)	(5.038)	(2.456)
tenure (in years)	-0.039***	-0.159	-0.081	-0.017	-0.058	-0.002
	(0.004)	(0.209)	(0.189)	(0.011)	(0.045)	(0.022)
tenure/10 squared	0.001***	0.009	0.005	0.001	0.002	0.000
	(0.000)	(0.010)	(0.009)	(0.001)	(0.002)	(0.001)
size of firm	-0.004***	0.054	0.035	-0.001	0.015	0.006
	(0.001)	(0.043)	(0.039)	(0.002)	(0.009)	(0.005)
size of firm/10 squared	0.000***	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	0.029	1.837	1.248	0.177**	0.545*	-0.133
	(0.022)	(1.136)	(1.029)	(0.061)	(0.243)	(0.118)
wage/10 squared	-0.012*	-0.528	-0.359	-0.057***	-0.133*	0.020
	(0.005)	(0.280)	(0.254)	(0.015)	(0.060)	(0.029)
Industry dummies	yes	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes
N	19243	19243	19243	19243	19243	19243
r2	0.167	0.003	.	0.128	0.004	0.019
p	0.000	0.000	0.000	0.000	0.000	0.000
F	66.396	4.365	2.371	50.297	3.893	6.453

Table 11: IV–estimates, hospitalisation (men)

dependent variable	overall	cancer	heart	mental	other	respiratory	stroke
days unemployed (after)	0.231	-0.029	0.023	0.212*	0.018	0.027	-0.020
	(0.190)	(0.056)	(0.029)	(0.103)	(0.124)	(0.054)	(0.023)
age (in years)	-5.395	-3.062***	-0.436	1.396	-2.266	-0.322	-0.705*
	(2.830)	(0.839)	(0.434)	(1.533)	(1.850)	(0.805)	(0.349)
age/10 squared	14.170***	5.008***	1.264*	-1.109	7.280**	0.397	1.330**
	(3.577)	(1.060)	(0.549)	(1.937)	(2.337)	(1.018)	(0.440)
tenure (in years)	-0.055	-0.013	0.005	-0.024	-0.008	-0.011	-0.004
	(0.032)	(0.010)	(0.005)	(0.017)	(0.021)	(0.009)	(0.004)
tenure/10 squared	0.003	0.001	-0.000	0.001	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
size of firm	0.002	-0.002	-0.000	0.004	0.001	-0.001	-0.000
	(0.007)	(0.002)	(0.001)	(0.004)	(0.005)	(0.002)	(0.001)
size of firm/10 squared	-0.000	0.000	0.000	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-0.408*	-0.037	-0.003	-0.144	-0.325**	0.077	0.025
	(0.180)	(0.053)	(0.028)	(0.097)	(0.118)	(0.051)	(0.022)
wage/10 squared	0.024	0.003	-0.003	0.010	0.033	-0.012	-0.006
	(0.036)	(0.011)	(0.005)	(0.019)	(0.023)	(0.010)	(0.004)
Industry dummies	yes	yes	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes	yes
N	33352	33352	33352	33352	33352	33352	33352
r2	0.013	0.004	0.004	0.003	0.012	0.001	0.003
p	0.000	0.000	0.000	0.000	0.000	0.957	0.009
F	7.554	2.199	2.542	1.763	6.967	0.708	1.492

Table 12: IV–estimates, hospitalisation (women)

dependent variable	overall	cancer	heart	mental	other	respiratory	stroke
days unemployed (after)	0.888***	0.101	0.047	0.240	0.455**	0.054*	-0.009
	(0.230)	(0.072)	(0.042)	(0.134)	(0.149)	(0.026)	(0.020)
age (in years)	-15.175***	-0.283	-0.609	4.271	-15.303***	-1.266**	-1.986***
	(3.780)	(1.177)	(0.692)	(2.206)	(2.450)	(0.434)	(0.326)
age/10 squared	22.545***	1.793	1.228	-5.024	19.821***	1.707**	3.020***
	(5.038)	(1.569)	(0.922)	(2.941)	(3.265)	(0.578)	(0.435)
tenure (in years)	-0.058	0.022	-0.008	-0.015	-0.053	-0.001	-0.002
	(0.045)	(0.014)	(0.008)	(0.026)	(0.029)	(0.005)	(0.004)
tenure/10 squared	0.002	-0.001	0.000	0.000	0.002	0.000	0.000
	(0.002)	(0.001)	(0.000)	(0.001)	(0.001)	(0.000)	(0.000)
size of firm	0.015	0.002	-0.001	0.004	0.010	0.002	-0.001
	(0.009)	(0.003)	(0.002)	(0.005)	(0.006)	(0.001)	(0.001)
size of firm/10 squared	-0.000	-0.000	0.000	-0.000	-0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	0.545*	-0.199**	0.023	0.045	0.667***	0.049	-0.041
	(0.243)	(0.076)	(0.044)	(0.142)	(0.157)	(0.028)	(0.021)
wage/10 squared	-0.133*	0.052**	-0.006	-0.024	-0.152***	-0.011	0.008
	(0.060)	(0.019)	(0.011)	(0.035)	(0.039)	(0.007)	(0.005)
Industry dummies	yes	yes	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes	yes	yes
N	19243	19243	19243	19243	19243	19243	19243
r2	0.004	0.004	0.003	0.005	0.008	0.003	0.006
p	0.000	0.000	0.967	0.000	0.000	0.062	0.000
F	3.893	1.785	0.686	2.086	4.553	1.300	1.947

Table 13: IV–estimates, drugs (men)

dependent variable	overall	specific	psychosomatic	psychotropic	non–specific
days unemployed (after)	0.124	0.027	-0.002	0.029*	0.097
	(0.104)	(0.018)	(0.011)	(0.014)	(0.101)
age (in years)	-6.341***	0.344	0.004	0.339	-6.685***
	(1.551)	(0.269)	(0.159)	(0.203)	(1.510)
age/10 squared	12.657***	0.169	0.418*	-0.250	12.488***
	(1.960)	(0.340)	(0.201)	(0.257)	(1.908)
tenure (in years)	0.013	-0.000	0.001	-0.001	0.014
	(0.018)	(0.003)	(0.002)	(0.002)	(0.017)
tenure/10 squared	-0.000	-0.000	-0.000	0.000	-0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
size of firm	-0.001	0.001	-0.000	0.001**	-0.002
	(0.004)	(0.001)	(0.000)	(0.001)	(0.004)
size of firm/10 squared	0.000	0.000	0.000	-0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-0.106	-0.043*	0.001	-0.043***	-0.063
	(0.099)	(0.017)	(0.010)	(0.013)	(0.096)
wage/10 squared	0.012	0.006	-0.001	0.007**	0.006
	(0.020)	(0.003)	(0.002)	(0.003)	(0.019)
Industry dummies	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes
N	33352	33352	33352	33352	33352
r2	0.015	0.010	0.011	0.004	0.012
p	0.000	0.000	0.000	0.000	0.000
F	8.697	5.736	6.226	2.845	7.181

Table 14: IV–estimates, drugs (women)

dependent variable	overall	specific	psychosomatic	psychotropic	non–specific
days unemployed (after)	-0.100	0.004	0.004	-0.000	-0.104
	(0.112)	(0.028)	(0.014)	(0.024)	(0.107)
age (in years)	-2.694	-0.587	-0.759**	0.172	-2.107
	(1.842)	(0.461)	(0.236)	(0.388)	(1.762)
age/10 squared	8.863***	2.001**	1.759***	0.242	6.862**
	(2.456)	(0.614)	(0.315)	(0.517)	(2.348)
tenure (in years)	-0.002	-0.003	-0.003	-0.000	0.001
	(0.022)	(0.005)	(0.003)	(0.005)	(0.021)
tenure/10 squared	0.000	0.000	0.000	0.000	0.000
	(0.001)	(0.000)	(0.000)	(0.000)	(0.001)
size of firm	0.006	0.002*	0.001	0.002	0.003
	(0.005)	(0.001)	(0.001)	(0.001)	(0.004)
size of firm/10 squared	-0.000	-0.000	-0.000	-0.000	-0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
wage (in 100 Euros)	-0.133	0.026	0.027	-0.001	-0.159
	(0.118)	(0.030)	(0.015)	(0.025)	(0.113)
wage/10 squared	0.020	-0.009	-0.007	-0.002	0.029
	(0.029)	(0.007)	(0.004)	(0.006)	(0.028)
Industry dummies	yes	yes	yes	yes	yes
Regional dummies	yes	yes	yes	yes	yes
Time dummies	yes	yes	yes	yes	yes
N	19243	19243	19243	19243	19243
r2	0.019	0.018	0.020	0.007	0.013
p	0.000	0.000	0.000	0.000	0.000
F	6.453	5.956	6.839	2.364	4.517

A Appendix

Table A.1: Health Indicators

Indicator	Definition
Consultations	Includes all costs[1] arising from consultations by a physician
Drugs	Includes all costs arising from prescribed or selfmedicated drugs
Psychosomatic drugs:	Includes drugs targeted at treating psychosomatic afflictions (e.g. migraine therapeutics, antiinflammatory drugs)
Psychotropic drugs:	Includes drugs targeted at treating psychological stress (e.g. sedatives, benzodiazepins, antidepressants)
Specific drugs:	Includes psychosomatic and psychotropic drugs
Overall:	Includes all drugs
Hospitalisation	Includes costs due to hospitalisation. These costs are classified by the main diagnosis of the hospitalisation (ICD–9 codes)[2]
Cancer:	Includes ICD–9 Codes 140–239
Heart:	Includes ICD–9 Codes 391, 392.0, 393–398, 402, 404, 410–429
Mental:	Includes ICD–9 Codes 290–319, V70.1, V70.2, V71.0
Respiratory:	Icludes ICD–9 Codes 460–519
Cerebrovascular:	Includes ICD–9 Codes 430–438
Other:	Includes hospitalisation due to all other reasons
Overall:	Includes hospitalisation due to any cause
Incapacity to Work	Includes all costs arising from being on sick leave ("Krankengeld")
Overall costs	Includes the overall costs from consultations, drugs, hospitalisaiton, and days on sick leave

1: All variables measured in (nominal) Euros.

2: Classification taken from Keefe et al. (2002).

Table A.2: Health indicators: descriptives (overall and by sex)

	NPC		PC		Total	
Variable	Men	Women	Men	Women	Men	Women
Overall costs	985.689	1110.194	1479.233	1399.813	1111.931	1175.859
	(4948.317)	(4013.993)	(8319.608)	(5588.906)	(5997.652)	(4422.039)
Sick leave	430.677	259.357	936.035	539.394	559.941	322.850
	(4422.917)	(3383.554)	(7634.586)	(4689.789)	(5432.737)	(3721.856)
Consultations	192.547	351.953	155.092	324.849	182.966	345.807
	(249.639)	(340.373)	(226.271)	(316.313)	(244.419)	(335.253)
Hospitalisations						
Overall	240.476	316.424	279.315	378.418	250.410	330.480
	(931.59)	(1004.235)	(1176.500)	(1327.716)	(1000.085)	(1086.329)
Cancer	14.222	23.941	11.828	32.696	13.610	25.926
	(282.71)	(297.681)	(220.719)	(346.402)	(268.219)	(309.413)
Heart	8.592	4.853	9.579	6.133	8.843	5.143
	(139.637)	(108.716)	(157.99)	(273.819)	(144.552)	(161.667)
Mental	26.359	33.429	40.623	50.056	30.008	37.199
	(540.000)	(572.354)	(652.555)	(885.88)	(570.930)	(656.706)
Other	172.278	240.275	193.005	269.325	177.58	246.862
	(623.673)	(695.232)	(736.377)	(743.119)	(654.402)	(706.459)
Respiratory	15.226	12.008	20.444	17.179	16.561	13.180
	(144.615)	(125.347)	(399.35)	(144.374)	(237.400)	(129.919)
Stroke	3.799	1.917	3.836	3.029	3.808	2.170
	(112.820)	(86.722)	(110.63)	(111.533)	(112.262)	(92.928)
Drugs						
Overall	121.989	182.460	108.791	157.151	118.613	176.722
	(672.666)	(765.827)	(628.816)	(549.882)	(661.742)	(722.61)
Specific drugs	17.975	33.496	18.608	26.248	18.137	31.853
	(118.012)	(153.312)	(106.763)	(114.037)	(115.238)	(145.369)
Psychotropic drugs	6.642	15.547	7.661	11.137	6.902	14.547
	(91.72)	(121.181)	(87.715)	(74.044)	(90.712)	(112.256)
Psychosomatic drugs	11.333	17.950	10.947	15.112	11.235	17.306
	(66.509)	(87.199)	(53.085)	(81.641)	(63.346)	(85.977)
Other drugs	104.014	148.964	90.183	130.903	100.476	144.869
	(653.697)	(739.596)	(609.202)	(527.228)	(642.629)	(697.168)
n	24’821	14’880	8’531	4’363	33’352	19’243
	39’701		14’602		52’595	

Note: Standard deviation in parentheses.

Table A.3: Summary statistics

Variable	NPC	PC	Total
Female	0.375	0.325	0.361
	(0.484)	(0.468)	(0.48)
Age (years)	36.631	34.857	36.154
	(10.278)	(10.569)	(10.386)
Blue collar worker	0.470	0.619	0.510
	(0.499)	(0.486)	(0.500)
Wage (one year after)	21493.956	14045.658	19491.119
	(9979.616)	(9461.949)	(10382.261)
Wage (one year before)	207.687	171.944	198.925
	(98.098)	(102.121)	(100.284)
Size of firm (one year before)	821.933	62.563	617.74
	(2413.559)	(84.498)	(2091.439)
Industry (employer)			
Agriculture	0.005	0.006	0.005
	(0.071)	(0.075)	(0.072)
Mining	0.005	0.002	0.004
	(0.068)	(0.042)	(0.062)
Construction	0.091	0.221	0.126
	(0.288)	(0.415)	(0.332)
Manufacturing	0.317	0.284	0.308
	(0.465)	(0.451)	(0.462)
Transportation	0.046	0.044	0.045
	(0.210)	(0.204)	(0.208)
Wholesale trade	0.066	0.052	0.062
	(0.248)	(0.223)	(0.242)
Retail trade	0.081	0.080	0.081
	(0.272)	(0.271)	(0.272)
Information, finance	0.091	0.068	0.085
	(0.288)	(0.252)	(0.279)
Other services	0.193	0.157	0.183
	(0.395)	(0.363)	(0.387)
Region (employer)			
Outside Upper Austria	0.125	0.128	0.126
	(0.331)	(0.334)	(0.331)
Inside Upper Austria	0.780	0.846	0.798
	(0.414)	(0.361)	(0.402)
Region unknown	0.095	0.026	0.077
	(0.294)	(0.16)	(0.266)

Summary statistics, continued

Variable	NPC	PC	Total
Reference date			
Year = 1998	0.000	0.117	0.031
	(0.000)	(0.321)	(0.175)
Year = 1999	0.313	0.387	0.333
	(0.464)	(0.487)	(0.471)
Year = 2000	0.330	0.305	0.323
	(0.470)	(0.460)	(0.468)
Year = 2001	0.357	0.191	0.312
	(0.479)	(0.393)	(0.463)
Month = January	0.071	0.053	0.066
	(0.257)	(0.224)	(0.248)
Month = February	0.083	0.051	0.075
	(0.276)	(0.220)	(0.263)
Month = March	0.082	0.083	0.082
	(0.274)	(0.276)	(0.274)
Month = April	0.077	0.088	0.080
	(0.266)	(0.284)	(0.271)
Month = May	0.085	0.068	0.081
	(0.279)	(0.252)	(0.272)
Month = June	0.095	0.092	0.094
	(0.293)	(0.290)	(0.292)
Month = July	0.082	0.055	0.075
	(0.274)	(0.229)	(0.263)
Month = August	0.079	0.047	0.070
	(0.269)	(0.211)	(0.255)
Month = September	0.081	0.091	0.084
	(0.273)	(0.288)	(0.277)
Month = October	0.090	0.081	0.088
	(0.287)	(0.273)	(0.283)
Month = November	0.077	0.068	0.075
	(0.267)	(0.251)	(0.263)
Month = December	0.098	0.222	0.131
	(0.297)	(0.415)	(0.338)
Tenure in last 5 years (years)	3.218	2.017	2.895
	(1.892)	(1.816)	(1.946)
days unemployed (one year before)	15.502	36.775	20.717
	(55.712)	(76.797)	(62.229)
days unemployed (one year after)	17.107	83.680	35.009
	(59.429)	(105.443)	(80.268)
n	39’701	14’602	52’595