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Abstract

We study the short-run effect of involuntary job loss on comprehensive measures of public health costs. We focus on job loss induced by plant closure, thereby addressing the reverse causality problem of deteriorating health leading to job loss as job displacements due to plant closure are unlikely caused by workers' health status, but potentially have important effects on individual workers' health and associated public health costs. Our empirical analysis is based on a rich data set from Austria providing comprehensive information on various types of health care costs and day-by-day work history at the individual level. Our central findings are: (i) overall expenditures on medical treatments (hospitalizations, drug prescriptions, doctor visits) are not strongly affected by job displacement; (ii) job loss increases expenditures for antidepressants and related drugs, as well as for hospitalizations due to mental health problems for men (but not for women); and (iii) sickness benefits strongly increase due to job loss.

JEL classification: I12, I19, J28, J65
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1 Introduction

This paper studies the causal effect of job loss due to plant closure on public expenditures for health care. Understanding this effect is important for at least four reasons. First, ill health and job loss are the two major risks during an individual's working life. While a large literature has studied the interactions between job loss and health, the literature has barely addressed the issue how job losses affect public health costs. Second, understanding the causal relationship between job loss and health costs is important for both labor market policy and health policy. Labor market policies that focus on preventing job loss might be even more beneficial to society if they are providing employment to job losers and avoid deteriorating health conditions at the same time. Health policy makers are interested in this relationship to assess the effects of changing conditions on the labor market on the expenditures for health care. Third, the effects of job loss on public health costs may also depend on institutional rules. The public health care systems of many European members of the OECD do not only cover the direct health care costs (doctor visits, hospitalizations, and medical drugs) but they also provide insurance against income losses in case of sickness. Understanding which component of health care contributes to overall costs is crucial. Fourth, health care costs have risen strongly in the last decades in most industrialized countries (Hagist and Kotlikoff, 2005) and it is thus interesting to know how the dynamics of these costs relate to job instability and loss of employment.

The aim of this paper is to provide empirical evidence on the causal effect of job loss on comprehensive measures of public health costs. The empirical analysis is based on data from Austria – a country that is ideally suited to addressing the role of job loss in health care costs for various reasons. On the one hand, health insurance in Austria is mandatory for all employed individuals and their dependants. While subjective health status can not be measured in our setting, the fact that health insurance coverage is universal suggests that health care costs are more informative on the evolution of underlying health status than in settings where health insurance is not mandatory. On the other hand, the Austrian system does not only cover costs associated with take-up of health provisions (such as doctor visits, hospitalizations, and medical drugs) but also provides insurance against income losses. However, while direct take-up of health provisions is informative on the health status of an individual, public health costs associated with sickness benefits are also driven by institutional rules and incentives created by such rules. Aiming to provide comprehensive information, our empirical analysis will distinguish between costs associated with take-up of health provisions and costs due to sickness benefit payments.[1]

[1]When we talk about "public health costs" associated with unemployment, we strictly refer to costs that are associated with payments by the public health insurance system, i.e. sickness benefits and take-up of health provisions. From the point of view of public health insurance, additional costs arise due to reduced health

However, in contrast to typical European health insurance systems, deductibles in the Austrian system are non-negligible. Moreover, the Austrian health insurance system is embedded in an unemployment insurance system that is more restrictive than in other European countries and closer to the U.S. system. Regular unemployment benefits are paid for at most 30 weeks and the net replacement ratio (i.e. unemployment benefits relative to previous net earnings) is about 55 percent. This means that studying the Austrian context allows assessing the overall financial and non-financial repercussions of job loss on health care costs. However, assessing the causal effect of job loss on public health costs is difficult because deteriorating health status can be a cause rather than a consequence of job loss. In other words, health-driven selection of the unemployed may lead to a bias in the causal effect of unemployment on health costs in cross-sectional data.[2] In order to address the problem of reverse causality, we focus on the effects of job loss following plant closure on public health care costs. The shut-down of a firm strongly disrupts a worker's employment career as it leads to job loss with certainty. Yet workers' health is unlikely to cause a plant closure, except in the case of self-employment.

This paper goes beyond the existing literature by combining rich administrative data, using plant closures as the identification strategy, and several measures of take-up of primary health care and then especially drug prescription. There are three important aspects of our data. First, we study the effects of job loss on costs associated with take-up of primary health care rather than on direct (self-reported or diagnosis-based) measures of a worker's health. As the Austrian system provides comprehensive coverage of health care benefits for all employed workers, the public health care system faces potentially high additional costs associated with unemployment. It is thus of primary interest to policy makers to have reliable information on the health costs that are causally related to workers' employment status. Second, our study aims to give a broad picture of the overall health costs to the public health insurance associated with the experience of job loss. The Austrian system does not only cover costs associated with medical treatment (such as doctor visits, drug prescriptions, and hospitalizations) but also grants sickness transfer payments both for employed workers incapable of working due to health problems and for unemployed workers incapable of searching for a new job. In our empirical analysis we will assess the causal effect of job loss on overall costs. Moreover, we also analyze the cost structure, i.e. how these overall costs are divided into the interesting subcategories. Third, in contrast to most previous studies, we use a very large and informative data set. Our data come from the

insurance contributions when an individual loses his or her job.

[2]Stewart (2001) shows that the more unhealthy are more likely to enter unemployment and hence the unhealthy are over-represented in the unemployment stock. Martikainen and Valkonen (1996) show that the relationship between unemployment and mortality weakened in Finland as unemployment rose, suggesting that health selection varies over the business cycle. See also the discussion on the effects of health on labor market attachment in Currie and Madrian (1999).

Austrian health insurance register and cover all health-care related payments to private sector employees in one large Austrian region.[3] For the period 1998 – 2002, we can link the health cost data with social security register data (reporting a worker's employment and earnings history), and our analysis is based on a large sample of workers. One obvious advantage of these data sets is their accuracy. Because data collection is associated with the entitlement to, and the actual payment of, social benefits there is little measurement error both with respect to health-cost and employment-status information. Another advantage is that all workers have the same health insurance coverage which is given by a standardized catalogue of health care benefits that are covered by the public health insurance system. Hence our measure of health costs is also highly informative on the workers health status.[4] In terms of identification, our paper expands on the extensive literature that tries to assess the causal impact of job loss on health outcomes by employing modern econometric evaluation methods. In particular, our identification strategy uses plant closure as exogenous source of job loss, and we employ propensity score matching techniques to make plant-closure and non-plant closure workers well comparable.[5]

Our empirical analysis yields four major results. First, plant closure does not cause a significant increase in public health costs associated with take-up of health provisions in the year after plant closure. Public health costs associated with hospitalizations, medical drugs do not increase, and doctor visits even decrease somewhat.[6] Second, we find no anticipatory effects on overall health costs. In terms of health cost subgroups, we find no anticipatory effects for men. In contrast, women spend more days on sick leave in the half-year before plant closure likely due to pregnancy related work absences. Third, while overall take-up is not significantly affected, we find – for males, but not for females – a significant increase in the prescriptions of antidepressants and related drugs ("psychotropic drugs"). Moreover, we find that, for males only again, job loss results in an increase in hospitalizations for mental health reasons. This suggests that job loss causes significant mental health problems for males. Fourth, we find that

[3]Our study focuses on Upper Austria which is one of totally nine Austrian states. Upper Austria, located in the north and bordering Germany and the Czech Republic, comprises roughly one sixth of the Austrian population and work force.

[4]The public health insurance system aims at a basic coverage of all major health risks. Individuals with demand for services not covered by the public health insurance system (mainly better quality, such as one-bedroom hospitalization) can purchase such services from private health insurance companies. Private companies cover costs beyond the public system.

[5]From a methodological point of view, our analysis is close in spirit to the Swedish study by Eliason and Storrie (2009) who study the impact of job loss on mortality and the Danish study by Browning *et al.* (2006) who look at the impact of job loss on hospitalizations.

[6]While our paper focuses on the impact of individual unemployment on public health costs for the same individual, note that a different literature which looks at relationships at the more aggregate level provides similar results. Studying aggregate health in good times and bad times, Ruhm (2000) finds lower mortality rates during recessions. This is in line with predictions of the economic theory of health production which holds that reduced opportunity costs of time increase incentives to undertake health investments through time-consuming activities which may improve health during times of high unemployment (Grossman, 1972).

the public health costs due to sickness benefit payments strongly increase after a job loss. Plant closure more than doubles expenditures on sickness benefits: Overall health care costs increase by 360 Euros for men and by almost 212 Euros for women in the span of one year. However, this increase in costs does not necessarily reflect a deteriorating health status of displaced workers, but may also relate to sickness benefit rules: For employed workers, employers have to bear sickness benefits for up to 12 weeks (depending on job tenure) whereas for unemployed workers it is the public health insurance which pays the sickness benefits.[7] Since plant closure workers spend more time in unemployment than non-plant closure workers this increase in costs is largely mechanical. This is confirmed when we look at days on sick leave, which are recorded in the same way both for employed and non-employed individuals. For males, we do not find that job loss due to plant closure causes more sickness days. For females, however, we find a significant increase in the number of days on sickness benefits.

The rest of this paper is organized as follows. In the next section we provide a brief review of the previous literature. Section 3 presents the data and definitions of the crucial variables. In section 4 we discuss the econometric methodology and the empirical strategy to identify the causal impact of job loss on public health costs. Section 5 presents the empirical results on the relationship between job loss and associated costs to the public health care system. Section 6 concludes.

2 Related literature

Our study is related to various strands of the literature that analyzes the impact of job loss on take-up of public health care provisions to job loss (or unemployment). Iversen *et al.* (1989) find rising hospital admissions in a sample of Danish workers after a large shipyard closure and Keefe *et al.* (2002) report excess risk of self-harm leading to hospitalization or death in a sample of workers displaced after bankruptcy of a meat-processing plant. Browning *et al.* (2006), using a large sample of the Danish males over the period 1981-1999, find no significant effect of job loss on rates of hospitalization for stress-related diseases such as high blood pressure and heart diseases. Carr-Hill *et al.* (1996) and Field and Briggs (2001) find that the jobless workers in the UK do consult general practitioners more often than employed workers with similar characteristics. Similar evidence was found for a large furniture plant closure in Austria (Studnicka *et al.*, 1991). D'Arcy and Siddique (1985) provide evidence from the Canadian health care survey that the unemployed use public health care more heavily than workers with a job. Such evidence may

[7] When a worker gets sick during an unemployment spell, the time of regular unemployment benefits is interrupted and the worker becomes eligible for sickness benefits so each day on sickness benefits prolongs the maximum duration of regular unemployment benefits.

indicate that unemployment leads to health problems. However, it is also consistent with the economic theory of health production (Grossman, 1972), which predicts increased incentives to invest in time-consuming health activities during periods of reduced opportunity cost of time such as unemployment. Other studies find that the unemployed make less use of the public health care system even when they are eligible to health care services. Ahs and Westerling (2006) and Virtanen (1993) study Scandinavian experiences and find that unemployment is associated with lack of unmet care needs, particularly among unemployed who suffer from psychological symptoms. One possible explanation for such a result is based upon the behavioral model of health care use (Andersen, 1995), which stresses that the take-up of health care benefits is not only influenced by need of care but also by individual predisposition and social context.

Our study is most closely related, both in data and methodology, to Browning *et al.* (2006). Unlike Browning *et al.* (2006) (and the other above studies) we consider take-up of all kinds of health care provisions covered by public health insurance to get a full picture how job losses affects the public care costs.

A second related literature studies the relationship between unemployment and sickness insurance use. Johansson and Palme (1996, 2005) study how changes in the income replacement level affect the incidence and duration of sick leave spells in Sweden (see also Henrekson and Persson (2004) for a related study). Askildsen *et al.* (2005) argue that the negative relationship between unemployment and sickness insurance use may be due to worker moral hazard in a situation of full insurance against income loss. While our study is related to this literature, we do not assess the incentive effects of health insurance rules. Our paper contributes to this literature by studying the effects of exogenous job loss on public healt costs associated with take-up of sickness benefits.

In a broader perspective, our paper is related to the large literature on the effect of job loss (or unemployment) on individual health.[8] Early studies (e.g. Moser *et al.*, 1987; Morris *et al.*, 1994) find that the unemployed have significantly higher mortality rates.[9] Nylen *et al.* (2001) and Voss *et al.* (2004) examine mortality of Swedish twins in relation to unemployment and find that experiencing unemployment in the year 1973 is associated with a higher probability to commit suicide or die from undetermined causes during the period 1974-1996. Sullivan and von Wachter (2006), using administrative data from two US states, estimate a 15-20% excess risk of death in the 20 years following a job loss. Eliason and Storrie (2009) provide similar evidence

[8]Cook (1985), Morris and Cook (1991) and Jin *et al.* (1995) survey the early literature. Platt (1984) documents the effects of unemployment on suicidal behavior. For recent surveys see Kasl and Jones (2000, 2006).

[9]An important strand of the literature has studied the impact of aggregate unemployment on mortality. The early work of Brenner (1979) points to a positive relationship. However, the more recent literature has convincingly demonstrated that recessions and high local unemployment rates reduce rather than increase mortality (Ruhm, 2000, 2003, 2005, Gerdtham and Ruhm, 2006).

for job losers in Sweden. Kessler *et al.* (1987, 1989) look at the impact of unemployment and re-employment on self-reported health. Turner (1995) investigates the relative importance of financial strain and emotional distress for health problems after losing the job. Burgard *et al.* (2005) show that health effects are strongest for those who experience a health shock after a job loss or who lose their jobs for health reasons. However, adverse health effects are also existent for other workers experiencing a job loss. Our study focuses on costs associated with morbidity (rather than mortality) and uses public health cost measures (rather than self-reported health) to investigate the relationship between job loss and health.

A further strand of the literature studies the effect of unemployment on subjective well-being. Warr (1987) emphasizes the importance of environmental features of work such as opportunity of control, interpersonal contact, and a socially valued position for subjective well-being. As a result, the loss of a job detrimentally affects well-being and may cause serious problems for mental health. Clark and Oswald (1994) and Winkelmann and Winkelmann (1998) document the close relationship between unemployment and unhappiness, and Stutzer and Lalive (2004) show that this effect depends on the social norm to live off one's own income. Theodossiou (1998) finds that the unemployed suffer more from anxiety, depression and loss of confidence compared to otherwise similar employed individuals. Bjorklund (1985) finds evidence that unemployment has detrimental health effects in Sweden. Other studies focus on youth workers and find detrimental effects of unemployment on well-being (e.g. Goldsmith *et al.* (1996) for the United States and Korpi (1997) for Sweden). Our study indirectly addresses related issues by exploring the impact of job loss on more detailed health costs categories such as the consumption of antidepressants and similar medical drugs as well as hospitalization for mental reasons. Effects on such public health costs arguably mirror a detrimental impact of job loss on subjective well-being.

3 Data and definition of variables

3.1 Data sources

We draw on social security register data that can be linked to data from the statutory health insurance fund of a large region in Austria ("Upper Austria").[10] Data from the statutory health insurance record all payments by the health insurance fund related to a worker's take-up of health care benefits and cover the five-year period from January 1, 1998 to December 31, 2002. We also use data from the Austrian Social Security Database (ASSD), which covers

[10]The administration of the health insurance is divided into regional units ("Gebietskrankenkassen", GKK) and our data set comes from the GKK of Upper Austria, one of the nine Austrian states and located in the north of the country. This region covers about one sixth of the total Austrian population and work force.

individuals employed in the private sector and provides information, on a daily basis, on the workers' earnings and employment history.[11] The data do only include workers in dependent employment and do not include the self-employed, as a separate public insurance agency for the self-employed covers health risks of sole proprietor owners not included in our data. The data also contain relevant individual characteristics (such as age, sex, and broad occupation) but lack other relevant information (such as education and family background).

The combination of these two data sets provides rich information on a worker's employment and public health costs. Two additional features make these data ideally suited for the present analysis. A first feature is that the data cover the universe of the private sector employees (more than 80% of the active state population) in the region.[12] Moreover, because each employed worker can be linked to a particular firm via a unique firm identifier and because the data set covers the universe of workers, we can perfectly reconstruct firms. A "firm" is simply defined as the set of individuals observed under a given employer social security number ("firm identifier") at a given date. The possibility of linking firm- and worker-information is particularly helpful for our estimation strategy which relies on a firm characteristic: the date of shut-down of a plant. Firm information is also helpful in making plant-closure workers better comparable to workers in ongoing firms. A second feature is that these two data sets provide high-quality and comprehensive information on expenditures associated with a worker's health status. As health insurance is mandatory for Austrian employees and covers all costs associated with primary health care such as treatment by physicians, drug prescriptions, and hospitalized care, the data give a very detailed and comprehensive picture of the health expenditures caused by a given individual.[13]

The payments recorded in the data can be broadly divided into the following four categories (see Table A.1 in the appendix for a definition of these and more detailed categories used in the empirical analysis below):

[11]The data are collected for the primary purpose of calculating a worker's old age social security benefits. The Central Social Security Administration gets its data from the health insurance funds and processes this information for the purpose of calculating 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 health insurance fund.

[12]There are separate funds for private-sector employees, self-employed, farmers, public sector workers, and employees of several public utility firms. The data available to us comprises the universe of private sector workers only.

[13]On top of mandatory public health insurance, individuals may purchase supplementary insurance offered by private insurance companies. The main provisions provided by these companies are higher quality standards during hospitalization (e.g. single bedrooms) which amount to more than 80% of all benefits paid by private insurers. Costs covered by these supplementary contracts are on top of provisions covered by public health insurance. Hence no substitution of public health costs by private health insurance takes place. Overall the fraction of expenditures covered by private health insurance contracts well below 10 percent of total health expenditures. In 2003, total costs covered by the private health insurers amounted to 1.3 billion Euros which compares to health expenditures of 16.7 billion Euros covered by the the public health insurance system. Moreover, private health insurance is purchased predominantely by high-income individuals which are underrepresented among plant closure workers (Versicherungsverband Österreich, 2005).

(i) Sickness benefits. These are payments during periods of sickness to employed workers not capable of searching for a new job or unemployed workers not capable of working. When unemployed, sickness benefits are roughly equal to unemployment benefits. Additionally, days of sickness benefits do not reduce the number of remaining days for which an unemployed worker is eligible for regular unemployment benefits. When employed, a worker initially continues to receive his wage during up to the first 12 weeks of his sick leave spell (depending on previous tenure). Thereafter the health insurance provides sickness benefits amounting to 80% of the previous wage. In order to claim sickness benefits, a physician has to approve and repeatedly check a worker's impaired health situation. Our data cover all days on sick leave but only the sickness benefits paid by health insurance. We therefore provide separate results for sickness benefits and days on sick leave. Sickness benefits may be higher for workers getting ill after a plant closure because the closing plant can not continue to pay the wage for the initial 12 week period or because plant closure workers are more likely to enter sickness insurance from unemployment. Plant closure workers are thus more likely to be receiving sickness benefits paid by health insurance. The situation is different for a worker getting sick in an ongoing firm. This means that sickness benefits increase mechanically for workers in plant closure firms as compared to workers in continuing firms. However, days on sick leave are recorded for all workers alike.

(ii) Consultations. Doctors have contracts with the public health insurance and get paid a standardized rate for each consultation.

(iii) Hospitalization. The data record each hospitalization and detail the particular reason for the hospitalization. In particular, it classifies the costs by the main diagnosis of the hospitalization according to the ninth revision of the International Classification of Diseases and Related Health Problems (ICD-9). We aggregate the diagnoses based on ICD-9 codes into the following causes for hospitalization: cancer, heart disease, mental health problems, respiratory diseases, cerebrovascular diseases, hospitalization related to pregnancy, and all other hospitalizations. We thereby focus on major causes of death, some of which are potentially related to stress and thus to involuntary job loss.[14] The exact classification is largely borrowed from Keefe *et al.* (2002).

(iv) Drug prescriptions including detailed types of prescribed drugs. The data record all payments to drug stores or refunds to individuals for prescribed and self-medicated drugs. The data are extremely detailed concerning the type of drugs. We classify the drugs into a category that is "specific" to treat health problems associated with job loss and unemployment and a residual category of non-specific drugs. Among specific drugs we distinguish between "psychosomatic"

[14]Unfortunately, the data do not contain the ICD9 codes indicating self-inflicted injuries or other external injuries. This may signify either that self-inflicted injuries are not prevalent or that these diagnoses have been recoded into other codes. In any case, our data do not permit discussing separate results for self-inflicted injuries.

drugs targeted at psychosomatic afflictions (such as migraine therapeutics, anti-inflammatory drugs, and so on) and "psychotropic" drugs treating psychological distress (such as, for example, sedatives, benzodiazepins, and antidepressants).

Individuals who take up public health care provisions have to pay a non-negligible fraction of actual health costs themselves. According to the rules that were in place in 2003, immediately after the end of our observation period, the deductible was a fixed amount of 4.25 Euros for each prescription of a medical drug, 3.63 Euros for doctor consultation, 10.90 Euros for each outpatient treatment (with a maximum of 73.67 Euro per year). No deductible accrues for inpatient treatments. Hofmarcher et al. (2004) estimate the total amount of these co-payments to about 11 percent of overall health expenditures (excluding sickness benefits) in 2002.

3.2 Definition of plant closure

Because we study the causal impact of job loss on public health costs using plant closure as exogenous source of job loss, we have to make precise how we define a plant closure and how we define a job loss due to a 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. A firm is considered as a plant closure firm if the following criteria are met: (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% of the employees switch to the same employer at date $t+1$. This latter criterion is adopted to rule out misclassification of a take-over as a plant closure. Whenever more than 50% of the employees are found under an identical new firm identifier these observations are excluded from the sample. To make the distinction between plant closure firms and non-plant closure firms as clear-cut 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.[15] We also excluded all firms with less than 3 employees from the data because if such a firm disappears, it is likely that this is just a recoding of the firm identifier rather than a plant closure. We consider all plant closures that take place between January 1999 and December 2001, using the 10th of each month as the baseline date. This ensures that we have at least one year of health insurance information before and after the plant closure date for each observation.

[15] A distressed firm is defined as a firm with (i) a large drop in its workforce of at least 30% between t and t+1, and (ii) it does not recover quickly, i.e. its workforce remains under 80% of its original workforce (in period t) for the three succeeding months. The second criterion ensures that firms with a strong seasonal employment pattern do not count as plant closures.

Definition of plant closure and non-plant closure workers. Our plant closure sample (PC) consists of all workers, who are employed in the month of plant closure or who were employed at least one month during the year before plant closure in the case that they left before the effective shut-down of the plant and hence our sample covers both "stayers" and "early leavers". Our control sample consists of all workers who are neither employed in a plant closure nor a distressed firm in a given point in time. Notice that we allow workers to be included in the control sample repeatedly.[16]

We measure monthly health care costs relative to the plant closure date for plant closure workers and relative to the reference date for non-plant closure workers. The plant closure date is the 10th day of the month before the plant closes for "stayers" and the 10th day of the month before leaving the firm for "early leavers".[17] The reference date for control workers is the 10th day of the month in which the control workers are sampled.[18] In the following, we use the term "plant closure date" to identify the plant closure date for plant closure workers and the reference date for control workers.

Figure 1 about here

Figure 1 illustrates the construction of our dataset. We first identify all closing firms for each reference date between January 1999 and December 2001. In a second step, we identify all workers employed in the closing firms. In the third step, we draw a stratified random sample of workers who are employed in firms that do not close (stratified by the size of the firm). The fourth and final step consists of constructing individual information on the work history and the take-up of health care costs during the year before and the year after the plant closure or reference date, respectively.

[16]Due to the huge number of potential control workers, we draw a random sample of workers employed in non-plant closure firms. Non-plant closure workers are sampled randomly among all workers employed in non-plant closure firms and non-distressed firms. Specifically, on each reference date between January 1999 and December 2001, we take a 2.5% random sample 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). However, because our empirical strategy relies on the comparison of the PC group with a selected group of the control workers only, it will also take care of the sampling scheme using unequal probabilities.

[17]For instance, suppose a firm is active on the 10th of January 2000 but no longer active in any of the subsequent 12 months. The plant closure date of workers who are employed in this firm on the 10th of January 2000 is the 10th of January 2000. An "early leaver" is a worker who has been employed in this firm on the 10th of February 1999 (10th of March 1999, ..., 10th of December 1999). The plant closure date for this worker is the 10th of February 1999 (10th of March 1999, ..., 10th of December 1999).

[18]For instance, suppose a control worker is included in the random sample drawn on 10th of January 2000. This individual's reference date is the 10th of January 2000. Moreover, this individual is going to be used to estimate the counterfactual for all workers employed in plants that close between the 10th of January 2000 and the 10th of February 2000.

4 Empirical strategy

4.1 Comparing PC and NPC workers using propensity score matching

Clearly, estimating the causal effect of job loss on health by cross section or panel data may potentially lead to a bias because of the endogeneity of a job loss.[19] To tackle the problem of endogeneity we focus on job loss due to plant closure. The central idea is that being employed in a plant closure firm is resulting in job loss with certainty whereas being employed in a non-plant closure firm results in job loss with much lower probability. Moreover and more importantly, being employed in a plant closure firm is likely to be unrelated to a worker's ex-ante health status. This means that we can study the effect of job displacement on public health costs by comparing PC workers to NPC workers. Let Z_i be a binary variable that equals 1 if a person is employed in a plant closure firm at the plant closure date and 0 if a person is employed in a firm that continues to exist at the very same date. Further, define $Y_{it}^{Z_i}$ as the payments incurred by the health insurance fund that are associated with take-up of health insurance provisions of a particular individual i in the period $t \in \{b, a\}$, where $t = b$ is the period before the reference date and $t = a$ is the year after the reference date (as defined in Figure 1. Y_{it}^1 thus refers to the health costs in the case of actual job loss and Y_{it}^0 refers to health costs accruing in the case of no job loss. Our aim is to recover the average causal effect of job loss due to plant closure on public health costs for workers actually experiencing job loss from the data:[20]

$$E(Y_{ia}^1 - Y_{ia}^0 | Z_i = 1) \tag{1}$$

This is the average causal effect of plant closure induced job displacement on workers employed in plant closure firms. Note that plant closure induced job loss is not exactly the same as job loss. Job loss due to plant closure both tends to be unexpected and unrelated to individual performance on the job. Of course, some job losses also occur in NPC firms, mainly because of poor performance on the job or because firms downsize their workforce in response to negative shocks. However, it is unlikely that not accounting for involuntary job loss in the control group will bias our estimates. On the one hand, most employment relationships in NPC firms are not dissolved at the reference date. On the other hand, many employment relationships that are actually dissolved are voluntary quits and result in job-to-job moves. As a result there is almost a one-to-one relationship between being employed in a plant closure firm and involuntarily losing

[19]A similar endogeneity problem has been discussed in studies estimating the causal effect of education on health (Chevalier and Feinstein, 2006).

[20]Clearly, the second term of the difference in not directly observed and must be estimated from the group of NPC workers. Imbens and Wooldridge (2009) provide an up-to-date survey of empirical methods dealing with this fundamental problem.

one's job. The key assumption necessary to identify the causal effect of job loss via plant closure on public health costs states that plant closure is independent of potential health cost outcomes, conditional on observed characteristics X_i (including individual- and firm-specific variables) and workers' health status before plant closure Y_{ib}:

$$(Y_{ia}^1, Y_{ia}^0) \perp\!\!\!\perp Z_i | X_i, Y_{ib} \tag{2}$$

Assumption (2) essentially states that plant closure is as good as randomly assigned, once differences in X_i and Y_{ib} are taken account of.[21] This implies that the health status of a worker must not cause the plant closure, once observable characteristics X_i and the workers' pre-PC health status Y_{ib} have been taken into account. In principle, plant closure might affect health through channels other than job loss. For instance, tighter local budgets might imply deteriorating quality of health care which might negatively affect health in turn. We believe that it is unlikely that such spillovers give rise to direct effects of plant closure on health for two reasons. First, our descriptive analysis indicates that plant closures are small compared to the average employer within a region hence it is unlikely that they generate major regional spillover effects. Second, regional spillover effects would also affect treatment and control group alike thus leaving the difference between the two groups largely unaffected.

We control for potential confounding variables by matching treated observations with non-treated observations using propensity scores which is defined as the conditional probability of being employed in a plant closure firm, $Pr(Z_i = 1|X_i, Y_{ib})$.[22] To estimate the propensity score, we use a vector of control variables X_i which includes age, tenure, days in employment, days in unemployment, overall health costs, days on sick leave, white collar status, firm size as well as dummy variables for region and industry of the employer and for calendar year and month.[23] All socio-demographic background variables and firm size are measured at the date immediately before the plant closure. Health measures are based on quarters 4 and 3 before the plant closes (or the reference date). We do not match on health costs in the half-year immediately preceding the plant closure so as to take potential health effects stemming from anticipation of job loss

[21] The second key assumption states that we observe both treated and control units for all possible values of the covariates, implying that the conditional distribution of Z_i given the covariates completely overlaps.

[22] Rosenbaum and Rubin (1983) show that matching on the propensity score is equivalent to matching on every dimension that feeds the score. See Caliendo and Kopeinig (2008) for a recent survey of matching methods based on the propensity score.

[23] In terms of health cost measures, we have opted for a very parsimonious model specification for the estimation of the propensity score because we are interested in how well a parsimonious specification is able to balance covariates. It turns out that this parsimonious specification suffices to achieve balance for a large number of covariates - including the detailed health costs (see new Table 1). Moreover, Table A.2 in the appendix shows that - as expected - health costs are not very important predictors of being a plant closure worker. We have therefore decided to keep the parsimonious specification of the propensity score.

into account. The estimation of the propensity score is performed separately for women and men to account for the pronounced differences in labor market attachment between women and men.[24] We then look, for each treated individual, for its nearest neighbor in terms of the estimated propensity score. To match treated and controls we use a simple two step algorithm. The first step estimates the propensity score using information on pre-determined variables X_i and pre-plant closure health Y_{ib}. The second step matches one control observation (i.e. an observation with $Z_i = 0$) to each treated observation (i.e. observations with $Z_i = 1$), using control observations potentially several times.[25]

4.2 Quality of the matching procedure

Table 1 compares descriptive statistics of PC, all NPC and matched NPC workers for the year before the plant closure date. Panel A of table 1 reports pre-PC health cost indicators whereas panel B reports descriptives relating to individual characteristics and pre-PC labor market indicators.[26] To assess the balance in covariates, table 1 also shows the standardized bias both before and after matching as suggested by Rosenbaum and Rubin (1985).[27]

Table 1 about here

For males, we see that total health costs during the year before the plant closure averages 499 Euros for PC workers but only 434 Euros for NPC workers. Is this a large or a small difference? The standardized bias in health measures before plant closure is below 5 – a threshold deemed small (Caliendo and Kopeinig 2008) – for all health measures except for consultations and days on sick leave. Matching is highly effective in reducing standardized bias below 5 for days on sick leave and to -7 for consultations. For females, standardized bias before matching is low for all health measures except for days on sick leave. Matching is again effective in reducing standardized bias from 9.8 to 7.0. Overall, differences in pre-PC health costs appear rather small to begin with on average and are for the most part substantially reduced by our matching

[24] We use a probit model to estimate the propensity score. Table A.2 in the appendix reports the corresponding coefficients.

[25] Inference is somewhat complicated because the propensity score needs to be estimated. Bootstrapping accounts for the variability of the propensity score estimates but is computationally intensive. We therefore report both bootstrap standard errors (based on 500 bootstrap samples) and on conventional standard errors assuming that we have information on the true propensity score. Lechner (2002) shows that ignoring sampling variance due to propensity score estimation does not lead to different inference compared to bootstrap estimates of standard errors.

[26] Note differences in health measures in the year prior to plant closure that remain after matching could reflect anticipatory effects. We discuss anticipatory effects in Table 3.

[27] The standardized bias is defined as the absolute value of the difference in sample means between treated and control units as a percentage of the square root of the average of the two sample variances We also show the proportional reduction in the standardized bias, which is defined as the proportional reduction in the standardized bias after matching. A standardized value below 5 would clearly be judged as sufficient, as noted by Caliendo and Kopeinig (2008, p.48). Rosenbaum and Rubin (1985) view standardized bias above 20 as large and note that the percent reduction in bias is unstable for lower values before matching.

procedure. This suggests that using health costs before the plant closure date in the matching procedure is probably of minor importance only, relative to the importance of pre-PC labor market outcomes.

The matching procedure looks particularly good in terms of individual characteristics and pre-PC labor market outcomes (see panel B of table 1). The major differences between PC workers and the full NPC sample refer to job tenure for men and wage and firm size for women. These differences disappear almost entirely when we compare the PC workers to the matched NPC sample. The reduction in standardized bias shows that our matching procedure is able to eliminate most of the existing imbalance in covariates. This holds for males and females alike.

A final check of the quality of the matching procedure comes from a comparison of the distribution of propensity scores of PC and NPC workers (see figure A.1 in the appendix). While the distribution of the estimated propensity score of the unmatched NPC workers has a very high density at low scores and is thus very different from the distribution of matched NPC workers, the distribution of the matched workers closely resembles the distribution of PC workers, and there is thus almost complete overlap in the estimated propensity score[28]. We conclude that the matching procedure works very well for our purpose and that confounding factors should not contaminate a comparison of PC and matched NPC workers.

5 Results

5.1 The causal effect of involuntary job loss on public health costs

Our estimate of the causal effect of job loss on public health costs is based on a comparison of post displacement histories of PC workers with matched NPC workers. In table 2 we provide first evidence on differences between these two groups as regards post-displacement health costs. We immediately see that overall health costs are higher for male PC workers than for male matched NPC workers. This difference is substantial and amounts to 468 Euros during the first year after the plant closure. Interestingly, the difference is almost entirely due to sickness benefits whereas the difference with respect to direct costs for health care provisions (consultations, hospitalizations, and medical drugs) is very small and insignificant. Digging deeper reveals that consultations of doctors of PC workers is significantly lower whereas hospitalizations and medical drug expenditures are somewhat higher, albeit no significant.[29]

[28]For men, 87 out of 8310 treated units are outside the common support (or about 1%). For women, only 19 out of 4257 treated units lie outside the common support (less than 0.5%). Moreover, because those observations outside the common support have very similar average propensity score as their matched control observations, we decided to keep these observations in the analysis.

[29]The numbers in tables 1 and 2 show that health costs not only increase for PC workers but for matched NPC workers as well. There are several possible reasons for this. First, one of the most important predictors of health

Table 2 about here

Table 2 shows that the bulk of the increase in health costs after a plant closure is due to a huge increase in sickness benefits. Male PC workers draw on average sickness benefits amounting to 691 Euros in the first post displacement year. This is a dramatic increase in sickness benefit payments, as during the pre-displacement year only 253 Euros were spent on PC workers. Almost the same amount (235 Euros) was spent for the matched control group, implying that plant closure increases expenditures by 453 Euros (or 180 percent) within the first post-displacement year. However, there are several explanations for this huge increase. First, increases in sickness benefits could indicate actual health problems because sickness benefits are only paid after a medical check by a physician. Hence workers receiving these benefits are, arguably, in an adverse health situation. Second, sickness benefits are higher than unemployment benefits, suggesting that unemployed workers have an incentive to get access to these benefits. Moreover, sickness benefits interrupt unemployment benefit payments and thus postpone the date when unemployment benefits lapse, implying that take-up of sickness benfits may partly reflect incentives created by these rules rather than adverse health only. A third reason relates to administrative rules governing the payment of sickness benefits. For employed workers, sickness benefits have to be paid by the employer for the first 12 weeks since the start of health-related workplace absence. For unemployed workers, in contrast, sickness benefits are paid by the public health insurance fund right from the start. As unemployment increases strongly after a job loss due to plant closure, sickness benefits for PC workers may increase mechanically due to sickness benefit rules, because we only observe payments made by the public fund. We can assess which of the above reasons is driving the increase in sickness benefit payments. The data set does not only report the amount of sickness benefits paid to the worker but also the number of days a worker draws such benefits (see row 4 of table 2). Interestingly, days on sick leave do not change among male PC workers. On average, PC and matched control workers are receiving sickness benefits over 12.9 and 11.4 days, respectively. The difference is significantly different from zero, but much smaller relatively than the corresponding increase in sickness benefits and thus suggests that both direct health effects and incentive effects (i.e. gaining access to higher and longer benefits) are of minor importance. The bulk of the increase in sickness benefits is driven by the fact that PC workers enter unemployment which in turn raises sickness benefits

costs, age, increases by one year for all PC and NPC workers. Second, this increase also reflects the general strong upward trend in public health expenditures (overall health costs increased by 6% from 1998 to 1999). Third, workers in the PC and matched NPC sample have to be employed in order to be included in our sample. Being employed, they are more likely to experience a positive health shock (leading to a negative health cost shock). Simple mean reversion might therefore explain a substantial part of the increase in health expenditures after the reference date.

to be paid by the public insurance agency.

A closer look at outcomes for core health care categories indicates that costs associated with consultations of physicians are considerably lower for PC workers than for matched NPC workers (table 2, row 5). PC workers see doctors less often and incur costs on the order of 85 Euro in the year after the reference date. The corresponding figure is 95 Euros for matched NPC workers, giving rise to a sizeable and statistically significant difference of 10 Euros in costs. However, recall that these costs have been lower for PC workers already in the pre-displacement year. This calls for a careful investigation of the sensitivity of this result with respect to an identification strategy that controls more directly for differences in pre-displacement health costs. Concerning expenses related to hospitalizations and the prescription of medical drugs, the empirical results point to slightly, though insignificantly, higher expenditures for PC workers compared to matched NPC workers (table 2, rows 6 and 7).

Unlike for men, results for women do not indicate a significant difference in terms of overall health costs (table 2, row 1). Whereas average public health costs in the post-displacement year amount to 934 Euros for female PC workers and are thus almost the same as for male workers, the corresponding amount for matched NPC women is only 732 Euros. The resulting difference of 202 Euros is not significantly different from zero.

Interestingly, separating overall health costs into costs related to sickness benefits and remaining health costs reveals a pattern that is very much in line with the pattern that shows up for men. Sickness benefit payments are almost twice as high for women employed in closing plants (441 Euros) compared to sickness benefits going to women employed in surviving plants (238 Euros). The difference of 202 Euros is both statistically and economically significant. Again we can check to which extent this increase is driven by bad health and/or an effect on incentives, or by mechanical increases in these payments that arise from a high incidence of unemployment after a plant closure. We find that the situation is similar for women. The difference in days claiming sickness benefits between the treated and the control group is substantial and amounts to about 15 percent. Nevertheless, this compares to differences in sickness benefits payments between the two groups of almost 100 percent. Hence, similar to the situation for males, we conclude that for female PC workers the increase in public health costs is also dominated by the mechanical increase due to sickness benefit rules. Results on doctor visits, hospitalizations, and drug prescriptions are for the most part not significantly different from zero (table 2, rows 5-7).

5.2 Dynamic evolution of health costs

Figure 2 shows the evolution of the difference in overall health costs between PC workers and matched NPC workers by quarter to/since the date plant closure, separately for men (panel a) and women (panel b). This figure clearly shows that overall health costs are balanced in all four quarters before the reference date, albeit this holds true almost by construction for the second half-year before the plant closure date because overall health costs in this half-year enter the estimation of the propensity score. The difference between treated and controls of males and females lies with the range of minus 25 to plus 10 Euros per quarter during the entire year before the plant closure. In contrast, public health costs shoot up in the first and second quarter after plant closure for both male and female PC workers. The point estimates for excess health expenditures per quarter lie between 75 and about 160 Euros per quarter for men, and somewhat less for women. We also see that excess health costs are significantly different from zero for men during the first two post-displacement quarters, level off thereafter and are no longer significant in the remaining two quarters. For women, the time pattern of the point estimates is quite similar, but most of the estimates are not significantly different from zero, mainly due to large standard errors.

Figure 2 about here

Figure 3 provides more detailed evidence on the dynamics of public health costs immediately before and after the plant closure. Panel a) shows that the time pattern of excess sickness benefit payments is driving the dynamics of overall health costs. Both male and female PC workers cause a larger amount of sickness benefit payroll for the public health agency than matched NPC workers. The difference is strongly significant for men and attains marginal statistical significance for women in the second quarter after plant closure. Panel b) shows the dynamics of days on sickness benefits. We see a significant increase in excess days claiming sickness benefits during the last quarter before the plant closure and the first quarter after the plant closure for both men and women. To the extent that days on sickness benefits reflect actual health problem this suggests that mental or physical disorders may already emerge prior to the plant closure date in anticipation of a job loss. Panel c) shows excess health costs excluding payments for sickness benefits. Both for men and for women, excess health costs do not show a particular temporal pattern. Both male and female PC workers cause costs of about the same amount as their matched NPC counterparts, both before and after plant closure. Panel d) displays excess costs for doctor visits. These costs are already lower for male PC workers than for the matched NPC workers before plant closure. The difference in consultation costs widens somewhat in the second and third quarter after plant closure, thereby yielding significantly lower expenses due to doctor visits identified in table 2. Yet, the fact that costs due to doctor visits are lower in the periods before the plant closure is consistent with unobserved time-invariant heterogeneity introducing a downward bias into the simple contrast between PC workers and matched NPC workers. Panels a) and b) of figure 4 show that the excess costs for hospitalizations and medical drugs do not show a systematic time patters and are very similar before and after the plant closure. The remaining two panels of figure 4 show excess costs related to mental health problems (hospitalization due to mental health problems and costs accruing from the prescription of psychotropic drugs. For both indicators, there emerges an interesting difference between men and women. While for women the dynamics of excess health costs related to mental diseases do not seem to be affected by job loss, we see a significant pattern for men. For male PC workers, both health cost indicators are significantly higher than for matched NPC workers.

Figures 3 and 4 about here

To study potential effects from anticipating the plant closure, table 3 compares health costs incurred in the half-year immediately preceding the reference date in the PC and matched NPC sample. There is no significant difference in overall costs. Basing inference on bootstrap standard errors, we find no effect on any health cost subgroup for men. In contrast, women tend to spend 1.6 days more on sick leave already in the half year before plant closure. While this effect may signify deteriorating health from the anticipation of job loss, the simultaneous absence of any effect on both overall and detailed health costs may rather suggest that part of the female workforce of closing firms leaves the labor force before the actual shut-down of the firm by applying for sickness benefits rather than unemployment benefits. We speculate that this may be related to pregnancy induced reasons among women.

Table 3 about here

5.3 Sensitivity analysis

Table 4 discusses the sensitivity of our main results in Table 2 by adding the full list of control variables discussed in the previous section to control for any imbalances in covariates remaining after the matching procedure. Moreover, we account for unobserved time-invariant heterogeneity by taking first differences in health outcomes. Column 1 in table 4 simply reproduces the main result of table 2, column 2 adds controls, and column 3 displays the estimates from using first differences.[30] For males, the key result that health costs are higher for PC workers than for

[30]Recall that health care costs in the half year prior to plant closure might be affected by anticipatory effects. We therefore define the difference in health care costs to reflect health costs during the year after the plant closure minus twice the health costs during quarters 4 and 3 before plant closure.

matched NPC workers remains present, whether we control for covariates or we use differences in health outcomes (columns 2 and 3). Whereas the baseline result suggests that health costs increase by 468 Euros, adding controls reduces this effect to 432 Euros, and using first-differences decreases it somewhat less to 441 Euros. Incremental health costs are primarily due to increases in sickness benefits, estimated to be between 383 Euros (first differences) to 453 Euros (without controls). Interestingly, the negative effect on expenditures due to consultations as well as the effect on days on sick leave from the baseline estimates disappear when adopting a difference specification. This likely indicates that the ex-ante differences in expenditures due to doctor visits are driving the baseline results rather than being a genuine effect of plant closure induced job displacement. None of the remaining health measures are sensitive to adding controls or to estimating in first differences.

Table 4 about here

The results for women indicate that the baseline effect on overall health costs for women is statistically different from zero (when inference is based on robust standard errors), both in the specification that adds controls and the specification that looks at first differences. This suggests that there is a lot of heterogeneity in health expenditures that is related to observed and unobserved ex-ante differences between women. Again, the sensitivity analysis confirms the main conclusion that health costs increase due to sickness benefits – the magnitude of the effect is much in line with the baseline result. None of the remaining health measures are sensitive to adding controls or to estimating in first differences.

5.4 Detailed results

We also provide results concerning more disaggregate health measures. Arguably, job loss is likely to be related to health conditions that have to do with mental health. Other serious health problems such as cancer, heart disease, respiratory diseases, and stroke are less likely to change immediately after job loss. We therefore provide separate results of the effects of job loss on these dimensions of health care. Table 5 provides the results for hospitalizations. The grouping of health conditions is based on ICD-9 codes associated with any medical expenditure contained in our dataset. The first line in this table repeats the entry regarding hospitalization from table 4.

Table 5 about here

Detailed hospitalization results for men indicate that there are no significant effects of job displacement on conditions associated with cancer, heart disease, respiratory disease or stroke.

In contrast, expenditures related to mental health conditions increase substantially. The baseline result that compare PC workers with NPC workers suggests that expenditures on mental health hospitalizations are 17 Euros higher for men. This baseline estimate turns out to be robust to controlling for observed characteristics (column 2) and unobserved time invariant characteristics (column 3). Thus, detailed hospitalization results for men suggest that the weak and insignificant overall effect for men is entirely due to an increase in mental health expenditures.

Columns 4 to 6 of table 5 present the corresponding results for women. We find that excess health costs due to hospitalization for health problems related to cancer, heart disease, mental problems, respiratory disease, and strokes are largely unaffected by job loss due to plant closure. However, women employed by closing plants incur 26 Euros higher public health costs related to a pregnancy. This suggests that (the anticipation of) a job loss induces mothers to adjust the timing of their children. This is in line with the argument that the loss of a job temporarily reduces the opportunity costs of having a child and thus may affect the timing of children.

We also provide more specific results for drug prescriptions. Table 6 groups drugs into "specific" and "non-specific" drugs. Specific drugs are those that are arguably used to treat symptoms potentially related to job loss. These include drugs that are used to treat psychosomatic disorders (such as back pains) and psychotropic drugs (e.g. antidepressants). The first line in Table 6 repeats the baseline estimate from table 4.

Table 6 about here

Results for men indicate that overall consumption of specific drugs remains unaffected by job loss. However, while psychosomatic drugs reveal a slightly negative point estimate, the effect on psychotropic drugs is positive and significantly different from zero. Men who are employed in closing plants cause about 2.8 Euros more costs for psychotropic drugs than similar men employed in continuing plants. This effect is not sensitive to adding control variables but gets somewhat smaller (about 1.7 Euros) when looking a first difference approach.

Detailed results for women do not suggest any effect of job loss on consumption of drugs. If anything, the point estimates indicate lower drug consumption among PC women compared to matched NPC women. These results reinforce the finding from the detailed hospitalization categories showing that costs related to mental health increase for men but do not change for women. The reason why women do not face mental health problem may be that women face less financial distress as many (particularly married) women have their basic economic needs guaranteed by other household income. Moreover, according to the traditional division of labor within the family women may find it easier to replace the emotional rewards formerly provided by their job with their role in the family causing less emotional distress. In fact, our result that job loss increases the likelihood of a pregnancy is also consistent with this latter hypothesis.

6 Conclusions

This paper studies the causal effect of job loss on public expenditures on health care. Our empirical analysis focuses on the case of Austria where public health insurance is mandatory for all employees. To tackle the problem of reverse causality we focus on analyzing job loss due to plant closure because plant closure leads to job loss without being caused by a worker's health. We assess the causal relationship between individual job loss and public health care costs by exploiting a data set that combines detailed information on a worker's earnings and employment history with detailed information on payments by the public health insurance authority. These payments are associated with the take-up of health care benefits and are comprehensive in that they include both treatment-related health care provisions (such as hospitalization, doctor visits, and drug prescriptions) and the dimension of income insurance (payment of sickness benefits).

Our empirical analysis yields several interesting results. First, it turns out that job loss following a plant closure does not cause a significant increase in public health costs associated with take-up of health provisions. Public health costs due to hospitalizations, doctor visits, and medical drugs' prescriptions do not increase significantly. Second, while overall take-up of health provisions is not significantly affected, we find – for males, but not for females – an increase in public health costs due to mental health problems. This result is in line with the hypothesis that unemployment causes mental health problems whereas physical health appears to be largely unaffected. Third, we find that the public health costs that are associated with payments of sickness benefits strongly increase after a job loss. However, this increase in costs does not reflect a deteriorating health status of displaced workers but is mainly due to sickness benefit rules. We do not find that male plant closure workers spend more days on sick leave. While there is an increase in days on sick leave for women, the effect is not robust and small compared to the overall increase in sick leave payments.

The estimated effects of short-run public costs due to direct health care provisions appear small. While such a result is in line with Browning et al. (2006) who do not find a significant impact of displacement on hospitalizations for stress-related diseases for Danish men, other recent studies have found that plant closures cause significant health problems for displaced workers. Gerdtham and Johannesson (2003) and Eliason and Storrie (2009) find that being unemployed increases mortality in Sweden over longer time horizons. Sullivan and von Wachter (2006) give similar results for the U.S. One reason might be our focus on short-run health costs.

Immediate health effects of unemployment may not show up in physical health conditions but more likely in mental health. In fact, for males, we find significantly higher public health costs associated with purchases of psychotropic drugs and also for hospitalizations due to mental health problems.

A further reason why the estimated health cost effects are small could be that our plant-closure sample of plant closure consists disproportionately of blue collar workers who are often subject to more dangerous and unhealthy working conditions. Job loss means temporary absence from such working conditions may reduce health differences between displaced and comparable non-displaced workers. Another reason could be take-up behavior. Deductibles are non-negligible and workers who experience extended periods of unemployment and substantial income losses may abstain from seeking medical treatment. However, disregarding such health problems in the short run, while reducing current public health costs, could materialize in worse health conditions and higher public health costs of job loss in the long run.

References

Ahs, A.M. and Westerling, R. (2006). Health care utilization among persons who are unemployed or outside the labour force. *Health Policy*, **78**, 178–193.

Andersen, R.M. (1995). Revisiting the Behavioral Model and Access to Medical Care: Does it Matter? *Journal of Health and Social Behavior*, **36**, 1–10.

Askildsen, J. E., Bratberg, E., and Nilsen, Ø. A. (2005). Unemployment, labor force composition and sickness absence: a panel data study. *Health Economics*, **14**(11), 1087–1101.

Bjorklund, A. (1985). Unemployment and Mental Health: Some Evidence from Panel Data. *The Journal of Human Resources*, **20**(4), 469–483.

Brenner, M. (1979). Mortality and the National Economy: A Review, and the Experience of Wales and England, 1936–76. *The Lancet*, **2**(8142), 568–573.

Browning, M., Dano, A. M., and Heinesen, E. (2006). Job displacement and stress-related health outcomes. *Health Economics*, **15**(10), 1061–1075.

Burgard, S. A., Brand, J. E., and House, J. S. (2005). Causation and Selection in the Relationship of Job Loss to Health in the United States. Mimeo, University of Michigan.

Caliendo, M. and Kopeinig S. (2008). Some practical guidance for the implementation of propensity score matching. *Journal of Economic Surveys*, **22**(1), 31–72.

Carr-Hill, R. A., Rice, N., and Roland, M. (1996). Socioeconomic determinants of rates of consultation in general practice based on fourth national survey of general practices. *British Medical Journal*, **312**.

Chevalier, A. and Feinstein, L. (2006). Sheepskin or Prozac: The Causal Effect of Education on Mental Health. IZA Discussion Paper No. 2231.

Clark, A. E. and Oswald, A. J. (1994). Unhappiness and Unemployment. *The Economic Journal*, **104**, 648–659.

Cook, D. G. (1985). A critical view of the unemployment and health debate. *The Statistician*, **34**, 73–82.

Currie, J. and Madrian, B. C. (1999). Health, Health Insurance and the Labor Market. In O. Ashenfelter and D. Card, editors, *Handbook of Labor Economics*, volume 3C, pages 3309–3416. Elsevier Science.

D'Arcy, C. and Siddique, C. (1985). Unemployment and Health: An Analysis of "Canada Health Survey" Data. *International Journal of Health Services*, **15**, 609–635.

Eliason, M. and Storrie, D. (2009). Does Job Loss Shorten Life?. *Journal of Human Resources*, forthcoming.

Field, K. S. and Briggs, D. J. (2001). Socio-economic and locational determinants of accessibility and utilization of primary health-care. *Health & Social Care in the Community*, **9**, 294–308.

Gerdtham, U. and Johannesson, M. (2003). A note on the effect of unemployment on mortality. *Journal of Health Economics*, **22**, 505–518.

Gerdtham, U. and Ruhm, C. J. (2006). Deaths Rise in Good Economic Times: Evidence from the OECD. Mimeo, Lund University and University of North Carolina.

Goldsmith, A., Veum, J., and Darity, W. (1996). The psychological impact of unemployment and joblessness. *The Journal of Socioeconomics*, **25**(3), 333–358.

Grossman, M. (1972). On the Concept of Health Capital and the Demand for Health. *Journal of Political Economy*, **80**(2), 223–55.

Hagist, C. and Kotlikoff, L. (2005). Who's Going Broke? Comparing Growth in Healthcare Costs in Ten OECD Countries. *NBER Working Paper No. 11833*.

Henrekson, M. and Persson, M. (2004). The effects on sick leave of changes in the sickness insurance system. *Journal of Labor Economics*, **22**(1), 87–114.

Hofmarcher, M.M., Riedel, M., and G. Rhrling (2004). Health System Watch I/2004, Institute for Advanced Studies, Vienna.

Imbens, Guido W. and Wooldridge, Jeffrey M. (2009). Recent developments in the econometrics of program evaluation. *Journal of Economic Literature*, **47**(1), 5–86.

Iversen, L., Sabroe, S., and M.T.Damsgaard (1989). Hospital admissions before and after shipyard closure. *British Medical Journal*, **299**, 1073–1076.

Jin, R. L., Shah, C. P., and Svoboda, T. J. (1995). The Impact of Unemployment on Health: A Review of the Evidence. *Canadian Medical Association Journal*, **153**, 528–540.

Johansson, P. and Palme, M. (1996). Do economic incentives affect work absence? empirical evidence using swedish micro data. *Journal of Public Economics*, **59**(2), 195–218.

Johansson, P. and Palme, M. (2005). Moral hazard and sickness insurance. *Journal of Public Economics*, **89**(9-10), 1879–1890.

Kasl, S. V. and Jones, B. A. (2000). The Impact of Job Loss and Retirement on Health. In L. Berkman and I. Kawachi, editors, *Social Epidemiology*. Oxford University Press.

Kasl, S. V. and Jones, B. A. (2006). Unemployment and Health. Mimeo, Department of Epidemiology and Public Health, Yale University School of Medicine.

Keefe, V., Reid, P., Ormsby, C., Robson, B., Purdie, G., Baxter, J., and Incorporated, N. K. I. (2002). Serious health events following involuntary job loss in New Zealand meat processing workers. *International Journal of Epidemiology*, **31**, 1155–1161.

Kessler, R. C., House, J. S., and Turner, J. B. (1987). Unemployment and Health in a Community Sample. *Journal of Health and Social Behavior*, **28**(51-59).

Kessler, R. C., House, J. S., and Turner, J. B. (1989). Unemployment, Reemployment, and Emotional Functioning in a Community Sample. *American Sociological Review*, **54**, 648–657.

Korpi, T. (1997). Employment, unemployment, labor market policies and subjective well-being among Swedish youth. *Labour Economics*, **4**, 125–147.

Lechner, M. (2002). Some practical issues in the evaluation of heterogeneous labor market programmes by matching methods *Journal of the Royal Statistical Society - Series A*, **165/1**, 59-82.

Martikainen, P. and Valkonen, T. (1996). Excess mortality of unemployed men and women during a period of rapidly increasing unemployment. *The Lancet*, **348**, 909–912.

Morris, J. and Cook, D. (1991). A critical review of the effect of factory closures on health. *British Journal of Industrial Medicine*, **48**, 1–8.

Morris, J., Cook, D., and Shaper, A. (1994). Loss of employment and mortality. *British Medical Journal*, **308**, 1135–1139.

Moser, K., Goldblatt, P., Fox, A., and Jones, D. (1987). Unemployment and mortality: comparison of the 1971 and 1981 longitudinal study census samples. *British Medical Journal*, **294**, 86–90.

Nylen, L., Voss, M., and Floderus, B. (2001). Mortality among women and men relative to unemployment, part time work, overtime work, and extra work: a study based on data from the Swedish twins registry. *Occupational and Environmental Medicine*, pages 52–57.

Platt, S. (1984). Unemployment and Suicidal Behavior. *Social Science and Medicine*, **19**, 93–115.

Rosenbaum, P. R. and Rubin, D. B. (1983). The Central Role of the Propensity Score in Observational Studies for Causal Effects. *Biometrika*, pages 41–55.

Rosenbaum, P. R. and Rubin, D. B. (1985). Constructing a control group using multivariate matched sampling methods that incorporate the propensity score. *American Statistician*, **39**(1), 33–38.

Ruhm, C. J. (2000). Are recessions good for your health? *The Quarterly Journal of Economics*, **115**(2), 617–650.

Ruhm, C. J. (2003). Good Times Make You Sick. *Journal of Health Economics*, **22**, 637–658.

Ruhm, C. J. (2005). Commentary: Mortality increases during economic upturns. *International Journal of Epidemiology*, **34**, 1206–1211.

Stewart, J. M. (2001). The impact of health status on the duration of unemployment spells and the implications for studies of the impact of unemployment on health status. *Journal of Health Economics*, **20**(5), 781–796.

Studnicka, M., Studnicka-Benke, A., Wögerbauer, G., Rastetter, D., Wenda, R., Gathmann, P., and Ringel, E. (1991). Psychological health, self-reported physical health and health service use. *Social Psychiatry and Psychiatric Epidemiology*, pages 86–91.

Sullivan, D. G. and von Wachter, T. (2006). Mortality, Mass–Layoffs, and Career Outcomes: An Analysis Using Administrative Data. *FRB of Chicago Working Paper No. 2006–21*.

Stutzer, A. and Lalive, R. (2004). The Role of Social Norms in Job Searching and Subjective Well-Being. *Journal of the European Economic Association,* **2***, 696-719.*

Theodossiou, I. (1998). The effects of low-pay and unemployment on psychological well-being: A logistic regression approach. *Journal of Health Economics*, **17**, 85–104.

Turner, J. B. (1995). Economic Context and the Health Effects of Unemployment. *Journal of Health and Social Behavior*, **36**(3), 213–229.

Versicherungsverband Österreich (2005). Jahresbericht.

Virtanen, P. (1993). Unemployment, re-employment and and the use of primary health care services. *Scandinavian Journal of Primary Health Care*, **11**, 225–227.

Voss, M., Nylen, L., Floderus, B., Diderichsen, F., and Terry, P. D. (2004). Unemployment and Early Cause–Specific Mortality: A Study Based on the Swedish Twin Registry. *American Journal of Public Health*, **94**(12), 2155–2161.

Warr, P. (1987). Work, Unemployment, and Mental Health. Oxford: Clarendon Press Oxford.

Winkelmann, L. and Winkelmann, R. (1998). Why are the unemployed so unhappy? evidence from panel data. *Economica*, **65**, 1–16.

Table 1: Health indicators and exogenous variables, one year before PC date

	Men						Women					
	PC	All NPC	Matched NPC	SB_{bm}	SB_{am}	ΔSB	PC	All NPC	Matched NPC	SB_{bm}	SB_{am}	ΔSB
A. Health indicators												
Overall health costs	499.406	434.298	484.969	2.133	0.516	75.825	481.593	467.367	506.123	0.778	−1.209	−55.358
	(3346.094)	(2727.971)	(2117.675)				(1988.511)	(1651.902)	(2068.531)			
Overall health costs	246.658	254.282	250.916	−1.050	−0.622	40.737	372.510	379.461	363.276	−0.847	1.182	−39.570
(excl. sick pay)	(737.204)	(714.658)	(626.665)				(829.723)	(811.628)	(729.268)			
Sick pay	252.748	180.016	234.053	2.608	0.744	71.483	109.083	87.906	142.847	1.543	−2.057	−33.322
	(3066.924)	(2479.106)	(1796.867)				(1451.160)	(1289.478)	(1812.100)			
Days on sick leave	12.549	10.797	11.656	8.601	4.217	50.968	11.747	9.866	10.358	9.807	6.998	28.638
	(21.041)	(19.687)	(21.339)				(19.659)	(18.686)	(20.042)			
Consultations	70.361	85.332	78.620	−12.337	−7.021	43.092	154.239	157.702	150.576	−2.023	2.258	−11.652
	(112.557)	(129.542)	(122.475)				(166.733)	(175.581)	(157.564)			
Hospitalizations	126.676	109.749	125.071	2.924	0.281	90.408	140.719	133.877	126.391	1.136	2.476	−117.991
	(603.311)	(553.279)	(538.577)				(652.709)	(547.182)	(493.445)			
Medical drugs	49.621	59.201	47.225	−3.202	1.058	66.957	77.552	87.882	86.309	−2.735	−2.390	12.615
	(271.376)	(324.657)	(170.257)				(308.342)	(436.070)	(416.356)			
B. Other variables												
Age (years)	36.219	37.414	36.000	−11.891	2.173	81.727	33.631	36.468	34.708	−27.275	−10.379	61.949
	(10.051)	(10.038)	(10.161)				(10.927)	(9.849)	(9.807)			
Tenure (years)	1.826	3.207	1.902	−73.771	−4.110	94.429	2.519	3.276	2.610	−41.546	−4.935	88.122
	(1.812)	(1.930)	(1.866)				(1.785)	(1.854)	(1.896)			
White-collar	0.251	0.406	0.259	−33.330	−1.712	94.864	0.631	0.678	0.591	−9.869	8.149	17.430
	(0.434)	(0.491)	(0.438)				(0.483)	(0.467)	(0.492)			
Wage (€ 100)	197.849	240.647	201.552	−43.855	−3.874	91.167	127.922	160.233	134.818	−39.410	−9.179	76.709
	(103.051)	(91.802)	(87.477)				(81.870)	(82.103)	(67.696)			
Days employed	321.015	354.857	328.209	−45.709	−9.045	80.211	343.395	353.609	347.915	−13.768	−6.194	55.010
	(85.811)	(59.996)	(72.693)				(79.907)	(67.989)	(65.317)			
Days unemployed	42.828	13.797	41.063	43.544	2.262	94.805	21.755	11.182	20.951	19.101	1.356	92.900
	(80.086)	(49.763)	(75.889)				(62.328)	(47.349)	(56.007)			
Size of the firm	55.094	636.152	51.691	−41.638	4.752	88.588	75.090	1097.696	56.125	−48.409	20.527	57.597
	(75.592)	(1972.087)	(67.380)				(99.983)	(2985.752)	(84.120)			

Notes: All variables (except days on sick leave) are measured in nominal Euros and cover the year before the plant closure (reference) date. NPC (PC) refers to the non plant closure (plant closure) workers. Standard deviations are in parentheses. See also table A.1 in the appendix for the definitions of the various health measures. SB_{bm} (SB_{am}) denotes the standardized bias before (after) matching and ΔSB denotes the proportional bias reduction.

Table 2: The effect of job loss on health costs

	Men			Women		
	PC	Matched NPC	ATT	PC	Matched NPC	ATT
Overall health costs	985.375	516.828	468.547	933.530	731.670	201.859
	(80.870)	(37.699)	(94.925)***	(76.054)	(55.751)	(116.997)*
			[116.987]***			[147.809]
Overall health costs (excl. sick pay)	294.490	279.445	15.045	492.850	492.966	−0.116
	(12.012)	(10.737)	(19.916)	(17.285)	(21.026)	(33.638)
			[32.511]			[65.315]
Sick pay	690.886	237.383	453.503	440.680	238.705	201.976
	(75.865)	(31.597)	(86.378)***	(68.835)	(44.114)	(99.994)**
			[100.549]***			[107.551]*
Days on sick leave	12.867	11.402	1.465	12.907	10.890	2.017
	(0.296)	(0.291)	(0.519)***	(0.426)	(0.460)	(0.775)***
			[0.732]**			[1.061]*
Consultations	84.734	94.675	−9.942	173.415	194.007	−20.592
	(1.699)	(2.252)	(4.102)**	(3.098)	(4.210)	(7.107)***
			[5.671]*			[9.698]**
Hospitalizations	149.923	136.910	13.013	237.429	202.385	35.043
	(9.939)	(9.130)	(17.102)	(14.514)	(16.395)	(28.079)
			[25.021]			[48.783]
Medical drugs	59.833	47.860	11.973	82.006	96.574	−14.568
	(4.699)	(2.277)	(5.564)**	(4.269)	(9.964)	(12.184)
			[8.758]			[19.741]
n		8310			4257	

Notes: Table entries show mean values (columns "PC" and "Matched NPC") and the difference in means (column "Difference"), respectively. Table entries in the column headed "Difference" correspond to the estimated average treatment effect on the treated. All variables (except days on sick leave) are measured in nominal Euros and cover the four quarters after the plant closure (reference) date. Conventional standard errors (clustered by individual) are in parentheses. Bootstrapped standard errors (based on 500 replications) are in brackets. PC denotes the group of all PC workers, matched NPC denotes the group of matched NPC workers. *, **, *** denotes statistical significance on the 10%, 5%, and 1% level, respectively.

Table 3: Anticipatory effects on health costs in the half-year preceding PC date

	Men			Women		
	PC	Matched NPC	ATT	PC	Matched NPC	ATT
Overall health costs	227.042	226.273	0.769	246.069	237.628	8.441
	(14.926)	(17.091)	(32.167)	(12.832)	(16.239)	(24.092)
			[44.838]			[44.490]
Overall health costs (excl. sick pay)	126.715	124.063	2.652	200.772	182.057	18.715
	(5.078)	(5.584)	(9.307)	(7.002)	(8.579)	(11.870)
			[27.372]			[23.044]
Sick pay	100.328	102.210	−1.883	45.298	55.571	−10.273
	(12.999)	(14.051)	(27.049)	(9.353)	(12.870)	(19.374)
			[31.169]			[31.625]
Days on sick leave	6.621	5.650	0.970	6.542	4.900	1.643
	(0.142)	(0.185)	(0.314)***	(0.198)	(0.223)	(0.340)***
			[0.841]			[0.598]***
Consultations	37.727	39.927	−2.200	83.560	76.964	6.596
	(0.785)	(1.129)	(1.703)	(1.636)	(2.003)	(3.176)**
			[4.248]			[4.657]
Hospitalizations	62.400	60.732	1.668	76.759	58.311	18.447
	(4.271)	(4.990)	(8.000)	(5.618)	(6.027)	(8.638)**
			[22.993]			[17.477]
Medical drugs	26.588	23.404	3.184	40.453	46.782	−6.329
	(1.841)	(1.192)	(2.369)	(2.530)	(4.928)	(6.193)
			[2.693]			[8.765]
n		8310			4257	

Notes: Table entries show mean values (columns "PC" and "Matched NPC") and the difference in means (column "Difference") respectively, of the corresponding health measure in the two quarters before the PC (reference) date. Table entries in the column headed "Difference" correspond to the estimated average treatment effect on the treated. All variables (except days on sick leave) are measured in nominal Euros and cover the four quarters after the plant closure (reference) date. Conventional standard errors (clustered by individual) are in parentheses. Bootstrapped standard errors (based on 500 replications) are in brackets. PC denotes the group of all PC workers, matched NPC denotes the group of matched NPC workers. *, **, *** denotes statistical significance on the 10%, 5%, and 1% level, respectively.

Table 4: Sensitivity analysis

	Men			Women		
Outcome measured in	Levels	Levels	Differences	Levels	Levels	Differences
Additional controls?	No	Yes	No	No	Yes	No
Overall health costs	468.547	431.713	441.211	201.859	242.091	267.803
	(94.925)***	(94.916)***	(116.275)***	(116.997)*	(105.565)**	(131.511)**
	[116.987]***	[101.422]***	[414.896]	[172.930]	[114.558]**	[153.632]*
Overall health costs	15.045	5.735	13.141	−0.116	12.854	43.283
(excl. sick pay)	(19.916)	(20.497)	(23.242)	(33.638)	(29.517)	(27.480)
	[29.830]	[25.665]	[43.135]	[60.307]	[42.202]	[43.750]
Sick pay	453.503	425.978	412.347	201.976	229.237	248.957
	(86.378)***	(86.013)***	(107.577)***	(99.994)**	(91.857)**	(120.544)**
	[98.718]***	[91.735]***	[335.063]	[118.597]*	[91.436]**	[128.433]*
Days on sick leave	1.465	1.163	1.619	2.017	2.202	2.524
	(0.519)***	(0.482)**	(0.713)**	(0.775)***	(0.723)***	(0.937)***
	[0.752]*	[0.653]*	[1.663]	[1.076]*	[0.906]**	[1.266]**
Consultations	−9.942	−9.118	2.174	−20.592	−17.398	−14.726
	(4.102)**	(3.585)**	(4.078)	(7.107)***	(6.399)***	(7.504)**
	[5.633]*	[4.571]**	[5.085]	[9.010]**	[8.040]**	[9.908]
Hospitalizations	13.013	3.904	13.141	35.043	41.198	43.283
	(17.102)	(17.698)	(23.242)	(28.079)	(24.826)*	(27.480)
	[27.145]	[22.325]	[43.135]	[42.669]	[32.755]	[43.750]
Medical drugs	11.973	10.949	13.548	−14.568	−10.946	−9.711
	(5.564)**	(5.712)*	(5.150)***	(12.184)	(11.330)	(8.611)
	[8.451]	[7.088]	[8.644]	[18.765]	[19.015]	[15.775]
n		8310			4257	

Notes: Table entries are differences in means of PC workers and matched NPC workers. All variables (except days on sick leave) are measured in nominal Euros and cover the four quarters after the plant closure (reference) date. Conventional standard errors (clustered by individual) are in parentheses. Bootstrapped standard errors (based on 500 replications) are in brackets. *, **, *** denotes statistical significance on the 10%, 5%, and 1% level, respectively. Additional control variables are the same as those used for estimating the propensity score (see table A.2 in the appendix).

Table 5: Detailed results, health costs due to hospitalization

	Men			Women		
Outcome measured in Additional controls?	Levels No	Levels Yes	Differences No	Levels No	Levels Yes	Differences No
All diagnoses	13.013	3.904	13.141	35.043	41.198	43.283
	(17.102)	(17.698)	(23.242)	(28.079)	(24.826)*	(27.480)
	[26.887]	[22.878]	[33.586]	[46.268]	[32.705]	[44.168]
Cancer	−3.491	−4.312	−5.121	−5.755	−2.694	−3.635
	(3.960)	(4.421)	(4.167)	(16.298)	(13.167)	(10.728)
	[7.018]	[6.744]	[6.488]	[40.968]	[18.250]	[23.792]
Heart	0.834	0.632	−1.610	3.938	4.579	3.408
	(1.922)	(1.961)	(2.595)	(4.284)	(4.696)	(4.426)
	[2.906]	[2.878]	[4.072]	[4.733]	[4.506]	[4.752]
Mental	16.293	13.234	13.694	23.779	23.388	17.274
	(6.036)***	(6.276)**	(10.592)	(10.092)**	(9.560)**	(11.262)
	[8.618]*	[9.256]	[16.352]	[12.799]*	[14.009]*	[18.235]
Other	−2.330	−7.245	2.609	9.031	12.125	30.591
	(13.656)	(13.432)	(18.130)	(19.139)	(17.818)	(21.622)
	[20.540]	[16.203]	[32.942]	[26.228]	[22.807]	[34.149]
Pregnancy	n/a	n/a	n/a	17.455	15.842	18.387
				(9.810)*	(9.642)*	(9.560)*
				[13.477]	[12.777]	[15.049]
Respiratory	0.252	0.178	2.076	2.953	2.642	−2.499
	(5.095)	(5.127)	(6.239)	(2.196)	(2.250)	(3.585)
	[5.042]	[5.232]	[6.859]	[3.499]	[3.470]	[5.151]
Stroke	1.455	1.415	1.494	1.098	1.158	−1.855
	(0.732)**	(0.711)**	(0.860)*	(0.731)	(0.785)	(3.043)
	[0.839]*	[0.814]*	[1.257]	[0.692]	[0.734]	[3.302]
n	8310			4257		

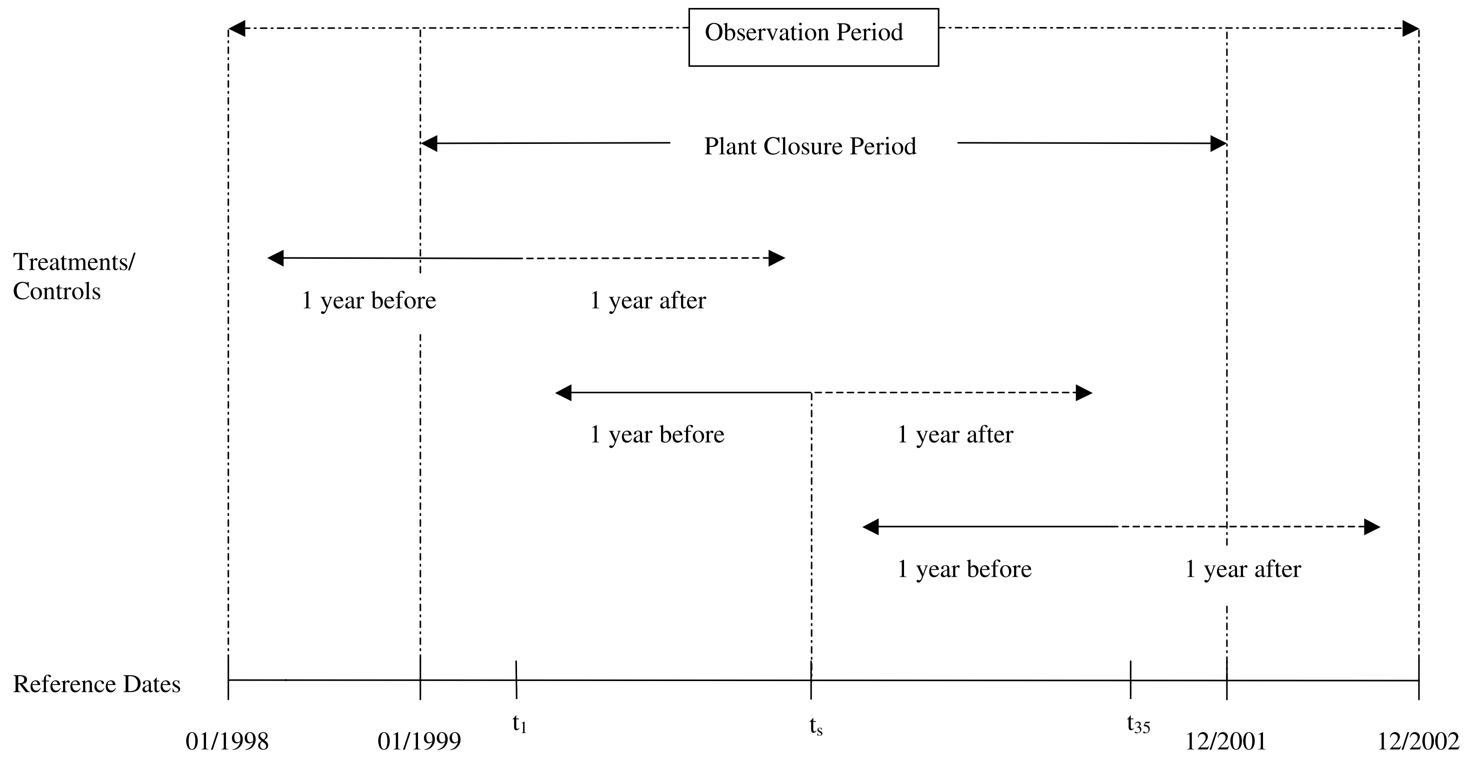
Notes: Table entries are differences in means of PC workers and matched NPC workers. All variables (except days on sick leave) are measured in nominal Euros and cover the four quarters after the plant closure (reference) date. Conventional standard errors (clustered by individual) are in parentheses. Bootstrapped standard errors (based on 500 replications) are in brackets. *, **, *** denotes statistical significance on the 10%, 5%, and 1% level, respectively. Additional control variables are the same as those used for estimating the propensity score (see table A.2 in the appendix).

Table 6: Detailed results, medical drugs

	Men			Women		
Outcome measured in	Levels	Levels	Differences	Levels	Levels	Differences
Additional controls?	No	Yes	No	No	Yes	No
All medical drugs	11.973	10.949	13.548	−14.568	−10.946	−9.711
	(5.564)**	(6.240)*	(5.150)***	(12.184)	(11.330)	(8.611)
	[8.999]	[6.976]	[9.029]	[23.465]	[18.830]	[15.900]
Specific	2.652	2.583	2.859	−0.665	0.331	−0.015
	(0.927)***	(1.033)**	(1.091)***	(2.592)	(2.523)	(2.278)
	[1.005]***	[1.076]**	[1.071]***	[5.810]	[5.240]	[4.763]
Psychosomatic	0.308	0.314	1.197	0.757	1.187	0.219
	(0.618)	(0.630)	(0.920)	(0.938)	(0.908)	(0.853)
	[0.685]	[0.715]	[0.812]	[1.389]	[1.296]	[1.135]
Psychotropic	2.344	2.270	1.663	−1.422	−0.856	−0.234
	(0.658)***	(0.720)***	(0.575)***	(2.395)	(2.339)	(2.155)
	[0.691]***	[0.754]***	[0.722]**	[4.991]	[4.517]	[4.258]
Nonspecific	9.321	8.366	10.689	−13.904	−11.277	−9.697
	(5.328)*	(6.060)	(4.992)**	(11.776)	(10.966)	(8.159)
	[9.264]	[6.902]	[8.695]	[20.136]	[18.868]	[15.269]
n		8310			4257	

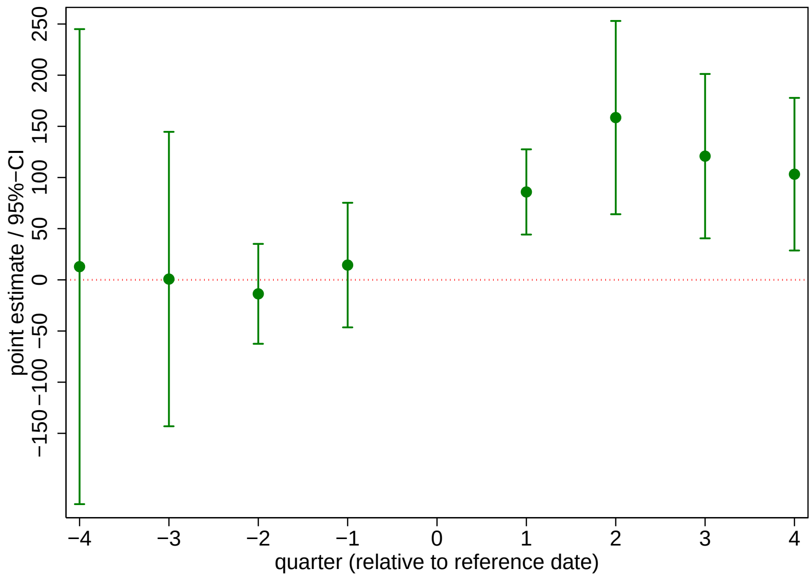
Notes: Table entries are differences in means of PC workers and matched NPC workers. All variables (except days on sick leave) are measured in nominal Euros and cover the four quarters after the plant closure (reference) date. Conventional standard errors (clustered by individual) are in parentheses. Bootstrapped standard errors (based on 500 replications) are in brackets. *, **, *** denotes statistical significance on the 10%, 5%, and 1% level, respectively. Additional control variables are the same as those used for estimating the propensity score (see table A.2 in the appendix).

Figure 1: Setup and definitions

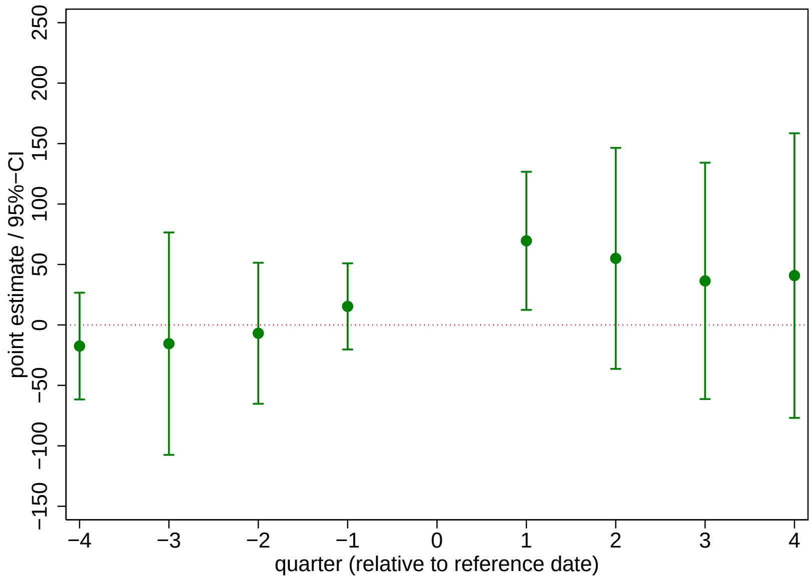


Notes: Reference dates are the 10th of each month, there are 35 such dates in total. t_1: January 10, 1999; t_2: February 10, 1999; …; t_{35}: December 10, 2001. If a plant closure occurs between t_s and t_{s+1}, t_s is the reference date. For each plant closure date, we draw a random sample of control observations among all employed workers. Plant closure workers are workers employed at dates t_{s-4}, t_{s-3}, t_{s-2}, or t_{s-1} in the PC firm. Workers in the control sample include all workers employed at the reference date. (Notice that the same worker may be repeatedly included in the control sample, if employed at more (or all) reference dates.)

Figure 2: Overall health costs



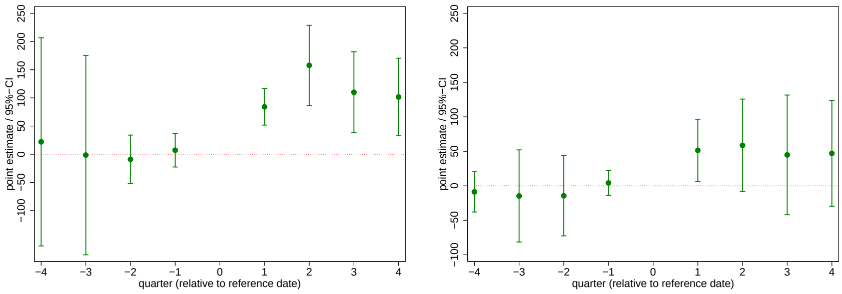
(a) Men



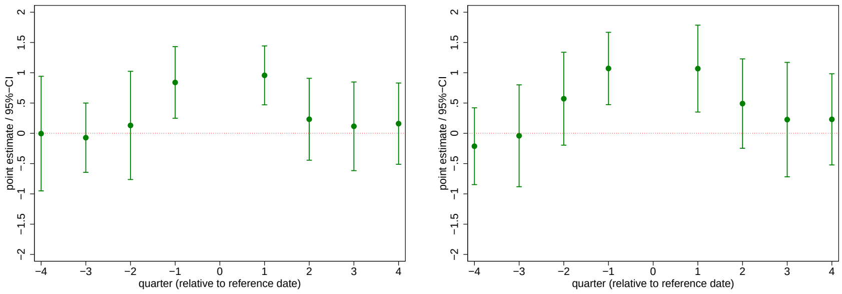
(b) Women

Notes: The graphs show the estimated treatment effect and its corresponding bootstrapped 95% confidence interval (based on 500 replications). The outcome variable is overall health costs for each of the eight quarters, centered around the plant closure (reference) date.

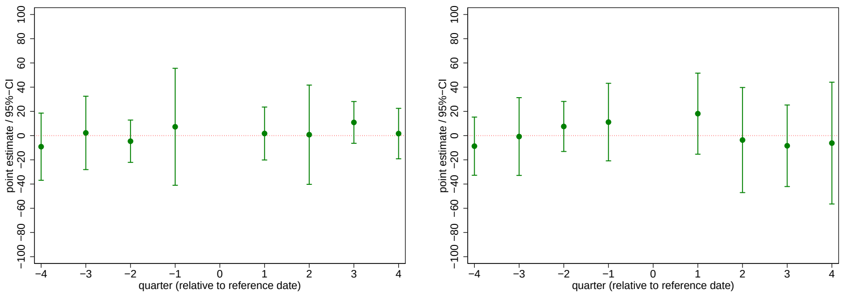
Figure 3: Detailed health costs



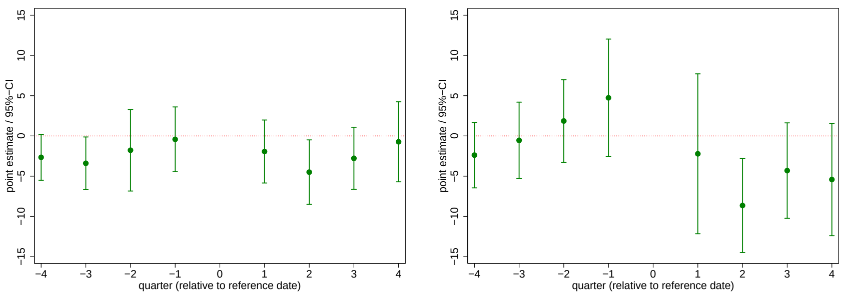
(a) Sick pay



(b) Days on sick leave



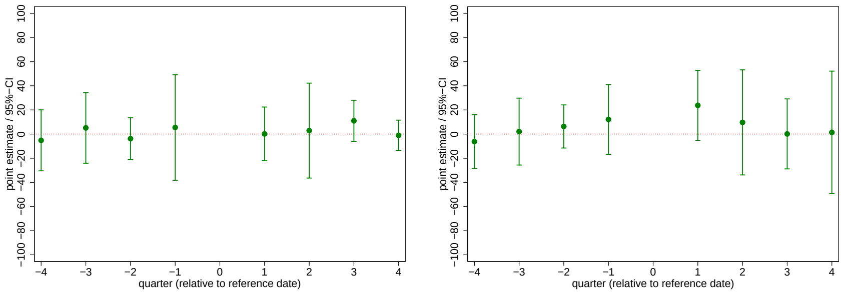
(c) Overall health costs (excl. sick pay)



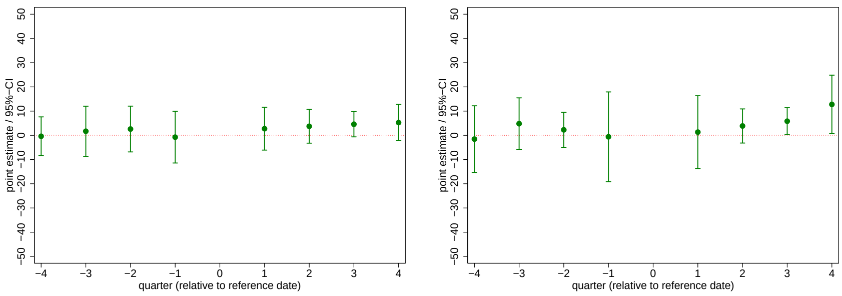
(d) Doctoral visits

Notes: The graphs show the estimated treatment effect and its corresponding bootstrapped 95% confidence interval (based on 500 replications). The figures on the left (right) show results for men (women). The outcome variable is the corresponding health measure for each of the eight quarters, centered around the plant closure (reference) date.

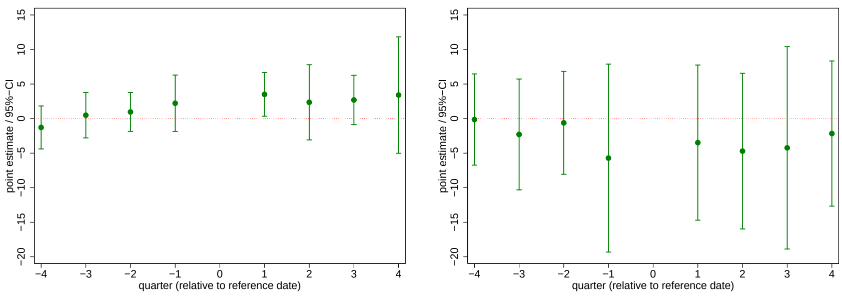
Figure 4: Detailed health costs, continued



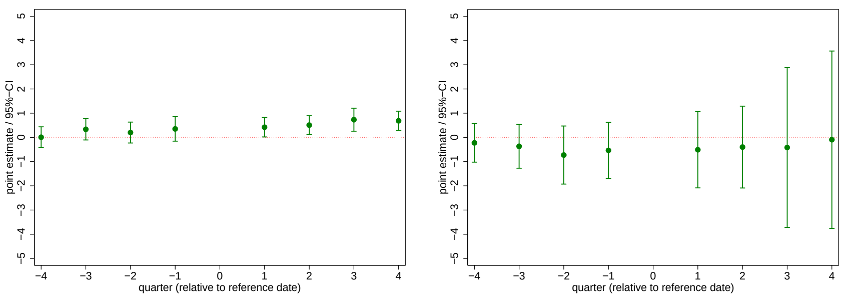
(a) Hospitalizations (all diagnoses)



(b) Hospitalizations (mental diagnoses only)



(c) Medical drugs (all)



(d) Medical drugs (psychotropic only)

Notes: The graphs show the estimated treatment effect and its corresponding bootstrapped 95% confidence interval (based on 500 replications). The figures on the left (right) show results for men (women). The outcome variable is the corresponding health measure for each of the eight quarters, centered around the plant closure (reference) date.

A Appendix

Table A.1: Health Indicators: Definitions

Indicator	Definition
Consultations	Includes all costs 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
Hospitalization	Includes costs due to hospitalization. These costs are classified by the main diagnosis of the hospitalization (ICD-9 codes)
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:	Incudes ICD-9 Codes 460–519
Cerebrovascular:	Includes ICD-9 Codes 430–438
Other:	Includes hospitalization due to all other reasons
Overall:	Includes hospitalization due to any cause
Pregnancy:	Includes ICD-9 Codes 630–676
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

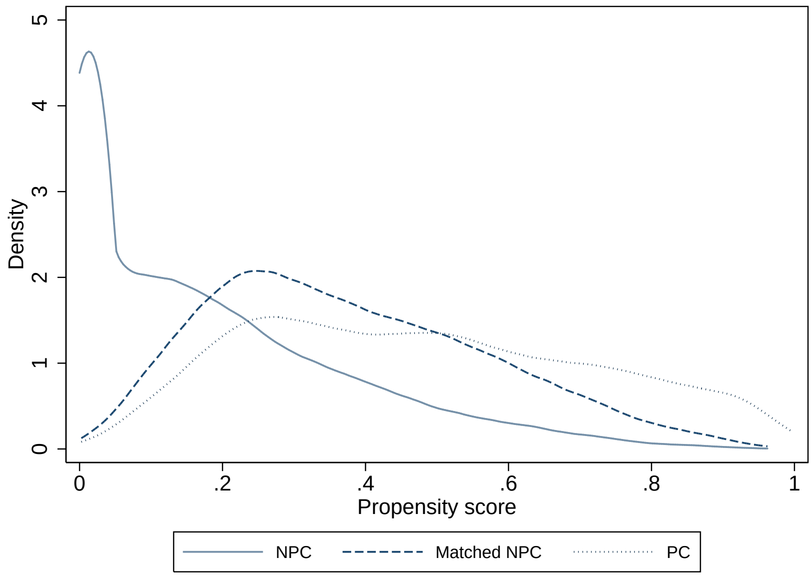
Notes: All variables covering health costs are measured in nominal Euros. The classification of main causes of hospitalization is largely taken from Keefe *et al.* (2002).

Table A.2: Coefficient estimates, propensity score

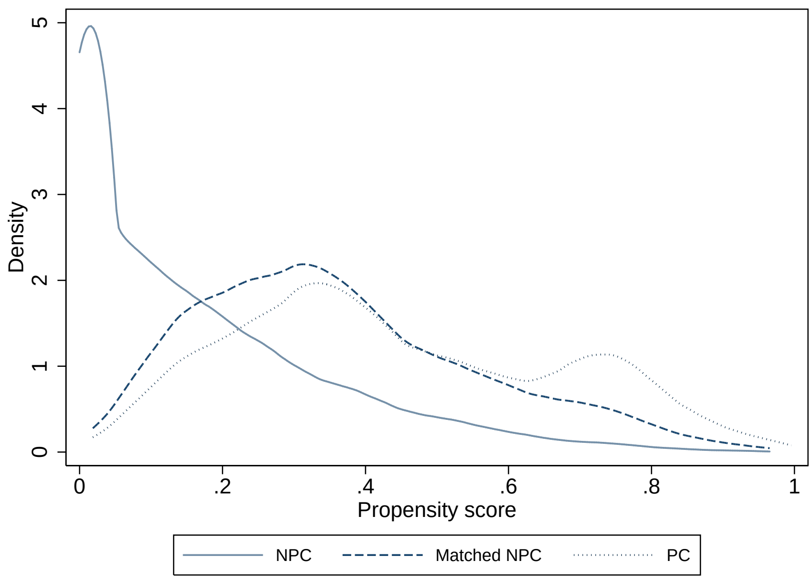
	PC = 1	
	Men	Women
Mean	0.261	0.227
Standard deviation	0.439	0.419
Age (in years)	0.004***	−0.005***
	(0.001)	(0.001)
Tenure within the last five years (in years)	−0.147***	−0.085***
	(0.006)	(0.008)
White-collar	−0.101***	0.098***
	(0.024)	(0.029)
Wage (in 100 €)	0.001***	−0.001***
	(0.000)	(0.000)
Days employed (before)	−0.005***	−0.004***
	(0.000)	(0.000)
Days unemployed (before)	0.000**	−0.000
	(0.000)	(0.000)
Number of employees	−0.004***	−0.003***
	(0.000)	(0.000)
Overall health costs (3 quarters before)	−0.000	0.000
	(0.000)	(0.000)
Overall health costs (4 quarters before)	0.000	−0.000*
	(0.000)	(0.000)
Days on sick leave (3 quarters before)	0.001	0.001
	(0.001)	(0.002)
Days on sick leave (4 quarters before)	−0.000	0.002
	(0.001)	(0.002)
n	31,851	18,784
LL	−13032.373	−7207.593
Pseudo R^2	0.287	0.283
p-value (χ^2)	0.000	0.000

Notes: *, **, *** denotes statistical significance on the 10%, 5%, and 1% level, respectively. The table shows coefficients from a probit model where the PC dummy is the dependent variable. There are 8 industry dummies, 28 regional dummies and 15 time dummies (year and month).

Figure A.1: Distribution of the propensity score



(a) Men



(b) Women

Notes: The figure shows the kernel density estimate of the distribution of the propensity score. Table A.2 shows the corresponding parameter estimates.