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Job loss, disability insurance and health expenditure

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A B S T R A C T

We analyse the causal effect of job loss on disability insurance enrolment on a five-year horizon and the implications on health expenditure. Using administrative panel data from Hungary, we follow individuals displaced due to a mass lay-off and compare their labour force status to non-laid-off individuals with similar employment and health history. According to our estimates, being laid off increases the transition probability to disability 1.5-fold (or by 1.4% points) in four years, and half of the excess transitions occur within the first year. The four-year mortality rate increases 1.7-fold (or by 0.4% point).

Total outpatient, inpatient and pharmaceutical expenditure increase threefold when a laid-off individual takes up disability benefit, and decrease slightly afterwards, but do not reach the pre-disability levels. The medium term increase in health expenditure corresponds to 20 – 25% of the additional disability payments. Detailed medication data show that physical health shocks, the diagnosis of chronic physical conditions, such as hypertension or diabetes, and the deterioration of mental health all contribute to the observed surge in health expenditure.

1. Introduction and related literature

The aims of this paper are twofold: to estimate the extent to which job displacement increases participation in social programmes for the disabled, and the implications on health expenditure.

The high share of working-age individuals receiving disability benefits is a major social and economic problem in many developed countries. Liebman (2015) documents a substantial increase in the share of disability insurance recipients within the working-age population in the United States, rising from 2.2% in the late 1970s to 4.6% in 2013. Banks et al. (2015) report for Great Britain that the number of disability recipients more than doubled from the 1970s to 2013. According to OECD statistics, 5.6% of the working age population in OECD countries received disability benefits in 2007 (the middle of our examined period), with much higher than average rates in Hungary (12%), Sweden, Norway, Finland and the Netherlands (8 – 11%) (OECD, 2009, Figure 4.1). To make the problem more severe, very few recipients of disability benefits return to the labour market.

Consequences on government expenditures are substantial. According to Eurostat (2019), spending on disability benefits amounted to 1.9% of GDP in the European Union (EU27) in 2007. In most OECD countries these expenditures are much larger than expenditures on any other income-replacement programme for working-age individuals (OECD, 2009). It is, thus, of great policy importance to understand and potentially reduce the employment-related channels of disability claims. Such reductions can not only increase the employment rate of the working-age population, but can also have beneficial effects on the public healthcare budget – a previously undocumented aspect, which is the focus of our analysis.

We know from previous literature that job loss has a lasting negative effect on future labour market position (Böheim and Taylor, 2002; Eliason and Storrie, 2006) and a particularly scarring effect on consecutive earnings (Arulampalam, 2001; Gregory and Jukes, 2001; Jacobson et al., 1993; Ruhm, 1991; among many others). Also, disability insurance recipiency has a substantial work disincentive effect on the beneficiaries (e.g. Chen and Klaauw, 2008; French and Song, 2014; Maestas et al., 2013). However, less is known about the effect of job loss on the uptake of social security benefits.

If eligible, a displaced worker can claim unemployment benefits. However, once the benefit period expires, the individual either has to return to work or needs to secure other social security benefits so as to receive some income and maintain social insurance status. It has been shown that unemployment benefits and disability benefits are to some extent substitutes (Koning and Vuuren, 2007; Koning and Vuuren, 2010 for the Netherlands; Bratsberg et al., 2013 for Norway), although Riphahn (1997) (using data from Germany) rejects this hypothesis.

The availability of disability benefits is likely to affect labour force status after a job loss. Indeed, as Autor and Duggan (2003) point out, the characteristics of the disability insurance system influence the propensity of labour force exit for workers who faced adverse shocks.

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The more generous the disability benefit is, the more likely it is for workers to exit the labour market. Similarly, Rege et al. (2009) and Bratsberg et al. (2013) show for Norway that job loss significantly increases the risk of disability benefit uptake. Looking at the period of the Great Recession, both Maestas et al. (2015) and Jiménez-Martín et al. (2018) find that the recession had an increasing effect on disability applications, but due to the increased rate of denials, there is no clear effect on the stock of disability benefit recipients. Scharle (2008) shows on county-level data from Hungary that local labour market conditions are correlated with disability insurance claims.

In the first part of this paper, we contribute to this literature by estimating the causal effect of job loss on disability insurance enrolment and analysing the time-varying patterns of the transition rates based on individual-level administrative data from Hungary between 2003 and 2011. To overcome the endogeneity of job loss, we exploit mass lay-offs and match laid-off to non-laid-off workers with propensity score matching. We then follow individuals in the matched sample and obtain that job loss implies a 1.5-fold (or by 1.4% points) higher transition to disability insurance in four years. Half of the excess transitions occur within the first year, and the transition probability returns to the value in the control group after about three years.

The increased uptake of disability benefits after a job loss may be a moral hazard issue. As evidence for this, Gruber and Kubik (1997), Duggan and Gruber (2014) show that disability insurance plan characteristics and denial rates have stronger effects on the labour supply of the healthier, more able individuals; Campolieti (2002) shows that the generosity of the disability benefit system affects the prevalence of hard-to-diagnose conditions among the recipients. On the other hand, the increased transition to disability may also stem from genuine health shocks associated with unemployment. Indeed, we find that the four-year mortality rate increases 1.7-fold (or by 0.4% point) as a result of the lay-off, suggesting the presence of genuine health shocks.

Disentangling the moral hazard and the health shock channels is not straightforward, even if data on healthcare use or health expenditure is available, because non-employment may affect the demand for health services through various pathways. First, unemployment and inactivity may have direct health effects, although the literature on it is mixed (see e.g. Browning et al., 2006 and Schmitz, 2011 for non-significant results; Schaller and Stevens, 2015 for negative average effects and Schiele and Schmitz, 2016 for negative effects on those in initial bad health). Second, even if health status is constant, non-employment may reduce healthcare use because of the decreased incentives for health maintenance and possibly because of a change in insurance status. Kuhn et al. (2009) and Schaller and Stevens (2015) find little evidence for an overall effect of job loss on healthcare use, although the latter paper shows that doctoral visits and prescription drug usage decrease if the lost job was the primary source of insurance.

Specifically, the application for and maintenance of disability benefit may have profound, time-varying impact on healthcare use. At the time of the application, healthcare use may increase because of the expanded incentives for being diagnosed with various chronic conditions, and also because of the need to check health status during the review process. Afterwards, receiving disability benefit may reduce incentives for health maintenance, thus lowering healthcare use.

In the second part of our paper, we examine these channels, i.e. we analyse the relationship between health expenditure – an indicator of healthcare use – and the uptake of disability benefit. Our focus is on the health spending of individuals who claim disability benefit after a job loss. Such an investigation is novel in the literature. One would expect that becoming a disability beneficiary is associated with increased health spending both due to poor health (i.e. disability) and to the application process, although little is known about the magnitudes of health spending around disability uptake.

According to our results, claiming disability benefit after being laid off is associated with a fivefold surge in inpatient and a 2.5-fold surge in outpatient and pharmaceutical expenditure. Although the expenditure declines after the uptake of the benefit, it does not reach its pre-disability level. More detailed data on medication categories show that, beyond physical health shocks, the diagnosis of chronic physical conditions, such as hypertension or diabetes, and the deterioration of mental health all contribute to the observed surge in health expenditure. Thus, the increase in disability insurance enrolment after a job loss is neither purely a moral hazard issue nor exclusively a consequence of genuine health shocks. These results extend and partly contradict the findings of Rege et al. (2009), who identify the mental health effect of job loss as the key driver of the increase in disability benefit uptake.

2. Institutional background

2.1. Disability, unemployment benefit and old-age pension

The following brief summary of the disability insurance system in Hungary is based on MISSOC (2018), OECD (2012) and Scharle (2011).

Disability insurance in its current form was introduced in 1983. As part of the social security system, disability benefits are paid from the public budget. During the first part of the analysed period (up to 2008), people with at least 67% incapacity for work could apply for disability pension. The amount of the benefit was influenced by the average wage before disability, the incapacity ratio and the length of the insurance period. The replacement rate typically varied between 40 – 65%. Eligibility terminated if the pensioner was no longer incapable of work, or worked on a regular basis, earning an income comparable to what could have been earned in the specific occupation prior to becoming disabled. Disability pension recipiency could start immediately after the termination of employment, without a compulsory waiting period. The evaluation of claims was rather generous. However, as public spending on disability benefits steadily increased, governments began to acknowledge the need for reform. As a result, rehabilitation allowance was introduced in 2008. It is paid to a person with a required number of service years who suffers from 50 – 79% damage to health (comparable to the 67% incapacity for work in the previous system), is unable to pursue a former job but is capable of rehabilitation. It is 20% more generous than disability pension but may be paid only for the necessary period of rehabilitation and for a maximum of three years. Recipients of the allowance have to participate in a comprehensive rehabilitation plan devised by the employment office with a view to recover their work capacity. Those who suffer from at least 50% damage to health, but for whom rehabilitation is not proposed, can apply for disability pension.

Our data does not allow to distinguish between these types of benefits, so we will examine them jointly under the name 'disability benefit'. According to ONYF (2012), while the average monthly amounts of rehabilitation allowance and disability pension were similar in 2011 (around 73,000 HUF $\approx$ 233 EUR), there were 305 thousand disability pension recipients and only 25 thousand rehabilitation allowance recipients, out of the total population of around 10 million in Hungary. Even between 2008 – 2011, when the two schemes existed simultaneously, there were 2.5-fold more new disability pensioners than new rehabilitation allowance recipients.

An application for disability benefit is evaluated by a committee, which considers the social circumstances of the applicant as well as the medical evidence for disability. Social circumstances, such as access to public transportation, caring responsibilities, characteristics of the social network all influence whether rehabilitation is recommended.[1] The medical evidence is provided by the general practitioner (GP), based on certificates and discharge notes issued by specialists, and possibly by hospitals. Thus, the process requires the involvement of both primary care and secondary care physicians. The committee then evaluates the

[1] The evaluation process is regulated in detail by Decree 7/2012. (II. 14.) of the Hungarian Ministry of National Resources. During our analysis period (2003–2011), there did not exist a similar detailed regulation.

rate of incapacity for work based on the medical evidence. A similar process exists for the review of eligibility, which occurs every 1 – 5 years (depending on the condition of the applicant). This implies that the application for and review of disability both increase health expenditure. In the analysed period, the approval rate of disability insurance applications was around 30% (ONYF, 2012).

The system of disability insurance was again reformed in 2011, mostly due to the high public payments on disability benefits and to the alleged widespread abuse of the system. The new, stricter legislation came into effect in 2012, which is outside our observation period. Since then, disability benefits are no longer considered to be part of the pension system, but rather as a type of sickness allowance.

A major risk of the system is that, despite the screening of applicants for disability benefits, individuals might still use them as a substitute of unemployment benefits. Over the analysed period (between 2003 – 2011), Hungary had a two-tier unemployment insurance scheme. Unemployment benefit in the first tier depended on the income the year before unemployment, and could be received for, at most, 270 days. After the exhaustion of the first tier of unemployment benefits, the unemployed could receive a flat amount of unemployment assistance for an additional 3 months. Afterwards, low-income individuals could claim welfare benefits.

Upon reaching old-age retirement age, disability benefits are replaced by old-age pension. Hungary has a mandatory, pay-as-you go pension system, where pensions are based on earnings before retirement, and eligibility is conditional on 20 years of service. In the analysed period, the majority of individuals retired at the statutory early retirement age, which was 60 years for men and increased from 57 to 59 years for women. (For more details on the pension system, see Bíró and Elek, 2018.)

2.2. Healthcare system

The Hungarian healthcare system is a single-payer system, where services are financed from contributions and state subsidies, administered by the National Health Insurance Fund Administration (NHIFA). The vast majority of individuals – the employees, the unemployed, the pensioners and those on various benefits – are automatically insured (in the case of employees, the employers are obliged to pay the social insurance contributions for them). So as to remain insured, inactive people not belonging to any of the previous categories have to pay a monthly fee for health insurance coverage, however, those with low income are still exempt from the payment of the fee. Thus, in practice, job loss and subsequent labour market transitions have no effect on health insurance status.

The majority of healthcare services, including both outpatient and inpatient care, do not require co-payments, although informal payments are common for a wide range of services (Gaál et al., 2006; Szende and Culyer, 2006). This implies for our study that any observed increase in health expenditure might be coupled with an unobserved increase in out-of-pocket informal payments. Also, people willing to provide informal payments might be able to collect the medical evidence for disability benefit application faster or can secure more favourable medical evaluations. People may opt for using private care (which was common only in certain specialties; e.g. in dental care or gynecology, during the examined period) when they have to pay fee for the services. User fees for medication depend on the amount of subsidies from the NHIFA, which varies greatly across substances. On average, patients have to cover slightly less than half of the price of a medication: the rest is paid by the social security. A more detailed overview of Hungary's healthcare system is provided by Gaál et al. (2011).

3. Data

The empirical analysis is based on a unique administrative panel dataset from Hungary. The data cover a random half of the 5 – 74 years-old population in 2003, who were followed until 2011. It was created by linking administrative data from the Hungarian tax authority, the pension and the health authorities, among others.[2] In this research, we concentrate on the 35 – 54 years old age group, which includes most of the transitions to disability, but excludes the vast majority of old-age pensioners. By cutting the sample at age 54, we focus on individuals of active age and exclude the analysis of the choice between disability benefit and old-age pension.

We use various segments of the dataset. Gender, year of birth and settlement of residence (corresponding to year 2003) are recorded for each individual. The labour market and benefit segment contains monthly information on wages, employment, pension and other benefit status. Therefore, we can track on a monthly basis whether an individual was employed, was a pensioner or received unemployment, disability or other benefits. Occupation (ISCO) codes of employment spells are collected for employees. Level of education is not observed but can be approximated for each occupation code (and thus for each individual) as the median education level of workers with the same occupation in the Labour Force Survey.

Based on our dataset, employees of the same firm can be identified. The sector of the employer (public or private) is also observed. The size of the firm can be approximated as twice the number of its employees in the sample, although this estimate is not very accurate for micro-firms.

Fig. 1 shows the rates of the most important benefits by gender and age. The employment rate (not shown in the figure) is 60 – 70% for males of the examined ages. The ratio of disability benefit recipients increases heavily with age and goes above 10% among those aged 50 and above, while unemployment benefit is received by around 5% of the population at all examined ages. The ratio of old-age pensioners (not shown) is below 3%, even among those aged 50 – 54.

In the main analysis, we will follow the labour market outcomes of workers who were laid off during a mass lay-off, which we consider as an involuntary job loss. An event is classified as a mass lay-off if the size of the company decreases by at least 30% in a given month, remains below 70% of the original size throughout the following year, and no more than 15% of its employees move to the same employer. Various definitions of mass lay-off have been advocated in the literature, with 30% as a widely used cut-off (see Handwerker and Mason, 2012 for an overview, and Jacobson et al., 1993; Sullivan and Wachter, 2009 for specific examples). Our mass lay-off definition includes company closures as well. Since the size of micro-firms cannot be determined precisely in our 50% sample, we examine only the mass lay-offs of companies with at least five employees in the dataset (i.e. at least ten employees on average).

In Appendix C, we check the robustness of our results to the use of 20% and 40% dismissal rates in the definition of mass lay-off, and to two alternative definitions of job loss – company closure (including early leavers) and the official definition of collective redundancy in Hungary. The main results are qualitatively robust to these alternative definitions.

We make the following sample restrictions. We focus on individuals aged 35 – 54 years, who were continuously employed in the last six months by a firm with at least ten (estimated) employees, and did not receive unemployment, disability or maternity benefits in the last month of employment. We concentrate on years between 2005 – 2009 to ensure that we have a two-year long history and also a two-year long follow-up period for each individual. Altogether we examine 28,169 laid-off workers, out of the approximately 1 million workers aged 35 – 54 years. Descriptive statistics are provided in Table 1.

Health expenditure is observed on the annual level in the dataset. We have information on the annual public spending on specialist out-

[2] The linked dataset is under the ownership of the Central Administration of National Pension Insurance, the National Health Insurance Fund Administration (NHIFA), the Educational Authority, the National Tax and Customs Administration, the National Labour Office, and the Pension Payment Directorate of Hungary. The data was processed by the Institute of Economics, Centre for Economic and Regional Studies (CERS).

Table 1
Descriptive statistics of the employed, the matched mass lay-off and matched control sample.

	Employed		Mass lay-off (matched)		Control (matched)		Standardized difference (matched)
	Mean	S.D.	Mean	S.D.	Mean	S.D.	
Year							
2005	0.202	0.402	0.173	0.378	0.173	0.378	0.0%
2006	0.201	0.401	0.161	0.367	0.161	0.367	0.0%
2007	0.202	0.402	0.152	0.359	0.152	0.359	0.0%
2008	0.201	0.401	0.253	0.435	0.253	0.435	0.0%
2009	0.193	0.395	0.261	0.439	0.261	0.439	0.0%
Male	0.464	0.499	0.538	0.499	0.538	0.499	0.0%
Age group							
35–39	0.247	0.431	0.257	0.437	0.261	0.439	-0.9%
40–44	0.232	0.422	0.231	0.422	0.229	0.420	0.5%
45–49	0.244	0.429	0.237	0.425	0.236	0.425	0.2%
50–54	0.277	0.448	0.275	0.446	0.274	0.446	0.2%
Region (2003)							
C Hungary	0.289	0.453	0.285	0.452	0.284	0.451	0.3%
C Transdanubia	0.127	0.332	0.130	0.337	0.128	0.334	0.7%
W Transdanubia	0.116	0.32	0.111	0.314	0.109	0.312	0.5%
S Transdanubia	0.091	0.287	0.083	0.277	0.083	0.276	0.1%
N Hungary	0.118	0.322	0.138	0.345	0.141	0.348	-0.8%
N Great Plain	0.137	0.343	0.141	0.348	0.146	0.353	-1.3%
S Great Plain	0.123	0.328	0.111	0.314	0.108	0.311	0.7%
Settlement type (2003)							
Budapest	0.164	0.37	0.153	0.360	0.152	0.359	0.4%
County-level town	0.217	0.412	0.187	0.390	0.188	0.391	-0.2%
Other town	0.321	0.467	0.326	0.469	0.326	0.469	-0.1%
Village	0.298	0.457	0.334	0.472	0.334	0.472	0.0%
Estimated level of education (based on occupation)							
Primary	0.140	0.347	0.207	0.405	0.206	0.405	0.2%
Lower secondary	0.377	0.485	0.544	0.498	0.543	0.498	0.2%
Upper secondary	0.276	0.447	0.172	0.378	0.173	0.378	-0.2%
Tertiary	0.207	0.405	0.077	0.267	0.078	0.268	-0.4%
Firm characteristics							
Size	4811	8970	209	554	182	522	5.0%
10–24 employees	0.121	0.326	0.214	0.410	0.229	0.420	-3.7%
25–49 employees	0.079	0.269	0.183	0.387	0.196	0.397	-3.2%
50–99 employees	0.089	0.284	0.181	0.385	0.190	0.392	-2.3%
100–249 employees	0.113	0.316	0.172	0.378	0.170	0.376	0.6%
250–4999 employees	0.308	0.462	0.214	0.410	0.187	0.390	6.8%
5000- employees	0.292	0.455	0.036	0.185	0.028	0.165	4.4%
Size 1 year ago if non-missing	3831	7632	220	576	181	565	6.9%
Size 2 years ago if non-missing	3038	6454	167	479	141	516	5.2%
Size 1 year ago non-missing	0.852	0.355	0.795	0.404	0.791	0.406	1.0%
Size 2 years ago non-missing	0.727	0.445	0.595	0.491	0.572	0.495	4.6%
Government sector	0.292	0.455	0.030	0.172	0.027	0.161	2.3%
Labour market history, number of months							
Employment in prev. 12 months	11.87	0.71	11.59	1.21	11.58	1.24	0.6%
Employment in prev. 13–24 months	11.36	2.21	10.31	3.50	10.18	3.66	3.7%
Disability benefit in prev. 12 months	0.003	0.14	0.007	0.22	0.005	0.20	0.6%
Disability benefit in prev. 13–24 months	0.010	0.32	0.021	0.45	0.022	0.46	-0.2%
Unemployment in prev. 12 months	0.066	0.55	0.20	0.93	0.19	0.93	1.0%
Unemployment in prev. 13–24 months	0.20	1.20	0.55	1.91	0.55	1.92	-0.4%
Maternity in prev. 12 months	0.026	0.42	0.028	0.45	0.037	0.51	-1.9%
Maternity in prev. 13–24 months	0.099	0.98	0.11	1.07	0.14	1.19	-2.6%
Total wage in prev. 13–24 months, M HUF	2.05	4.15	1.30	1.60	1.27	1.48	1.8%
Health expenditure history, gender- and age-corrected percentiles							
Outpatient, 1 year ago	47.5	30.1	45.1	31.5	45.2	31.0	-0.4%
Outpatient, 2 years ago	47.5	30.0	45.0	31.2	45.0	30.8	0.1%
Inpatient, 1 year ago	9.6	26.7	9.9	27.1	10.2	27.5	-1.3%
Inpatient, 2 years ago	9.6	26.7	9.6	26.7	9.8	27.0	-0.8%
Pharma, 1 year ago	46.7	31.2	43.6	32.2	43.2	32.0	1.2%
Pharma, 2 years ago	46.6	31.3	43.5	32.2	43.1	32.0	1.1%
Days of sick-leave in prev. 13–24 months	3.9	17.0	4.8	19.6	5.3	21.8	-2.3%
Number of observations	*		28,169		28,169		

*: No. of individuals: 1,074,888. No. of person-months: 38.4 – 38.9 million, depending on the variable. See text for sample restrictions. S.D.: standard deviation. Standardized difference: the difference of means divided by the square root of the average of the two individual variances.

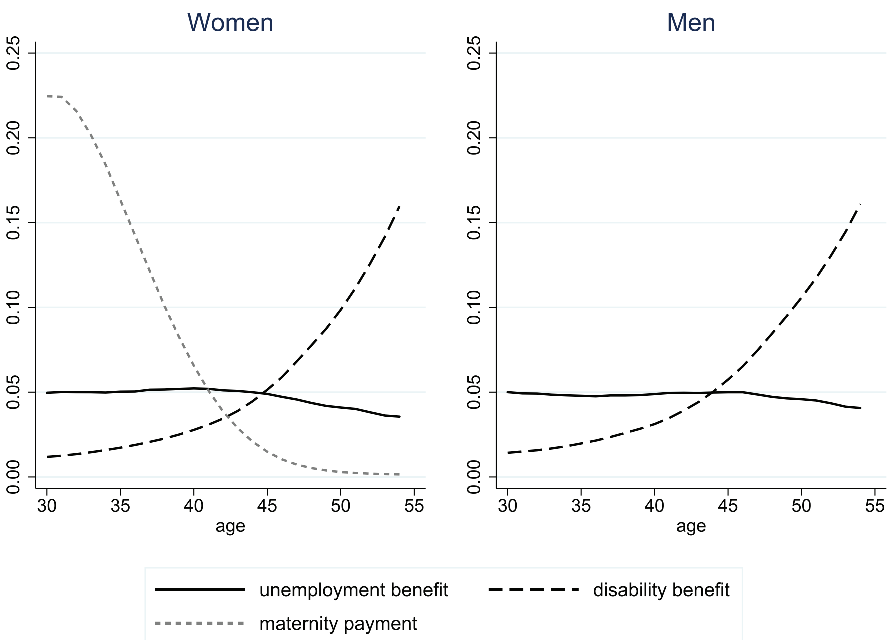

Fig. 1. Rates of some benefits by gender and age group.

patient care and inpatient care, and on the annual public plus private (out-of-pocket, OOP) expenditure on prescribed pharmaceuticals. Altogether, we track around 60% of total healthcare expenditure (based on the expenditure categories of Gaál et al., 2011). The most important excluded items are services provided by GPs, and OOP payments on non-prescribed medications and on medical services. Although GP care is not covered by our data, total outpatient care expenditure is reasonably well captured because of the high usage of outpatient specialist care in Hungary (see Elek et al., 2015). According to Gaál et al. (2011), public expenditure on outpatient specialist care is almost twice as much as on primary care, and made up around 17% of spending on curative services and around 10% of total public healthcare expenditure in the examined period. In 2009, the per capita annual number of outpatient specialist contacts was 12.0 in Hungary, the third highest in Central- and South-Eastern-Europe, and higher than in any Western-European country. In any case, since contacts with primary care physicians are needed for referrals to specialist care and for the provision of medical certificates for disability, it is unlikely that an observed disability-related increase of specialist care use would be coupled with a reduced use of primary care.

In addition to outpatient, inpatient and pharmaceutical expenditure, more detailed medication data that provide pharmaceutical spending on the 3rd level ATC (Anatomical Therapeutic Chemical) groups are also available for years 2009 – 2011 for 42% of the individuals in the sample.[3] For these people, we will examine specifically the expenditure on eight main 1st level ATC groups that altogether make up more than 90% of pharmaceutical spending, and also drug categories on the 3rd ATC level for four major diseases (antidepressants, lipid modifying agents, antihypertensives and antidiabetics).[4]

4. Methods

4.1. Treatment – control comparisons

We examine the medium-term effect of involuntary job loss on taking up disability benefit and on other outcomes. We compare e.g. disability insurance enrolment of laid-off workers to those non-laid-off workers who were similar in their measured characteristics at the time of layoff. Similarity is defined in terms of the variables of Table 1, which include calendar time, individual demographic characteristics (gender, age, region, settlement type), characteristics of the current job (firm size, occupation[5]), history of labour market and benefit status in the last 24 months, history of health expenditure and sick leave in the last two calendar years (but not in the current year) and the change of the size of the employee's firm in the last two years.

Since we do not observe health status directly, we can only use lagged health expenditure as a proxy for health. Bíró and Elek (2018) show using the same data that health expenditure, in particular pharmaceutical expenditure, is a strong predictor of mortality as far as six years ahead, thus likely captures health status reasonably well.

We include the one- and two-year lagged indicators of health spending and sick leave among the similarity variables. In principle, if the mass lay-off was preceded by worsening work environment then the lagged health indicators could already be affected. This would imply that our estimated effect of mass lay-off on disability insurance enrolment is a lower bound of the true effect. On the other hand, the de-

[3] This medication dataset originates from NHIFA, and was processed by CERS. The sample is a 50% random sample of the Hungarian population, but it was drawn independently from the baseline sample used elsewhere in our analysis. Since the baseline and the medication data do not have the same (anonymised) identifiers, we conduct a probabilistic matching between the two datasets. First, we create gender – monthly date of birth – district of residence cells in both datasets, with an average cell size of about 26 people. Second, for each individual in the baseline sample, we search for a pair in the medication sample who belongs to the same cell, and whose outpatient, inpatient and pharmaceutical expenditures are the most similar to those in the baseline dataset. (These expenditure items are observed in both datasets for 2009 – 2011, albeit with measurement error, so there are 9 matching variables.) Similarity is defined by maximising the number of equal expenditure items out of the non-zero items during the three years; if more than one pair is found then the sum of the absolute differences of the corresponding (non-equal) expenditure items is minimised; finally, one candidate is randomly picked in case of a draw. The matching is regarded appropriate if the number of equal, non-zero expenditure items is larger than half of the number of non-zero expenditure items of a person in the baseline sample. Using this procedure, we find a pair for 42% of the baseline sample, which is close to the theoretical maximum (50%).

[4] See the footnote of Table 5 or Fig. 5 for the precise definitions.

[5] A detailed occupational (ISCO-based) classification with 34 items, not shown in the Table, is used.

scriptive statistics of Table 1 suggest that the average health spending history of the laid-off individuals is similar to that of the whole sample of workers, thus there is no direct evidence that a mass lay-off would be preceded by increased health expenditure. In any case, our strategy of focusing on mass lay-offs helps to ensure the similarity of laid-off and non-laid-off individuals in terms of health status because mass lay-offs are less health-dependent than ordinary lay-offs.

We perform 1:1 nearest neighbour propensity score matching, applying a logit model with the above similarity variables.[6] Following, for example, Austin (2011), a caliper of 0.2 standard deviation of the logit score is enforced to exclude matches that are far from a laid-off worker in treatment propensity.[7] Exact matching is conducted on gender and monthly date, and matching is performed without replacement on the individual basis. That is, if a person belongs to the treated group or is chosen as a control observation, then she/he cannot be in the control group at another date. However, the control group may contain individuals whose firms are affected by mass lay-off but themselves are not laid off.

The last column of Table 1 shows that the laid-off and the matched control sample are sufficiently similar to each other with respect to the examined variables, the standardized differences[8] being below 7% (0.07) in all cases, less than the 0.10 difference treated as an appropriate balance in propensity score studies (e.g. Austin, 2009). Fig. A1 in the Appendix also confirms that the estimated propensity scores are balanced in the treatment (laid-off) and the matched control group.

After finding a suitable control group, we show graphically how the ratio of disability benefit recipients, the three-month transition probability to disability as well as other labour market outcomes evolve in the matched laid-off vs. control samples. Beyond a graphical analysis, we estimate simple linear probability and logit models of some outcomes at $t = 24$ and $t = 48$ months on the joint sample of the laid-off (treatment) and control observations, with the treatment dummy as the explanatory variable. Here $t = 0$ denotes the time of inclusion into the matched sample (which is the time of lay-off in the treatment group). Following Abadie and Spiess (2019), in the regression models we estimate standard errors by clustering at the level of matched pairs. This method provides consistent standard error estimates if matching is done without replacement, which holds in our case.

In the regression models we concentrate on three outcome variables. First, the probabilities of being disabled at $t = 24$ and at $t = 48$ months are analysed. Second, to investigate whether genuine health shocks are present, we look at the two- and four-year mortality rates. Third, based on the medication data on ATC categories, we compare the rates of people in the matched laid-off vs. control sample at $t = 24$ and $t = 48$ months who are disability insurance recipients and at the same time use specific drug categories (i.e. we examine joint probabilities). This approach follows Rege et al. (2009) and provides insight into the types of diseases that lead to disability insurance uptake. A larger joint probability in the treatment vs. the control group indicates that the additional disability pensioners due to job loss consume the particular medication category. If, on the other hand, the rates in the treatment and control group are similar, that suggests no (or small) consumption of the medication category among the additional disability recipients.

Also, to measure heterogeneous lay-off effects, we estimate linear probability models of the probability of being disabled at two and four years, respectively, where the lay-off dummy is interacted with individual characteristics such as gender, level of education, age group, region specific unemployment rate (measured at $t = 0$) and – to capture baseline health status – the dummy for hospitalization in the last year before $t = 0$.

4.2. Event study analyses

We investigate, with event study analyses, the time pattern of health expenditure of displaced workers who became disabled some time after the job loss. We regress, in a fixed-effects setting, the annual health expenditure measures on the years elapsed since (or before) the uptake of disability benefit within the sample of laid-off individuals receiving disability benefit:

$$h_{is} = \eta_0 + \sum_{k \neq 0} \eta_k D_{is}^{(k)} + c_i + \xi_s + u_{is}, \quad (1)$$

where i denotes the individual, s the calendar time in years, h_{is} is an indicator of health expenditure, $D_{is}^{(k)}$ $(-2 \leq k \leq 2)$ is the time (in years) after or before the uptake of disability benefit, ξ_s is the calendar year fixed effect, c_i captures individual fixed effects (controlling for all time-invariant individual characteristics such as gender or initial health status) and u_{is} denotes the error term. The parameters η_k are of main interest.

We use various health expenditure indicators as outcome variables. First, we simply analyse the values of the three expenditure categories (outpatient, inpatient and prescribed pharmaceutical expenditure). Second, due to the non-negligible fraction of zero expenditure (i.e. of not using the given category of healthcare at all in a given year) and to the high skewness of the expenditure distributions, we analyse the probability of positive (non-zero) health expenditure and the logarithm of the positive expenditure separately, in a two-part (hurdle) model setting, for the three expenditure items. The hurdle model allows an explicit distinction between the extensive margin (zero versus non-zero expenditure) and the intensive margin (amount of expenditure if non-zero), as widely used in health economics (see Deb and Norton, 2018; Pohlmeier and Ulrich, 1995, among many others). Finally, we estimate Eq. (1) with pharmaceutical purchases by medication (ATC) categories as outcome variables.

5. Results

5.1. Descriptive analysis

Table 1 displays descriptive statistics of the general employed population, of workers displaced in mass lay-offs, and of workers in the matched control sample.

According to Table 1, mass lay-offs peaked during the financial crisis in 2008–2009, and affected males, the lower educated and the employees of smaller firms disproportionately more often. Furthermore, laid-off workers earned one third less and spent one month less in employment, 0.3 month more in unemployment and 0.9 day more on sick leave in the 13–24 months preceding their displacement than the general employed population. On the other hand, the two-year health expenditure history is not particularly different in the laid-off and in the general working population, as measured by outpatient, inpatient and pharmaceutical expenditure percentiles. The percentiles were calculated according to the (five-year) age group- and gender-specific expenditure distributions (covering both workers and non-workers).[9]

Fig. 2 displays the time pattern of some labour force indicators of the matched laid-off vs. control workers (disability benefit recipiency is plotted on Fig. 3). The pre-trends of the two groups are identical, apart from the severance pay effect observed in monthly wages of laid-off

[6] Using more than one nearest neighbour would decrease the variance of the estimates at the cost of increased bias (Caliendo and Kopeinig, 2008; Dehejia and Wahba, 2002). However, since we have a large sample, even the 1:1 matching yields reasonably precise estimates.

[7] This adjustment affects only 4% of the treated sample; hence Table 1 does not display descriptive statistics separately on the laid-off and the matched laid-off sample.

[8] The standardized difference is obtained by dividing the mean difference with the standard deviation of the variables. The latter is approximated as the square root of the average of the two individual variances.

[9] The average inpatient percentile is around 10 for both groups because of the low rate of hospitalisation.

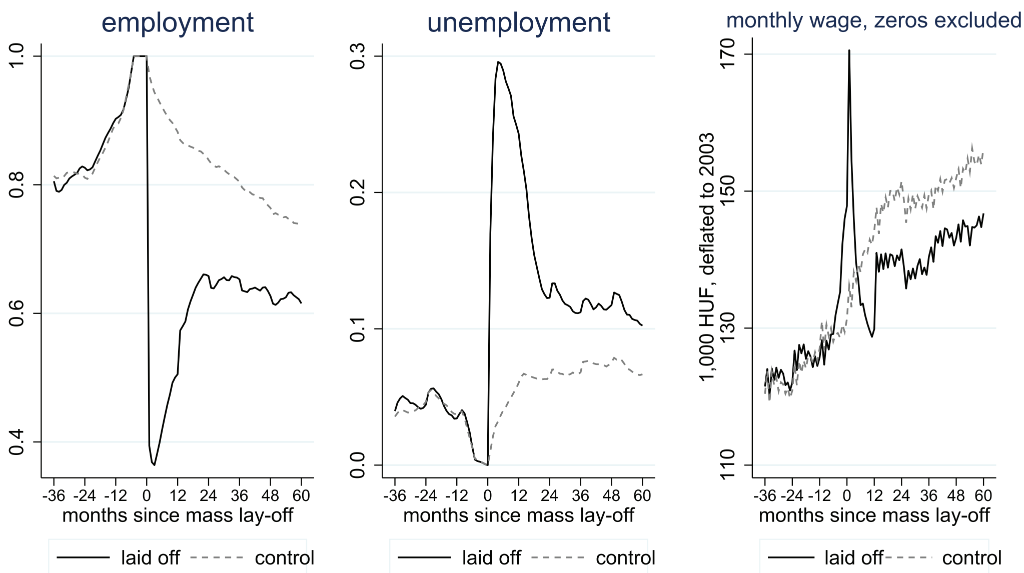

Fig. 2. Labour force indicators around the time of mass lay-off.

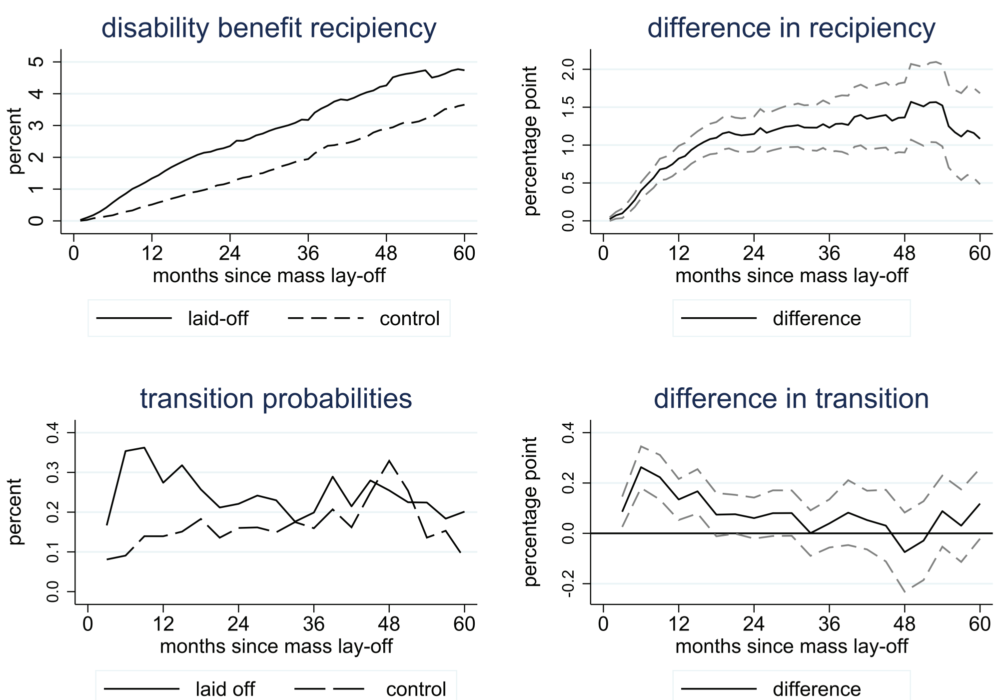

Fig. 3. Disability benefit recipiency rates and three-month transition probabilities in the mass lay-off and control groups as well as the treatment – control differences (with 95% confidence intervals).

workers just before the lay-off. The employment rate falls substantially at the time of mass lay-off and partly reverts afterwards, while the unemployment rate shows the opposite pattern. Meanwhile, the stock of disability benefit recipients increases much faster after the job loss than in the control group (Fig. 3).

5.2. Disability benefits

The top right plot in Fig. 3 shows that the difference between the disability benefit recipiency rate in the mass lay-off and control groups increases for more than four years in the observation period. Table 2 displays the probability of receiving disability benefit specifically at $t = 24$ and $t = 48$ months. The ratio of disability benefit recipients is 2.3% in the laid-off and 1.2% in the control group after two years, hence the difference is 1.1% points, which increases to 1.4% points after four years. In line with these figures, a simple logit model, containing only the lay-off dummy gives an odds ratio of 1.97 after two years and 1.49 after four years.[10] The average marginal effects from the logit models (not shown here) are almost identical to the linear estimates.

For the sake of comparison, we show in Table B1 in the Appendix that mass lay-off decreases the probability of employment by 13 – 17%

[10] The sample size is smaller than reported in Table 1 even for the two-year horizon model because future disability benefit status is missing in some cases due to e.g. moving abroad or death.

Table 2
Effect of mass lay-off on the probability of receiving disability benefit two and four years later.

Probability of receiving disability benefit				
	at 2 years		at 4 years	
in (matched) control group	0.0121		0.0290	
in (matched) laid-off group	0.0236		0.0426	
difference (with S.E.)	0.0114***	(0.0012)	0.0136***	(0.0023)
Logit model odds ratios on receving disability benefit				
	at 2 years		at 4 years	
	coeff. (OR)	S.E.	coeff. (OR)	S.E.
mass lay-off	1.971***	(0.136)	1.492***	(0.102)
constant	0.012***	(0.001)	0.030***	(0.002)
Number of observations	53,114		25,760	

With cluster-robust standard errors (S.E.), clustering at the level of matched pairs. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 3
Linear probability models with controls and interactions for the effects of mass lay-off on the probability of receiving disability benefit two and four years later.

	Probability of receiving disability benefit			
	at 2 years		at 4 years	
	coeff.	S.E.	coeff.	S.E.
Interaction of mass lay-off with				
male	0.0017	(0.0024)	0.0061	(0.0047)
age group (baseline = 35–39 years)				
- 40–44 year	0.0043*	(0.0022)	−0.0034	(0.0046)
- 45–49 year	0.0069***	(0.0026)	0.0052	(0.0055)
- 50–54 year	0.0180***	(0.0033)	0.0288***	(0.0062)
education (baseline = primary)				
- lower secondary	−0.0030	(0.0034)	0.0012	(0.0063)
- upper secondary	0.0054	(0.0039)	0.0198***	(0.0075)
- tertiary	−0.0023	(0.0043)	0.0110	(0.0089)
hospitalization in year before $t = 0$	0.0278***	(0.0062)	0.0225**	(0.0105)
region specific unemployment rate	−0.0225	(0.0295)	0.0899	(0.1070)
constant	0.0030	(0.0039)	−0.0116	(0.0090)
Main effects (differences in probabilities in the control group)				
male	0.0012	(0.0014)	−0.0003	(0.0030)
age group (baseline = 35–39 years)				
- 40–44 year	0.0024*	(0.0012)	0.0129***	(0.0031)
- 45–49 year	0.0073***	(0.0015)	0.0268***	(0.0036)
- 50–54 year	0.0199***	(0.0019)	0.0390***	(0.0038)
education (baseline = primary)				
- lower secondary	−0.0054***	(0.0020)	−0.0129***	(0.0044)
- upper secondary	−0.0111***	(0.0021)	−0.0278***	(0.0047)
- tertiary	−0.0105***	(0.0025)	−0.0261***	(0.0057)
hospitalization in year before $t = 0$	0.0228***	(0.0035)	0.0365***	(0.0066)
region specific unemployment rate	0.0841***	(0.0223)	0.1773**	(0.0691)
year at $t = 0$ (baseline = 2005)				
- 2006	−0.0059***	(0.0022)	−0.0057**	(0.0029)
- 2007	−0.0073***	(0.0023)	−0.0111***	(0.0028)
- 2008	−0.0107***	(0.0020)		
- 2009	−0.0156***	(0.0024)		
constant	0.0093***	(0.0027)	0.0135**	(0.0060)
Number of observations	53,114		25,760	

Cluster-robust standard errors (S.E.), clustering at the level of matched pairs. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

points and increases the probability of unemployment by 3.7 – 5.3% points over the two- and four-year time horizons, with no significant effect on the receipt of maternity benefits. Job loss decreases non-zero earnings by 16 – 17% over these time spans, which is in line with other results in the literature (Jacobson et al., 1993 and Stevens, 1997, among others).

The bottom plots of Fig. 3 show the three-month transition probabilities to disability and the differences between the laid-off and the control group. The transition probability jumps high in the laid-off group after the expiry of unemployment benefit (at 6–12 months), while it increases slowly in the control group. The difference of transition probabilities is statistically significantly positive in the first three years and reaches zero afterwards. Overall, around half of the total excess transitions of four years occur within the first year.[11]

Looking at the linear probability model with heterogenous effects in Table 3, the interaction terms of individual characteristics with mass

[11] Compared to the stock of disability benefit recipients, the transition rate to the opposite direction is negligible: only around 0.6% of the recipients return to work and stop receiving the benefit in a given year.

Table 4
Effect of mass lay-off on mortality.

	Probability of death			
	within 2 years		within 4 years	
in (matched) control group	0.0034		0.0049	
in (matched) laid-off group	0.0056		0.0085	
difference (with S.E.)	0.0022***	(0.0006)	0.0036***	(0.0010)
	Logit model odds ratios of death			
	within 2 years		within 4 years	
	coeff. (OR)	S.E.	coeff. (OR)	S.E.
mass lay-off	1.639***	(0.213)	1.738***	(0.267)
constant	0.0034***	(0.0003)	0.0050***	(0.0006)
Number of observations	56,338		27,344	

With cluster-robust standard errors (S.E.), clustering at the level of matched pairs.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table 5
Effect of mass lay-off on the joint probability of disability benefit recipiency and the usage of specific medication categories two and four years later.

2 years later	ATC A	ATC B	ATC C	ATC J	ATC L	ATC M
control group	0.0040	0.0024	0.0042	0.0027	0.0007	0.0035
laid-off group	0.0087	0.0058	0.0105	0.0060	0.0007	0.0078
difference	0.0047***	0.0034***	0.0063***	0.0033***	0.0000	0.0043***
(with S.E.)	(0.0013)	(0.0010)	(0.0014)	(0.0011)	(0.0003)	(0.0012)
logit OR of lay-off	2.186***	2.469***	2.522***	2.227***	1.039	2.236***
(with S.E.)	(0.472)	(0.677)	(0.517)	(0.577)	(0.600)	(0.514)
	ATC N	**ATC R**	**anti-depressants**	**lipid mod. agents**	**anti-hypertensives**	**anti-diabetics**
control group	0.0038	0.0028	0.0021	0.0020	0.0040	0.0007
laid-off group	0.0072	0.0051	0.0037	0.0057	0.0097	0.0016
difference	0.0034***	0.0023**	0.0016*	0.0037***	0.0057***	0.0009*
(with S.E.)	(0.0012)	(0.0010)	(0.0009)	(0.0010)	(0.0013)	(0.0006)
logit OR of lay-off	1.883***	1.926**	1.775*	2.868***	2.449***	2.253*
(with S.E.)	(0.423)	(0.536)	(0.544)	(0.839)	(0.519)	(1.113)
Number of observations				15,855		
4 years later	ATC A	ATC B	ATC C	ATC J	ATC L	ATC M
control group	0.0116	0.0096	0.0166	0.0094	0.0026	0.0119
laid-off group	0.0176	0.0142	0.0213	0.0127	0.0021	0.0164
difference	0.0060***	0.0047**	0.0047*	0.0033*	-0.0004	0.0044**
(with S.E.)	(0.0022)	(0.0020)	(0.0025)	(0.0019)	(0.0009)	(0.0022)
logit OR of lay-off	1.525***	1.498**	1.292*	1.354*	0.824	1.375**
(with S.E.)	(0.242)	(0.263)	(0.178)	(0.244)	(0.320)	(0.220)
	ATC N	**ATC R**	**anti-depressants**	**lipid mod. agents**	**anti-hypertensives**	**anti-diabetics**
control group	0.0119	0.0063	0.0055	0.0090	0.0152	0.0027
laid-off group	0.0165	0.0109	0.0081	0.0100	0.0199	0.0035
difference	0.0046**	0.0046***	0.0026*	0.0010	0.0047*	0.0008
(with S.E.)	(0.0022)	(0.0017)	(0.0015)	(0.0018)	(0.0024)	(0.0010)
logit OR of lay-off	1.390**	1.735***	1.485*	1.109	1.315*	1.289
(with S.E.)	(0.222)	(0.363)	(0.343)	(0.213)	(0.189)	(0.433)
Number of observations				11,548		

Cluster-robust standard errors (S.E.), clustering at the level of matched pairs
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.
ATC group definitions: A – alimentary tract and metabolism; B – blood and blood forming organs; C – cardiovascular system; J – antiinfectives for systemic use; L – antineoplastic and immunomodulating agents; M – musculo-skeletal system; N – nervous system; R – respiratory system. Antidepressants (psychoanaleptics): N06; lipid modifying agents C10; antihypertensives: C02-C03 and C07-C09; antidiabetics: A10.

lay-off show that job loss increases the probability of receiving disability benefit particularly among individuals aged 45–54 and among those in bad health, as measured by the dummy for hospitalisation in the year preceding job loss. After adjusting for these differences, the interaction terms with gender, education level and micro-regional unemployment rate – a proxy for local labour market conditions – are statistically insignificant. These results imply that mass lay-off might serve as an incentive to apply for disability benefit among older individuals and those in worse health. Using the terminology of Inderbitzin et al. (2016), the stronger effect of job loss on disability benefit uptake among the older suggests a complementarity between (early) retirement and disability benefits, i.e. the latter might serve as an option for an early exit from the labour force. It is also possible that job loss has a stronger health effect on those who were in worse health previously, leading to a stronger effect on disability enrolment. We analyse the underlying health mechanisms in the next subsections.

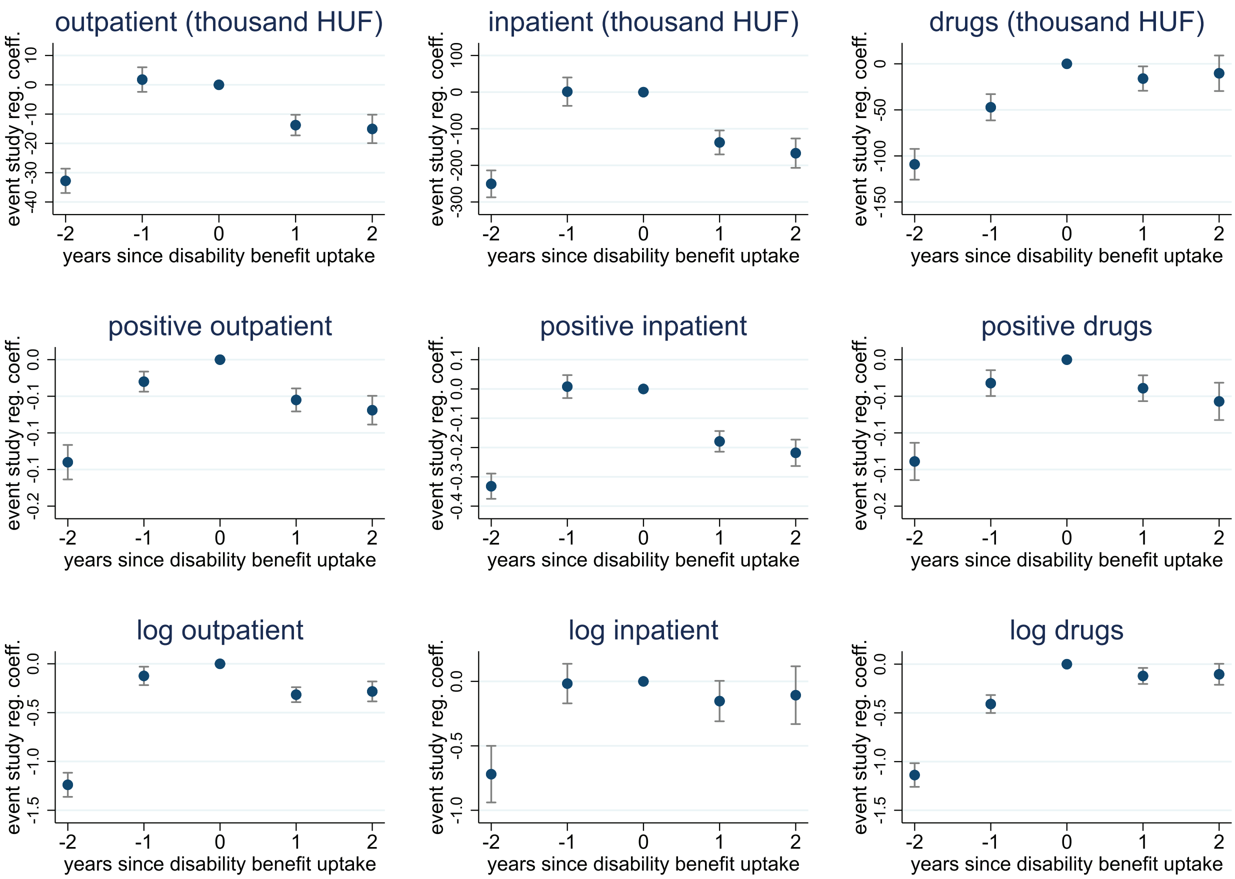

Fig. 4. Event study analysis of health expenditure around the uptake of disability benefit Notes: Regression estimates of Eq. (1) are plotted. Number of individuals: 1,290; number of person-years: 5,879. 95% confidence intervals are displayed, based on cluster-robust standard errors (clustering on the individual level). The average expenditure on outpatient care, inpatient care and drugs at time 0 are 56, 307 and 189 thousand HUF, respectively. The average usage rates of outpatient care, inpatient care and drugs at time 0 are 0.985, 0.658 and 0.958, respectively. The average logarithmic values of outpatient, inpatient and drug expenditure at time 0 are 10.66, 12.78 and 11.26, respectively.

The lower panel of Table 3 displays the differences of the baseline, i.e. the non-laid-off, disablement probabilities by the explanatory variables. The interaction terms should be interpreted in light of the fact that the older, the lower educated, those in bad health and those living in higher unemployment regions are more likely to transition to disability in the control group. Hence, for instance, local labour market conditions have an impact upon the transition to disability, but this impact does not seem to vary by treatment status (i.e. by being laid-off or not).

5.3. Mortality and the consumption of medication categories

According to Table 4, the mortality rate is 0.56% in the laid-off and 0.34% in the control group within two years after the mass lay-off, hence their difference is 0.22% point, which increases to 0.36% point if we look at a horizon of four years. In line with these figures, a simple logit model, containing only the lay-off dummy gives an odds ratio of 1.64 within two years and 1.74 within four years. Thus, our results suggest that job loss indeed increases the risk of mortality.

Using the additional medication data, Table 5 shows the rates of people in the treatment and the control group who are disabled and also consume various types of pharmaceuticals two and, respectively, four years after the layoff, as well as the treatment – control differences. We also present the results of simple logit models, containing only the lay-off dummy as regressor. After two years, the rates are significantly and substantially larger (generally twice as large) in the treatment than in the control group for most pharmaceutical categories. The only exception is the group of antineoplastic and immunomodulating agents (L), where the estimated difference is essentially zero. Compared to the control level, the consumption probability and odds in the treatment group is particularly large (around 2.5-fold) for drugs of the cardiovascular system (C), including lipid-modifying agents and antihypertensive medications. The estimates are qualitatively similar after four years, although statistically significant in fewer cases and the relative estimated effects (logit odds ratios) are smaller. These results suggest that beyond physical health shocks as evidenced by the larger mortality rate, both the diagnosis of chronic physical conditions (e.g. hypertension, high cholesterol level, diabetes) and mental health problems (measured by the consumption of antidepressants) contribute to the higher uptake of disability insurance among the laid-off. Note, however, that the findings should be interpreted with some precaution because the treatment and the control group are only balanced with respect to lagged overall pharmaceutical expenditure and not to lagged expenditure on specific pharmaceutical categories, which is available only for 2009–2011.

5.4. Health expenditure

To gain insight into the time pattern of health expenditure around disability benefit uptake among individuals who become disabled due to a mass lay-off, Fig. 4 shows the estimated η_k parameters of the event study regressions of Eq. (1).

According to the figure, all three expenditure categories peak in the year when individuals first receive disability benefit. The absolute in-

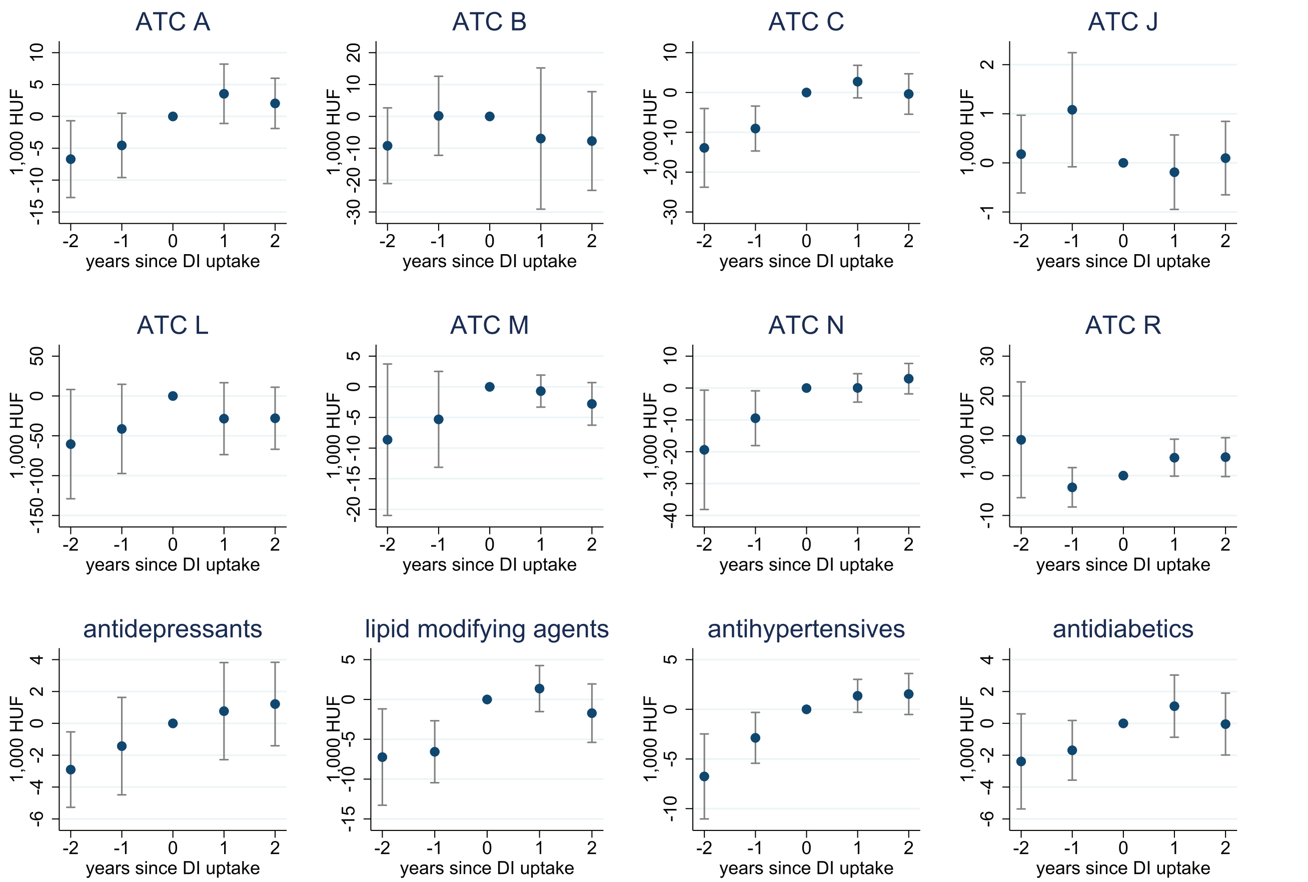

Fig. 5. Event study analysis of categories of pharmaceutical expenditure around the uptake of disability benefit Notes: Regression estimates of Eq. (1) are plotted. 95% confidence intervals are displayed, based on cluster-robust standard errors (clustering on the individual level). DI: disability insurance. ATC group definitions: A – alimentary tract and metabolism; B – blood and blood forming organs; C – cardiovascular system; J – antiinfectives for systemic use; L – antineoplastic and immunomodulating agents; M – musculo-skeletal system; N – nervous system; R – respiratory system. Antidepressants (psychoanaleptics): N06; lipid modifying agents C10; antihypertensives: C02-C03 and C07-C09; antidiabetics: A10.

crease in spending is the largest on inpatient care, followed by spending on drugs and then on outpatient care. Overall, inpatient expenditure increases fivefold, and the other two categories around 2.5-fold in the two years before disability insurance enrolment. Similar patterns can be observed for the probabilities of non-zero expenditure (the peak is strongest for inpatient care with 33% points) and for the logarithms of non-zero expenditure. After claiming the benefit, all categories of health expenditure start to decline but do not reach their pre-disability levels. From the peak, inpatient expenditure decreases the most, while pharmaceutical expenditure the least. Altogether, the expenditure categories remain $1.5 - 2.5$ times higher in the medium term compared to two years prior to claiming disability benefit.

Fig. 4 reflects that health expenditure already starts to increase $1 - 2$ years before disability insurance enrolment. No matter if genuine health shocks lead to disability claims or the propensity to claim disability benefits drives healthcare use, the collection of medical evidence and the application procedure itself require time, which explains this phenomenon.

The descriptive plots presented in Fig. D3 in Appendix D are in line with the event study regression estimates. Irrespectively of how much time passed from the lay-off until the uptake of the disability benefit, the uptake is associated with raised health expenditure, which declines after claiming the benefit but does not fall back to its pre-disability levels. At the same time, we do not observe a noteworthy pattern among the control pairs of the laid-off people who become later disabled; or among the laid-off but not disabled individuals. Fig. B2 in Appendix B also shows that mass lay-off in general (including non-disabled laid-off individuals) has only a small (negative) effect on health spending.

Finally, Fig. 5 shows the event study estimates for eight 1st level ATC categories and four widely used medication groups. Roughly in line with the results of Table 5, the categories on which expenditure significantly increases $1 - 2$ years before disability benefit uptake and remains elevated afterwards are drugs acting on the cardiovascular system (C) (in particular lipid modifying agents and antihypertensives), on the nervous system (N) (in particular antidepressants) and on alimentary tract and metabolism (A) (that include antidiabetics). Changes in the other categories are not significant. Although this event study analysis does not allow the identification of the causal relationship between particular illnesses and disability benefit uptake, it still provides insight into the mechanisms that increase health spending around the time of claiming the benefit. Overall, it is not possible to identify a narrow category of conditions that cause the surge in health expenditure, but the diagnosis of chronic physical conditions, deterioration in mental health and physical health shocks might all be potential driving factors.

6. Discussion and conclusions

Using individual-level administrative panel data from Hungary, we analysed the effect of job loss on disability benefit uptake and its relationship with health expenditure, particularly with expenditure on different medication categories. To establish the causal effects of job loss, we made use of mass lay-offs, and matched laid-off individuals to non-laid-off workers with similar employment and health history. We then examined the uptake of disability benefit and health expenditure on the matched sample.

According to our results, job loss implies a $50-100\%$ increase in the transition to disability insurance in 2–4 years. The large and statistically significant effects are in line with the conclusions of related studies from Norway (in between the effects estimated by Bratsberg et al., 2013 and Rege et al., 2009). To our knowledge, our study is the first that explicitly analyses the time-varying patterns of the transition rates. We obtain that around half of the excess transitions to disability occur within the first year, and transition rates become very similar in the laid-off and control groups after three years.

In line with previous evidence in the literature (Browning and Heinesen, 2012; Eliason and Storrie, 2009; Sullivan and Wachter, 2009), we find that job loss significantly increases the risk of mortality on the four-year horizon. In addition, we provide evidence that the uptake of disability benefit after a job loss is associated with a surge in health expenditure. Compared to two years prior to claiming disability benefit, components of health expenditure increase $2.5-5$ times, and start to decline afterwards but remain elevated in the medium term (at $1.5-2.5$ times the original values). Altogether, the additional health expenditure as a share of annual disability payments reaches 40% in the first year of disability and $20-25\%$ in the medium term.[12] Although we cannot claim that the additional healthcare expenditure is *caused* by the uptake of disability benefit after a job loss, our results still suggest that reducing the employment-related channels of disability claim would have beneficial effects on the public healthcare budget.

In principle, worsening health status, the diagnosis of previously undetected chronic diseases, or unnecessary healthcare visits in order to cheat the disability system, may all lead to the expenditure increase. Additional medication data indicates that several categories of pharmaceutical expenditure increase around the uptake of disability benefits, hence the diagnosis of chronic physical conditions such as hypertension and diabetes, the deterioration in mental health, and physical health shocks might all contribute to the observed surge in health expenditure.

[12] Compared to two years prior to claiming disability benefit, health expenditure is higher by 370 thousand HUF in the first year of disability insurance enrolment and by 220 thousand HUF two years later. Meanwhile, the average annual disability benefit was 920 thousand HUF in the laid-off, disabled sample.

Based on our results, we conclude that the rise in disability benefit uptake after a job loss is not purely a moral hazard issue. Besides the evidence for genuine health shocks, we also find that the effect of job loss on disability insurance utilisation is stronger among those in worse health. Individuals in poor health might continue working if they are not laid off to maintain their income level, however, once laid-off, they are more likely to apply for disability benefits.

Overall, our results indicate large causal effects of job loss on disability insurance use, which are, in turn, associated with substantial increases in health expenditure. Out of 100 laid-off workers, roughly 1.4 claim disability benefit *due to the job loss* within four years of the lay-off. Compared to the pre-lay-off health expenditure levels, these individuals more than triple their annual health expenditure. These findings point to the importance of ensuring employment possibilities to workers affected by mass lay-offs. Otherwise, disability benefits serve as a substitute for employment which increases public expenditure not only due to benefit payments, but also due to the higher public health expenditure of the benefit claimants.

Compliance with ethical standards

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Declaration of Competing Interest

None.

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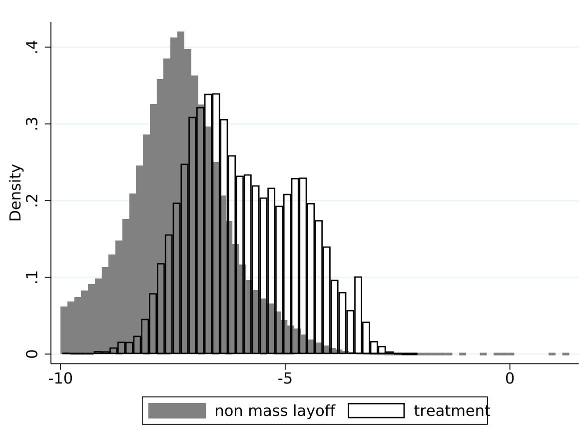
Appendix A. Propensity score matching, balance plot



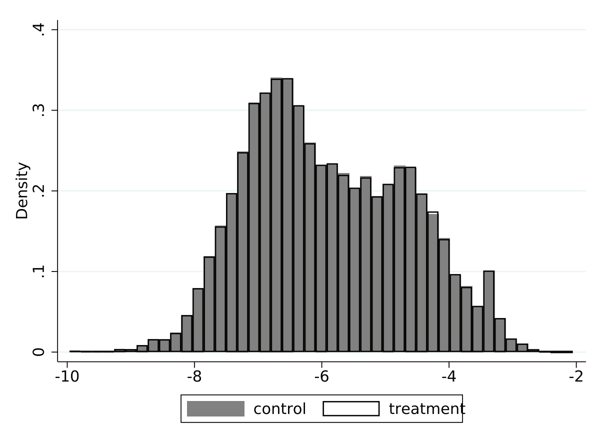


Fig. A1. Histograms of the propensity scores (linear predictions after logit model).

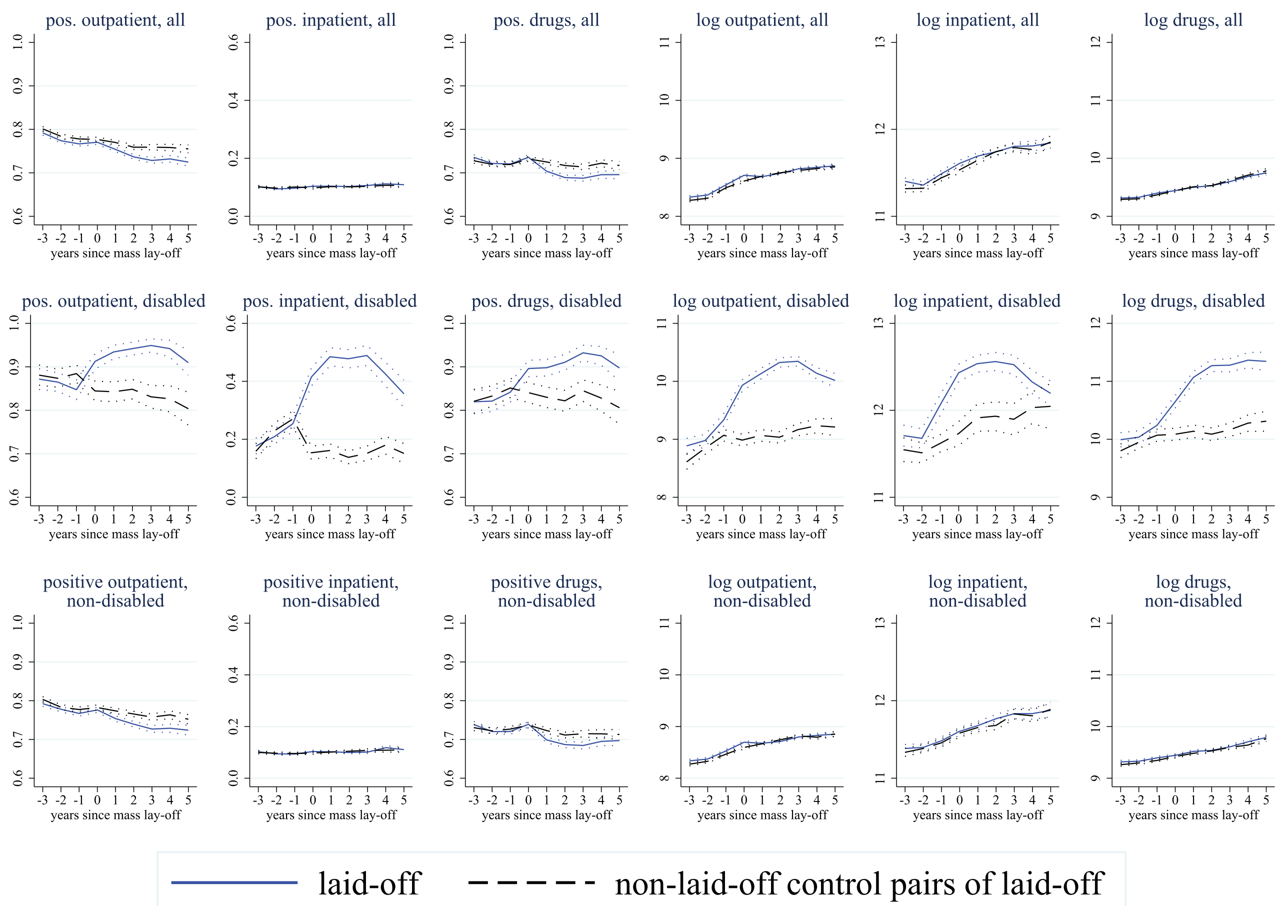


Fig. B2. Effect of job loss on health expenditure among the laid-off, laid-off and later disabled, laid-off and later not disabled workers and their matched control groups, with 95% confidence intervals. The probability of positive expenditure and the logarithm of positive expenditure are displayed.

Appendix B. Effect of mass lay-off on labour market indicators and health expenditure

Table B1 shows the effect of job loss on labour market indicators after two and four years, while Fig. B2 displays the effect on health expenditure in general (i.e. not focusing on the later disabled group). The estimates show the difference between the treatment (laid-off) and matched control (non-laid-off) groups. When constructing the second and third rows of Fig. B2, we repeated the matching algorithm described in Section 4.1 separately on the subsample of workers who received disability benefits any time after the mass lay-off and also on the subsample of workers whom we do not observe receiving disability benefits after the mass lay-off.

According to the first row of Fig. B2, after the mass lay-off, the probabilities of positive outpatient and positive pharmaceutical expenditure decrease slightly in the laid-off compared to the control group. The third row shows that this small negative effect is driven by the large group of laid off workers who did not become disabled afterwards. In contrast, in the second row, we see major upward jumps in all measures of health expenditure among the later disabled (in line with Fig. D3). As discussed in Section 5.2 (Fig. 3), the uptake of disability benefits increases already within the first year after the mass lay-off. This is reflected by the increasing health spending soon after lay-off within the group of disability recipients. Appendix D provides further details on the dynamics of health spending of the disability recipients.

Appendix C. Alternative definitions of job loss

We check the robustness of the main results to the definition of job loss. First, we define mass lay-off more liberally, i.e. if the firm size decreases by at least 20% in a given month (instead of the 30% used in the baseline specification), it remains below 80% (instead of 70%) of the original size in the following year, and no more than 10% (the half of 20%, instead of the half of 30%) of the employees move to the same employer. Second, we use a more conservative definition: the firm size decreases by at least 40% in a given month, it remains below 60% of the original size in the following year, and no more than 20% of the employees move to the same employer.

The next alternative measure is company closure, including early leavers. We treat a firm as a closing firm if it existed in the past 12 months, but not afterwards, and no more than 15% of its employees moved on to the same employer after the closure. We follow individuals who left the company at most 12 months before the closure. This might include some voluntary leavers as well, who are likely to transit to another job, not to unemployment or disability insurance.

The final measure is based on the Hungarian legal definition of collective redundancy. It occurs when an employer makes at least 10 employees redundant from a firm with 20 – 99 employees; or makes at least 10% of the employees redundant from a firm with 100 – 299 employees; or makes at least 30 employees redundant from a firm with at least 300 employees. Again, we exclude firms from which more than 15% of the

Table B1
Effect of job loss on earnings and labour force status.

	Log monthly earnings			
	at 2 years		at 4 years	
in (matched) control group	11.6306		11.6279	
in (matched) laid-off group	11.5729		11.5418	
difference (with SE)	−0.0577***	(0.0087)	−0.0861***	(0.0129)
Number of observations	39,808		17,944	
	Employment probabilities			
	at 2 years		at 4 years	
in (matched) control group	0.8386		0.7640	
in (matched) laid-off group	0.6580		0.6570	
difference (with SE)	−0.1806***	(0.0037)	−0.1370***	(0.0056)
Number of observations	53,201		25,846	
	Unemployment probabilities			
	at 2 years		at 4 years	
in (matched) control group	0.0650		0.0755	
in (matched) laid-off group	0.1228		0.1174	
difference (with SE)	0.0578***	(0.0025)	0.0419***	(0.0036)
Number of observations	53,201		25,846	
	Probability of receipt of maternity benefits (females)			
	at 2 years		at 4 years	
in (matched) control group	0.0132		0.0116	
in (matched) laid-off group	0.0154		0.0130	
difference (with SE)	0.0022	(0.0015)	0.0014	(0.0020)
Number of observations	24,825		11,930	

With cluster-robust standard errors (S.E.), clustering at the level of matched pairs.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

Table C2
Probabilities of disability insurance enrolment, other definitions of job loss.

	Disability insurance probabilities			
	at 2 years		at 4 years	
	after mass lay-off, 30% cut-off (baseline)			
in (matched) control group	0.0121		0.0290	
in (matched) laid-off group	0.0236		0.0426	
difference (with S.E.)	0.0114***	(0.0012)	0.0136***	(0.0023)
Number of observations	53,114		25,760	
	after mass lay-off, 20% cut-off			
in (matched) control group	0.0129		0.0267	
in (matched) laid-off group	0.0250		0.0463	
difference (with SE)	0.0121***	(0.0012)	0.0196***	(0.0023)
Number of observations	55,119		26,144	
	after mass lay-off, 40% cut-off			
in (matched) control group	0.0104		0.0247	
in (matched) laid-off group	0.0225		0.0422	
difference (with SE)	0.0121***	(0.0014)	0.0175***	(0.0029)
Number of observations	33,391		15,088	
	after firm closure and early leavers			
in (matched) control group	0.0124		0.0275	
in (matched) laid-off group	0.0190		0.0375	
difference (with SE)	0.0066***	(0.0013)	0.0099***	(0.0023)
Number of observations	51,640		32,413	
	after collective redundancy			
in (matched) control group	0.0096		0.0200	
in (matched) laid-off group	0.0212		0.0249	
difference (with SE)	0.0116***	(0.0005)	0.0049***	(0.0005)
Number of observations	204,250		100,473	

With cluster-robust standard errors (S.E.), clustering at the level of matched pairs.
*** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$.

employees move on to the same employer after the redundancy. Since the reason of leaving a job cannot be observed in our data, we cannot distinguish between redundancy and voluntary separation. Among larger firms, the legal definition classifies even a separation rate below 10% as a collective redundancy. Therefore, due to data limitations, it is likely that some voluntary separations are included in this definition of lay-off. This is less of an issue under our baseline specification (at least 30% downsizing), since voluntary separation is less likely if the size of a firm decreases by at least 30%.

Table C2 compares the probabilities of receiving disability benefit in the alternative laid-off groups to their control groups chosen with propensity score matching (as explained in Section 4.1). The upper panels of the table indicate that changing the cut-off point of mass lay-off has little impact on the estimated effect of mass lay-off on disability benefit uptake.

Looking at firm closures and collective redundancies, the estimated effect of “lay-off” on disability benefit uptake is smaller than in the baseline specification (for collective redundancies, only at four years), albeit still significantly positive. The smaller estimated effect is likely due to the inclusion of voluntary early leavers in the firm closure and the collective redundancy samples. To illustrate this, we compared the pre-layoff (one year earlier) annual health expenditure of individuals leaving a firm due to mass lay-off and due to firm closure. Examining the gender- and age-corrected percentiles, we see that those leaving a firm due to mass lay-off have, on average, 1–2 percentage points higher outpatient, inpatient and pharmaceutical expenditure (all three differences being statistically significant). This supports that individuals included in the firm closure sample are on average of better health, hence are more likely to transition voluntarily to another job, instead of applying for disability (or other) benefits.

Appendix D. Health expenditure around the uptake of disability benefit

Fig. D3 displays the health expenditure patterns of laid-off, disabled individuals, split into four subgroups according to the timing of the disability benefit uptake. Albeit the event study regressions net out calendar year and individual fixed effects, the descriptive plots still show similar time patterns as the event study estimates reported in Fig. 4. The

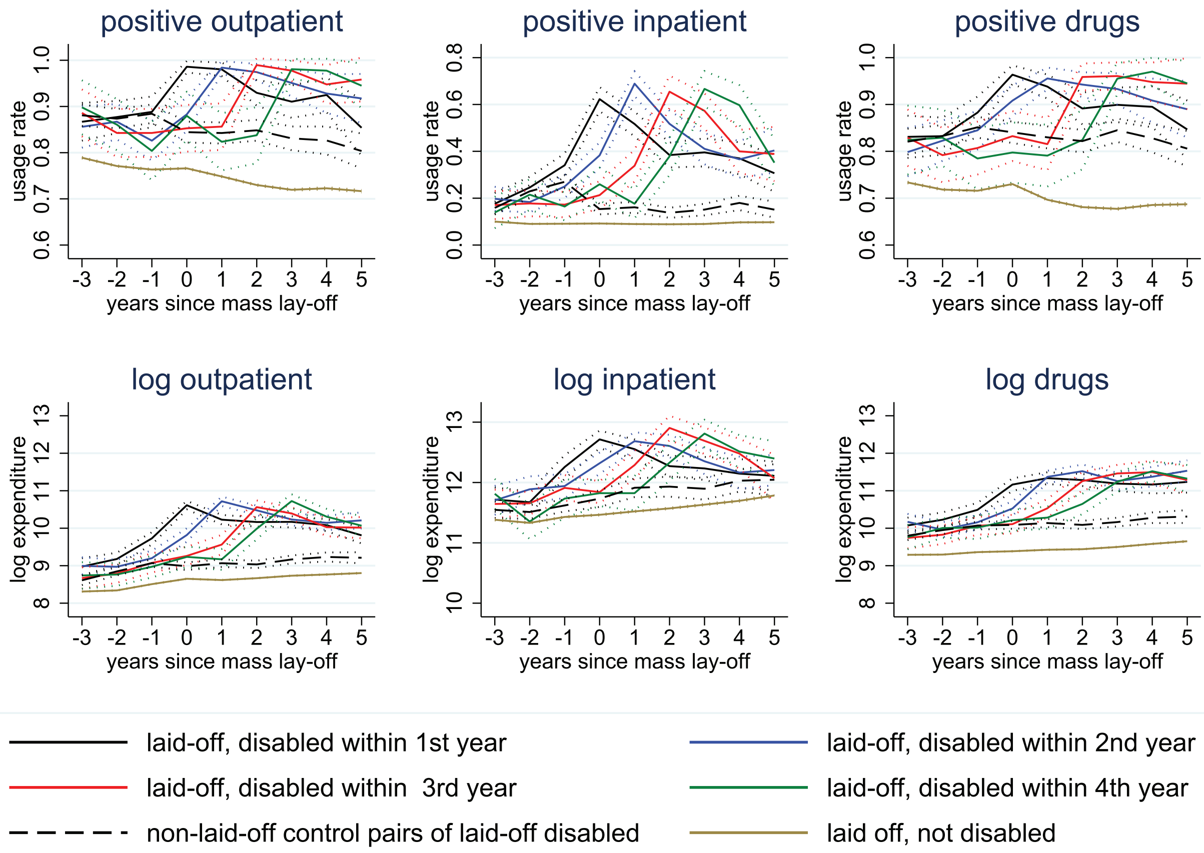


Fig. D3. Health expenditure of the laid-off, disabled workers by the time gap between the uptake of disability benefit and mass lay-off, in the matched control group and in the laid-off but not disabled sample, with 95% confidence intervals. The probability of positive expenditure and the logarithm of positive expenditure are displayed.

uptake of disability benefit is associated with raised health expenditure, which declines after claiming the benefit but does not fall back to its pre-disability levels.

We do not observe a noteworthy pattern among the matched control observations, i.e. among the matched non-laid-off pairs of the laid-off and eventually disabled individuals. Initially, we had four different control groups for the four different disabled samples according to the time spent between mass lay-off and disability benefit uptake, but the health expenditures of the four control groups do not differ significantly, hence we display only their average values in Fig. D3.

Similarly, there is no jump in the health expenditure of the laid-off but not disabled individuals. The lines for the latter group are consistently below those for the other groups, since the later disabled laid-off workers are in worse health (as captured by health spending) even before the lay-off. This is in line with the results of Table 3, showing that the impact of job loss on disability benefit uptake is stronger among those who were in worse health even before the job loss. Importantly, our matching algorithm takes into account such differences in health expenditure before job loss – as the dashed line on Fig. D3 indicates, the health expenditure of the laid-off disabled and their matched control (non-laid-off) pairs is similar.

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