Unemployment, labour force composition and sickness absence. A panel data study

by

Jan Erik Askildsen

Espen Bratberg*

Øivind Anti Nilsen

Department of Economics, University of Bergen, Fosswinckelsgt. 6

N-5007 Bergen, Norway.

March 2002

Abstract:
Sickness absence tends to be negatively correlated with unemployment. This may suggest disciplining effects of unemployment but may also reflect changes in the composition of the labour force. A panel of Norwegian register data for the years 1990-1995 is used to analyse sickness absences lasting more than two weeks. We estimate fixed effects models of the probability of absence and the number of days on sick leave conditional on absence. The county unemployment rate is found to affect the probability of absence negatively. When restricting the sample to workers who are present in the whole sample period, the negative relationship between absence and unemployment remains. The evidence on duration goes in the same direction. This indicates that the revealed procyclical variation in sickness absence is not driven by changes in the composition of the labour force.

JEL classification: H55, J22, J28, J32
Keywords: Sickness absence, unemployment, panel data.

*Corresponding author. E-mail address: espen.bratberg@econ.uib.no

1. Introduction

Rising absence rates, implying productivity losses as well as increased public expenditures, are a source of public debate and concern. Whereas it is common to relate the level of absences to the generosity of the sickness and disability insurance systems, changes in absences are often explained by the development of the labour market. In this paper we focus on what seems to be an empirical regularity in several countries: Sickness absence tends to be negatively correlated with the unemployment rate, i.e., when the unemployment rate declines, absence increases. However, it is not clear what explains this pattern. It may be explained by individual costs of absences when unemployment changes, or alternatively by the composition of the labour force which varies over the business cycle.

Typically sickness and disability insurance are organised either as collective arrangements on the workplace or as social insurance, thus reducing adverse selection problems. As these arrangements have improved income security in the developed world, the last 20-30 years have seen an increasing take-up of sickness and disability insurance. This trend has led to questions whether generous insurance not only compensate for sickness and disability but also induce such outcomes. Countries such as the Netherlands, Sweden, and Germany have initiated changes in the sick payment schemes that reduce the economic compensation to be received during sick leaves. Available studies indicate that changes in the compensation ratios do affect absence behaviour. As indicated, it is less clear what explains a procyclical development of absence rates for a given insurance system and compensation level.

Sickness absence can be costly for the workers in three ways. Firstly, if the replacement ratio is less than 100%, there is a direct loss of income for a worker when absent. Secondly, there are individual costs of absences due to risk of loosing the job if the absence is related to shirking (Shapiro and Stiglitz, 1984; Barmby et al., 1994), primarily considered relevant for short-term absences, and commonly used as an explanation for a negative correlation between absence and the unemployment rate. Thirdly, there may be individual costs from absences that affect long-term sickness spells as well. Depending on how absences affect profitability, firm survival, and wage and career development, each worker will to varying degrees internalise costs of absences. Specifically, costs of absences representing a threat to the firm is more likely to be internalised by the insider workers in periods of high unemployment than in periods of low unemployment, thus inducing a procyclical pattern also in the long-term absence behaviour. When labour market conditions are good or improving, and unemployment is low, the insider workers may have more frequent and longer absences since their unemployment risk is very low. The two latter explanations both give reasons why absences may be negatively related to unemployment, a phenomenon which is confirmed in several studies including Leigh (1985), Kenyon and Dawkins (1989), Drago and Wooden (1992), Johansson and Palme (1996), Thalmaier (1999), Dyrstad and Ose (2001), Arai and Thoursie (2001).

Alternatively, the negative relation between absence rates and unemployment may be due to labour force composition effects from changes in labour demand. Employers may wish to screen workers, and if possible offer jobs first to those with the best experience rating and favourable absence records. When labour is scarce, however, also “marginal” workers who are more prone to be absent, e.g. due to poor health conditions or social problems, are offered jobs. Note also that the objectives of an active labour market policy may include efforts to mitigate marginalisation and temporary as well as permanent expulsion from the labour force. Relevant measures involve labour market training and assistance in finding a job. The policy is aimed at those who become unemployed as well as those who have not succeeded in establishing themselves in the labour market. If some of these individuals are more prone to absence for health or other reasons, increasing absence rates may be an adverse side effect of the active labour market policy.

In addition to disciplining and labour force composition effects, there is a third hypothesis to explain the association between absence and unemployment. Booming periods may put strains on workers, thereby causing health problems and sickness absence. Studies that relate absence to working conditions tend to find a connection between psychosocial conditions, stress and physical working conditions on the one hand, and absence on the other. However, it is hard to find studies providing evidence that variation in absence behaviour is caused by changes in working conditions over the business cycle.

This paper considers Norway, which has a very generous sick leave scheme as part of a mandatory social insurance system. Expenditures associated with the Norwegian sick leave scheme are significant, in the order of 2.5% of GDP. In 1999 the National Insurance Administration's sick pay expenditures were 18.8 billion NOK, a 13% increase from the previous year.[1] Compared to the other Nordic countries, in 1990 Norwegian sickness absence rates were the second largest, after Sweden. Contrary to Norway, Sweden reduced the compensation ratio and introduced a qualifying period in the early nineties, and in 1998, the absence rate in Norway was the largest in the Nordic countries (NOSOSCO 2000). In the present study, we analyse individual level register data from a 10% sample of the labour force covering the period 1990-95. The data include sickness absences reimbursed by social insurance, i.e. lasting more than two weeks, in addition to quite extensive individual background information. Our strategy is first to establish whether there is a negative effect of the unemployment rate on these long-time sickness absences. If that is the case, we investigate whether the effect is due to changes in labour force composition by analysing a sub-sample of stable workers.

The next section provides some institutional details and an overview of the data. Section 3 gives a short account of our empirical approach. Section 4 reports the empirical results, and section 5 contains concludes.

2. Data and institutional background

Norwegian sickness insurance is mandatory and regulated by law, covering all employees who have been with the same employer for at least two weeks. Once this requirement is met, coverage is 100 per cent from the first day, but with an upper limit of 6*G*, where *G* is the basic unit used in the pension system (NOK 39 230 in 1995). However, most large firms and the public sector will compensate the workers earning above the insurance ceiling, so that the 100% replacement rate is relevant for the bulk of the work force. A medical certificate is necessary for absences lasting more than three days. For sickness spells lasting more than eight weeks the physician is obliged to provide a more detailed certificate to the Social Insurance authorities, stating diagnosis and a prognosis assessment. The first 16 days (14 days until 1998) are paid by the employer, the employer period, whereas the remaining period is paid by social insurance, organised under the National Insurance Administration (NIA). The maximum period of benefits is one year, including the employer period. NIA expenses are covered jointly by wage earners' income taxes and employers' payroll taxes.

Our data source is the KIRUT database (a Norwegian acronym) containing detailed individual information on socio-economic background, labour market participation, and social insurance payments for the period 1989-1996 for a random 10% sample of the Norwegian population aged 16-67. All data come from public registers. No survey information is included. Notably, KIRUT contains individual level information on sickness payments from

[1] Currently 1 EURO ≈ 8NOK.

the NIA with exact dates for the beginning and end of each sickness spell. There is, however, no information about absences during the employer period, which for the period under investigation covered the 14 first days of a sickness absence period.

The sample used in this paper consists of individuals in KIRUT who were recorded in the employers' register for at least one calendar year in the period 1990-95, except those employed by the central government.[2] Employers are obliged to report to this register all new employees who are expected to stay in the job for at least three days, and they must also report the termination of an employment period. Although this sampling scheme excludes some workers with marginal attachment to the labour market, this number of excluded workers is so small that there is no reason why our sample should not give a fair representation of the labour force in this period. The years 1989 and 1996 were excluded because of incomplete absence records these years.

With the exception of the sickness insurance and employment records, the variables are recorded on an annual basis. From the sample we constructed a six-year unbalanced panel. It is unbalanced because an individual is only included in year *t* if s/he is recorded in the employers' register throughout that year. The full sample consists of 170 471 individuals aged 16-66 (born 1924-1979). In the estimations we confine the sample to workers aged 30-55 in year *t*. The motivation for excluding younger and older workers is due to our objective of investigating whether marginal workers drive absence changes over the business cycle, the labour force composition hypothesis. Then we do not want to include workers who are moving into or out of the labour force due to life cycle phenomena. After missing-information exclusions, this leaves us with a full sample including 96 892 individuals with 400 094 person-year observations. We also constructed a restricted sample consisting only of those

[2] State employees must be excluded because NIA does not register sickness absence on an individual basis. Individuals employed by the municipal or country authorities are included, however.

who were present in the employers' register for all the six years. As noted in the introduction: if the alleged effect of unemployment is driven by labour force composition only, the effect should go away, or at least be smaller in this "stable worker" sample than in the full sample. Because we are using panel data we did not construct a “marginal workers” sample – they are typically present for only one or two years.

The data from KIRUT do not include information about unemployment rates and were therefore merged with county unemployment rates from the Directorate of Labour. Counties represent a relevant local labour market since it is possible to commute on a daily basis within most counties.

(Figure 1 about here)

We proceed with some aggregate evidence on the development of absence over time. Figure 1 shows monthly inflow rates for the full sample together with monthly unemployment rates (county averages). The inflow rates were constructed by dividing the number of new spells each month by the number of individuals present in the employers’ register throughout the year. Both variables have been adjusted for seasonal variation by regression on monthly dummies. The curves suggest a negative correlation between the two rates but with the absence rates lagging somewhat behind the unemployment peak. From mid-1993, however, there seems to be a positive trend in the absence rates.

(Figure 2 and 3 about here)

In Figure 2 we have plotted monthly stocks, i.e. the total number of ongoing sickness spells, defined as rates, and Figure 3 shows monthly numbers of sickness days per employee. The resulting patterns are similar to Figure 1 but with the upward trend in absences starting somewhat later. This may suggest that the seemingly negative connection between sickness absences and unemployment is due to increased inflow rates to a larger extent than to increased durations. Finally, Figure 4 shows new sickness spells aggregated on a yearly basis as they will be in the regression analysis. The tendency is the same as in the previous figures.

(Figure 4 about here)

Bearing in mind that short time absence, which presumably is most responsive to economic incentives, is not included here, it is somewhat remarkable that the negative correlation between sickness absence and unemployment comes out as clearly as it seemingly does. The figures provide only eyeball evidence, however. Moreover, a potential explanation could be changes in the labour force composition and that the pattern suggested by the figures goes away when controlling for individual characteristics. To investigate whether that is the case, the next section provides a panel analysis at the individual level. Before that, we turn to sample characteristics.

(Table 1 about here)

Table 1 shows the distribution of yearly sickness spells in the sample covering individuals aged 30-55. We have defined a sickness spell as belonging to year *t* if the spell started that year. This definition is consistent with inflow at the aggregate level. We note that the majority of the sampled individuals have no sickness spells in the six years period, and that there is an overweight of women among those who have. Furthermore, there are very few individuals with more than two absences in a given year.

(Table 2 about here)

In Table 2, we report sample characteristics of variables that will be used in the econometric models. The explanatory variables include yearly income, experience, and family variables, in addition to the county specific unemployment rates. To avoid endogeneity problems, we use lagged values of the income variables. For more precise definitions, see Table A1. We note that females are slightly less educated than men, have shorter experience and are more prone to work part-time. We also find that women have more absence days than men, where the number of absence days is the sum of all sickness days from sickness spells lasting more than two weeks given that these spells start in year t. This gender difference is present when including zero absence (consistent with Table 1) and for positive absences, indicating that females have longer as well as more frequent sickness spells (see also Mastekaasa and Olsen (1998)). Finally, as expected, we also find that average absence days are fewer in the sample that is restricted to the "stable workers" who are present in the employers' register for all six years.[3]

3. Empirical specification

When analysing sickness absence it is natural to distinguish between incidence and duration. At the individual level this means differentiating between the probability of being absent and the expected duration of absence, once absent. We use reduced form models and do not formalise any underlying utility maximising structure here. Such models may be found in e.g. Allen (1981).[4]

The discrete outcome variable indicates whether an individual had at least one absence spell starting in year t.[5] Accordingly, the duration variable is defined as (the log of) the number of calendar days for spells starting in year t. Hence, the definitions are,

---

[3] We refer to Table A2 for descriptive statistics covering the part of the sample that is used in the fixed effect logit regressions.

[4] Typically such models augment the standard neo-classical labour supply model by making utility health dependent and introducing a penalty function in the budget constraint, where the penalty function is increasing in absence and also in the unemployment rate. Thus there is a disciplining effect of unemployment on absence. In accordance with efficiency wage theory, one may also make the penalty increasing in the wage rate. Then the effect of the wage rate on absence is indeterminate, even if sick pay gives full wage compensation and absence is a normal good.

[5] We could also have chosen to define the discrete outcome variable indicating whether the individual was absent sometime during year t. We have, however, chosen to define the discrete variable based on whether s/he has at least one absence spell starting in year t because it fits best with raw data, and as such the definition of absence is consistent with inflow at the aggregate level.

• Y_{it} = 1 if individual i has at least one sickness absence period starting in year t, 0 otherwise

• D_{it} = the duration of all sickness spells starting in year t.

Note that D_{it} may be the sum of several spells lasting more than two weeks.

Starting with the model describing the probability of being absent, we denote individual i's propensity of sickness absence in period t by $Y_{it}*$ and propose an error component model

(1) $Y_{it}* = b'X_{it} + dU_{it} + m_i + e_{it}$.

where b and d are coefficients, X_{it} is a vector of observable characteristics, m_i is an individual specific effect, U_{it} denotes the unemployment rate, and e_{it} is white noise. The vector of explanatory variables X_{it} includes factors that affect the cost of absence and the marginal utility of leisure. Finally, the individual specific effect m_i picks up the effect of all unobserved individual characteristics, in particular health. Clearly, an individual's health condition affects sickness absence. Our sample does, however, not include any information about health. Using panel data methods to control for unobserved characteristics alleviates this problem.

$Y_{it}*$ is unobservable. Instead we define an indicator variable which measures whether individual i was absent in period t or not, $Y_{it} = 1(Y_{it}* > 0)$. Equation (1) may then be estimated with a panel discrete choice model. We use the fixed effect (conditional) logit estimator, which differences out m_i. As already pointed out, our panel allows us to control for unobserved individual characteristics. We have chosen to use the fixed effect logit model since a random effect model would rest on the implausible assumption that all the explanatory variables are uncorrelated with individual specific effects. This is especially problematic since the unobserved characteristics include health. Notably, there is evidence that health is correlated with socio-economic factors (Wagstaff and van Doorslaer, 2000). One drawback of the conditional logit estimator is that the conditioning is on the individual means of Y_{it}, and only individuals who change status at least once are used in the estimation. This may reduce the estimating sample dramatically. On the other hand, those individuals that actually change state at least once, are the ones who actually are affected by the explanatory variables.[6]

The length of a sickness absence, the number of absence days in period t, is modelled as

$$(2) \quad \log D_{it} = g'X_{it} + qU_{it} + h_i + u_{it},$$

with obvious notation. Clearly, (2) may only be estimated conditional on $Y_{it} = 1$. We estimate this equation using the standard linear within groups estimator.[7] The regressions on log duration are conditional on $Y_{it} = 1$ and therefore utilise fewer person-year observations than the conditional logit estimations. However, an individual who is present in the sample for, say, 2 years and has sickness spells each year will be included. Consequently, the number of individuals present in these regressions may be (and actually is) larger than in the logit estimations.

[6] Table A2 in the appendix shows sample characteristics for the estimating samples.
[7] We do not perform any correction for sample truncation. Obviously inference is conditional on the truncated sample and the results cannot be interpreted in terms of the expected duration for a random individual in the population.

4. Regression results

In this section we report results from estimating equation (1) by fixed effect logit and equation (2) by the linear fixed effects estimator.[8] Due to the differences revealed by the descriptive statistics, the regressions are performed by gender.

(Table 3 about here)

Table 3 reports the fixed effect logit results. Our main focus is, of course, on the effect of the unemployment rate. The upper panel shows that after having controlled for observable individual characteristics and the unobserved fixed effects, there is still a negative effect of the county unemployment rate (but only significant at the 10% level for males). In the lower panel, where the sample is restricted to workers who clearly are outside the "marginal worker" definition, the negative effect of unemployment remains. In fact, it increases and is more precisely estimated. Of course, this does not mean that the excluded group is less prone to be absent – Tables 1 and 2 show clearly that the opposite is true. It does, however, indicate that variations in the probability of a sickness absence are not driven by changes in the composition of the labour force.

Turning to the other results, we find that for most of the explanatory variables there are only minor differences between the results in the upper and lower panels of Table 3. Somewhat surprisingly, there is a negative effect of age on the probability of absence. For women, from the second order term, the effect becomes positive at about 45 years of age (upper panel). The effects of experience and tenure, on the other hand, are positive for men, and insignificant for women. This could be explained by a larger degree of job security for experienced workers, given their age.[9] Income increases the probability of absence, with a

---

[8] We have also estimated count data models with results qualitatively similar to the logit results reported below. Estimating equation (1) with a linear probability model also gave quite similar results in terms of signs and statistical significance.

[9] This interpretation is consistent with Riphahn and Thalmaier (2001) who, using German GSOEP data, find that absence increases after probation periods.

stronger effect for females than for males. If income variation is caused mainly by variation in the wage rate, this is opposite to what efficiency wages theory would predict: that high-wage workers should have less absence because the cost of a potential job loss is greater. However, if there is no such potential "penalty", the sign could be explained as an income effect if time spent absent is a normal good. This is consistent with the concavity of the effect – recall that there is a maximum sick pay level which accords to about NOK 240 000 per year. Above that level, there is a substitution effect because absence is costly. In fact, the turning point is at NOK 295 000 for males (upper panel) – above that, the income effect is negative. An alternative, or supplementary, explanation could be that if high income up to some level is caused mainly by working longer hours, the effect could follow from strain. This is consistent with part time workers, mostly females, having a lower absence probability. We also note that the group of divorced and separated individuals have an increased risk of absence, and that there are no significant effects of spouse income and the number of small children, even for women.

(Table 4 about here)

Table 4 shows the results from estimating linear fixed effects models for the number of absence days, equation (2).[10] The results were obtained after dropping variables that did not reach 5% statistical significance. In interpretation, one should be aware that the large constant term (the average fixed effect) means that the model explains only a small part of the observed absences. The remaining effects are qualitatively similar to those in Table 3. However, there is no statistical significant effect of the unemployment rate for the full sample, though the signs are still negative. But again, in the restricted sample the effect of unemployment effect is significantly negative, and also of relatively high magnitude.

Increasing the unemployment rate (measured in %) with one unit leads to a 4.1% reduction in the number of absence days for those who were absent.

5. Concluding remarks

In this paper we have investigated the connection between sickness absence and the unemployment rate. For this purpose we used a 6 years panel with an estimating sample consisting of more than 30 000 individuals with at least one absence record. Using county specific unemployment rates as proxies for unemployment in the local labour markets, we find a quite clear negative effect of unemployment on the probability of having a sickness spell in a given year. When we restricted the sample to only the insiders, those who were in the labour force for the full observation period, the effect did not go away but to the contrary became clearer. Also for the duration of absence there was a negative effect in the restricted sample but the evidence was more mixed. The latter result is not unreasonable, given that duration may be more dependent on pure health factors.

It is a popular idea that procyclical variation in sickness absence is driven by changes in the composition of the labour force due to entrance of "marginal" workers in economic upturns. When we find that insiders respond to changes in the unemployment in the local labour market, this is taken evidence supporting that marginal workers do not explain the fluctuation of absences longer than two weeks. "Stable" workers, those who are in the labour force for a long period, do change behaviour. We do not claim, however, to have revealed the actual mechanisms driving these changes. The efficiency wage hypothesis may seem best suited for explaining shorter absences. We cannot rule out that there actually are detrimental

[10] The results in Table 4 are not directly interpretable as duration models, because several absences may be aggregated for each individual. If there was only one absence spell per year per individual, the results could be interpreted as stemming from a lognormal duration model.

health effects of economic booms, or that workplace conditions are affected adversely. But we think it is important to realise that general policies to reduce sickness absence may be more efficient than policies directed towards "marginal" groups. It might be considered a weakness of the data that only absences of more than two weeks were available. In our opinion, however, this makes the established effect even more striking.

The results are also interesting for the discussion of an active labour market policy. To avoid expulsion and give room for as many as possible to participate in the labour market, most European countries have for a long period tried to combat long-term unemployment by measures involving labour market training and assistance in finding jobs. The policy is aimed at those who become unemployed as well as those who have not succeeded in establishing themselves in the labour market. The Norwegian experience in the early 1990-ies, which is covered by our sample period, is interesting in this context. A dramatic increase in unemployment initiated extensive programmes involving labour market training and several other measures to prepare people for returning to work. An objective was to keep people engaged in activities that kept skills, human capital and health intact, instead of becoming disabled or long term sick, with a danger of leaving the labour force altogether. Furthermore, persons with a more loose connection to the labour market, either due to health problems or other social conditions, were intentionally attracted to these programmes. One might argue that higher absence rates are "costs" necessarily implied by these policies. In our view, the results in this paper suggest that this pessimistic view is not necessarily true.

References

Allen, S.G., 1981, “An Empirical Model of Work Attendance,” *Review of Economics and Statistics 63*, 77-87.

Arai, M. and P. Skogman Thoursie, 2001, “Incentives and Selection in Cyclical Absenteeism,” FIEF Working Paper No. 167, Trade Union Institute for Economic Research, Stockholm.

Barmby T, J.G. Sessions, and J.G. Treble, 1994, “Absenteeism, Efficiency Wages and Shirking,” *Scandinavian Journal of Economics 96,* 561-566.

Drago, R. and M. Wooden, 1992, “The Determinants of Labour Absence: Economic Factors and Workgroup Norms Across Countries,” *Industrial and Labor Relations Review 45*, 764-78.

Dyrstad, J. M. and S. O. Ose, 2001, “Non-linear Unemployment Effects in Sickness Absence: Discipline or Composition Effects?” mimeo, Department of Economics, Norwegian University of Science and Technology, Trondheim, Norway.

Johansson, P. and M. Palme, 1996, “Do Economic Incentives Affect Work Absence? Empirical Evidence Using Swedish Micro Data,” *Journal of Public Economics 59,* 195-218.

Kenyon, P. and P. Dawkins, 1989, “A Time Series Analysis of Labour Absence in Australia,” *Review of Economics and Statistics 71,* 232-39.

Leigh, J. P., 1985, “The Effects of Unemployment and the Business Cycle on Absenteeism,” *Journal of Economics and Business 51*, 159-170.

Mastekaasa, A. and K. M. Olsen, 1998, “Gender, Absenteeism and Job Characteristics: A Fixed Effects Approach,” *Work and Occupations*, 25, 195-228.

Nordic Social-Statistical Committee (NOSOSCO), 2000, *Social Protection in the Nordic Countries 1998. Scope, Expenditure and Financing.* NOSOSCO 14:2000, Copenhagen.

Riphahn, R. T. and A. Thalmaier, 2001, “Behavioral Effects of Probation Periods: An Analysis of Worker Absenteeism,” *Journal of Economics and Statistics 221*, 179-201.

Shapiro, C. and J.E. Stiglitz, 1984, “Equilibrium Unemployment as a Worker Discipline Device,” *American Economic Review 74*, 433-444.

Thalmaier, A, 1999, "Bestimmungsgrunde von Fehlzeiten: Welche Rolle spielt die Arbeitslosigkeit?" Discussion Paper No. 62, Institute for the Study of Labor (IZA), Bonn.

Wagstaff, A. and E. van Doorslaer, 2000, "Equity in Health Care Finance and Delivery," in A. J. Culyer and J. P. Newhouse (eds.), *Handbook of Health Economics Volume 1B*, Amsterdam, Elsevier.

Table 1 Distribution of yearly sickness spells 1990-95

	Total sample aged 30 - 55							
	All				Logit sample[1]			
	Males		Females		Males		Females	
Spells	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
0	187813	89.8	160353	84.0	45691	70.3	57345	67.4
1	18562	8.9	26019	13.6	16932	26.0	23850	28.0
2	2536	1.2	4080	2.1	2159	3.3	3548	4.2
3	268	0.1	406	0.21	221	0.3	334	0.4
4	29	0.0	25	0.0	15	0.0	21	0.0
5	1	0.0	2	0.0	1	0.0	2	0.0
Total	209209	100	190885	100	65019	100	85100	100
	Restricted sample (present all six years)							
	All				Logit sample[1]			
	Males		Females		Males		Females	
Spells	Freq.	Percent	Freq.	Percent	Freq.	Percent	Freq.	Percent
0	116618	90.2	95378	84.2	33266	72.8	40442	69.8
1	11008	8.5	15247	13.5	10855	23.8	15008	25.9
2	1462	1.1	2365	2.1	1400	3.1	2286	3.9
3	154	0.1	230	0.2	143	0.3	213	0.4
4	21	0.0	11	0.0	13	0.0	10	0.0
5	1	0.0	1	0.0	1	0.0	1	0.0
Total	129264	100	113232	100	45678	100	57960	100

[1]Only individuals with at least two different outcomes are used in the fixed effect logits

Table 2 Descriptive statistics. Sample averages 1990-95 for employees aged 30-55.

	Full sample				Restricted sample			
	Males		Females		Males		Females	
Variable	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Absence days	8.57	40.30	14.14	51.69	7.09	34.22	12.51	46.18
Positive abs. days	83.76	97.90	88.41	100.68	72.51	85.03	79.35	90.67
Age	42.00	6.85	42.62	6.81	42.59	5.77	43.32	5.71
Education[1]	11.41	2.57	10.75	2.27	11.32	2.52	10.59	2.15
Experience	19.77	5.55	15.01	5.65	20.82	4.90	16.10	5.49
Tenure	6.89	5.43	6.00	4.63	7.83	5.56	7.00	4.82
Income	27.75	13.20	16.05	7.06	28.36	12.05	16.62	6.77
Spouse income	9.52	10.94	19.63	21.84	9.88	11.69	19.90	21.45
Part time	0.02	0.14	0.22	0.42	0.01	0.10	0.20	0.40
Unmarried	0.17	0.38	0.12	0.33	0.14	0.35	0.11	0.31
Married	0.71	0.45	0.71	0.45	0.74	0.44	0.72	0.45
Prevmar	0.12	0.32	0.16	0.37	0.11	0.32	0.17	0.37
Kids < 11	0.54	0.88	0.42	0.75	0.53	0.86	0.31	0.64
Unemployment	4.94	0.92	4.97	0.91	4.94	0.92	4.96	0.91
Observations	209209		190885		129264		113232	
Individuals	50141		46751		21544		18872	

[1]Years of education. Not used in the regressions.

Table 3 Fixed effect logit results. 1990-95 panel of employees aged 30-55

	Full sample								
	All			Males			Females		
	Coef.	St. err.	P>z	Coef.	St. err.	P>z	Coef.	St. err.	P>z
Age	-0.246	0.055	0.000	-0.579	0.133	0.000	-0.179	0.063	0.005
Age^2	0.002	0.000	0.000	0.001	0.000	0.007	0.002	0.000	0.000
Experience	0.090	0.050	0.071	0.469	0.129	0.000	-0.019	0.055	0.731
Tenure	0.006	0.003	0.047	0.012	0.004	0.009	0.002	0.005	0.628
Income	0.073	0.004	0.000	0.059	0.007	0.000	0.090	0.007	0.000
$Income^2$	-0.001	0.000	0.000	-0.001	0.000	0.000	-0.001	0.000	0.000
Spouse income	0.002	0.001	0.053	0.001	0.003	0.861	0.002	0.001	0.066
Part time	-0.249	0.063	0.000	-0.264	0.167	0.115	-0.241	0.068	0.000
Married	0.102	0.099	0.302	0.070	0.138	0.614	0.154	0.145	0.291
Prevmar	0.348	0.107	0.001	0.343	0.150	0.022	0.374	0.155	0.016
Kids < 11	0.006	0.020	0.762	-0.010	0.029	0.728	0.034	0.028	0.234
Unemployment	-0.032	0.011	0.003	-0.030	0.016	0.071	-0.037	0.014	0.010
Log likelihood	-55201			-23525			-31653		
Individuals	30078			12940			17138		
Observations	150119			65019			85100		
	Restricted sample (present in all 6 years)								
	All			Males			Females		
	Coef.	St. err.	P>z	Coef.	St. err.	P>z	Coef.	St. err.	P>z
Age	-0.308	0.081	0.000	-0.793	0.237	0.001	-0.227	0.091	0.013
Age^2	0.002	0.000	0.000	0.001	0.001	0.012	0.002	0.000	0.000
Experience	0.155	0.076	0.042	0.668	0.235	0.004	0.043	0.082	0.603
Tenure	0.005	0.004	0.152	0.011	0.005	0.031	1.9E-04	0.005	0.972
Income	0.083	0.006	0.000	0.071	0.010	0.000	0.106	0.010	0.000
$Income^2$	-0.001	0.000	0.000	-0.001	0.000	0.000	-0.001	0.000	0.000
Spouse income	0.003	0.001	0.031	0.004	0.004	0.249	0.003	0.002	0.095
Part time	-0.333	0.090	0.000	-0.555	0.276	0.044	-0.301	0.096	0.002
Married	0.104	0.134	0.440	-0.076	0.181	0.673	0.318	0.204	0.120
Prevmar	0.350	0.143	0.014	0.147	0.194	0.449	0.581	0.215	0.007
Kids < 11	0.028	0.025	0.263	0.022	0.034	0.513	0.047	0.037	0.206
Unemployment	-0.049	0.013	0.000	-0.048	0.020	0.015	-0.051	0.018	0.004
Log likelihood	-38169			-16480			-21671		
Individuals	17273			7613			9660		
Observations	103638			45678			57960		

Dependent variable = 1 if at least one NIA absence record starting in year *t*

Table 4 Days absent. Linear fixed effect results. 1990-95 panel of employees aged 30-55

	Full sample								
	All			Males			Females		
	Coef.	St. err.	P>t	Coef.	St. err.	P>t	Coef.	St. err.	P>t
Age	-0.218	0.082	0.008	-0.211	0.174	0.226	-0.207	0.095	0.029
Age^2	0.001	0.000	0.005	0.001	0.001	0.051	0.001	0.000	0.061
Experience	0.196	0.078	0.012	0.178	0.171	0.300	0.195	0.088	0.027
Tenure	0.009	0.004	0.012	0.003	0.005	0.616	0.014	0.005	0.004
Income	0.045	0.006	0.000	0.034	0.010	0.000	0.054	0.010	0.000
$Income^2$	-0.001	1.2E-04	0.000	-4.1E-04	1.5E-04	0.008	-0.001	0.000	0.005
Kids < 11	0.013	0.022	0.567	-0.039	0.032	0.222	0.065	0.031	0.038
Unemployment	-0.019	0.012	0.112	-0.022	0.019	0.239	-0.017	0.015	0.275
Constant	7.600	2.077	0.000	6.919	3.882	0.075	7.766	2.580	0.003
Individuals	33213			14310			18903		
Observations	51928			21396			30532		
	Restricted sample (present in all 6 years)								
	All			Males			Females		
	Coef.	St. err.	P>t	Coef.	St. err.	P>t	Coef.	St. err.	P>t
Age	-0.305	0.121	0.012	-1.005	0.323	0.002	-0.204	0.132	0.122
Age^2	0.001	0.000	0.035	0.000	0.001	0.635	0.001	0.000	0.037
Experience	0.279	0.117	0.017	1.023	0.320	0.001	0.158	0.126	0.209
Tenure	0.002	0.004	0.590	-0.005	0.006	0.409	0.008	0.005	0.126
Income	0.053	0.008	0.000	0.037	0.014	0.008	0.065	0.013	0.000
$Income^2$	-0.001	1.6E-04	0.000	-4.7E-04	2.2E-04	0.037	-0.001	0.000	0.005
Kids < 11	0.002	0.026	0.946	-0.068	0.036	0.064	0.070	0.037	0.058
Unemployment	-0.041	0.014	0.002	-0.046	0.022	0.032	-0.037	0.018	0.033
Constant	9.892	2.999	0.001	24.184	6.965	0.001	7.636	3.572	0.033
Individuals	17368			7652			9716		
Observations	30500			12646			17854		

Dependent variable = log(calendar days absent in year *t*)

Estimates conditional on at least 1 absence period paid by NIA in year *t*

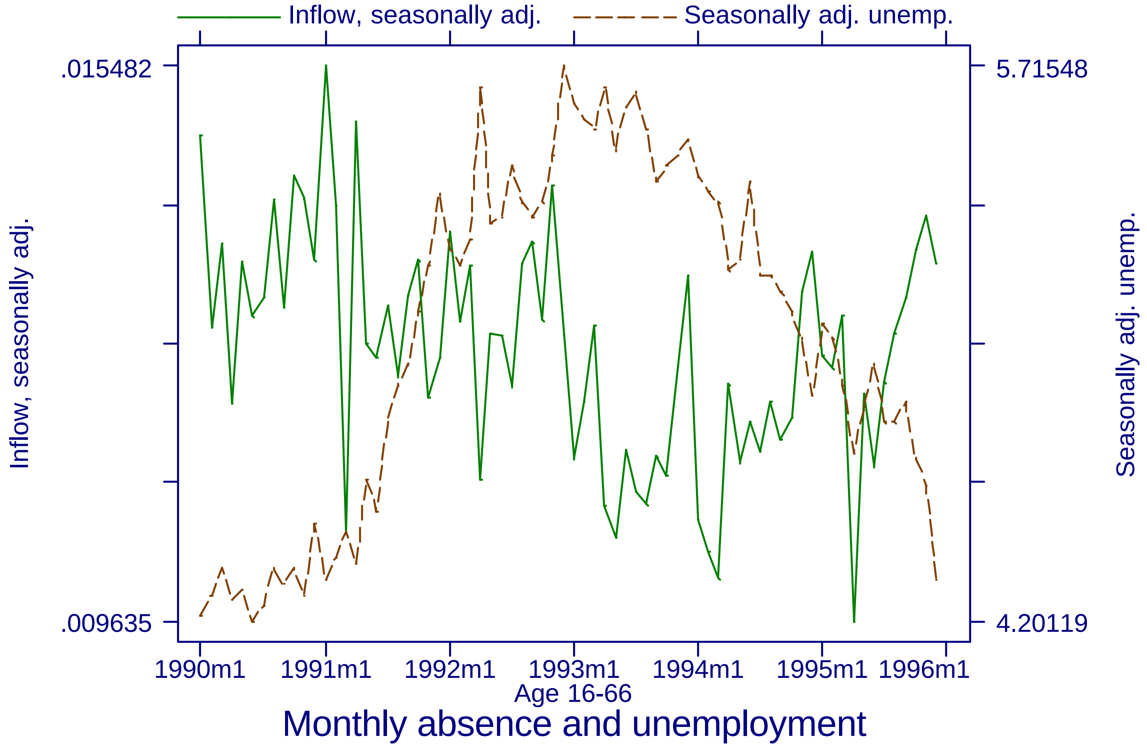

Figure 1 Monthly inflow to sickness absence as fraction of employment

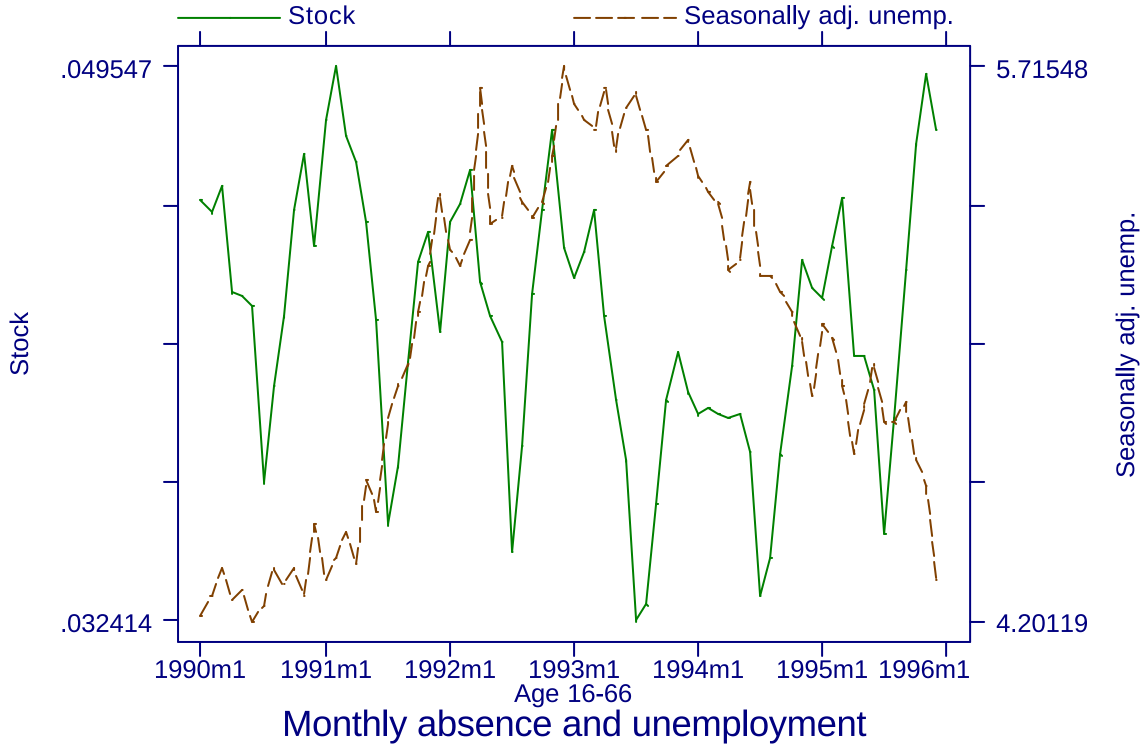

Figure 2 Monthly ongoing sickness spells as fraction of employment

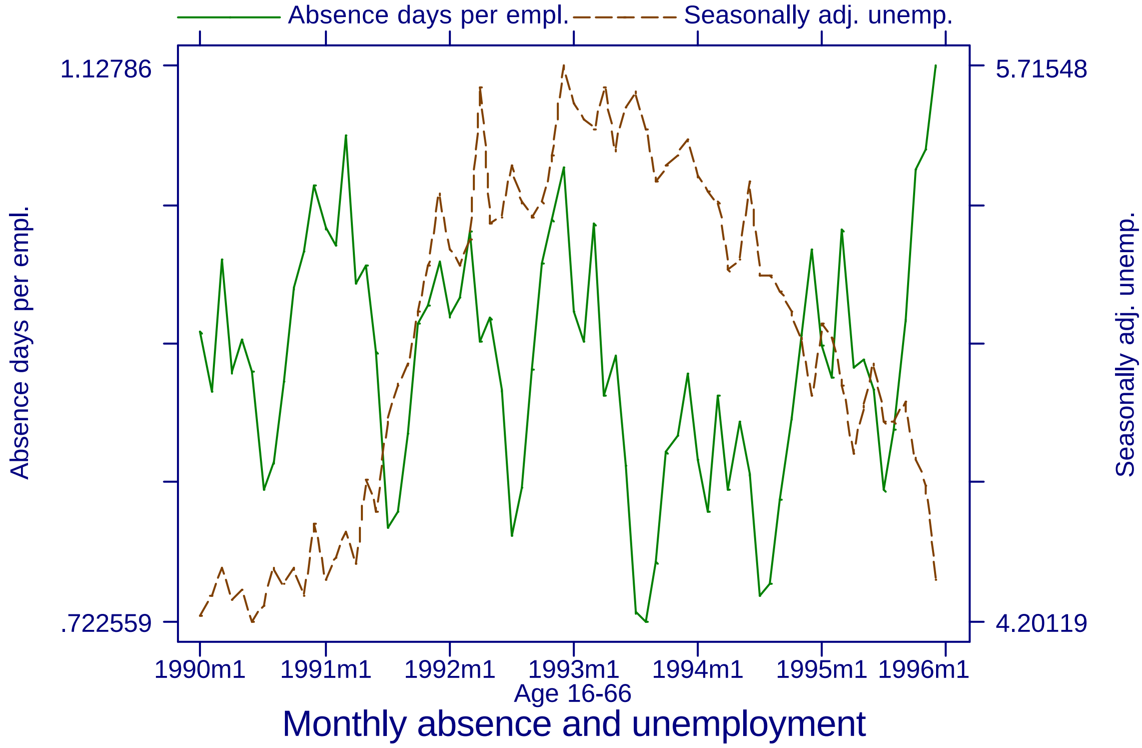

Figure 3 Absence days per employed

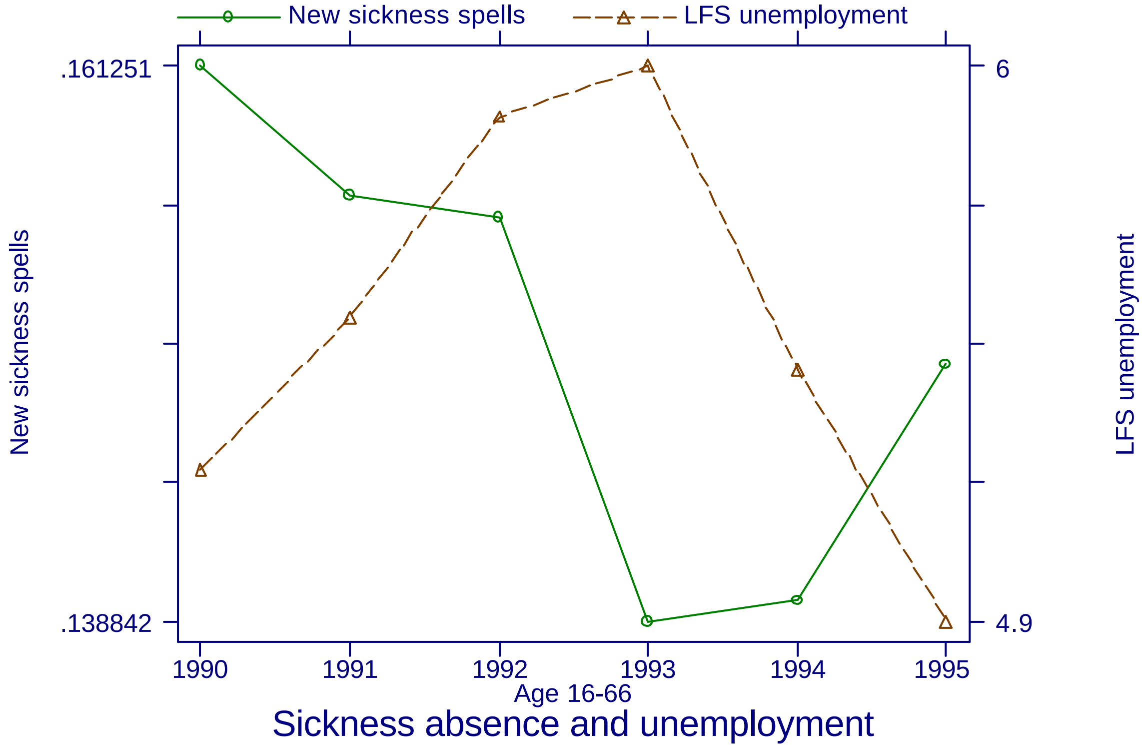

Figure 4 Yearly new sickness spells and unemployment

Appendix

Table A1 Variable definitions. All measurements as of year t, t = 1990,.., 1995

Variable	Definition
Absence days	Sickness absence (calendar) days paid by NIA starting in year t
Age	Age in year t
Experience	Years with income above 1G, where G is basic counting unit in pension system (NOK 39 230 in 1995)
Tenure	Years with current employer
Income	Gross taxable income in 10 000s 1995 NOK (lagged one year in the regressions)
Spouse income	Gross taxable income of spouse in 10 000s 1995 NOK (lagged one year in the regressions)
Part time	Dummy indicating working less than 20 hours/week
Unmarried	Dummy indicating individual is not married (reference in regressions)
Married	Dummy indicating individual is married
Prevmar	Dummy indicating individual is separated, divorced or widow(er)
Kids < 11	Number of children less than 11 years of age
Unemployment	Average % county unemployment (Directorate of Labour, based on register unemployment)

Table A2 Descriptive statistics for the fixed effext logit samples. Averages 1990-95

	Full sample				Restricted sample			
	Males		Females		Males		Females	
Variable	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.	Mean	St. dev.
Absence days	24.02	63.81	27.95	69.04	19.68	54.88	24.00	61.90
Positive abs. days	80.80	95.44	85.68	98.32	72.41	85.25	79.41	90.97
Age	42.81	6.60	43.12	6.58	42.98	5.82	43.49	5.77
Education[1]	10.60	2.25	10.49	2.19	10.55	2.20	10.38	2.10
Experience	20.85	5.06	15.43	5.48	21.46	4.65	16.13	5.37
Tenure	7.49	5.54	6.30	4.66	8.19	5.61	6.99	4.78
Income	24.84	9.26	16.10	6.31	25.11	8.82	16.40	6.16
Spouse income	8.86	8.62	18.53	15.11	9.08	8.60	18.61	14.86
Part time	0.02	0.13	0.21	0.41	0.01	0.10	0.19	0.40
Unmarried	0.16	0.37	0.11	0.31	0.14	0.35	0.10	0.30
Married	0.69	0.46	0.69	0.46	0.71	0.45	0.70	0.46
Prevmar	0.15	0.35	0.19	0.40	0.14	0.35	0.20	0.40
Kids < 11	0.46	0.83	0.38	0.72	0.45	0.81	0.30	0.64
Unemploy-ment	4.99	0.91	5.00	0.90	4.98	0.91	4.98	0.91
Observations	65 019		85 100		45 678		57 960	
Individuals	12 940		17 138		7613		9660	

[1]Years of education. Not used in the regressions.

Only individuals with at least one change in absence status are included in the logit samples.