Economic Incentives, Business Cycles, and Long-Term Sickness Absence

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We investigate long-term absenteeism in Norway, on the basis of register data covering 8 years and more than two million absence spells. Key findings are that: (1) a tighter labor market yields lower work resumption rates for persons who are absent, and higher relapse rates for persons who have already resumed work; and (2) the work resumption rates increase when sickness benefits are exhausted, but work resumptions at this stage tend to be short-lived.

Introduction

THE PURPOSE OF THIS PAPER IS TO EVALUATE HOW ECONOMIC INCENTIVES FOR EMPLOYERS and employees affect long-term worker absenteeism in Norway, with a focus on the design of the health insurance system and the state of the business cycle. The overall level of sickness absence in Norway is high compared to most other industrialized countries (only Sweden and the Netherlands have higher absence rates); see, e.g., Bonato and Lusinyan (2004). On a typical working day, 6–7 percent of Norwegian employees are absent due to sickness. In total, sickness absence insurance payments amount to approximately 41 billion Norwegian Kroner (NOK) per year (2004), or around 2.4 percent of the GDP. Except for a negative shift caused by tightened sickness benefit regulations in July 2004, sickness absence has been increasing inexorably in Norway since the early 1990s. Most of this increase can be attributed to a higher level of long-term sickness absence. To a large extent, economic expansions are associated with longer and more frequent sickness absence spells. However, whether this cyclicality reflects a causal relationship between labor market tightness and individual absence behavior or only a cyclical sorting of employees, remains an unresolved question.

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INDUSTRIAL RELATIONS, Vol. 48, No. 2 (April 2009).
Published by Blackwell Publishing, Inc., 350 Main Street, Malden, MA 02148, USA, and 9600 Garsington Road, Oxford, OX4 2DQ, UK.

In the present paper, we take advantage of a Norwegian database, which from 1992 to 1999 contains a complete account of all absence spells that lasted more than 2 weeks. Our methodological approach is based on a hazard rate framework. We set up a comprehensive multivariate mixed proportional hazard (MMPH) model (Abbring and Van den Berg 2003), in which we seek to explain:

1. Transitions from long-term sickness back to work attendance as well as to more lasting health insurance schemes such as rehabilitation and disability (exit from the labor force); and,

2. In cases of work resumption, the *subsequent* transitions into new sickness spells (relapses) and into rehabilitation/disability (delayed exits).

Our model is designed to examine two topics. The first is the extent to which business cycle fluctuations have a *causal* impact on employees' absence behavior. In order to do this, we need to disentangle the causal impact from the observationally similar *sorting* effect that arises if individuals with poor health have particularly cyclical employment behavior. The strategy of the present paper is to isolate the causal effects of economic fluctuations on work resumption propensities for ongoing absence spells by conditioning on the degree of labor market tightness at the time of entry into sickness absence. This implies that it is the changes in macroeconomic conditions that occur during longer-term absence spells that identify the causal effects. The second topic is the extent to which the progression of sickness absence spells is causally influenced by financial incentives embedded in the sickness insurance system. In order to answer this question, we take advantage of the fact that the replacement ratio declines sharply after 12 months of absence, when generous sickness benefits are replaced by much lower rehabilitation or disability benefits. Our strategy is to look for spikes in the work resumption hazard that can be attributed to this drop in the replacement ratio, similar to the approach often used to assess moral hazard problems in unemployment insurance systems, see, e.g., Katz and Meyer (1990), Hunt (1995) and Card and Levine (2000).

The prevalence of a procyclical pattern in aggregate sickness absence behavior has been demonstrated in a number of studies; see, e.g., Leigh (1985), Audas and Goddard (2001), and Askildsen, Bratberg, and Nilsen (2005). Interestingly, the cyclicality tends to be strongest in countries with the highest overall absence rates (Bonato and Lusinyan 2004). The existing literature identifies three channels by which business cycle fluctuations may causally affect individuals' absence behavior:

1. *Employee incentives (discipline effects)*: Economic fluctuations affect the employees' expected cost of being absent (Barmby, Sessions, and Treble 1994). The better the business cycle conditions—i.e., the safer the job and the easier it is to get a new one—the less severe are the consequences of being caught shirking. Therefore, in good times employees lower the sickness threshold at which they claim sickness benefits.[1]

2. *Employer incentives*: Economic fluctuations affect employers' costs of having absent employees (Audas and Goddard 2001). The better the business cycle conditions—i.e., the higher the product demand and the more difficult it is to obtain replacements for absent workers—the more costly it is to have absent employees. Therefore, in good times firms step up monitoring and other efforts to prevent absenteeism.[2]

3. *Direct health and work-environment effects*: Economic fluctuations affect employees' health condition directly (Ruhm 2000; 2003). The stronger the economy, the more stressful is the work environment and the higher is the frequency of workplace accidents and stress-related diseases.

While channels 1 and 3 contribute to a procyclical pattern in sickness absence, channel 2 contributes to a counter-cyclical pattern. Hence, the net causal effect is theoretically ambiguous.

There exists a small literature attempting to disentangle the net causal effect from the pure sorting mechanism that occurs if workers with high individual absence propensities are the first to be laid off in a downturn and the last to be hired in an upturn. Askildsen et al. (2005) examined the procyclical long-term absence pattern observed in Norway, based on register data from 1990 to 1996. They found that the negative correlation between sickness absence and aggregate unemployment was stronger among workers who remained in the labor force throughout this period than it was among all workers, and concluded that the relationship is causal at the

[1] Existing evidence indicates that job security has a significant impact on absence behavior. For example, Ichino and Riphahn (2005), using individual data from an Italian bank, found that sickness absence for newly employed persons increased after completion of the probation period. Lindbeck, Palme, and Persson (2006) examined a reform in Sweden implying weaker employment protection in small firms, and found that sickness absence fell in the affected firms.

[2] In bad times, absent employees may even be economically advantageous for the firm, since the wage costs (for workers who may be temporarily redundant anyway) can be passed on to the social security system.

individual level.[3] Similar results have been reported for Sweden (Johansson and Palme 1996), based on a semi-parametric random-effects model. By contrast, more recent evidence from Sweden (Johansson and Palme 2002) based on a model with fixed individual effects indicates that the causal relationship between labor market tightness and individual absence behavior is *counter-cyclical*. There is also a literature regarding the relationship between the level of sickness benefits and absenteeism (see Barmby, Ercolani, and Treble 2002, for an overview). Given the rarity of exogenous variation in sickness benefits, recent contributions to the literature take advantage of institutional reforms that have imposed some kind of change in the incentives structure, see, e.g., Meyer, Viscusi, and Durbin (1995) for the United States, and Johansson and Palme (2002) and Henrekson and Persson (2004) for Sweden. These papers demonstrate convincingly that economic incentives matter and that sickness absence cannot always be interpreted as a deterministic response to a purely medical condition. But to our knowledge, no evidence exists regarding the impact of the duration limits of sickness benefits.

Our own results indicate that workers' sickness absence behavior responds to economic fluctuations in a procyclical fashion. Once a long-term absence spell is started, the probability of resuming work is lower the better the macroeconomic developments are. And once work is resumed, the probability of a relapse is greater the higher the level of economic activity is. The role of economic incentives is confirmed by the finding of a sharp increase in the work resumption hazard in the period just prior to exhaustion of sickness benefits. But work resumptions occurring at this late stage of the absence spell have a much higher "failure-rate" in the form of relapse to some sort of health-related benefit later on, than work resumptions occurring earlier in the spell. Hence, ignoring events occurring some time after work resumption may lead to an overly optimistic view regarding the achievements of financial work incentives. With the exception of these very long absence spells, we find that a longer-term sickness absence spell sometimes can be viewed as a health investment, in the sense that it reduces the probability of subsequent relapse significantly; i.e., a longer absence spell "now" substitutes for more absence later on.

[3] The method used by Askildsen et al. (2005) entails a potential selection problem in a different disguise, since the condition of being active in the labor force from 1990 to 1996 clearly has a different connotation in the beginning of the observation window (where it requires stable employment during the next 6 years) than it has at the end (where it says nothing about subsequent employment). If "current" sickness absence is negatively correlated with future employment propensities, the stable employment selection criterion induces a positive time trend in sickness absence, which may obscure the identification of the causal effect.

Data, Institutions, and Business Cycles

The Norwegian sickness insurance system is generous. The replacement ratio is normally 100 percent from the first day of absence, with a maximum duration of 1 year. This is paid for by the employers the first two weeks, after which the National Insurance Administration (NIA) covers the costs up to an earnings ceiling corresponding to a yearly coverage of around 45,000 Euro (2006), while employers (in most cases) add the amount necessary to ensure a 100 percent replacement ratio. The maximum duration of sickness benefits is 1 year, and at least 6 months of work are required in order to be eligible for a new 1-year period. After that, a 100-percent replacement ratio is no longer available. The person must then either resume work, enroll in some kind of rehabilitation program, or apply for disability benefits. The latter option usually requires that rehabilitation has been tried first. Rehabilitation and disability benefits typically provide replacement ratios around 60 percent.

The data used in the present paper only include absence spells paid for by the public purse through the NIA, i.e., spells lasting more than 2 weeks. This may be viewed as a drawback; first, because the spells included in our analysis only cover around two-third of the total sickness absence (Bjerkedal and Thune 2003), and second, because economic incentives are typically assumed to be more important for short-term than for long-term absence. If the hazard rates out of long-term and short-term spells are governed by the same behavioral model, our data also entail a left-truncation problem (to which we return in the next section). However, there are important differences between short-term and long-term spells that would render a common behavioral model questionable. In particular, while short-term spells are almost entirely dominated by "everyday diseases" like colds, flus, and headaches (with virtually a zero probability of the spell stretching beyond one month), the longer-term spells considered in the present paper are dominated by musculoskeletal diseases and mental illnesses (these two diagnoses alone account for approximately two-thirds of the absence spells lasting more than 2 weeks). All the spells analyzed in the present paper also require a medical certificate from a general practitioner (GP).

The data we use in the present analysis are collected from NIA registers, and contain monthly observations of all absence spells during 1992–1999 for persons below 60 years. We trace each spell until it ends in either work resumption or in some alternative (and more lasting) form of social security benefit (rehabilitation or disability).[4] In the case of work resumption, we

[4] The reason why we do not distinguish between rehabilitation and disability is that most disability transitions are preceded by rehabilitation attempts. Indeed, Norwegian social security regulations imply that rehabilitation is to be considered before a disability pension can be provided. Since this may sometimes be a lengthy process, we are not able to identify the outcome of all the rehabilitation spells that we observe.

TABLE 1

Descriptive Statistics

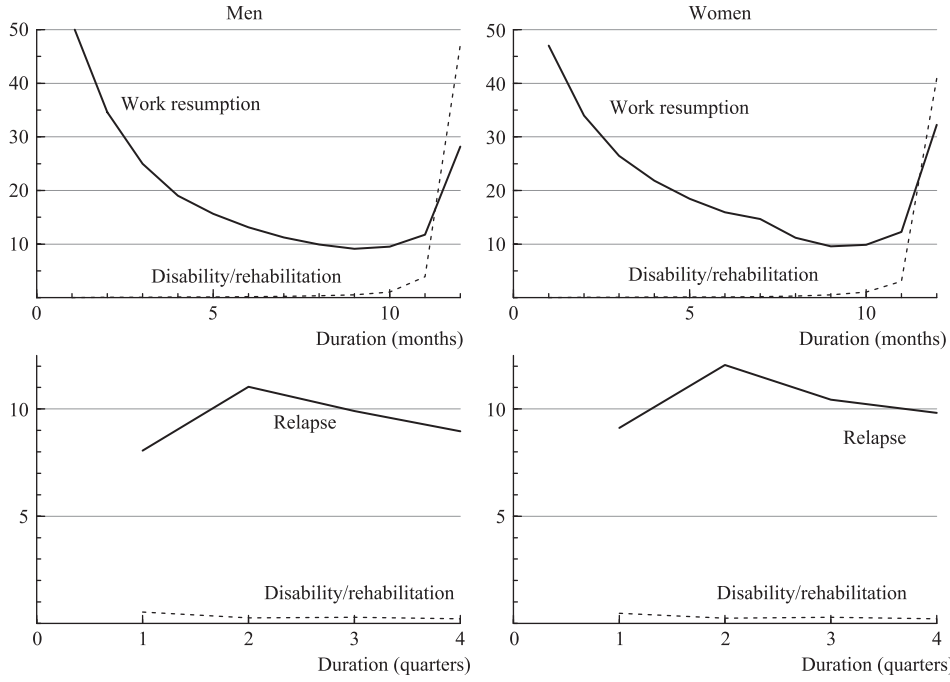
	Men	Women
Number of individuals	439,509	567,739
Absence spells:		
Total number	865,016	1,246,347
Out of which ended in (percent):		
Work resumption	90.66	91.73
Rehabilitation, disability, or other benefits	5.52	4.58
Censored at the end of the observation period	3.81	3.68
Average duration (months, including censored spells)	3.00	3.05
Work resumption spells:		
Total number	784,245	1,138,898
Out of which ended in (percent):		
Relapse into absence within 6 months	16.75	18.43
Relapse into absence after 6–12 months	12.62	13.18
Rehabilitation/disability within 6 months	2.06	2.06
Rehabilitation/disability after 6–12 months	0.33	0.33
Censored within 12 months	12.40	12.35
Resumption spell lasting at least 12 months	55.84	53.65
Total number of spell sequences	805,861	1,153,848
Fraction of individuals with multiple spell sequences	45.02	53.23

trace the person for the next 12 months as well, in order to identify relapses into absence spells or subsequent (delayed) transitions to rehabilitation/disability. If a relapse spell occurs within the first six months after the previous absence spell was completed, the two spells belong to the same 1 year benefit duration limit; hence the relapse spell will have a maximum duration of less than 1 year. In the terminology used in this paper, such continuation spells belong to the same *spell sequence*, together with the intervening work resumption spells. Hence, a new spell sequence can only be started after at least 6 months of work without any recorded sickness. A spell sequence is terminated, without being followed by a new one, if a transition to rehabilitation or disability is recorded. It is terminated and followed by a new one if a new sickness spell is recorded after 6–12 months of work resumption. It is right-censored when one of the following four events occur: (1) work has been resumed for an uninterrupted period of 1 year; (2) the person becomes 60 years of age; (3) the person dies; or (4) the observation period has come to an end.

Table 1 provides some essential statistics. A little more than 1 million individuals experienced at least one recorded absence spell during the

FIGURE 1

Observed Monthly Transition Rates from Sickness Absence to Work Resumption and Disability/Rehabilitation by Sickness Spell Duration (Upper Panels) and Quarterly Transition Rates from Work Resumption to Relapse and Disability/Rehabilitation by Work Resumption Duration (Lower Panels)

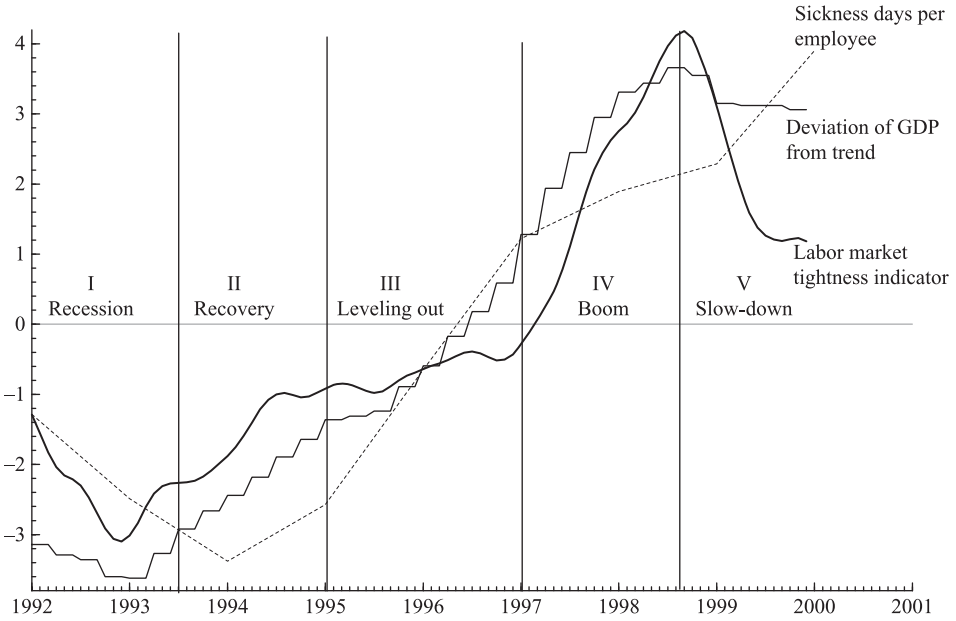


whole 8-year period. Around 90 percent of these spells ended in work resumption.[5] But more than 30 percent of these work resumptions were short-lived, in the sense that a new long-term absence spell started within the first year. Figure 1 reports mean monthly/quarterly transition rates by duration of the absence/work resumption spell. Around 50 percent of the

[5] Note that we do not actually observe work resumption; rather we infer that work resumption has occurred when sickness benefits are terminated without being replaced by other kinds of benefits. This induces an element of measurement error in our work resumption indicator. We may erroneously infer that work resumption has occurred in cases were workers pull out of the labor market without rehabilitation or disability benefits. This is the main reason why we have restricted the analysis to persons below 60 years of age (and hence well below the age-floor in the most common early retirement schemes).

FIGURE 2

Business Cycle Developments and Sickness Absence in Norway 1992–1999



Note: Deviation of GDP from trend is measured as percentage deviation from an estimated trend; see Johansen and Eika (2000). The business cycle indicator is collected from Gaure and Røed (2007) and normalized to match the mean and range of the GDP deviation. The number of sickness days is collected from the NIA and measured on a yearly basis. The numbers are matched to the mean and range of the GDP deviation (the real numbers were 9.3 days per employee in 1992 and 12.3 in 2000).

absence spells end with work resumption during the first month. The work resumption frequency then declines sharply, down to around 10 percent after 10 months, before it increases toward the end of the sickness benefit period. Around 10 percent of those who return to work have a relapse during the first quarter. The transition rate to rehabilitation/disability is generally very low, except toward the end of the sickness absence period.

The observation period used in this paper was characterized by relatively large changes in labor market tightness. This is illustrated in Figure 2, where we have plotted two business cycle indicators: the deviation from the estimated trend in the quarterly GDP level (collected from Statistics Norway, see Johansen and Eika 2000), and the estimated human-capital-adjusted monthly transition rate from unemployment to employment. The latter series is collected from Gaure and Røed (2007);

see also Carlsen, Johansen, and Røed (2006).[6] Both indicators reveal a deep recession during 1992, after which a steady recovery took over. From the autumn of 1996 and 2 years onwards, Norway's economy boomed, after which a new slowdown emerged. While the level of sickness absence declined during the early 1990s, along with the deterioration in business cycle conditions, it grew constantly after 1994, despite the new economic downturn toward the end of the decade. Hence, during the period covered by this paper there was no crystal clear cyclical pattern in absence rates.

Identification and Estimation of Causal Effects

Our choice of statistical modeling tool is motivated by the considerations of (1) being able to examine changes in the behavior of absentees that occur as the cyclical environment changes and as the point of sickness benefit exhaustion approaches; and (2) being able to assess the cyclical pattern in subsequent relapse propensities. For these purposes, we set up an MMPH model with two alternative origin states—absence (a) and work resumption (w)—and three alternative destination states—absence (a), work resumption (w), and rehabilitation/disability (r). This implies that there are four hazard rates to estimate: from absence to work resumption and rehabilitation/disability, and from work to absence and rehabilitation/disability. Note that transitions to rehabilitation/disability can be made from both origin states. To simplify the analysis, we assume that the impacts of covariates on the rehabilitation/disability hazard are the same, regardless of origin state. We allow, however, the *level* of the hazard to depend on the current state and on the time already spent in that state. The way we construct the data set ensures that the first origin state in each spell sequence is sickness absence. In this section, we explain how the hazard rates are modeled and provide a brief intuitive discussion of identification and estimation. Details regarding the estimation technique are provided in Appendix 1.

Let i be the subscript over individuals, let j denote origin state, and k denote destination state. Let d denote process time (spell duration). Finally, let x_{ijd} be a vector of time-varying explanatory variables and let v_{ki}

[6] The human-capital-adjusted transition rate is designed to capture the pure calendar time changes in the hazard rate out of unemployment. It is obtained by estimating a hazard rate model for unemployment durations in 1992–2001 with separate dummy variables for all calendar months represented in the data, in addition to a large number of individual characteristics (including human capital variables). The business cycle indicator is obtained by smoothing the estimates attached to the calendar month dummy variables; see Gaure and Røed (2007) for a more detailed exposition.

be a time-invariant unobserved characteristic.[7] The four hazard rates are then defined and specified as

$$\theta_{dijk} = \lim_{\Delta d \to 0} \frac{P(d \leq D \leq d + \Delta d, K = k \mid D \geq d, i, j)}{\Delta d} = \exp(\beta_k x_{ijd} + v_{ki}), \quad (1)$$
$$j = a, w; \quad k = a, w, r; \quad j \neq k.$$

Note that the unobserved covariates v_{ki} can be interpreted as individual intercepts in the hazard rates; hence, there are no constant terms embedded in the vector of observed characteristics x_{ijd}. Since we observe state occupation at discrete points in time only, the statistical model we formulate is set up in terms of grouped hazard rates, on a monthly basis for absence spells, and on a quarterly basis for work-resumption spells. Provided that the transition probabilities within each time interval are low, the estimated hazard rates will approximate the probabilities of making the transitions within these month and quarter intervals, respectively. According to equation (1), the hazards depend on *observed time-varying* and *unobserved time-invariant* characteristics. We include a large number of individual characteristics in x_{ijd}, including age, education, income, region, nationality, and marital status; see Appendix 2 for a full description. For transitions to rehabilitation/disability, we also include a dummy variable describing the present state ($j = a,w$). The variables that we focus on, however, are those related to *spell duration* and *macroeconomic fluctuations*. Absence duration is modeled in terms of 13 dummy variables (0 (no ongoing absence spell), 1, . . . , 12 months). Work resumption duration is modeled in terms of four dummy variables (1, 2, 3, 4 quarters). For work-resumption spells, we also include 12 dummy variables indicating the length of the *completed* absence spell (1, . . . , 12 months).

Macroeconomic conditions are represented in the model by the level of and the change (from last month) in the business cycle indicator presented in the Data, Institutions, and Business Cycles section (Figure 2). A key point is that we control for macroeconomic conditions both *at the time of entry into absence* and *at current time*. While the former of these is constant within each spell sequence, the latter is updated every month/quarter. Macroeconomic conditions at the time of entry are included in order to control for unobserved cyclical variation in the selection into absence, while

[7] While some of the variables in x vary with calendar time (such as macroeconomic conditions), others vary with duration (such as spell duration dummy variables). We simplify the notation by using only one time subscript, namely duration d.

the economic developments during the spell sequence are included to capture the causal effects on individual absence behavior.

An implicit assumption in our model is that calendar time changes in the hazard rates are completely captured by our macroeconomic indicators. If the sickness absence behavior has changed over time for other reasons, which are spuriously correlated to our macroeconomic indicators even conditional on all the explanatory variables, we may get biased results. We emphasize, however, that there were no important institutional changes in the sickness insurance system during the period covered by our analysis. According to the regular health surveys conducted by Statistics Norway there were also no significant changes in the general (self-reported) health status of the Norwegian population, conditioned on age. We also emphasize that the business cycle developments during our estimation period contain virtually all the phases of a full cycle (see Figure 2); hence, secular trends in, say, social norms and work environments, will not correlate strongly with our business cycle indicators.

A common problem in duration analyses is disentangling the effects of spell duration (duration dependence) from the influences of unobserved heterogeneity. The source of this difficulty is that persons that are, for example, only mildly hit by a disease will tend to resume work quickly, leaving behind persons with more serious diseases. And since the seriousness of the disease cannot be observed, this implies that—conditional on everything that can be observed—there tends to be a negative correlation between spell duration and work resumption prospects even when there is no *causal* relationship at all between duration and work resumption prospects. It has been proved, however, that the MMPH model of the type we use is nonparametrically identified under some regularity assumptions, given that there is at least some cross-sectional variation in observed explanatory variables that affect the hazard rates in question (Abbring and Van den Berg, 2003; Elbers and Ridder 1982; Heckman and Singer 1984b). The intuition is that the "selection consequences" of a given value of an unobserved covariate depends on the corresponding values of the observed covariates in a manner that can be traced out from the proportionality assumption. In our data, there are also two sources of information that can be used to disentangle true duration dependence from unobserved heterogeneity without reliance on proportionality. The first is the existence of *repeat spell sequences* for the same individuals. Since we assume the unobserved covariates v_{ki} to be constant for each individual, this introduces a powerful source of model identification (Van den Berg 2001). The second source of identification is the existence of *time-varying* covariates (Brinch 2007; McCall 1994). The basic idea is that persons who, according to observed

covariates have experienced, say, a high probability of work resumption earlier in their absence spell without actually resuming work, have revealed a low expected value of their unobserved work resumption propensity, *ceteris paribus*.[8]

The fact that we only observe spells lasting more than 2 weeks entails a left-truncation problem. This also yields a potential identification problem, since unobserved heterogeneity affects the likelihood of being omitted from the estimation sample in a way that is not statistically independent of other variables in the model. As a result, all time-invariant variables may, in general, be correlated to unobserved characteristics, and the estimated parameters will reflect this correlation as well as their causal effects. Given that most of the "lost" spells in our case are of a different nature than those included (refer to the discussion in the previous section), we do not view this problem as devastating. However, it does call for particular care in the interpretation of effects of time-invariant variables. In our analysis such variables are included for control purposes rather than for identification of causal effects, and their control roles are clearly not damaged by correlation with unobserved characteristics. Many of these variables are also likely to be correlated to unobserved characteristics for reasons that are not related to the left-truncation problem. For example, it is a well-established fact that health status is strongly correlated to educational attainment. An important point to note, however, is that the time-varying business cycle indicator used to identify the key parameters in our model is not correlated to unobserved characteristics (conditional on the business cycle situation at the time of entry), since developments that occur strictly after the month of entry cannot have affected the probability of survival through the entry month and, hence, of being sampled.

Our model is estimated by means of the nonparametric maximum likelihood estimator (NPMLE). This implies that we first derive the likelihood function conditional on each individual's unobserved characteristics $v_i = (v_{ai}, v_{wi}, v_{ri})$. We then integrate the unobserved heterogeneity out of the likelihood function on the basis of a discrete joint distribution. As a first step, we assume that this discrete distribution only contains two support points and maximizes the likelihood function with respect to the parameters of interest (β_k) together

[8] A reservation regarding these sources of identification of unobserved heterogeneity is that they only identify heterogeneity that has a constant effect at the individual level on the various hazard rates. We cannot identify unobserved heterogeneity in the degree of duration dependence itself, i.e., in the way recovery prospects change over spell duration. Given that different types of health problems are associated not only with different recovery prospects as such, but also with different recovery profiles over time, we suspect that the influences of unobserved heterogeneity cannot be entirely removed from our estimates of spell duration effects.

with the seven parameters characterizing the heterogeneity distribution ($2 \times 3 = 6$ locations and 1 probability). We then add an additional support point to the heterogeneity distribution and repeat the exercise. We continue adding support points as long as we are able to improve the likelihood function. When this is no longer possible, we have arrived at NPMLE. A more detailed description of the method—including the derivation of the likelihood function—is provided in Appendix 1.

Results

We estimated separate models for men (439,509 individuals) and women (567,739 individuals). For men, we found that eight mass points were required in the heterogeneity distribution in order to maximize the likelihood function, while for women it sufficed with six points. The total number of parameters to be estimated was 219 for men and 211 for women. In this section, we only present the key results related to duration dependence and business cycle effects. None of these results were sensitive toward the *exact* number of support points in the heterogeneity distribution, although the estimated duration dependence typically becomes more positive (or less negative) as more support points are added.[9] A more comprehensive list of estimation results, also including the impact of observed characteristics such as age and education, is provided in Appendix 2. In this appendix, we also report results from models estimated without unobserved heterogeneity. It turns out that most of the parameters are only modestly affected by the modeling of unobserved heterogeneity.

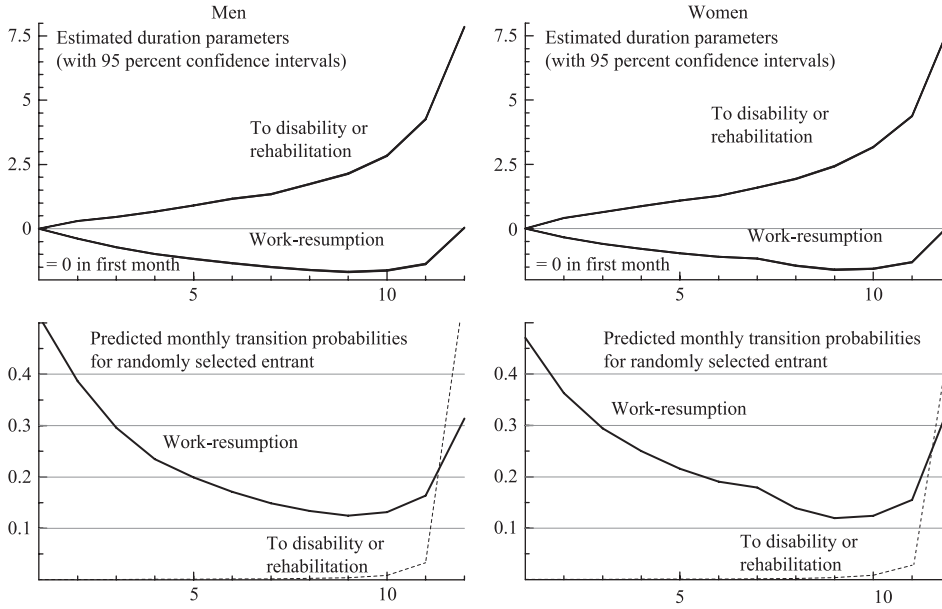
We start out by displaying the expected progression of absence spells in terms of transition rates to work resumption and rehabilitation/disability, see Figure 3. The two upper panels plot the estimated duration parameters with the first duration month used as a reference and with 95 percent confidence intervals. The two confidence interval boundaries are hardly visible, which highlights the point that statistical uncertainty is not a major issue in this analysis, given the large sample sizes. Based on the point estimates, the two lower panels depict the implied monthly transition probabilities for representative entrants into sickness absence.[10] The probability of resuming work during

[9] The estimated business cycle effects were remarkably stable across models with different numbers of support points, and the main conclusions presented in this section would have been basically the same even if we based them on models without unobserved heterogeneity.

[10] Representative entrants are constructed by scaling the first month transition probabilities to the average observed transition rates in the first duration month.

FIGURE 3

Estimated Spell Duration Parameters with 95 Percent Point-Wise Confidence Intervals (Upper Panels) and Predicted Monthly Transition Probabilities for Representative Entrant into Absence (Lower Panels)



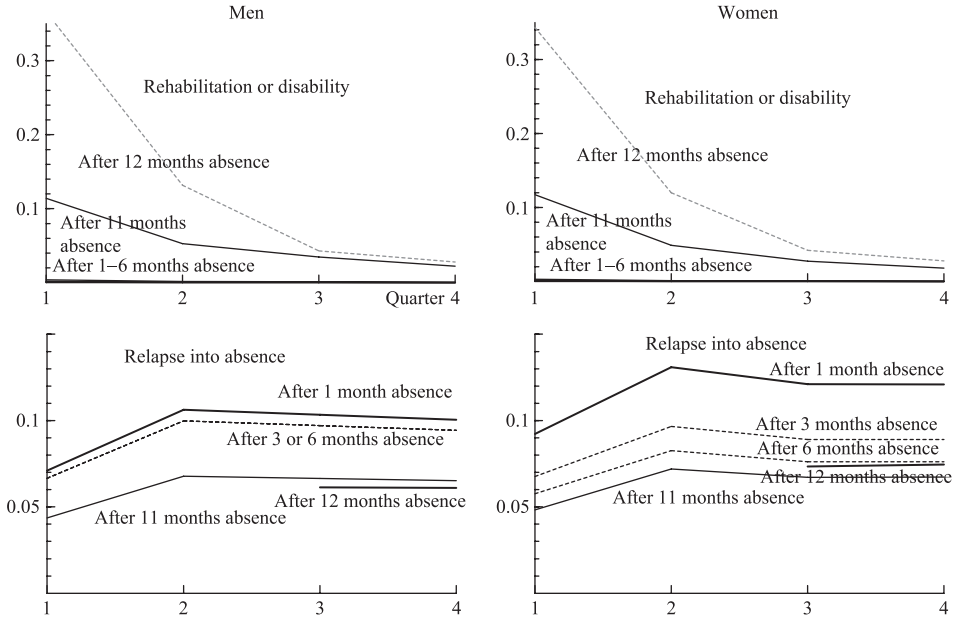
Note: The 95 percent confidence intervals around the profiles in the upper panels are so narrow that the printed line overlaps the confidence band.

the course of the first month is 51 percent for men and 47 percent for women. It then declines monotonically until it reaches a trough after 9 months at around 12 percent. Then, in the last month of the eligibility period, it again rises to 30–35 percent. The model-based duration profiles shown in Figure 3 are in fact not very different from the observed average profiles depicted in Figure 1. The main difference is, as expected, that the degree of negative duration dependence is somewhat smaller in the estimated model.

The work resumption peak identified after 11–12 months coincides with the point of benefit exhaustion. It is hard to believe that this has nothing to do with the termination of sickness benefits. Yet, the result must be interpreted with care, since, at this point, benefit exhaustion forces some kind of transition. It may be the case that attempts to resume work fail, such that the start of rehabilitation or the take-up of disability pension is only delayed for a short time period. We return to this issue below.

FIGURE 4

PREDICTED TRANSITION PROBABILITIES TO REHABILITATION/DISABILITY AND RELAPSE INTO ABSENCE DURING FIRST FOUR QUARTERS OF WORK RESUMPTION, FOR DIFFERENT DURATIONS OF THE INITIAL ABSENCE SPELL (CALCULATED FOR A RANDOMLY SELECTED ENTRANT INTO WORK RESUMPTION SPELL)



The probability of making a transition to disability or rehabilitation is negligible during most of the absence spell. However, having reached the end of the eligibility period entails a very high probability (above 40 percent for our representative individual) of making that transition. This reflects that persons who at this point are still not able to resume work for health reasons, are entitled to rehabilitation or disability transfers.[11]

Figure 4 describes the progression of the subsequent work resumption spells, conditional on the duration of the completed absence spell (note that the time unit in Figure 4 is in quarters rather than months). For persons with short initial absence spells, the probability of making a subsequent

[11] Note that there is not a 100 percent probability of escaping sickness benefits in the presumed final month of the benefit period. This is related to the fact that we do not measure absence duration accurately; there are probably some cases in which benefits are exhausted in the 11th or the 13th months. In the analysis, we interpret the few absence spells lasting more than 12 months as continuing with the spell duration dummy variables "frozen" at 12 months.

transition to rehabilitation or disability is close to zero. The probability is an order of magnitude higher when sickness benefits were about to become exhausted at the time of work resumption. In particular, the probability of entering into rehabilitation or disability during the first quarter is around 35 percent for persons who have exhausted their entire sickness benefit entitlement. The probability of a relapse into long-term sickness typically lies between 5 and 10 percent for each quarter. And this probability is higher the shorter was the initial absence spell, *ceteris paribus*. In particular, it seems that very short spells (only 1 month) is associated with a relatively high relapse probability. For example, if the initial absence spell lasted 3 months, rather than just one, the relapse hazard is reduced by 6.6 percent (0.8 percent) for men and as much as 32.4 percent (0.7 percent) for women (standard errors in parentheses). The latter finding suggests that absence spells to some extent may be viewed as a health investment, in the sense that having a longer absence spell "now" reduces the probability of a relapse in the future.

As we pointed out above, transition rates out of absence may give an incomplete picture of how the institutional characteristics of the benefit system affect absence behavior, since some persons may return to absence soon after an "apparent" work resumption transition or simply move on to rehabilitation or disability. Figure 5 summarizes the pattern of work resumption, relapse, and disability transitions, combining the processes depicted in Figures 2 and 3 in the form of a *joint probability* of work resumption and *not* returning to absence or transit to a rehabilitation/disability state within the subsequent 12 months; i.e., the probability of "lasting" work resumption. We see that the probability of making this kind of "lasting" transition out of the social insurance system is substantially lower than the "short-term" probability of resuming work (note that the dotted lines in Figure 5 are the same as the solid lines in the lower panels of Figure 3). Moreover, the spike in the transition rate around the time of benefit exhaustion becomes less pronounced, implying that a part of the increase in the work resumption rate around the time of benefit exhaustion is short-lived.

We now turn to the impacts of the business cycle, see Table 2. The two business cycle indicators are both normalized such that they have unit range, i.e., a positive change of one unit corresponds to a change from the worst state (or largest decline) of labor market tightness that was observed during the estimation period to the best state (or largest increase). This implies that (*exp(parameter estimate)-1*) can be interpreted as the relative change in the corresponding hazard rate that is predicted to occur when macroeconomic conditions (or the change in macroeconomic conditions) change from the lowest to the highest value. Higher economic activity

FIGURE 5

PREDICTED MONTHLY PROBABILITIES OF RESUMING WORK WITH AND WITHOUT CONDITIONING ON NO RELAPSE OR REHABILITATION/DISABILITY TRANSITION IN THE SUBSEQUENT 12 MONTHS

TABLE 2

ESTIMATED EFFECTS OF THE BUSINESS CYCLE AT THE TIME OF POTENTIAL TRANSITION (STANDARD ERRORS IN PARENTHESES)

	Men			Women		
Destination state	Work resump.	Rehab. disab.	Relapse	Work resump.	Rehab. disab.	Relapse
Level of business cycle at the moment of potential transition	–0.168 (0.018)	–0.414 (0.031)	0.111 (0.020)	–0.259 (0.014)	–0.320 (0.026)	0.198 (0.016)
Change in business cycle at the moment of potential transition	–0.046 (0.009)	0.121 (0.028)	0.073 (0.013)	–0.053 (0.007)	0.145 (0.023)	0.084 (0.010)

during a business cycle upturn tends to reduce the work resumption rates, and increase the relapse rates, substantially, both through a level and a difference effect. The effects of business cycles are statistically, as well as substantively, significant. For men, we find that when the labor market is both tight and tightening, the work resumption hazard is 15–20 percent

TABLE 3

Estimated Selection Effects of the Business Cycle at the Time of Entry into Absence (Standard Errors in Parentheses)

	Men			Women		
Destination state	Work resump.	Rehab. disab.	Relapse	Work resump.	Rehab. disab.	Relapse
Level of business cycle at the moment of entry into absence	–0.182	0.272	0.170	–0.097	0.314	0.096
	(0.018)	(0.029)	(0.019)	(0.014)	(0.024)	(0.016)
Change in business cycle at the moment of entry into absence	0.174	–0.062	–0.068	0.140	–0.043	–0.083
	(0.009)	(0.034)	(0.013)	(0.007)	(0.029)	(0.010)

lower, and the relapse hazard 15–20 percent higher than when the labor market is both slack and slackening. For women, the work resumption hazard is as much as 25–30 percent lower, and the relapse hazard 25–30 percent higher in a tight and tightening labor market (compared to a slack and slackening).

The probability of entering into disability or rehabilitation declines quite substantially with the level of the business cycle indicator, but increases with its difference. One may speculate that strain and stress at the workplaces are related to large *increases* in economic activity more than to high activity itself. Hence, it may be more difficult for employees with poor health to resume work during times of increasing demand, and, as a result, more workers are pushed into rehabilitation or disability.

Finally, we take a brief look at the effects of business cycles on the composition of entrants into absence, see Table 3. Recall that the estimates reported here are designed to measure systematic cyclical variation in unobserved health status among entrants into sickness absence. Since good health is associated with a high work resumption propensity and low rehabilitation/disability and relapse propensities, we expect the corresponding parameters to be of opposite sign. This is confirmed by the numbers in Table 3, and the signs of these coefficients are also clearly as expected. Economic upturns are associated with more healthy entrants into absence spells, with higher work resumption hazards and lower relapse hazards, *ceteris paribus*. Our results at this point therefore fit well into the discipline hypothesis; i.e., that it is more tempting to consider a given health problem as justifying an absence spell when macroeconomic conditions are improving than when they are deteriorating. However, the level of economic activity seems to have exactly the opposite effect. Persons who become sick during favorable, but stable, business cycle conditions tend to have poor work resumption prospects and high relapse propensities, *ceteris paribus*. We

interpret this as a confirmation of the "sorting hypothesis," i.e., that the average health condition among employed workers is negatively related to the level of employment.

Concluding Remarks

In this paper, we have investigated the transition rate pattern out of sickness absence spells, on the basis of Norwegian register data containing more than 2 million absence spells distributed over a period of 8 years. A main objective has been to take advantage of the huge dataset to avoid unjustified restrictions on the way observed, as well as unobserved, heterogeneity affect the transition rates. For this purpose, we have set up and estimated a dependent competing risks transition rate model for direct transitions into work resumption and rehabilitation/disability, as well as for delayed transitions into rehabilitation/disability and relapses into sickness absence. Our main conclusions are as follows:

First, business cycle developments during sickness absence spells have substantial effects on the work resumption behavior. Favorable business cycle developments imply lower work resumption rates and higher relapse rates (even when the business cycle conditions at the moment of entry are controlled for). These effects are both statistically and substantively significant, and they are stronger for women than for men. The results indicate that the cyclical pattern in absenteeism is primarily driven by employee behavior (direct health effects and/or discipline effects) and not by employer behavior.

Second, unobserved health status among entrants into sickness absence tends to improve when the economic activity level increases, indicating that the threshold for claiming sick might be slightly reduced in good times. However, a persistently high level of economic activity is associated with poor health status among new entrants into absence, indicating that lasting good times pull less healthy individuals into the labor market.

Third, the work resumption propensity increases substantially around the time of benefit exhaustion after one year of absence. A large part of this increase is subsequently diluted, however, through higher relapse and disability rates. Hence, financial incentives seem to have a significant, but limited effect on work behavior at this late stage of absence spells.

Fourth, there is a cost associated with taking up work too quickly, in the sense that a speedy return to work increases the relapse probability later on. Hence, a longer spell of absence may in some cases be considered a health investment.

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Appendix 1: The Statistical Model

This section explains how we estimate the model described in the Identification and Estimation of Causal Effects section, on the basis of observations of explanatory variables and transitions. All spell sequences are split into monthly/quarterly observation periods. Let K_{id} be the set of feasible transition states for individual i at duration d and let y_{idk} be an outcome indicator variable which is equal to 1 if the corresponding observation period ended in a transition to state k, and 0 otherwise. Furthermore, let Y_i be the set of outcomes available for individual i. The contribution to the likelihood function formed by a particular individual, conditional on the vector of unobserved variables $v_i = (v_{iw}, v_{ir}, v_{ia})$ can then be formulated as

$$L_i(v_i) = \prod_{y_{idk} \in Y_i} \left[\begin{array}{l} \prod_{k \in K_{it}} \left[\left[\left(1 - \exp\left(- \sum_{k \in K_{id}} \exp(\beta_k x_{ijd} + v_{ki}) \right) \right) \dfrac{\exp(\beta_k x_{ijd} + v_{ki})}{\sum_{k \in K_{id}} \exp(\beta_k x_{ijd} + v_{ki})} \right]^{y_{idk}} \right] \\ \times \left[\exp\left(- \sum_{k \in K_{id}} \exp(\beta_k x_{ijd} + v_{ki}) \right) \right]^{\left(1 - \sum_{k \in K_{id}} y_{idk}\right)} \end{array} \right] \tag{A1}$$

where $K_{id} = \{w, r\}$ when $j = a$ and $K_{id} = \{a, r\}$ when $j = w$, except in cases where work is resumed $j = w$ after full exhaustion of sickness benefits, in which case $K_{id} = \{r\}$ during the subsequent two quarters.

Equation (A1) cannot be used directly for estimation purposes since it contains unobserved covariates. We use a nonparametric approach to account for unobserved heterogeneity. This implies that the unobserved variables v_{ki} are jointly discretely distributed (Lindsay 1983) with the number of mass-points chosen by adding points until it is no longer possible to increase the likelihood

function (Heckman and Singer 1984a). Let W denote the optimal number of support points. In terms of observed variables, the likelihood is then given as

$$L = \prod_{i=1}^{N} \sum_{l=1}^{W} q_l L_i(v_l), \quad \sum_{l=1}^{W} q_l = 1 \tag{A2}$$

where q_l is the probability of the particular combination of unobserved variables v_l. Our estimation procedure is to maximize (A2) with respect to all the model and heterogeneity parameters repeatedly for alternative values of W. We start out with $W = 1$, and then expand the model with new support points until the model is "saturated," in the sense that we are not able to increase the likelihood any further. Our estimation procedure is the same as that described in Gaure, Røed, and Zhang (2007), which also contains a Monte Carlo investigation of the method's performance showing that i) it robustly recovers the true parameters of the data generating process (DGP), and ii) standard statistical inference can be performed *as if* the correct number of support points was prior knowledge.

Appendix 2: Estimation Results

TABLE A1

Selected Nonparametric Maximum Likelihood Estimation Results (Preferred Model with Unobserved Heterogeneity)

	To work resumption				To rehabilitation/disability				Relapse			
	Men		Women		Men		Women		Men		Women	
	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
Age												
<20	0.356	0.017	0.239	0.016	–0.956	0.148	–0.483	0.155	–0.551	0.039	–0.469	0.036
20–24	0.217	0.006	0.059	0.005	–0.121	0.026	–0.114	0.025	–0.281	0.012	–0.286	0.010
25–29	0.109	0.005	–0.005	0.004	–0.046	0.021	–0.097	0.019	–0.137	0.010	–0.184	0.007
30–34	0.044	0.005	–0.006	0.004	–0.031	0.019	–0.081	0.017	–0.039	0.009	–0.084	0.007
35–39	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
40–44	–0.039	0.005	–0.014	0.004	0.020	0.019	0.019	0.016	0.005	0.009	0.051	0.007
45–49	–0.100	0.005	–0.057	0.004	0.080	0.020	0.039	0.016	0.038	0.009	0.093	0.007
50–54	–0.192	0.005	–0.114	0.004	0.160	0.020	0.058	0.016	0.100	0.010	0.156	0.007
55–59	–0.338	0.006	–0.207	0.005	0.309	0.021	0.097	0.017	0.251	0.010	0.239	0.009
Education												
Unknown	–0.085	0.010	–0.089	0.009	–0.113	0.036	–0.104	0.035	0.287	0.019	0.160	0.017
Comp. only	–0.062	0.006	–0.120	0.004	0.006	0.022	0.005	0.017	0.386	0.011	0.395	0.008
Lower sec.	–0.046	0.006	–0.062	0.004	0.032	0.022	0.021	0.016	0.331	0.011	0.242	0.007
Higher sec. general	0.019	0.005	–0.041	0.004	0.017	0.022	–0.004	0.018	0.141	0.011	0.238	0.008
Higher sec. vocational	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
College	0.038	0.008	0.033	0.005	–0.092	0.031	–0.126	0.022	–0.138	0.015	–0.120	0.010
University	0.094	0.007	0.043	0.004	–0.300	0.031	–0.287	0.020	–0.198	0.014	–0.073	0.008
Income												
<1G	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
1–2G	–0.012	0.020	–0.098	0.009	–0.148	0.056	0.043	0.032	0.218	0.040	0.161	0.017
2–3G	–0.095	0.019	–0.104	0.008	–0.307	0.054	–0.029	0.031	0.343	0.038	0.289	0.016
3–4G	–0.113	0.019	–0.131	0.008	–0.438	0.053	–0.095	0.031	0.492	0.037	0.401	0.016
4–5G	–0.051	0.018	–0.102	0.008	–0.637	0.052	–0.189	0.031	0.612	0.037	0.468	0.016
5–6G	–0.009	0.018	–0.088	0.009	–0.729	0.052	–0.253	0.032	0.535	0.037	0.380	0.016
>6G	–0.035	0.019	–0.050	0.009	–0.694	0.053	–0.080	0.034	0.421	0.038	0.262	0.017

TABLE A1 (cont.)

	To work resumption				To rehabilitation/disability				Relapse			
	Men		Women		Men		Women		Men		Women	
	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
Duration of ongoing absence spell (months)												
0					1.349	0.068	1.474	0.064				
1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.				
2	–0.388	0.004	–0.345	0.003	0.297	0.085	0.406	0.078				
3	–0.719	0.005	–0.601	0.004	0.459	0.088	0.638	0.079				
4	–0.989	0.006	–0.794	0.005	0.665	0.087	0.870	0.079				
5	–1.176	0.007	–0.960	0.005	0.902	0.086	1.083	0.079				
6	–1.343	0.008	–1.100	0.006	1.162	0.083	1.267	0.079				
7	–1.494	0.009	–1.170	0.007	1.343	0.082	1.595	0.075				
8	–1.608	0.010	–1.447	0.008	1.736	0.077	1.932	0.072				
9	–1.684	0.011	–1.604	0.010	2.139	0.073	2.427	0.068				
10	–1.626	0.012	–1.565	0.010	2.835	0.067	3.167	0.063				
11	–1.374	0.011	–1.311	0.010	4.259	0.061	4.376	0.058				
12	0.039	0.008	0.182	0.006	7.856	0.060	7.967	0.057				
Duration of completed absence spell (months)												
1					Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
2					0.249	0.051	0.053	0.049	–0.056	0.006	–0.182	0.005
3					0.463	0.060	0.217	0.057	–0.066	0.008	–0.324	0.007
4					0.776	0.066	0.376	0.064	–0.045	0.010	–0.421	0.008
5					1.006	0.070	0.737	0.065	–0.067	0.012	–0.455	0.010
6					1.307	0.073	1.143	0.063	–0.066	0.014	–0.488	0.011
7					1.755	0.069	1.592	0.060	–0.094	0.016	–0.532	0.013
8					2.306	0.063	2.309	0.056	–0.079	0.018	–0.378	0.015
9					2.665	0.060	2.980	0.052	–0.171	0.021	–0.343	0.017
10					3.587	0.050	3.839	0.044	–0.235	0.022	–0.410	0.018
11					4.708	0.041	4.872	0.037	–0.441	0.025	–0.605	0.020
12					6.007	0.040	6.062	0.036	–0.478	0.024	–0.552	0.018

Duration of ongoing work-resumption spell (quarters)												
1					Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
2					–0.792	0.091	–0.904	0.083	0.422	0.006	0.372	0.004
3					–1.219	0.095	–1.498	0.086	0.392	0.006	0.288	0.005
4					–1.665	0.096	–1.919	0.086	0.363	0.007	0.287	0.005
Business cycles (BC)												
Current BC level	–0.168	0.018	–0.259	0.014	–0.414	0.031	–0.320	0.026	0.112	0.020	0.198	0.016
Current BC change	–0.046	0.009	–0.053	0.007	0.121	0.028	0.145	0.023	0.073	0.013	0.084	0.011
BC level at inflow	–0.182	0.018	–0.097	0.014	0.272	0.029	0.314	0.025	0.170	0.019	0.096	0.016
BC change at inflow	0.174	0.009	0.140	0.007	–0.062	0.034	–0.043	0.029	–0.068	0.013	–0.083	0.010
Married	0.076	0.003	0.011	0.002	–0.039	0.012	0.017	0.009	–0.137	0.006	–0.148	0.004
Immigrant from outside OECD	–0.038	0.007	–0.059	0.007	–0.271	0.026	–0.275	0.029	0.472	0.014	0.393	0.014

NOTE: The following variables, for which we do not report the estimation results, were also included: region (6 dummies), month in the year (12 dummies), and sickness degree (4 dummies). In transitions to rehabilitation/disability, we included separate work-resumption duration dummies for individuals who exhausted their sickness benefits, and hence were not eligible for sickness benefits the first two quarters of their work-resumption spell.

TABLE A2

SELECTED RESULTS FROM MODEL WITHOUT UNOBSERVED HETEROGENEITY

	To work resumption				To rehabilitation/disability				Relapse			
	Men		Women		Men		Women		Men		Women	
	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
Age												
<20	0.332	0.014	0.238	0.014	–0.563	0.136	–0.244	0.132	–0.558	0.037	–0.495	0.035
20–24	0.188	0.005	0.065	0.004	0.009	0.021	–0.064	0.021	–0.266	0.010	–0.298	0.009
25–29	0.092	0.005	0.007	0.004	0.021	0.017	–0.079	0.016	–0.122	0.008	–0.203	0.007
30–34	0.037	0.004	0.001	0.003	–0.004	0.016	–0.083	0.015	–0.032	0.008	–0.093	0.006
35–39	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
40–44	–0.031	0.004	–0.015	0.004	0.025	0.016	0.023	0.014	–0.003	0.008	0.047	0.006
45–49	–0.085	0.004	–0.053	0.004	0.064	0.016	0.033	0.013	0.016	0.008	0.076	0.006
50–54	–0.160	0.005	–0.101	0.004	0.115	0.015	0.048	0.013	0.048	0.008	0.117	0.006
55–59	–0.277	0.005	–0.177	0.004	0.227	0.016	0.086	0.014	0.133	0.009	0.145	0.007
Education												
Unknown	–0.067	0.008	–0.081	0.008	–0.121	0.028	–0.100	0.029	0.243	0.014	0.131	0.013
Comp. only	–0.048	0.005	–0.109	0.004	–0.037	0.017	–0.015	0.014	0.345	0.009	0.345	0.006
Lower sec.	–0.037	0.005	–0.057	0.003	–0.012	0.017	0.004	0.013	0.301	0.009	0.216	0.006
Higher sec. general	0.017	0.005	–0.037	0.003	0.006	0.017	–0.019	0.015	0.138	0.009	0.220	0.006
Higher sec. vocational	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
College	0.031	0.006	0.029	0.004	–0.060	0.024	–0.102	0.018	–0.123	0.013	–0.100	0.008
University	0.076	0.006	0.038	0.004	–0.220	0.024	–0.241	0.016	–0.165	0.012	–0.057	0.007
Income												
<1G	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
1–2G	–0.019	0.016	–0.096	0.008	–0.100	0.051	0.037	0.028	0.218	0.037	0.155	0.016
2–3G	–0.099	0.016	–0.100	0.008	–0.228	0.049	–0.032	0.027	0.340	0.036	0.273	0.015
3–4G	–0.120	0.015	–0.125	0.008	–0.334	0.048	–0.103	0.027	0.474	0.035	0.370	0.015
4–5G	–0.054	0.015	–0.096	0.008	–0.516	0.047	–0.201	0.027	0.591	0.035	0.437	0.015
5–6G	–0.012	0.015	–0.080	0.008	–0.579	0.048	–0.253	0.028	0.518	0.035	0.344	0.015
>6G	–0.030	0.015	–0.044	0.008	–0.540	0.048	–0.094	0.030	0.392	0.035	0.245	0.016

Duration of ongoing absence spell (months)												
0					1.074	0.067	1.237	0.063				
1	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.				
2	–0.511	0.003	–0.416	0.003	0.440	0.084	0.517	0.077				
3	–0.892	0.004	–0.711	0.003	0.673	0.087	0.809	0.079				
4	–1.195	0.005	–0.928	0.004	0.922	0.087	1.079	0.079				
5	–1.405	0.006	–1.111	0.005	1.187	0.085	1.316	0.078				
6	–1.590	0.007	–1.262	0.006	1.462	0.082	1.513	0.078				
7	–1.756	0.009	–1.343	0.006	1.649	0.081	1.847	0.075				
8	–1.881	0.010	–1.627	0.008	2.042	0.076	2.179	0.072				
9	–1.967	0.011	–1.789	0.009	2.436	0.072	2.659	0.067				
10	–1.919	0.011	–1.754	0.009	3.106	0.066	3.363	0.062				
11	–1.676	0.011	–1.503	0.009	4.442	0.061	4.477	0.058				
12	–0.270	0.007	–0.026	0.006	7.499	0.058	7.613	0.055				
Duration of completed absence spell (months)												
1					Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
2					0.446	0.050	0.222	0.048	0.182	0.006	0.004	0.004
3					0.740	0.059	0.471	0.056	0.263	0.007	–0.037	0.006
4					1.106	0.064	0.690	0.063	0.333	0.009	–0.071	0.007
5					1.387	0.068	1.093	0.063	0.348	0.011	–0.058	0.009
6					1.710	0.070	1.521	0.061	0.374	0.013	–0.063	0.010
7					2.181	0.065	1.980	0.057	0.376	0.014	–0.093	0.012
8					2.699	0.060	2.683	0.053	0.398	0.016	0.093	0.013
9					3.066	0.056	3.290	0.048	0.328	0.018	0.152	0.015
10					3.862	0.046	4.038	0.041	0.271	0.020	0.090	0.016
11					4.826	0.038	4.918	0.035	0.103	0.022	–0.075	0.018
12					5.813	0.036	5.867	0.033	0.404	0.022	0.220	0.017

TABLE A2 (cont.)

	To work resumption				To rehabilitation/disability				Relapse			
	Men		Women		Men		Women		Men		Women	
	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.	Est.	S.E.
Duration of ongoing work-resumption spell (quarters)												
1					Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.	Ref.
2					–1.023	0.090	–1.103	0.082	0.337	0.006	0.297	0.004
3					–1.556	0.094	–1.794	0.085	0.218	0.006	0.132	0.005
4					–2.043	0.096	–2.258	0.086	0.117	0.007	0.064	0.005
Business cycles (BC)												
Current BC level	–0.157	0.017	–0.257	0.014	–0.610	0.025	–0.477	0.022	0.143	0.019	0.197	0.015
Current BC change	–0.034	0.009	–0.039	0.007	0.237	0.023	0.204	0.020	0.020	0.013	0.035	0.010
BC level at inflow	–0.107	0.017	–0.033	0.014	0.371	0.023	0.374	0.021	–0.004	0.019	–0.074	0.015
BC change at inflow	0.143	0.008	0.119	0.007	0.014	0.028	0.023	0.025	–0.033	0.012	–0.048	0.010
Married	0.065	0.003	0.014	0.002	0.002	0.009	0.035	0.008	–0.118	0.005	–0.150	0.004
Immigrant from outside OECD	–0.029	0.006	–0.055	0.006	–0.239	0.021	–0.247	0.024	0.416	0.010	0.348	0.010

NOTE: The following variables, for which we do not report the estimation results, were also included: region (6 dummies), month in the year (12 dummies), and sickness degree (4 dummies). In transitions to rehabilitation/disability, we included separate work-resumption duration dummies for individuals who exhausted their sickness benefits, and hence were not eligible for sickness benefits the first two quarters of their work-resumption spell.