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WORKING PAPER

Starting in a high strain job…short pain?

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Abstract

Karasek (1979) defined a stressful job as a job with an imbalance between the demands of the job and the control one can exercise in that job (a 'high strain job'). Previous research showed that starters in a high strain job are indeed less satisfied. They are also not compensated for the high workload they face. In this paper, we raise the question whether this strain ('high strain job') is only temporary. The results of our duration analysis show that those starting in a high strain job leave their job significantly sooner than those in an active job. However, this is no guarantee that the strain is only temporarily, since there is a significant probability of still having a high strain job at the age of 26. This finding determines our policy implication: the discussion on work stress should focus on those trapped in high strain jobs.

Keywords: duration analysis, job-demand-control model of Karasek, job mobility
JEL-code: J62

1. Introduction

Karasek (1979) emphasised the importance of a balance between the demands in the job (i.e. workload) and the control one can exercise in that job (i.e. the autonomy one has). A job with high workload and low autonomy (a 'high strain job') is supposed to be a stressful job, whereas a high demanding job with a lot of autonomy (an 'active job') results in learning opportunities.
Previous research shows that young workers who start in a high strain job are less satisfied than their counterparts (De Witte et al., forthcoming) and that they are not compensated for this aggravating work situation in terms of a higher wage (Verhofstadt et al., 2004).

Because workers starting in a high strain job seem to be worse off, we want to find out whether this strain is temporary. Do young workers who start in a high strain job leave their job faster than those in an active job? What is the influence of the job type on the probability of being unemployed in the near future? And are these young workers better off later on in their career, or are they 'locked up' in high strain jobs?

We first of all model job search on the basis of the wage-search model of Mortensen (1986). We incorporated various aspects of the job in this model (by not only considering the wage but also the utility of the job).

We will use duration analysis to answer our first research questions. We compare the job duration of high strain and active jobs by using non parametric, semi-parametric and parametric estimations. Multinomial logit models will be used to analyse the impact of the first job type on the probability of unemployment in the near future and on the probability of still having a high strain job at the age of 26.

2 Theoretical framework

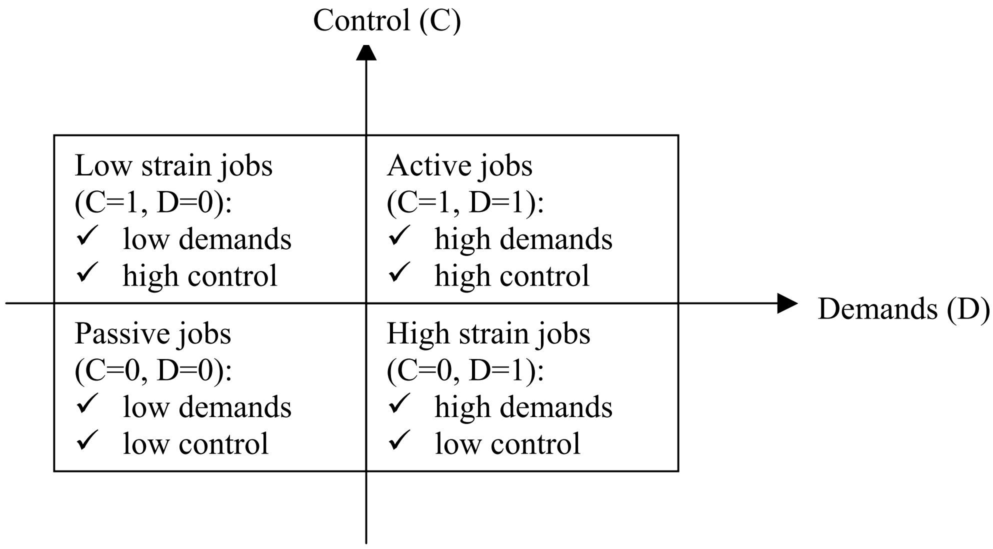
In this theoretical part, we introduce the Karasek Job-Demand-Control model, and the framework used to analyse the job duration of the different job types of the first (significant) job.

2.1 The Karasek Job-Demand-Control model (1979)

The job-demand-control model of Karasek (1979) achieved a dominant position within work and organizational psychology. One of the reasons is it simplicity, since it distinguishes only two basic dimensions when analysing jobs. The combination of psychological job demands and control or decision latitude gives rise to four job types, as described in figure 1. We define both control (C) and demand (D) as binary variables. On the basis of the combination of both dimensions, Karasek formulated two hypotheses. The stress-hypothesis states that high demands combined with low decision latitude (a 'high strain' job) causes stress. The learning hypothesis states that the combination of high demands with a high level of control (an 'active' job) gives opportunities for growth and for the increase of one's competencies (Karasek, 1979).

According to the Karasek model, high workload is not per definition problematic, as it can be a source of motivation when combined with a high level of control. Expressed in terms of preferences, we can summarise the Karasek model as follows: the utility is decreasing with an increase in demands, and increasing with an increase in control.

Figure 1: Jobtypes in the Karasek model (Karasek, 1979)



The Karasek model has been the focus of a large amount of empirical research (e.g. De Jonge & Kompier, 1997; Karasek & Theorell, 1990; van der Doef & Maes, 1999). The main focus is on the stress hypothesis. Research concerning the learning hypothesis is rather scarce. In general, research confirms the stress hypothesis. In their review of 20 years of empirical research on the Job Demand Control model, van der Doef and Maes (1999) conclude that most studies support the hypothesis that employees in high strain jobs are worse off: they experience a lower level of psychological well-being, less job satisfaction, more burnout and more job-related psychological distress. Epidemiological studies equally show that workers in a high strain job exhibit lower levels of various aspects of physical health, such as cardiovascular diseases (De Jonge & Kompier, 1997). Most studies show that both job characteristics distinguished by Karasek exhibit main effects on these (psychological and physical) outcome variables: an increase in job demands is associated with a decrease in health and well-being, whereas an increase in job control is associated with an increase in these outcome variables. As a conclusion, research demonstrates that more job demands are stressful, whereas more control in the job leads to a decrease in stress among workers.

A previous test of the Karasek model with the SONAR dataset (i.e. the dataset used in this paper) confirms both the stress and the learning hypothesis. The combination of high demands and low control did result in lower overall job satisfaction (De Witte et al., forthcoming). This combination is typical for a high strain job, and can be considered as a particularly stressful situation. The combination of high demands and high job control (an 'active job') resulted in an increase in skills, as hypothesised in the learning hypothesis. The Karasek model has rarely been used to predict turnover. However, some of the outcome variables of the model, such as strain and dissatisfaction are often mentioned as antecedents of job mobility (e.g. Maertz & Campion, 2001).

2.2. Modelling job duration

As a starting point for our analysis, we use the wage search model of Mortensen (1986), extended by the possibility of workers looking for a job while they are employed (Burdett, 1978). We elaborate this model by not only considering the wage of the offered job, but by also including non pecuniary characteristics of the work as indicators for the search process (Blau, 1991). As a consequence, we do not define the wage as the unique determining element in the search process. We instead highlight the utility of the job. We define $U = f(C, D; X)$: the utility is determined by the level of control (C) and demand (D) in the job and by X, which is a vector of other job and personal characteristics (including the wage).

Economic agents spent resources (time, telephone costs, transportation costs, stamps, …) while searching for jobs. For simplicity, we assume that the cost of this search is identical for both employed and unemployed. An important implication of this assumption is that the reservation utility of an unemployed worker is the utility of leisure. Assuming that the cost of job search is the same whether one is employed or not, implies that the economic agent accepts the first job which compensates for the value of abandoned leisure and continues to search for a better job (i.e. a job with a higher utility) while exercising his job. We also assume that the returns to more intensive job search diminish. We incorporate these assumptions in the model by assuming that the offer arrival rate is proportional to the worker's job search effort (λs) and by assuming that the cost of job search is an increasing convex function of search effort ($c(s)$).

We restrict our attention to modelling the probability of leaving the first job. $rU(\bar{u})$ denotes the discounted future utility when the economic agent is employed in a job with utility $\bar{u}$, given that the optimal job search strategy is followed in the future.

$$rU(\bar{u}) = \max_{s \geq 0} \left[\bar{u} - c(s) + \lambda s \int_0^\infty \left\{ \max\left[U(u), U(\bar{u})\right] - U(\bar{u}) \right\} dF(u) \right] \quad (1.1)$$

The job search effort in the current period only affects the cost of job search in the current period and the probability of generating an offer in the next period. So, the optimal value of the job search effort maximizes the sum of the utility of the current period (i.e. utility net of search costs in the current period, $\bar{u} - c(s)$ when employed at $\bar{u}$) and the expected utility gain, which is attributable to job search. The expected utility gain attributable to job search, consists of the product of the offer arrival rate (λs) (which is proportional to the search effort) and the expected difference between the utility when accepting and working in a job with utility u and the utility when staying in the job which provided the utility $\overline{u}$.

The economic agent determines the search intensity so that the optimal job search effort equals the marginal returns and costs of continuing the search effort in the next period. The optimal search effort can be derived from equation (1.1). Let $s^*(u)$ be the optimal search intensity choice of the economic agent when he is employed in a job with utility u . The optimal search intensity declines with the utility obtained while employed. So, the higher the utility while employed the lower the optimal search intensity ($s^*(u)$). At a certain high level of u, the marginal return of continuing the search effort will not be sufficient to compensate for the marginal costs of that search effort (> 0). This utility level (u^*) is the reservation utility.

Formally:

$$(\lambda / r)\int_{u^*}^{\infty}\left[u-u^*\right]dF(u) = c'(0) \qquad (1.2)$$

Equation (1.2) suggests that the marginal return of continuing the search effort equates the marginal cost of zero search effort ($s^*(u)=0$). Because C'(s)>0, this equation (1.2) implies that the economic agent will not exercise any search effort anymore when he accepts a job offer with a utility of u^* (the reservation utility).

The probability that an individual working at utility $\overline{u}$ will exit the initial state (in our case the first significant job) within a short interval, conditional on having survived up to t, the starting time of the interval, is expressed by the hazard rate $\phi(U(C,D;X),t)$. This probability is the product of the rate at which the economic agent receives job offers, the optimal search intensity and the probability that the offered job is acceptable.

Formally:

$$\begin{aligned}
&\phi(U(C,D;X),t) = \lambda s^*\left(U(C,D;X),t\right)\left[1-F\left(U(C,D;X),t\right)\right] \\
&\text{with } \ \lambda\text{: the rate of job offers} \\
&\qquad \text{F(u,t): the cumulative job offer distribution} \\
&\qquad \text{s}^*(u,t)\text{: optimal search effort when employed at utility u}
\end{aligned} \qquad (1.3)$$

Since in equation (1.3) we implicitly assume that all job mobility is voluntary, we will also include ψ expressing involuntary mobility. Gronberg and Reed (1994) introduce involuntary mobility into the Mortensen job search model by including the exogenous separation rate of workers from firms into the expression for the hazard rate. We adapt this to our utility framework, but endogenize this term because it is reasonable to assume that certain personal and job characteristics will influence the probability that one will be forced to leave the company. So our expression becomes:

$$\phi(U(C,D;X),t) = (\psi(C,D;X),t) + \lambda s^{*}\left(U(C,D;X),t\right)\left[1 - F\left(U(C,D;X),t\right)\right] \quad (1.4)$$

This distinction between voluntary and involuntary mobility is frequently introduced in research, but addressed in different ways. Reed and Dahlquist (1994) , van Ommeren et al. (2000), Trevor (2001), Ruiz & Gomez (2002), Manning (2003), and Bradley et al. (2004), all distinguish quits and separations in their sample. In their estimations, however, they do not take the hypothesis into account that voluntary mobility can be influenced by the probability of forced mobility. Perticara (2004) addresses this issue by including the assumption “that workers are not aware that a layoff is coming until they are definitely laid off”.

2. Hypotheses and motivation

Young workers starting their career in a high strain job are worse of than their counterparts in active jobs. Therefore, we want to analyse the impact of the job type on the job mobility of young workers. Based on the developed framework, we advance the following hypotheses

- *Young workers in high strain jobs will leave their job sooner*

Since we assume that according to the Karasek model the utility of a high strain job is lower than that of an active job, individuals will want to leave that job sooner in order to obtain an active job. The model discussed above suggests that the utility level of the actual job will be lower for those working in a high strain job. Those in active jobs have already a higher utility level compared to those in a high strain job. As a consequence, the job search intensity of respondents in active jobs is lower compared to the intensity of respondents in high strain jobs.

We can thus advance that:

$$U(1,1,X) > U(0,1,X) \Rightarrow s^{*}\left(U\left(1,1,X\right)\right) < s^{*}\left(U\left(0,1,X\right)\right)$$

- *Young workers in active jobs will be the last to be forced to leave their job*

We expect that those in active jobs are not the first victims of forced mobility. Active jobs are per definition jobs with high demands and high autonomy, which results in learning opportunities and the development of new skills. An explanation for this reduction in turnover among active jobs can be

found in human capital theory (Becker, 1964). Firms will only offer learning opportunities if the benefits of these jobs are larger than the costs. Since the benefits are to be found in future productivity, it is less likely that workers in active jobs are the first to be laid off during business downturns. Parsons (1972) found strong support for the hypothesis that in industries where worker- and firm financed specific investments are sizeable, average quit and lay-offs rates will be lower.
Therefore we put forward:

$$\Pr(\psi|1,1,X)_t < \Pr(\psi|0,1,X)_t$$

These hypotheses suggest that those starting their career in a high strain job will have a shorter job duration than those starting in an active job. Next to the test of this main hypothesis, we also want to examine whether young workers who quit their jobs are better off further on in their career.

For those who were forced to leave their job, we test the probability to end up in an unemployment spell. Previous research (e.g. Mc Donald and Felmingham, 1999) suggests that the incidence of unemployment is high for workers who involuntary left their jobs. Combined with our hypothesis that involuntary mobility occurs sooner for those in high strain jobs, we wonder whether young workers starting in a high strain job have a higher probability of becoming unemployed after their first job.
For those who choose to leave their job, our theoretical model suggests that they get a better job. Therefore we test the hypothesis of job mobility from high strain jobs to active jobs.

3. Econometric specifications

3.1 Survival analysis

The hazard function $\phi(t)$ is the probability of exit from a state in the short interval of length dt after t, conditional on the state still being occupied at t (Lancaster, 1990).

In terms of the distribution function this probability equals:

$$\phi(t) = \frac{f(t)}{1-F(t)} = \frac{f(t)}{S(t)} \quad \text{with } f(t)\text{: density function of T}$$

$$F(t) = P(T \le t) \text{ the cumulative distribution function of T}$$

T is a nonnegative random variable that represents the failure time, in our case job duration. S(t) is the survivor function of T. This function gives the probability of survival beyond t or the probability that there is no failure event prior to t.

The analysis of survival data can be done in three ways: nonparametric, semi-parametric and parametric. Nonparametric analysis allows the dataset 'to speak for itself' without making assumptions about the functional form of the survivor function. Effects of covariates are not included in this kind of analysis.

Non parametric estimation of the survivor function is done by using the Kaplan-Meier estimator, which is given by (Cleves et al., 2002):

$$\hat{S}(t) = \prod_{t_j \le t} \left(\frac{n_{t_j} - d_{t_j}}{n_{t_j}}\right) \text{ with } t_j = \text{observed failure time}$$

n_{t_j} = the number of individuals at risk at time t_j

d_{t_j} = the number of failures at time t_j

Since we are interested in the different survival function for high strain and active jobs, we will estimate a survival function for each job type. We test the equality of the survivor functions across the job types by running a log-rank and a Wilcoxon test. Both are global tests, which means that they compare the overall survival functions and not at a specific time point. The tests compare the expected versus the observed number of failures for each group and combine these comparisons over all observed failure times. The difference between both tests is the weight they give to the contingency tables obtained at every failure time. The Wilcoxon test places additional weight to tables at earlier failure times (Cleves et al., 2002).

When we want to incorporate explanatory variables in the model, we have to conduct a parametric or semi-parametric analysis. Parametric analysis assumes a specific parametric family for the distribution of the failure times. Two specifications are possible.
A proportional hazard model has the following specification (Kiefer, 1988):

$$\phi(t) = \phi_0(t)e^{\beta X} \qquad (2.1)$$

with $\phi_0(t)$: the baseline hazard function

X: vector of explanatory variables and β the corresponding vector of coefficients.

In this model it is assumed that the hazard function is influenced proportionally by a change in the value of an independent variable. A proportional hazards parametric model gives a functional form to $\phi_0(t)$. When no particular parameterisation is given to the baseline hazard, we have the popular Cox model, which is called semi-parametric.
The alternative specification is the accelerated failure time (AFT) specification. Here we assume that the effect of explanatory variables on the failure time can be captured by rescaling time

$$T = e^{\beta X} T_0 \qquad (2.2)$$

with T_0 : the baseline failure time

X: vector of explanatory variables and β the corresponding vector of coefficients.

The $\exp(-\beta X)$ is also called the acceleration parameter and is assumed to be constant. If this acceleration parameter is larger than 1, failure would be expected to occur sooner (time is accelerated). The time scale for someone with characteristics X is $e^{\beta X} T_0$, whereas the time scale for someone with characteristics X=0 is T_0. If the acceleration parameter is smaller than 1, time is decelerated (failure would be expected to occur later).

For the distribution of the failure time, we opt for the Generalized Gamma specification. The generalised gamma distribution is a three-parameter distribution $(\beta_0, \kappa, \sigma)$ permitting a variable hazard shape. The exponential (constant hazard), Weibull (monotonically increasing or decreasing hazard) and log-normal (non-monotonic hazard) are all special cases of this distribution. Since it is not straightforward to predict duration dependence for job duration, we opt for this flexible Generalized Gamma specification.

To check whether this generalised gamma model is indeed the most adequate model (among all possible parametric models), we will run two tests. For testing whether the gamma model is preferred over the exponential, Weibull and log-normal model (which are nested in the gamma model) we will run a Wald and likelihood ratio test. We test the following hypotheses:

1. $H_0 : \kappa = 0$ if this is true, then the model is log-normal
2. $H_0 : \kappa = 1$ if this is true, then the model is Weibull
3. $H_0 : \kappa = 1,\ \sigma = 1$ if this is true, then the model is exponential

To make a choice between non nested models, the use of the Akaike Information Criteria is suggested (Cleves et all., 2002).

$AIC = -2\ln L + 2(k + c)$

with L: likelihood of the model

k: number of covariates in the model

c: number of model-specific distributional parameters

The first term of the AIC measures the goodness-of-fit of the model to the data, the second term is a penalty for an increasing number of parameters. The preferred model is the one with the lowest value of the AIC (Sawa, 1978).

We will provide the non parametric Kaplan Meier estimation, the semi-parametric COX proportional hazard estimations and the (parametric) generalised gamma model.

3.2 Binary and multinomial logit models

To test our additional research question, whether young workers are better off further on in their career, we make use of a number of limited dependent variables models. When testing the probability of working or not, the dependent variable is a binary variable, by means of which we are opting for a binary logit model (Greene, 2003):

$$P(\text{working}) = \frac{\exp(\alpha_j + \beta x)}{1 + \exp(\alpha_j + \beta x)}$$

We use a multinomial logit model to model the reason for leaving the first job and to estimate the impact of the first job on the situation at the age of 26 (in order to check whether the job type ameliorated over time). This kind of model is used since there are more than two alternatives without natural ordering. A convenient approach is to assume that all error terms (of the underlying relations between the latent variables and the observed characteristics) are mutually independent with a log Weibull distribution. This generates the multinomial logit model (Greene,2003).
The assumption of independent error terms is an important drawback of this method. In the literature this is known as the 'independence of irrelevant alternatives' (IIA). This property means that the ratio of the probabilities of choosing any two alternatives is independent of the attributes of any other alternative in the choice set (Hausman, 1984). Therefore, we will also run the Hausman test to check whether the multinomial logit specification is correct. This test examines whether the parameter estimates of the unrestricted and the restricted choice set (the choice set in which one or more alternatives are eliminated) are approximately the same. If this is the case, then the multinomial logit specification is not rejected (Hausman, 1984).

4. Data

The empirical analysis is based on the SONAR-data. We use the birth cohort of 1976. A sample of 3000 Flemish youth was surveyed at the age of 23 and a follow-up was realised when they were 26 years old. 2060 of them also participated in the follow-up survey. For a detailed overview of the SONAR dataset we refer to SONAR (2000) and SONAR (2004).
We calculated the duration of the first job by using the month to month registration of their labour market activities. In the SONAR-data, the first job is defined as the first job of at least one hour a week and with a tenure of at least one month. The observations of the job duration are right censored, since not all respondents already left their first job at the moment of the follow-up survey.

In general, one can measure job characteristics (such as job demands and job control) in two ways: observers can rate the job of a specific worker (a so called 'objective' measurement), or workers can rate their own jobs ('subjective' measurement; see e.g. Frese & Zapf, 1988). Both methods are in fact 'subjective', however, as both ratings have to be performed by an individual. The observer ratings have the advantage that the rating is performed separately from the respondent, thus excluding subjective evaluations and actual mood states. The disadvantage, however, is that the observer can only sample a specific (visible) part of the job performed, within a given time span. The self assessment of the worker has the advantage that he or she can take all possible aspects of the job into account, whether or not they are visible or scarce. The correlation between both methods, however, is rather high (Fried & Ferris, 1987; O'Brien, 1986). Fried & Ferris (1987) in their analysis of 15 studies analysing this issue found a median correlation of 0.63 between the so called 'objective' and 'subjective' rating, suggesting that both methods measure the same reality. As a consequence, it is warranted to use self descriptions of workers, collected during interviews.

We constructed a demand and control variable based on a list of 19 items about different job characteristics, tested in previous research (e.g. De Witte, 1990; Hooge & De Witte, 1998). The respondents had to rate these items on a 4-point scale, ranging from completely agree, rather agree, rather disagree, to completely disagree.

We used the items related to job demands and job control. For job demands we could use only one item, asking whether they had to work at a great pace or under time pressure[4]. To measure job control, we used an average of three items: were the interviewees able to decide (a) what to do on a particular day, (b) how much work they had to perform that day and (c) how to perform the job. For both job characteristics the answers "completely agree" and "rather agree" were considered as "high" and the answers "completely disagree" and "rather disagree" were considered as "low".

The vector X (i.e. the control variables) consists mainly of dummy variables, which were straightforward to construct and interpret. For the wage variable, we had different types of registrations. For some respondents the exact wage (point data) was available, while for others only the interval in which the wage was situated (in which the first and last wage interval were open-ended) was known. We constructed a wage variable which is the log of the hourly wage, based on the different registrations using maximum likelihood[5].

The SONAR dataset contains detailed information about the first and the actual job, including the reason why people left their job. For the whole period up to the moment they were surveyed, information is available about their position (employed or not). Since no detailed data about the second job is available, we cannot apply the Karasek typology to this second job. Therefore, we have to restrict the analysis to a comparison of the first and the actual job in order to test whether people succeed in getting a better job in terms of the Karasek typology.

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[4] In the first survey two items were used. In the follow-up survey, these were collapsed into one item. The two items in the first survey were reduced to one by strictly interpreting the 'or'.

[5] See Stewart (1983) for details.

5. Results

5.1 Descriptive results

In table 1, the mean duration for the different job types is presented. This mean duration is not corrected for censoring (i.e. some people are still in their job). One can see that the mean duration is significantly higher for active jobs than for high strain jobs. Since the highest proportion of censored cases can be found within the active jobs category, this result is already a reliable indication that high strain jobs have a shorter duration than active jobs.

Table 1: Mean duration of the first job for the different Karasek job types

Karasek Job type	Mean Job duration	Number of observations
Passive jobs	16.3	451
High strain jobs	19.3	1237
Low strain jobs	22.9	390
Active jobs	25.9	678

5.2 Results of the survival analysis

Non parametric estimations

Figure 2: Estimated cumulative survival for active and high strain jobs

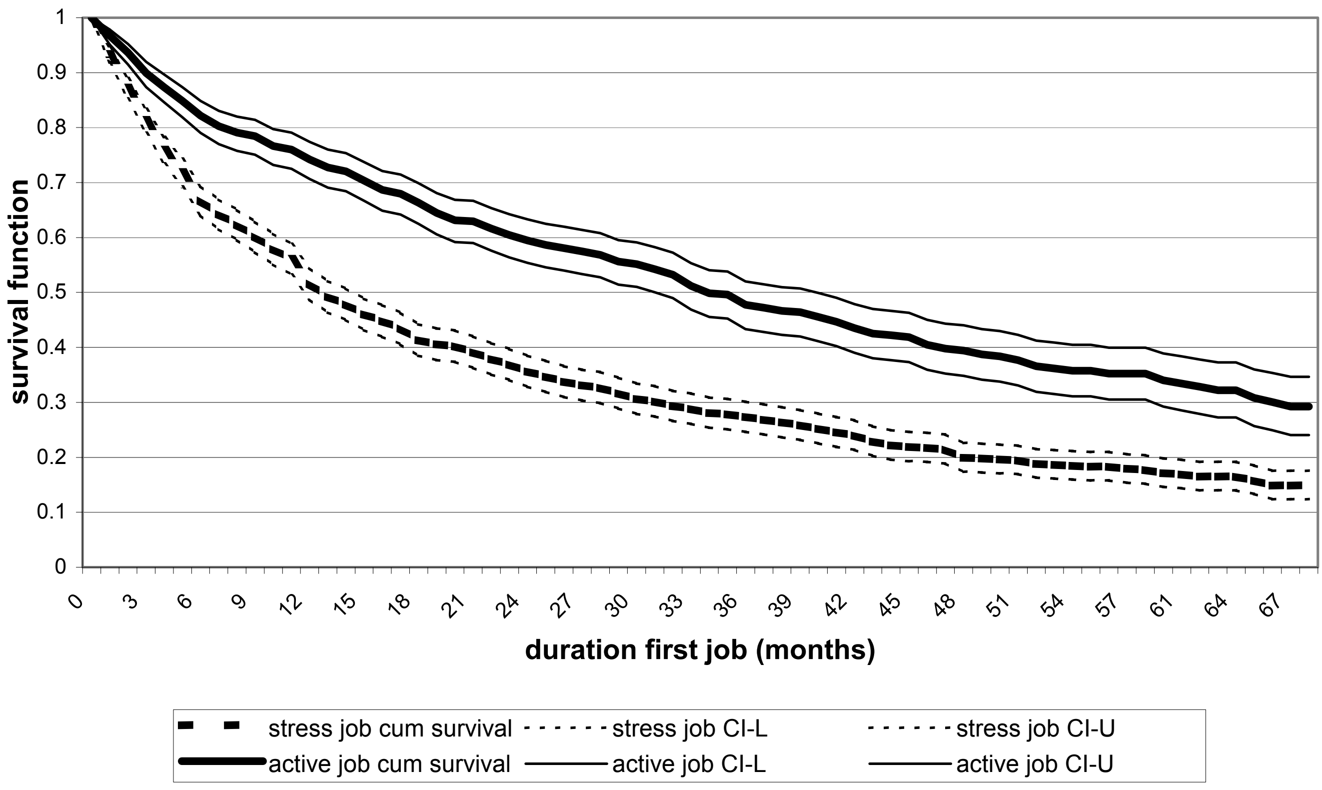

Figure 2 presents the cumulative survival function for the active and the high strain jobs with their 95% confidence interval. In the calculation of the survivor functions, censoring is taken into account. The cumulative survival function is the probability of leaving the job after t. The figure shows that the survival for active jobs is always higher than the survival for high strain jobs. This confirms our main hypothesis.

The probability of having an active job for more than t months is always higher than the probability of having a high strain job for more than t months. The results from both tests (log-rank and the Wilcoxon test) are identical: the probability that the observed differences occur by chance is less than 1%. So, the reported result is statistically significant.

Semi parametric estimations

In table 2, the results of the semi-parametric Cox regression are reported. The interpretation is the easiest in terms of the hazard. For example, having a high strain job instead of an active job increases the hazard by 55%, because exp(0.44)=1.55. So the results confirm our hypothesis that those in high strain jobs will leave their job faster than those in an active job. Since the impact of other covariates is not the focus of our study, we do not report and discuss these results.

Table 2: Results of the Cox regression

	Coefficient	**St. error**	Hazard ratio	**St. error**
passive job	0.56***	0.09	1.75	0.16
high strain job	0.44***	0.08	1.55	0.12
low strain job	0.19*	0.1	1.21	0.12
active job (reference)				
Number of observations	1933			
Log Likelihood	-9266.36			

* Significant at 10% level, ** significant at 5% level, *** significant at 1% level

Included control variables: gender, number of children, living together with partner, ethnicity, educational level, subjective evaluation of educational level, working in the same region as one lives, contract type, hourly wage, percentage of a full time job one works, night work, shift work, company size, sector of employment.

Parametric estimations

Table 3 presents the results of the Generalized Gamma regression. The active job is considered as reference group, to enable a comparison with the high strain jobs. We report the coefficients as well as the time ratios. A positive coefficient means a longer survival time, whereas a negative coefficient implies a shorter survival time than the reference group. The time ratios express the delay of the failure compared to the reference group. For example, if someone in an active job quits his job at t=1, than someone in a high strain job will do so at t=0.58 (=exp(-0.55)).

Table 3: Results of the generalized gamma regression

	Coefficient	St. error	Time ratio	St. error
passive job	-0.66***	0.11	0.52	0.06
high strain job	-0.55***	0.09	0.58	0.05
low strain job	-0.26**	0.12	0.77	0.09
active job (ref)				
constant	2.91***	0.52		
Number of observations	1933			
Log Likelihood	-2770.54			

* Significant at 10% level, ** significant at 5% level, *** significant at 1% level

Included control variables: gender, number of children, living together with partner, ethnicity, educational level, subjective evaluation of educational level, working in the same region as one lives, contract type, hourly wage, percentage of a full time job one works, night work, shift work, company size, sector of employment.

Again, our hypothesis that those in high strain jobs will leave their job sooner than those in an active job, is confirmed. As the non parametric and semi-parametric estimations suggested, passive jobs have the shortest duration and active job the longest. The time ratios in table 4 show that if an interviewee in an active job leaves his job at t=1, an interviewee in a passive job will do so at t=0.52, an interviewee in a high strain job at t=0.58 and an interviewee in a low strain job at t=0.77.

As discussed in the econometric part, we test whether this generalised gamma specification is indeed the most adequate parametric model. The test results (reported in appendix 1) support our model selection.

Conclusion

The non parametric, semi parametric and parametric estimations all support our hypotheses. Young workers starting in a high strain job will leave this job sooner than their counterparts starting in an active job. Thus far, however, we did not distinguish between leaving voluntary or involuntary. Therefore, we will examine the reasons for leaving the first job in the next section.

5.3 Reasons for leaving the first job

To examine the impact of the job type on the reasons for leaving the first job, we estimate a multinomial logit model. The Hausman test provides evidence for the hypothesis that the odds of two outcomes are independent of other alternatives. The results of the multinomial logit model are presented in appendix 2. There is no significant impact of being in a high strain job compared with being in an active one. Based on the estimated coefficients, we calculated the probability for starters in the different job types that they will leave that job for a certain reason. So, the probabilities in table

4 are the probabilities of a man, without children, who does not live with a partner and who completed higher secondary education, to end his job for a certain reason. This probability is calculated for four cases, depending on his first job. The differences between the high strain and active job type are rather small.[6] This suggests that young workers in high strain jobs do not leave their first job more often because of a specific reason. The already discussed hazard estimates have shown that those in high strain jobs leave their job sooner. So, if we consider a short time spell, those in high strain jobs will experience more voluntary as well as involuntary job mobility compared to their colleagues in other job types in that time spell. In the next section, we will examine whether they are better off later in their career.

Table 4: Estimated probabilities to end the first job for the different reasons

	Reason of leaving the first job					
	End of temporary contract	Individual lay off	Collective lay off	Resign	Another job offer	personal or other reason
Passive	24.19%	13.34%	11.03%	27.21%	15.24%	8.99%
High strain	14.58%	15.56%	9.50%	33.06%	14.76%	12.56%
Low strain	18.84%	16.28%	16.98%	22.76%	14.46%	10.67%
Active	11.52%	12.37%	17.08%	30.30%	15.01%	13.73%

5.5 What after the first job?

According to our theoretical model, young workers will leave their first job if they have a better alternative (voluntary mobility) or if they have to leave their job (forced mobility). For those who voluntary left their job, we thus assume that they have a better job immediately after leaving their first job. For those who were victims of forced mobility, this is not necessarily the case. For this sub sample, we estimate the probability of working one month after they had to leave their first job. The results (appendix 3) show no significant impact of the job type of the first job.[7] The educational level appears to be the most important determinant of the probability of working after one had to leave the job. Lower educated interviewees have a significant lower probability of working and higher educated interviewees a significant higher probability, compared to the reference group of middle educated

[6] The reported probabilities depend strongly on the considered reference person. The estimates (appendix 3) suggest a large impact of the educational level and so the probabilities differ remarkably for persons with different educational levels. Lower educated have a higher probability of lay off and higher educated get more job offers. Despite these differences, according to reference person, the comparison over the different job types is very similar.

[7] Individual lay off, collective lay off and end of temporary contract are considered as forced mobility. Leaving out the respondents who left because of end of temporary contract did not influence the result that there is no significant impact from the job type on the probability of having a job.

interviewees. So, although young workers in high strain jobs are premature victims of involuntary mobility, they are not more often confronted with unemployment after their lay off.

For those who voluntary left their job, we cannot compare the Karasek job types of the first and the second job, since we only have data about the first and the actual situation (see data description). Therefore, we estimate the impact of the type of the first job on the situation at the age of 26, using a multinomial logit model. Our theoretical model predicts that voluntary job changes occur in order to obtain a better job. As a consequence, we use no unemployment spells between the different jobs as a proxy for voluntary job changes. For those who had one or more months of unemployment after leaving a job, the reservation utility equals the utility of not working and not the utility of the previous job. So, only for those who had no unemployment spells, we expect a better job at the age of 26. The probabilities to be in a certain situation at the age of 26, can be found in appendix 4. We distinguish between the different job types, unemployment and studying. The reported results are for a reference man without children who does not live with a partner.

The probability for the reference man starting in a high strain job to obtain an active job, strongly depends on his educational level. For lower educated interviewees, this probability is considerable lower than for higher educated interviewees. The probability of obtaining an active job at the age of 26 is always higher when the first job was also an active job. So, although we can assume that people leave their job to obtain a better one, the results indicate only limited job mobility from high strain jobs to active jobs. At the same time, a considerable group are 'locked up' in a high strain job later in their career.

6. Conclusion

Previous research suggested that young workers with a high strain job (according to the Job-Demand Control model of Karasek) are less satisfied with their job and do not get a wage compensation for the strain that is associated with their job. We therefore raised the question whether they leave their job sooner than their colleagues in active jobs. Our results confirm this hypothesis. Using different models for estimating duration data (non parametric, semi-parametric and parametric), we consistently find that young workers leave their high strain jobs sooner compared with those in active jobs.

Next to the test of our main hypothesis (do starters in high strain jobs leave their jobs sooner?), we also examined whether they were better off later on in their career. The theoretical model predicts that young workers will leave their first job if they have a better alternative. Due to a lack of data, we could not test if this was true. Data only permitted to compare the job type of the first job with the job type at the age of 26. The results of this comparison show that a considerable part of the young starters in high strain jobs remain in a high strain job later on.

For those who had to leave their first job, we examined whether their job type also influenced the probability of being unemployed later on in their career. The estimation showed that this was not the case. So, although starters in high strain jobs are premature victims of forced mobility, their initial job

type does not affect their probability of becoming unemployed afterwards. Only the educational level was a relevant determinant of that probability.
We can thus conclude that the strain of a high strain first job is only temporary. There is however a significant probability to remain in a high strain job later on in the career.

The results of our study add to the current discussion on stress at work. First of all, not all jobs with a high workload seem to be stressful. Only jobs with an imbalance between the demands and the control one has, cause stress. Secondly, we found that a considerable part of those starting in a high strain job, obtain a "better" job later on in their career. So, a high strain first job seems to be temporary for some young workers, and could be a stepping stone to a 'better' job later on. We do not want to minimize the current problem of job stress among young starters with this statement. Stress is indeed a problem, but mostly for those who are not able to escape to another job and stay in high strain jobs or become unemployed. As a consequence, it is important to target these young workers, in order to get some understanding of the antecedents of those who are more prone to stay in high strain jobs. Some of our findings suggested that the lower educated who start in a high strain job are particularly vulnerable. Further research should therefore focus on the characteristics and antecedents of young workers who are unable to leave high strain jobs on their own.

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Appendix 1: Testing the parametric model choice

Wald test and Likelihood-ratio test for the nested models

	p-value of Wald test	p-value of likelihood-ratio test
$H_0 : \kappa = 0$ (log-normal)	0.050	0.048
$H_0 : \kappa = 1$ (Weibull)	0.000	0.000
$H_0 : \kappa = 1,\ \sigma = 1$ (exponential)	0.000	0.000

AIC for the different parametric estimations

Distribution	Log Likelihood	k	c	AIC
Exponential	-2865.499	23	1	5779.00
Weibull	-2848.8725	23	2	5747.75
Gompertz	-2821.3567	23	2	5692.71
Generalised gamma	-2770.5405	23	3	5593.08
Log-normal	-2772.4949	23	2	5594.99
Log-logistic	-2791.8799	23	2	5633.76

Appendix 2: Results of the multinomial logit model on the reason of leaving the job

	Coefficient	Std. Error	Sig.
Individual lay off			
Intercept	-0.194	0.455	0.670
less than higher secondary education	0.582	0.316	0.065
higher secondary education (ref)			
higher education	-1.876	0.343	0.000
passive job	0.061	0.401	0.879
high strain job	0.246	0.340	0.469
low strain job	0.312	0.454	0.491
active job (ref)			
Collective lay off			
Intercept	0.129	0.541	0.812
less than higher secondary education	0.518	0.378	0.171
higher secondary education (ref)			
higher education	-2.893	0.626	0.000
passive job	-0.452	0.465	0.331
high strain job	-0.570	0.389	0.143
low strain job	0.032	0.528	0.952
active job (ref)			
Resign			
Intercept	0.702	0.329	0.033
less than higher secondary education	0.396	0.285	0.165
higher secondary education (ref)			
higher education	-0.214	0.195	0.274
passive job	-0.123	0.279	0.660
high strain job	0.104	0.228	0.649
low strain job	-0.249	0.316	0.431
active job (ref)			
End of temporary contract			
Intercept	-0.265	0.327	0.417
less than higher secondary education	0.807	0.270	0.003
higher secondary education (ref)			
higher education	-0.394	0.186	0.034
passive job	0.727	0.262	0.006
high strain job	0.253	0.228	0.267
low strain job	0.530	0.290	0.067
active job (ref)			
Personal or other reason			
Intercept	-0.089	0.363	0.806
less than higher secondary education	0.762	0.295	0.010
higher secondary education (ref)			
higher education	-0.313	0.218	0.150
passive job	-0.439	0.310	0.157
high strain job	-0.072	0.247	0.769
low strain job	-0.215	0.336	0.522
active job (ref)			
Another job offer (ref)			
Number of observations	1574		
Log Likelihood	-536.27		

Other included control variables: gender, number of children and living together

Appendix 3: Results of the binary logit model on the probability of working after involuntary leaving the first job

	Coefficient	Odds	Standard Error
Constant	0.422		0.366
Passive job at 23 (ref)			
High strain job at 23	0.128	1.14	0.287
Low strain job at 23	0.366	1.44	0.267
Active job at 23	0.411	1.51	0.329
Man (ref)			
Woman	-0.183	0.83	0.179
Less than higher secondary education	-0.842***	0.43	0.209
Higher secondary education (ref)			
Higher education	0.618***	1.86	0.229
Number of children at 26	-0.122	0.89	0.2
Not living together with partner (ref)			
Living together with partner	-0.187	0.83	0.19
Number of observations	673		
Log Likelihood	-438.08		

* significant at 10% level, ** significant at 5% level, *** significant at 1% level

Appendix 4: Estimated probabilities for the situation at 26

Only for those who had no unemployment spell between their jobs

	Situation at 26					
	Passive	High strain	Low strain	Active	Unemployed	Studying
lower educated with... first job						
Passive	19.55%	22.04%	29.00%	18.98%	10.43%	0.00%
High strain	10.65%	30.27%	19.76%	28.41%	10.90%	0.00%
Low strain	10.67%	9.20%	44.50%	31.98%	3.65%	0.00%
Active	6.78%	12.34%	23.62%	46.73%	10.53%	0.00%
middle educated with... first job						
Passive	15.83%	24.09%	29.47%	28.48%	2.06%	0.08%
High strain	8.08%	31.00%	18.82%	39.95%	2.02%	0.13%
Low strain	7.67%	8.92%	40.13%	42.59%	0.64%	0.05%
Active	4.76%	11.71%	20.84%	60.86%	1.81%	0.02%
higher educated with... first job						
Passive	7.29%	16.42%	22.93%	52.40%	0.57%	0.38%
High strain	3.26%	18.50%	12.82%	64.37%	0.49%	0.55%
Low strain	2.95%	5.09%	26.10%	65.52%	0.15%	0.19%
Active	1.58%	5.74%	11.66%	80.57%	0.36%	0.08%