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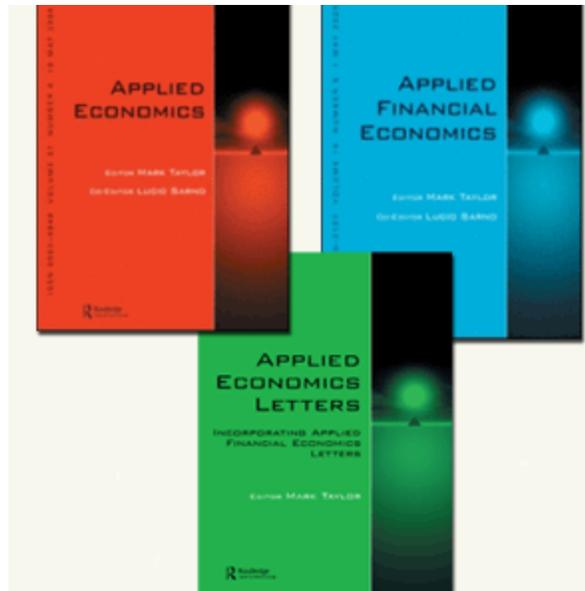
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## Does skill obsolescence increase the risk of employment loss?

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# Does skill obsolescence increase the risk of employment loss?

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## 1. Introduction

Older workers may face a decreasing productivity due to rapid changes in the world of work. The main motor of such change are the innovations based on information technology that are introduced all over the economy (Machin and Van Reenen, 1999). These innovations change the skills required in many jobs (Dickerson and Green, 2004). Therefore, the skills workers already possess will tend to lose their relevance for the labour market, and their place will be taken by skills that were previously less important or not required at all (Welch and Ureta, 2002). This skill obsolescence will lead to increasing job insecurity over the life course, making it difficult to maintain an adequate level of labour market participation of older workers. Although pension schemes often encourage early retirement of workers whose productivity is waning, involuntary early retirement is widespread, particularly in Continental Europe (Dorn and Sousa-Poza, 2010)

In this article, we analyze whether information technology induces skill obsolescence and loss of work, and how this is related to workers' participation in training and learning on the job. We will compare two conceptual models on the relationships between technological change, training participation, on-the-job learning, skill obsolescence and the chance of losing employment. The first model is a *static model*, in which training participation is exogenous. This model reflects the conventional

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3 wisdom on skill obsolescence and the probability of employment loss (cf. OECD 2001).  
4  
5 The second model is a *dynamic model* in which skill obsolescence reinforces life-long  
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7 learning, driven by technological change that takes place in the workplace. The latter  
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9 model predicts that when workers experience skill obsolescence more or less  
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11 continuously in their job, this may indicate a healthy dynamic situation in which  
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13 technological change and the concomitant on-the-job learning create their own learning  
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15 process.  
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20 Using panel data on older workers, we find that workers who experience skill  
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22 obsolescence appear to learn more on the job and participate more often in training.  
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24 Moreover, those who are employed in IT-intensive jobs are more likely to learn on-the-  
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26 job. Remarkably, perceived skill obsolescence is not related to a higher probability of  
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28 losing employment, whereas training participation decreases the risk of losing  
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30 employment. These results are consistent with the dynamic model of skill obsolescence  
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32 and employment loss we developed in this paper. Furthermore, we find that when  
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34 workers with long job tenures decrease their training participation, this is an early  
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36 indicator of future job loss.  
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41 These findings contribute to the literature on the labour market withdrawal of  
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43 older workers by emphasizing that skill obsolescence as well as investments in training  
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45 and on-the-job learning are all more or less structural characteristics of jobs that are  
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47 highly challenging and dynamic, and prevent that older workers withdraw from the  
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49 labour market at an early age.  
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## 52 53 54 55 **2. Two models of skill obsolescence** 56 57 58 59 60

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3 In this section, we will develop two conceptual models that could explain skills  
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In this section, we will develop two conceptual models that could explain skills  
obsolescence. First we will describe a static model, and then we will develop a more  
dynamic model that includes the learning of workers who face shifts in skill demanded in  
their jobs.

### *Static model of skill obsolescence*

We start from the worker-job matching assumption that the performance of a given  
worker in a given job is a function of the overlap between the skills actually possessed by  
a worker and the skills needed to do the job (e.g. Jovanovic, 1979). Only the skills  
required in the job contribute to the worker's performance. In contrast, the remaining part  
of the worker's skills does not contribute to a worker's productivity in the job.

Over time, technological change can induce shifts in the skills needed to perform  
in a given job. If we assume for the moment that the worker's own skill level remains  
relatively static, this will change the worker-job match. In principle, the shift in the skills  
needed in the job can be in any direction with respect to the existing skills of the  
incumbent. This means that changes in the job tasks resulting from technological change  
could lead to either an improvement or deterioration in the match between actual and  
required skills. However, there are vastly more ways in which a change can lead to  
deterioration in the match than ways in which a change can lead to an improvement.  
Consequently, it is safe to assume that, in the aggregate, a change in the skills demanded  
will lead to a decrease in the volume of skills that are productively utilized.

Such a change has serious consequences for both the employee and the employer.  
From the point of view of the employee, underutilization of skills has strong unwanted

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3 effects on earnings (see for example Van Smoorenburg and Van der Velden, 2000). By  
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5 contrast, the major concern of employers will be about skill shortages, which lead  
6  
7 directly to loss of potential output. In the ensuing discussion, we will concentrate on  
8  
9 effects relating to skill shortages.  
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13 As a result of the deterioration in a worker's performance, the worker's hold on  
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15 his or her job may become less secure. This particularly holds when wages are rigid (cf.  
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17 Weiss and Garloff, 2009). Compared to the initial situation, the employer has a greater  
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19 incentive to dismiss the current worker, and replace him or her by a worker with more  
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21 appropriate skills (Van Loo, De Grip and De Steur, 2001). Obviously, the worker's  
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23 prospects of obtaining a similar or better position after dismissal will be bad. We would  
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25 therefore expect that a higher skill gap increases the risk that the worker has to move to a  
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27 worse job, or lose employment altogether. This risk is likely to be particularly great in  
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29 countries such as the Netherlands where demand shifts away from unskilled labour tend  
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31 to be absorbed more by a lower job security than through wage adjustments (Maurin and  
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33 Postel-Vinay, 2005).  
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40 There are of course less drastic measures that can be used to reduce the skill gap  
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42 following technological change. Where change is accompanied or followed by formal  
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44 training, this can offset the negative effects of the change in required skills. If the  
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46 acquisition of new skills is sufficient to at least offset the shift in skill requirements as a  
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48 result of technological change, the worker's job security is not likely to be compromised,  
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50 and may even improve. However, if training does not take place, or is insufficient to  
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52 offset the shift in skill requirements, the worker may face a risk of losing his or her job.  
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54 This risk could accumulate during a worker's career. Recalling that this conceptualization  
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3 of the relation between technological change, skill obsolescence and training  
4 participation is based on the assumption that the worker's own skills remain relatively  
5 static except during periods of formal training, we call this the *static model* of skill  
6 obsolescence. Figure 1 summarizes the relations postulated by this model.  
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15 FIGURE 1 here  
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20 *Dynamic model of skill obsolescence*  
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22 When we drop the assumption that skill levels are static, a different model of the relation  
23 between technological change, skill obsolescence and labour market participation arises.  
24 Both the decision to train and the decision to organize work in such a way as to promote  
25 learning by doing may not be independent of technological change. On this point it is  
26 crucial to note that changes that are expected to give rise to skill mismatches according to  
27 the static model could create their own learning situation: workers in organizations  
28 undergoing change are likely to be exposed to a wider variety of experiences from which  
29 they can learn new skills. In addition, both employers and workers may respond or  
30 anticipate the changes in technology by making greater investments in training (cf.  
31 Acemoglu, 1997). In other words, workers may more or less automatically learn new  
32 skills as the skill requirements arise. Jobs may be deliberately structured so as to provide  
33 learning opportunities (e.g. Eraut, 2000). This *learning potential of the job* (Rosen, 1972)  
34 is likely to be greatest in cases where the learning of new skills is deemed most  
35 necessary, i.e. in precisely those jobs where skill requirements are also changing rapidly.  
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60 Whereas jobs characterized by repetitiveness, hierarchical control mechanisms and low

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3 levels of autonomy may stifle learning opportunities for workers, more complex jobs  
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5 with shifting job contents offer ample opportunities for lifelong learning. This suggests  
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7 that, rather than a situation in which the size of the skill gap after technological change is  
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9 dependent on investments in training and on-the-job learning, these investments may in  
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11 fact be dependent on the size of the initial skill gap and the new skill requirements  
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13 resulting from technological change.  
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17 If formal and informal learning are indeed endogenous to technological change,  
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19 this also changes the expected relation between obsolescence and labour market  
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21 participation. If workers in changing organizations are continuously updating their skills  
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23 to meet the changing requirements, they should be no more at risk of losing their jobs  
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25 than workers in more stable organizations. This *dynamic model* is summarized in Figure  
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34 FIGURE 2 here  
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39 The figure shows that of the effects predicted by the static model, only the predicted  
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41 positive relation between previous and current skill obsolescence remains in the dynamic  
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43 model. However, even this superficial similarity might have a different interpretation in  
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45 the two models. Whereas the static model views previous obsolescence as a burden that  
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47 has to be overcome above and beyond the additional obsolescence induced by  
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49 technological change, the dynamic model implies that, in some cases at least, skill  
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51 obsolescence is a more or less structural characteristic of the job. Far from being a  
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problem, in such jobs the perceived ‘obsolescence’ may be an indication of a healthy and dynamic situation with a high learning potential (Cf. Bartel and Sicherman, 1993).

As ‘old obsolescence’ is eliminated by investments in training and/or on-the-job learning, ‘new obsolescence’ will pop up to take its place, which will stimulate the worker and/or the employer to invest in further training, and so on. If this is the case, this has some important implications. Firstly, the development of human capital by participating in training and/or on-the-job learning will not reduce the skills gap. Secondly, the skill obsolescence perceived by the worker will not increase a worker’s risk of losing employment, as it merely indicates that a worker is employed in a dynamic job. Thirdly, although the dynamic model predicts no indirect effect of training on the probability of employment loss, it does predict a direct negative effect. This is because training is regarded as an investment, which both employers and employees would like to recoup by extending the employment relationship.

### 3. Data and variables

#### *Data*

For our analyses on the relationships between technological change, skill obsolescence and investments in human capital, we make use of data from the *OSA Labour Supply Panel*. The OSA Labour Supply Panel consists of a representative biannual survey among a representative sample of the Dutch working age population. Due to the relatively high rate of panel attrition, which is compensated by adding new respondents in each new wave, we only use the panel character of the OSA data in a limited way. In order to increase the number of available cases in the analyses – which is particularly important

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3 because most of the dependent variables we consider are quite heavily skewed dummy  
4 variables - we treat each wave as an independent sample, and pool data over the three  
5 successive waves of 1994, 1996 and 1998. To the data for each of these waves we add an  
6 indicator of skills obsolescence for the same respondents two years earlier, as well as an  
7 indicator of their labour market participation two years later. For example, the data for  
8 working respondents in the 1994 wave includes information on whether or not they  
9 suffered from skills obsolescence in 1992, and on whether or not they were still in paid  
10 employment in 1996<sup>1</sup>.  
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22 The data from the three waves is pooled, resulting in a pooled data set containing  
23 4,683 usable cases, comprising a main body of variables in the reference year, with the  
24 relevant variables from the previous and subsequent waves appended<sup>2</sup>. This is shown in  
25 Figure 3.<sup>3</sup> To correct for the multiple occurrence of individual respondents we use the ‘Cluster’  
26 option in STATA to estimate robust standard errors in our multivariate analyses.  
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36 FIGURE 3 here  
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41 In order to focus on the part of the workforce that is most at risk of losing its place in the  
42 labour market due to skill obsolescence, we include only respondents aged between 40  
43 and 62 at the time of the survey. The reason for choosing 62 as an upper bound is that  
44 then all respondents are still below the official mandatory retirement age of 65 two years  
45 later, when we again measure their labour market participation.<sup>4</sup>  
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55 *Variables*  
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3 In the analyses, *skill obsolescence* (both in the previous and current periods) is indicated  
4 by a respondent's answer to the following question: *How do you consider the relation*  
5 *between your knowledge and skills and your job?* Following the typology of skill  
6 obsolescence developed in De Grip and Van Loo (2002) that distinguishes between  
7 technical and economic obsolescence of skills, we consider those who reported either an  
8 'obsolescence of skills' or a 'skill shortage' in the period in question as workers who face  
9 skill obsolescence in their job. The reported 'obsolescence of skills' will particularly refer  
10 to technical obsolescence or depreciation of skills due to the wear of skills resulting from  
11 the natural ageing process, illness or injury, whereas skill shortages will include  
12 economic skill obsolescence due to external developments (such as changes in the  
13 technologies applied or changes in the organisation) which lead to new skill demands for  
14 a worker's job. *Loss of work* is indicated by respondents who were in paid employment in  
15 the reference period but not two years later. Technological change is indicated by the *IT-*  
16 *intensity* of a worker's job measured by the percentage of employees in the respondent's  
17 occupational group who used a personal computer in their work (Cf. Jorgenson, 2001). At  
18 first sight, one might wonder whether an aggregate measure of computer use adequately  
19 captures the kind of change we are interested in. We argue that an aggregate measure is  
20 in fact more appropriate than an individual measure, since a computer-intensive  
21 infrastructure forms part of the environment that allows – or forces – firms to innovate.

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48 Building on Sieben et al. (2009), we include the variable *on-the job learning*  
49 indicated by the time that the respondent expects to be needed for a comparably educated  
50 new employee to learn how to do the job. We need to emphasize here that the indicator  
51 does not refer to the actual induction time of the worker when he or she started in the job,  
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3 but estimates the time a hypothetical replacement would need to learn the ropes. On the  
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5 basis of the dynamic model, we assume that jobs that require a substantial amount of  
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7 initial learning are knowledge or skill-intensive jobs, of which learning is more or less a  
8  
9 structural characteristic. Of course, this assumption does not hold according to the static  
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11 model, which if anything would predict that a lot of learning early on would reduce the  
12  
13 need for later learning. This contrast makes this variable especially suitable for a  
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15 comparison of the two models. *Training participation* (both previous and current) is  
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17 indicated by (the natural logarithm of) the number of courses followed in the relevant  
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19 two-year period. In the case of previous training this is the two years prior to the  
20  
21 reference year. In the case of current training it is the period of a year prior and a year  
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23 subsequent to the reference period.<sup>5</sup> As control variables in several analyses we include  
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25 *tenure* (both a linear and a quadratic term), *occupational level*, *gender*, *age*, *cohort*  
26  
27 (survey year), *firm size*, and *economic sector*. Table 1 shows the means and standard  
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29 deviations of the interval level variables and the percentage distributions of the dummy  
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31 variables used in the analysis.  
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TABLE 1 here

#### 4. Estimation results

In the analyses that follow, we will test the applicability of the static and the dynamic model on the relations between the IT-intensity, training participation, on-the-job learning, skill obsolescence and loss of employment. First, we analyze the determinants of the skill obsolescence workers perceive in their current job. Second, we analyze the

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3 determinants of workers' probability of unemployment or labour market withdrawal in  
4 the subsequent period. As the results of these analyses support the dynamic model, we  
5 further test two other predictions of this model, namely that the IT-intensity and previous  
6 skill obsolescence are related to on-the-job learning as well as a worker's training  
7 participation.  
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### 10 11 12 13 14 15 16 17 18 *A. Current Skill Obsolescence*

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20 In the first analysis, we attempt to explain skill obsolescence in the current period.  
21 According to the static model, perceived skill obsolescence will be positively related to  
22 both previous skill obsolescence and IT-intensity, and negatively related to training  
23 participation. The dynamic model also predicts a positive effect of previous obsolescence  
24 – albeit for a different reason – but predicts no significant effect of either IT-intensity or  
25 training participation. This model does predict a positive effect of the amount of on-the-  
26 job learning on perceived skill obsolescence. The results of the analysis of the skill  
27 obsolescence workers perceive in their job are presented in Table 2.  
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41 TABLE 2 here

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43 The estimation results provide strong support for the dynamic model, and little or no  
44 support for the static model. The only result that is consistent with the static model - that  
45 previous skill obsolescence is a strong predictor of current skill obsolescence – is also  
46 predicted by the dynamic model. However, contrary to the predictions of the static model  
47 but consistent with those of the dynamic model, IT-intensity and training participation  
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3 have no effect, while on-the job learning has a positive effect on current skill  
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have no effect, while on-the job learning has a positive effect on current skill  
obsolescence.

### *B. Loss of work*

Having established that the pattern of determinants of skill obsolescence is more  
consistent with the dynamic than with the static model, we now turn to the effects of skill  
obsolescence on the risk of losing employment in the subsequent period. The static model  
predicts that skill obsolescence will increase this risk substantially, as the loss of  
productivity related to obsolescence makes the worker's grip on employment increasingly  
tenuous. By contrast, the dynamic model predicts no such effect; because both  
obsolescence and learning are regarded as more or less structural characteristics of jobs,  
workers who experience obsolescence will not be more likely to lose their job than those  
who don't. Also in contrast to the static model is the predicted effect of training  
participation. According to the static model, any effect of training on the risk of losing  
one's work will be indirect, through its supposed effect on skill obsolescence. By  
contrast, the dynamic model predicts a direct negative effect of training participation on  
losing one's job. This is because training is regarded as an investment, which both  
employers and employees would like to recoup by extending the employment  
relationship. Table 3 shows the results of this analysis.

TABLE 3 here

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3 Again, the results are more in line with the dynamic model than with the static model.  
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5 Skill obsolescence has no effect on the risk of losing one's work. On the other hand,  
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7 training participation does significantly reduce the risk of losing employment. Even  
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9 though training does not have a net effect on perceived skill obsolescence, it does reduce  
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11 the risk of losing employment, as expected in the dynamic model.  
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15 An interesting effect not directly predicted by either model is that of tenure.  
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17 Tenure shows a negative linear effect and positive quadratic effect on the risk of losing  
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19 employment. The negative linear effect suggests that, up to a point, additional experience  
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21 in a job adds to security in that job. This could be related to progressive acquisition of  
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23 human capital by learning on the job, although it could also indicate that the legal claim  
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25 to one's position gets stronger over time. However, as time progresses, the effect of  
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27 tenure on the probability of job loss becomes smaller, eventually leading to a higher risk  
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29 of job loss for those who are more than 18 years employed in the same job. This suggests  
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31 that a concentration of experience in a particular job eventually leads to stagnation and  
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33 lower employability in the longer term. Since we have controlled for age – which has the  
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35 expected positive effect on the chance of losing employment related to (early) retirement  
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37 -, this result cannot be attributed to life-cycle effects. Remarkably, women also have a  
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39 higher chance of losing employment than men.  
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### 48 *C. On-the job learning*

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50 As the results so far strongly support the dynamic model, we will proceed by testing a  
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52 number of more specific predictions of this model. The dynamic model predicts that  
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54 technological change as well as the perception of skill obsolescence will contribute  
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3 positively to on-the-job learning. The estimation results presented in Table 4 confirm  
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5 these expectations: both the IT-intensity and previous skill obsolescence positively affect  
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7 on-the-job learning.  
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13 TABLE 4 here  
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#### 17 *D. Training participation*

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19 A final prediction of the dynamic model is that training participation is also  
20  
21 endogenously influenced by both previous obsolescence and IT-intensity. In addition, the  
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23 model predicts that the on-the-job learning will have a positive effect on training  
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25 participation.  
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32 TABLE 5 here  
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36 The estimation results presented in Table 5 show that the prediction that a higher IT-  
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38 intensity leads to greater levels of training participation is not confirmed by the analysis.  
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40 Workers in IT-intensive jobs are not more likely to invest in formal training than other  
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42 workers. However, the estimation results confirm the expectation that workers' training  
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44 participation is positively influenced by prior skill obsolescence, as well as the  
45  
46 opportunities for on-the job learning. The latter finding reinforces the view that learning  
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48 requirements and opportunities are a structural characteristic of certain jobs. Even in the  
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50 case of older workers we analyze, the tendency to invest in training is strongly related to  
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52 on-the-job learning.  
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Although the effects of tenure and tenure squared are not statistically significant, the direction and size of the coefficients is consistent with the earlier results for probability of job loss as shown in Table 3. The latter show that workers become more secure in their jobs when they achieve more tenure. However, in time the effect of tenure on the probability of job loss becomes smaller, eventually leading to a higher risk of job loss. The coefficients in Table 5 suggest that participation in training may undergo a similar trend and reversal. In this case, the reversal takes place after 14 years, compared to 18 in the case of job loss. Although we must be cautious about interpreting non-significant results, this may indicate that when workers with long tenures decrease their efforts to keep their skills up-to-date, this is an early indicator of job loss due to a concentration of experience.

## 5. Conclusions

In this paper we developed a static as well as a dynamic model to explain the relationships between technological change, skill obsolescence, training and informal learning on the job and labour market exit. The static model treats learning processes as exogenous, and assumes a basically sequential causal chain, whereby technological innovations give rise to skill obsolescence that, in the absence of compensatory learning, leads to an increased risk of early exit from the labour market. By contrast, the dynamic model treats learning processes as endogenous to organizations that face a need to develop and change. In this model, skill obsolescence is largely structural by nature. That is to say, changes in skill requirements and the learning of new skills keep each other

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3 roughly in balance. As a consequence, this model does not predict an effect of skill  
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roughly in balance. As a consequence, this model does not predict an effect of skill  
obsolescence on the probability of early labour market exit.

The results of our empirical analyses provide virtually no support for the static  
model. The only result that was consistent with this model – that previous skill  
obsolescence is positively related to current skill obsolescence – is also predicted by the  
dynamic model. The other predictions of the static model are not borne out by the  
analyses. Workers in IT-intensive jobs are not more likely to perceive skill obsolescence  
than workers in less IT-intensive jobs. Nor does training participation reduce perceived  
obsolescence. Finally, and most tellingly, workers' skill obsolescence has no significant  
effect on the risk of loss of employment in the following period.

We found more evidence supporting the dynamic model. The above-mentioned  
absence of an effect of skill obsolescence on the chance of losing employment is  
consistent with this model. Whereas the static model views previous obsolescence as a  
burden that has to be overcome above and beyond the additional obsolescence induced by  
technological change, the dynamic model implies that skill obsolescence may be a more  
or less structural characteristic of many jobs. Moreover, training participation was found  
to have a significant negative effect on the probability of losing employment. However,  
contrary to the predictions of the static model, training participation does not reduce  
perceived skill obsolescence. This is consistent with the idea, incorporated in the dynamic  
model, that the training that is related to technological innovations represents an  
important investment in human capital, which employers and employees have an interest  
in recouping through a longer employment duration (cf. Bartel and Sicherman, 1993). A  
similar result is observed for job tenure. Initially, longer job tenure has a negative effect

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3 on the chances of loss of employment, indicating that workers accumulate valuable  
4 additional human capital through work experience. This effect decreases over time,  
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6 however, and after about 18 years additional tenure actually increases the probability of  
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8 employment loss, indicating that the experience build-up no longer dominates the  
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10 depreciation of the worker's skills.  
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15 On-the-job learning is found to be related with perceived skill obsolescence,  
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17 which supports the dynamic model. Moreover, those employed in IT-intensive jobs are  
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19 more likely to learn on the job. Furthermore, on-the job learning has a positive influence  
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21 on training participation. These results are consistent with the idea that skill obsolescence,  
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23 and investments in training as well as on-the-job learning are all more or less structural  
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25 characteristics of jobs that are highly challenging and dynamic. In this view, the skill  
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27 obsolescence that workers in these jobs perceive may remain relatively constant: as new  
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29 skills are acquired to fill a prior skill gap, and new requirements are thrown up, which  
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31 necessitates further learning in a subsequent period. Because this is driven by changes  
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33 that increase the net productive potential of jobs, this does not lead to an increased risk of  
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35 loss of employment. Instead, by stimulating further investments in the human capital of  
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37 the workers who are employed in these jobs, it decreases the probability that these  
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39 workers lose their employment.  
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For Peer Review

FIGURE 1: Static model of skill obsolescence and employment loss

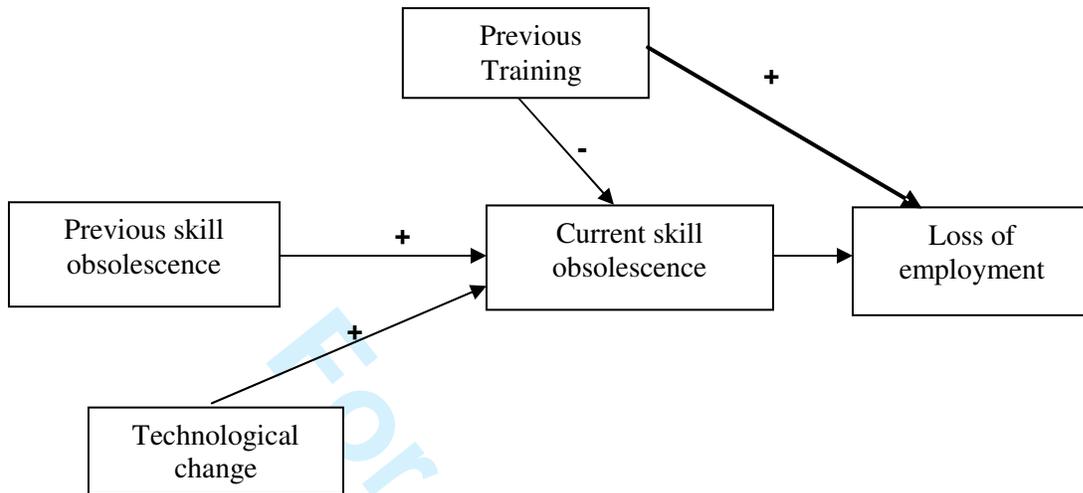
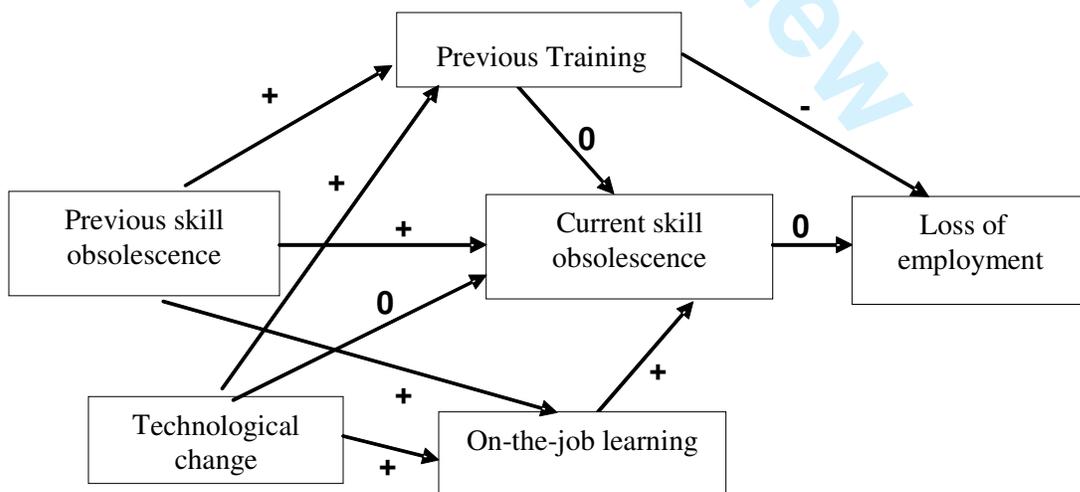


FIGURE 2: Dynamic model of skill obsolescence and employment loss



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**FIGURE 3: The pooled dataset**

Previous skill obsolescence	Main body of variables	Subsequent labour market participation
1992	1994	1996
+	+	+
1994	1996	1998
+	+	+
1996	1998	2000
=	=	=
1992+1994+1996	1994+1996+1998	1996+1998+2000

For Peer Review

**TABLE 1: Descriptive statistics of variables used in the analyses**

<i>Variable</i>	<i>%</i>	<i>Mean</i>	<i>Standard deviation</i>
Skill obsolescence	4.4	-	-
Loss of work	6.8	-	-
IT-intensity (% in occupational group)	-	57.63	31.42
Previous training participation	-	0.41	0.85
Current training participation	-	0.43	0.90
On-the-job learning	-	6.42	2.27
Previous skill obsolescence	5.6	-	-
Tenure (years)	-	14.27	10.09
<i>Low</i>	35.7	-	-
<i>Intermediate</i>	32.9	-	-
<i>High</i>	31.4	-	-
Gender (female)	37.4	-	-
Age	-	48.07	5.49
<i>Cohort 1994</i>	30.5	-	-
<i>Cohort 1996</i>	32.1	-	-
<i>Cohort1998</i>	37.4	-	-
Firm size	19.6	-	-
<i>10-99 employees</i>	39.0	-	-
<i>&gt;= 100 employees</i>	41.4	-	-
Economic sector			
<i>Agriculture, forestry and fisheries</i>	2.9	-	-
<i>Manufacturing and mining</i>	20.5	-	-
<i>Business services</i>	31.6	-	-
<i>Public services</i>	45.0	-	-

SOURCE: OSA Labour Supply Panel, 1992-2000

**TABLE 2: Logit estimation of skill obsolescence in the current job**

	B	Robust S.E.
Constant	-3.117**	0.836
IT-intensity	0.003	0.003
Previous training participation	0.025	0.034
On-the-job learning	0.113**	0.043
Previous skill obsolescence	1.478**	0.225
Tenure	0.017	0.026
Tenure-squared/100	-0.073	0.077
Occupational level (ref. intermediate level)		
• <i>Low level</i>	-0.473*	0.231
• <i>High level</i>	-0.177	0.174
Gender (female)	-0.064	0.185
Cohort (reference 1996)		
• 1994	-0.107	0.172
• 1998	-0.646**	0.187
Age	-0.008	0.015
Firm size (ref. category 10-99 employees)		
• < 10 employees	-0.129	0.223
• >= 100 employees	-0.149	0.166
Economic sector		
(ref, manufacturing and mining)		
<i>Agriculture, forestry and fisheries</i>	-0.250	0.531
<i>Business services</i>	0.163	0.209
<i>Public services</i>	-0.256	0.215

N= 4,528; Pseudo R<sup>2</sup> = 0.056

\* = p&lt;0.05; \*\* = p&lt;0.01

**TABLE 3: Logit estimation of loss of work**

	B	Robust S.E.
Constant	-11.670**	0.953
IT-intensity	0.001	0.003
Previous training participation	-0.109*	0.043
On-the-job learning	-0.056	0.036
Skill obsolescence	0.184	0.354
Tenure	-0.061**	0.024
Tenure-squared/100	0.166**	0.062
Occupational level (ref. intermediate level)		
• <i>Low level</i>	-0.092	0.201
• <i>High level</i>	-0.235	0.202
Gender (female)	0.579**	0.177
Cohort (reference 1996)		
• <i>1994</i>	0.356*	0.174
• <i>1998</i>	0.014	0.195
Age	0.182**	0.017
Firm size (ref. category 10-99 employees)		
• <i>&lt; 10 employees</i>	-0.195	0.221
• <i>&gt;= 100 employees</i>	0.118	0.175
Economic sector (ref, manufacturing and mining)		
<i>Agriculture, forestry and fisheries</i>	-0.188	0.477
<i>Business services</i>	0.145	0.209
<i>Public services</i>	-0.339	0.227
N= 3.236; Pseudo R <sup>2</sup> = 0.155      * = $p < 0.05$ ; ** = $p < 0.01$		

**TABLE 4: Regression analysis of on-the-job learning**

	B	Robust S.E.
Constant	5.935**	0.433
IT-intensity	0.009**	0.002
Previous skill obsolescence	0.421*	0.171
Occupational level (reference intermediate level)		
• <i>Low level</i>	-1.302**	0.113
• <i>High level</i>	0.344**	0.101
Cohort (reference 1996)		
• <i>1994</i>	0.308**	0.073
• <i>1998</i>	0.192*	0.081
Age	0.013	0.008
Firm size (ref. category 10-99 employees)		
• <i>&lt; 10 employees</i>	-0.222	0.139
• <i>&gt;= 100 employees</i>	0.297**	0.090
Economic sector (ref, manufacturing and mining)		
• <i>Agriculture, forestry and fisheries</i>	0.068	0.349
• <i>Business services</i>	-0.425**	0.120
• <i>Public services</i>	-0.947**	0.114

N= 3.131; Adjusted R<sup>2</sup> = 0.180\* =  $p < 0.05$ ; \*\* =  $p < 0.01$

**TABLE 5: Regression analysis of training participation**

	<i>B</i>	<i>Robust S.E.</i>
Constant	-2.316**	0.482
IT-intensity	0.003	0.002
Previous skill obsolescence	0.601**	0.233
On-the-job learning	0.139**	0.020
Tenure	0.022	0.015
Tenure-squared/100	-0.080	0.042
Occupational level (reference intermediate level)		
• <i>Low level</i>	-0.276*	0.123
• <i>High level</i>	-0.065	0.126
Cohort (reference 1996)		
• <i>1994</i>	-0.320**	0.081
• <i>1998</i>	-0.063	0.064
Age	-0.036**	0.009
Firm size (ref. category 10-99 employees)		
• <i>&lt; 10 employees</i>	-0.432**	0.124
• <i>&gt;= 100 employees</i>	0.045	0.112
Economic sector (ref, manufacturing and mining)		
• <i>Agriculture, forestry and fisheries</i>	-0.552**	0.212
• <i>Business services</i>	-0.169	0.134
• <i>Public services</i>	0.200	0.138
N= 3.235; Adjusted R <sup>2</sup> = 0.060      * = $p < 0.05$ ; ** = $p < 0.01$		

## NOTES

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1. As more recent waves of the OSA Panel lack data on variables needed in our analysis, we have to restrict the analyses to the period 1992-2000.
2. Because we pool data from different years, some respondents are represented more than once in the data. The data contain a total of 2,594 individual respondents, of which 1,211 appear in only one of related survey years (e.g. 1992, 1994 and 1996), 677 appear twice and 706 in all three years (See figure 4).
2. On average between 25% and 30% of respondents who participated in a given wave do not participate in the subsequent wave. Panel attrition shows little or no relation to key variables like skill obsolescence and on the job training. However, those who participated in training in a given period are somewhat less likely to drop out in the following wave. There is, however, no reason to expect that our results are affected by panel attrition, since this would require that both the dependent variables and at least some of the independent variables are related to the chance of participating in the following wave.
4. For more information on the OSA Panel, see <http://www.tilburguniversity.nl/osa/datasets>.
5. We use two different indicators of training, which play two different roles in our analyses. Training in the previous period is used as a *predictor* of current skill obsolescence and the chance of losing one's work. Training in the current period is used as a *dependent variable*, with among other things the percentage of computer use, the initial training time needed in the job and previous skill obsolescence as predictors. The fact that these two variables overlap partly does not present a problem, because they never appear together in any analyses.