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Are Objective, Official Measures of Disability Reliable?

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Abstract
The issue considered in this study is whether objective, official reports on disability status are reliable. While there is a rather large literature on the reliability of self-reported disability, evidence regarding objective data is scant. It seems to be a widely held view among researchers that, since individuals out of work are inclined to respond towards poor health, it would be best to have official data provided by the relevant administrative bodies. But we argue that such administrative data should be regarded with some suspicion, since the administrators also may have incentives to misreport. The empirical evidence, based on a large sample of Swedish jobseekers, suggests systematic misreporting by the Public Employment Service of objective, official disability measures due to incentives to exaggerate disability.

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Keywords: Work disability, classification error, Public Employment Service

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1 Introduction

Surveys indicate that the prevalence of disability in the working-age population is far from negligible in industrialised countries. On average, 14 per cent of those aged 20–64 regarded themselves as being disabled in the OECD countries in the late 1990's (OECD, 2003). The number of disability benefit recipients is also substantial, about 6 per cent. Since very few disability benefit recipients ever return to the labour market, public budgets have been put under pressure in many countries. This is highlighted by the fact that, among the non-employed in OECD countries, disability benefits are much more widespread than unemployment benefits.[1]

Yet there is no consensus on what disability means. Disability is notoriously difficult to measure and conceptions may be influenced by, e.g., ambiguity in clinical judgements and changing social values (see, e.g., Marin, 2003). Not surprisingly, there is a substantial literature on the validity of various health measures and the distinction between "subjective", i.e., self-reported, and more "objective" information, based on administrative sources, like mortality data or medical reports.[2] Throughout this paper we will follow the literature and use the term "objective" for disability information based on administrative sources. However, as we will show, objectivity in this sense does not guarantee reliability.

According to the literature, both subjective and objective disability may be reported with error. Subjective data may be biased due to a variety of reasons – responses being dependent on labour market outcomes one wishes to explain, justification of current or anticipated non-employment status or financial incentives to report a disability. In addition, both subjective and objective measures may contain non-systematic classification errors ("non-differential" errors in the terminology of Bound et al., 2001). For example, subjective health status may not be entirely comparable across respondents due to unobserved personal traits. Although more objective measures are commonly assumed to be less biased, they may be contaminated by non-systematic differential errors.

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[1] In 1999, 23 per cent of the non-employed received disability-related benefits, while 16 per cent were recipients of unemployment benefits (OECD, 2003).

[2] See, e.g., Aarts and de Jong (1992), Baker et al. (2004), Benitez-Silva et al., (1999, 2003, 2004), Bound (1991), Bound et al. (2001), Kerkhofs et al. (1999), Kreider (1999), Kreider and Pepper (2002, 2003), Kerkhofs and Lindeboom (1995) and Lindeboom and Kerkhofs (2003).

In particular, it has been pointed out that the fact that objective measures rarely consider work capacity introduces non-systematic error.

The validity of various health measures has important implications for econometric work on many policy-relevant issues. For example, if the purpose is to estimate the impact of the generosity of disability benefits on the probability of being awarded disability pension, it is common practice to include a measure of health in the regression in order to obtain an unbiased estimate of the effect of benefit generosity. However, the bias does not necessarily disappear; using a self-reported measure can either over- or underestimate the effect and an objective measure, not perfectly correlated with work capacity, leads to a downward bias with standard regression methods (Bound et al., 2001). One might think that the availability of more objective health measures based on work capacity would help researchers to overcome some of these econometric concerns.

In this study, we consider the validity of a particular objective measure of health status, namely disability data for individuals registered at the Swedish Public Employment Service (PES).[3] This objective, official measure, culled from the HÄNDEL events database of the National Labour Market Board over the period 1996–2001, actually takes work capacity into account. The validity of such a work-related objective measure has, to the best of our knowledge, not been examined in the previous literature. Every person registered with the public employment service (PES) in Sweden is classified according to work disability status in the events database. The classification is used by the PES officials in order to facilitate placement of unemployed persons in various labour market programmes for the work disabled. We contrast the PES data to contemporaneous, self-reported data on disability for the same individuals, extracted from the Labour Force Surveys (LFS), in order to explore the validity of the objective information. We argue that the objective measure may be biased, contrary to much of the conventional wisdom, although the information is based on an assessment of work capacity and is not self-reported.

Our concern for a flawed objective measure arises from the observation that there are incentives for disability classification errors, both among the PES officials and the jobseekers, who could attempt to influence the PES officials' decisions. One can think of several reasons for such errors to occur. First, PES

[3] Sweden is among the countries with the highest disability prevalence, the highest expenditures on disability benefits and the lowest outflow rate from those benefits (OECD, 2003).

officials may have incentives for classifying healthy individuals as disabled due to various quantitative targets. There are such targets with the respect to the placement of disabled workers in subsidised jobs as well as regarding the placement of unemployed workers in regular jobs. The latter goal can be more easily achieved by placing individuals with low qualifications in subsidised jobs for disabled workers. A classification as disabled is necessary for access to labour market programmes targeted to the disabled, such as subsidised employment and sheltered employment. Second, funding to the PES offices increases in the caseload of disabled jobseekers. Third, a disability classification may represent an attractive option also for non-disabled jobseekers, due to the reduced work pace and secure employment that characterise many jobs for the disabled.

In order to assess the validity of the objective disability classification, we investigate whether the individual's unemployment contributes to him or her being classified as disabled by the PES office. Given "true" disability status, this should not be the case. However, we cannot observe true health and using subjective health as a proxy for true disability status may be problematic for reasons discussed above. But if we find that the *difference* in the categorical disability classification between the PES and the self-reported LFS increases in accumulated unemployment of the individual, we interpret this as evidence of bias in the objective disability classification (resulting from behaviour on part of the PES officials or jobseekers). The method of differencing relies on weak identifying assumptions. We allow for the possibilities of reverse causality (unemployment affecting health), non-transportability of data (different thresholds applying for classifications as work disabled in the PES and LFS) and regarding influence of non-health considerations on the individuals' own assessment of health status.

We find that the likelihood that an individual is classified as disabled in the PES data, but not in the LFS, increases in accumulated months of unemployment, even after controlling for other individual characteristics. This result indicates systematic misreporting in the objective data and is consistent with the view that PES officials and jobseekers have incentives to exaggerate disability.

Our study differs from previous analyses of the reliability of health measures. In earlier work, the focus is mostly on the evaluation of self-assessed measures. It seems to be a widely held view among researchers that, since individuals out of work are inclined to respond towards poor health, it would be best to have official data provided by the relevant administrative bodies (like the Disability Insurance (DI) administration or the PES). The source of misreporting we identify is similar to the moral hazard effect discussed in the literature on DI and other types of social insurance.[4] However, the potential for moral hazard in the provision of labour market programmes for the disabled (which also can be regarded as a form of DI) seems not to have been considered before in the literature.

Our results can be contrasted to those of Benitez-Silva et al. (2004), who also compare objective, official data on disability with self-reports. Under the maintained assumption that official data are correct, the hypothesis that self-assessed health is an unbiased indicator of the Disability Insurance Administration's award decisions in the U.S. cannot be rejected. Here, we come to a rather different conclusion regarding the validity of the objective data, since unemployment increases the probability of an official classification as disabled. Another related study is Baker et al. (2004), where medical reports are used as the benchmark and related to objective, self-reported measures, i.e., survey reports of the incidence of chronic ailments. The evidence indicates that the latter are measured with considerable error. Like our study, Cullen (2003) raises the issue whether objective data on disability are reliable, but in a different context. She argues that school districts in the U.S. have financial incentives to classify students as disabled. The results suggest that disability rates increase in the generosity of reimbursements.

The paper is organised as follows. Section 2 describes the data, while the econometric framework is spelled out in Section 3. The results from the estimations are presented in Section 4 and a conclusion is given in Section 5.

2 The data

This study uses individual-level data matched from two sources: The HÄNDEL events database from the Public Employment Service offices (PES), compiled by the National Labour Market Board *(Arbetsmarknadsstyrelsen)*, and the

[4] For empirical studies on moral hazard in social insurance, see, e.g., Gruber and Kubik (1997) for U.S. disability insurance, Larsson (2004) and Johansson and Palme, (2005) for Swedish sickness insurance, and de Jong and Lindeboom (2004) for Dutch sickness insurance.

Labour Force Surveys (LFS), of Statistics Sweden. Before proceeding to a more detailed description of the sample, we discuss how work disability is defined in the PES and the LFS data and the incentives associated with such classifications.

2.1 Definitions and incentives in disability classifications

The PES data contain information on the incidence and type of work disability, reported by the PES office and this is the objective, official measure of health we use. Our self-reported data originate from the LFS, where the respondents are asked whether they consider themselves disabled, and if so, whether the capacity to work is reduced. There are also questions about the type of disability. Thus for each individual in the sample we have one subjective and at least one objective observation on disability status. However, we have information on the severity of the disability only in the surveys. (Further details on the definitions of disability in the two sources are given in Appendix A.)

Since the various problems associated with self-reported data on health have already been discussed extensively in the literature, we focus our attention on the reasons as to why the objective PES classifications may be biased. To this end, it is useful to consider objectives and administrative processes at the PES offices. These offices are part of the National Labour Market Administration (*Arbetsmarknadsverket*). Besides providing employment services, the PES offices make decisions about placements in active labour market programmes. Some of these programmes are designed exclusively for the work disabled. The two largest such programmes are subsidised employment (*lönebidrag*) and sheltered employment, of which *Samhall*, a state-owned company, is the main provider (Bergeskog, 2001). Subsidised employment engaged on average some 50,000 participants in 1999, according to the National Labour Market Board. There were 33,000 workers in sheltered employment, of which the majority – over 80 per cent – were employed in Samhall. In addition, all traditional labour market programmes are open for the work disabled, and many of them participate in educational programmes.

In an internal document, aimed at PES officials working with disabled jobseekers, the National Labour Market Board uses the following definition of occupational disability (Ams, 1999, p.2, in our translation): "An individual who, due to physical injury, brain damage/disorder or psychic vulnerability, has a somatic, psychic, intellectual or socio-medical impairment and has, or is expected to have, difficulties in getting or keeping gainful employment is considered to be work disabled…In order to provide those with work disabilities the same opportunities as other jobseekers there is the possibility of a disability coding. The coding makes it possible for persons with work disabilities to get access to specialised services and/or labour market programmes." The document continues: "Remember that the jobseeker should agree with a registration as work disabled…If you are uncertain about the extent of the impairment you are advised to consult an expert, e.g., a physician, psychologist or social welfare officer" (Ams, 1999, p.5).

A classification as work disabled is thus necessary for participation in a programme for the work disabled. Otherwise, the procedures regarding disability classifications are not strictly regulated, leaving some scope for the individual judgement of the PES officials (SOU 2003:95). If the jobseeker has a disability that is readily apparent to the PES official, or if a doctor's certificate is presented by the jobseeker, the coding may take place at the beginning of the registration period. In most cases, though, the coding is likely to take some time. This may be due to administrative inertia, as the PES official collects information about the jobseeker and possibly arranges for a medical examination, which may involve some waiting time. It may also be the case that the coding is initiated in connection with a discussion of placement in a labour market programme for the disabled, which typically occurs only after a long period of registration.

It is not unlikely that changes in labour market policy during the 1990's have had repercussions on the coding of disability at the PES. In 1996, the Government introduced a goal to halve open unemployment by 2000. At the same time, target levels for the number of persons in labour market programmes were announced. These quantitative goals represent a substantial departure from the traditional policy, which allowed more freedom for the PES offices in the choice of measures for reducing unemployment.[5] It has been argued that the strong focus on the open-unemployment goal implies an

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[5]In a questionnaire directed to employees at PES offices in 1996, nearly all of the respondents reported having quantitative goals, mostly formulated at the office level (Nyberg and Skedinger, 1998). About 90 per cent declared that the goals concerned the number of placements in active labour market programmes and over 60 per cent reported having goals specifically for the work disabled. Although few PES employees (around 15 per cent) stated that their own wages were linked to the fulfilment of the goals, a clear majority (60 – 80 per cent) reported that office funding was dependent on the performance in this respect.

obvious risk that active labour market programmes mainly serve as a means of reducing open unemployment (Zetterberg, 1997).

There are various quantitative targets that apply to programmes for the disabled. Thus officials at the PES offices may have incentives to classify healthy jobseekers as disabled. On the one hand, there are targets that should *directly* affect the number of individuals classified as disabled. On the other hand, there are targets that are likely to have *indirect* effects. The quantitative goals regarding placements in subsidised employment may be regarded as direct goals. During the period 1997–2002, the target volumes, which are specified as monthly averages and broken down by region, have increased from 50,000 to at 59,000 individuals, according to the Government's annual regulatory guidelines (*regleringsbrev*) for the National Labour Market Administration. There are also targets regarding the average level of subsidisation in these jobs. The targets have decreased from 60 to less than 58 percent of total pay during the same period (the remainder being paid by the employer). Quantitative targets like these may put pressure on PES officials to lower the threshold for disability classifications, since this increases the supply of eligible workers and also makes employers more willing to accept a candidate for a subsidised job. The targets operating in a more indirect way concern placements of unemployed workers in regular jobs. These goals can be more easily achieved by placing individuals with low qualifications in subsidised jobs for disabled workers.

Funding for subsidised employment is distributed according to "resource allocation models" (*resursfördelningsmodeller*). One model applies to allocation from the National Labour Market Board to the County Labour Boards (*länsarbetsnämnder*) and each board uses a model for allocation to the PES offices. Allocation to the PES offices – but not to the boards – is in part dependent on the caseload of disabled jobseekers. This may create incentives at the local level to classify healthy individuals as disabled. The allocation models have also been criticised by the Swedish Parliament for not creating incentives for the PES offices to help disabled individuals finding regular, or less subsidised, employment (Swedish Parliamentary Auditors, 2002/03:RR10).

Healthy jobseekers may also have incentives to be classified as disabled, as such a classification is a requirement for placements in subsidised employment and these jobs may represent an attractive option. In sheltered employment, average wages are slightly lower than the industry average but higher than unemployment benefits. The reduced work pace may make effort-adjusted wages attractive for more productive (and possibly non-disabled) workers (Haavisto et al., 1993). The presence of non-disabled employees in sheltered employment is documented in Skedinger and Widerstedt (2003). In addition, there is a high degree of employment security in sheltered employment, since employees are not laid off in response to declining demand as could be the case in a regular job. Thus there is a distinct possibility that such programmes are used for income support in ways not originally intended.

The discussion above suggests that the objective, official measure of health we use may be biased for various reasons. There is also reason to believe that the classification errors are systematically related to unemployment. Next we turn to a description of the sample.

2.2 The LFS and the PES data

The LFS have been conducted by telephone each month since 1970. We use the surveys carried out during the third quarters in 1996, 1998 and 2000, which were supplemented with questions about health status. The LFS samples are repeated random cross-sections of about 18,000 individuals in the resident population between 16 and 64 years of age. This data set has been matched with the PES data, which contains information about every individual registered at the PES offices. We have information about each spell in open unemployment and labour market programmes for the period 1991–2002, including background characteristics of the individuals, e.g., work disability. The matched data set can be regarded as a basically random sample of job-seeking individuals registered at the PES offices in 1996, 1998 or 2000, but not as a random sample of individuals in general.

A registration period in the PES data ends as the individual finds a regular job or leaves the labour force. An individual may have several such periods. The registration period may consist of a series of search category periods, in, e.g., open unemployment or a labour market programme. Work disability is registered at some point of time during a search period. Thus if an individual has many search periods, the disability classification may change during the registration period.

Our sample consists of 53,736 individuals in total. For various reasons a number of individuals had to be excluded, leaving us with sample of 44,532 individuals.[6] The sample thus consists of individuals with PES spells during the period 1991 to 2002, who were also in 1996, 1998 or 2000 interviewed about health status in the LFS.[7]

Before turning to the sample characteristics in general, we focus on the PES and LFS measures of work disability. Figure 1 shows aggregate disability data, i.e., not our sample, for the period 1992–2002. The data include all individuals registered as jobseekers by the PES offices on October 15 each year and all individuals in the supplementary LFS every second year during 1996–2002, i.e., regardless of whether the individuals are included in our sample or not. The figure also contains information on the number of jobseekers at the PES in relation to the labour force, i.e., the "jobseeker rate".[8] Since 1996, disability rates have declined somewhat in both the PES and LFS, to 12 and 10 per cent, respectively. During the same time the proportion of registered jobseekers has fallen dramatically. If incentives to reduce open unemployment bias the PES measure, we expect a positive relationship between the unemployment measure and the probability of a work disability classification at the PES. The data give no clear indication of this; there seems to be a positive relationship after 1998, but not before. The PES-LFS difference, which is the measure we focus on in this paper, widens during much of the period 1996–2002. This is suggestive of systematic misreporting at the PES offices. However, the tests in Figure 1 are not decisive. The PES data in the figure are not a random sample, but consist of currently unemployed or jobseeking individuals. Thus compositional effects may play a role for the incidence of work disability in the PES, as individuals

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[6] The following individuals were excluded, in order of exclusion: 1,725 with incorrect or missing dates for PES registration; 2,341 below the age of 18 at time of LFS; 2,509 with first PES registration before 1991 (the information regarding unemployment history is less reliable for individuals registered before 1991); 1,933 with first PES registration later than 2001; 538 with disability pension before first PES registration; 148 who emigrated before first PES registration; 10 with old age pension before first PES registration.

[7] It should be noted that 9,919 individuals, out of the 44,532, had at least one spell as either part-time unemployed or full-time employed looking for a new job, i.e., all their PES spells were not spent in open unemployment or programme activity.

[8] The jobseeker rate overstates the total unemployment rate, i.e., open unemployment plus participation in labour market programmes, since some of the included individuals are employed in regular jobs.

with certain health characteristics tend to be more or less likely to enter or leave unemployment over the business cycle.[9]

Figure 2 presents cross-sectional data, from our sample. The individuals have been aggregated into regions, which differ with respect to the unemployment levels. The unemployment measure refers to the total unemployment rate, i.e., the sum of open unemployment and participants in labour market programmes.[10] The data for municipalities with the same unemployment rate have been aggregated and plotted against the average work disability rate. There is evidence of a positive relationship between disability rates and unemployment in panel a, but mainly for PES disability rates. According to the regression lines, estimated by OLS, the relationship is significant in 1998 and 2000 for PES (t-ratios 2.2 and 2.6, respectively) and nearly significant for LFS in 2000 (t-ratio 1.7). A similar pattern emerges in panel b, which shows the PES-LFS difference. The relationship between unemployment and disability rates is positive and significant (t-ratio 2.1). For 2000, the positive relationship is close to significant (t-ratio 1.4).

Again, the data in Figure 2 represent but circumstantial evidence. Many other factors, besides unemployment, might influence disability rates and heterogeneity across regions in this respect is not accounted for in the figure. In the econometric section, we will explore in more depth whether the positive effect of unemployment on work disability rates, hinted at in the macro-data in Figures 1 and 2, survive when confronted with micro-data.

Sample characteristics are reported in Table 1, which shows disability and other characteristics for individuals in our LFS sample, i.e., individuals who at some time during 1991–2002 have been registered as jobseekers. On average, about 7.9 per cent of the respondents in LFS report a work disability, while 5.5 and 2.7 per cent classify themselves as partially and highly work disabled, respectively.[11] The incidence of overall work disability has been relatively

[9] On the one hand, the outflow from employment to unemployment during downturns is expected to be relatively larger among the disabled than the non-disabled, which contributes to a positive relationship between unemployment and the disability rate. On the other hand, the disabled who are out of the labour force may to a greater extent be discouraged from registering at the PES offices as unemployed, which is conducive to a negative relationship.

[10] The total unemployment rate in Figure 2 is similar, but not identical, to the jobseeker rate in Figure 1, as the latter includes some regularly employed persons looking for a new job.

[11] The levels of the series in the full LFS sample (Figure 1) and our LFS sample (Table 1) are not directly comparable, since Statistics Sweden uses a weighting procedure to calculate disability at the Swedish population level.

stable over time, while the highly work disabled category has increased somewhat across surveys.

Table 1 also includes data on disability characteristics for a sub-sample of individuals with contemporaneous information on work disability in the unemployment register. We have constructed a 6-month long “window” – 3 months before and after a survey, assuming it takes place in the middle of the third quarter, i.e., October – which means that the register information dates from a point in time that is at most 3 months away from the survey (although we experiment with longer time lengths later in the analysis). Such a window is available for about half the sample. Individuals recently registered by the PES as looking for a job tend to report disability to about the same extent as others in the LFS, but the incidence of more severe work disability is somewhat higher.[12] In contrast to Figure 1, Table 1 shows that more persons regard themselves as work disabled in the LFS than are classified as such at the PES (4.7 per cent). This should also be expected as the definition of disability seems to be stricter at the PES, something which is obscured in the PES data in Figure 1 due to the stock sampling of unemployed persons (on October 15 each year). Disabled persons are likely to be overrepresented due to this procedure.

It is also seen in Table 1 that the average number of months of previous unemployment increases over subsequent surveys. This may be explained by selection effects; the later one is sampled in the LFS, the longer one may have been registered as unemployed in the PES data since 1991. Since the unemployment rate decreases over the sample period, the later samples contain fewer, and presumably less employable, individuals.

The cross-tabulations of work disability in LFS and PES reveal that classifications, by and large, match quite well. About 90 per cent are classified in the same way – work disabled or not work disabled – in both sources. However, there are discrepancies worth noting. Almost 6 per cent of the individuals report a work disability in LFS, while having no such classification in PES. A potential explanation, besides changing health between measurement dates, is that the definition of work disability used in the unemployment register is stricter than the one used by self-reporting individuals. For instance, as discussed in Appendix A, it may well be the case that survey respondents tend to consider work capacity only in the current or previous job, while PES

[12] In the PES data, virtually all non-zero observations on disability are missing values. These have been set to zero by us.

officials should also take potential future occupations into account. Another possibility, however, is that fear of stigmatisation causes jobseekers to decline a classification as disabled at the PES, while more anonymity is provided in the LFS. Almost 3 per cent declare themselves not to be work disabled, but are classified as such in the unemployment register. For this type of discrepancy, it is conceivable that intentional misreporting of disability status (in PES) is involved, as discussed previously.

Table 1 also includes some background characteristics of the sample, regarding age, gender, education, as well as family and labour market status and region of birth. Further details on disability characteristics are presented in Appendix B. The table pertains to the window sample and shows a cross-tabulation of the classification of disability types in the LFS and PES data. The window is extended from 6 to 12 months in order to get more observations in the smallest cells. For comparability, some types in LFS had to be lumped together (see notes to the table). Motion impairment is the dominating disability in both the LFS and the PES. The results in the table support the hypothesis that classifications, in general, are similar in the two sources.[13]

3 Econometric framework

In this section, we put more structure on the problem whether objective, official data on disability are reliable. We discuss the possibility of testing if the objective classification is distorted by misreporting. To be specific, we consider whether the individual's unemployment history, given health status, affects disability classification. This represents a systematic, non-differential classification error. We first discuss the framework for PES classification and then we proceed to the LFS classification and we conclude with the identification and estimation of misreporting, using both classifications.

[13] The diagonal numbers, shown in bold face, refer to the number of individuals with the same classification. This number is in most cases large in relation to the number of individuals with other disability types (in the same row or column).

3.1 Framework for PES classification

Let $D(1)$ be the work disability classification at the PES if the individual is unemployed and let $D(0)$ be the classification for the same individual if he or she is employed. Both variables are dichotomous. The observed work disability classification for individual *i* can then be written as

$$D_i = D_i(0) + (D_i(1) - D_i(0))U_i \, , \tag{1}$$

where we initially define unemployment as a dichotomous variable: $U = 1$ if the individual is unemployed and $U = 0$ if he or she is employed.[14] A switching regression model, like (1), is a frequently used framework in the literature on treatment effects in, e.g., labour market programmes. In analogy with this literature, we regard unemployment as the "treatment" and the PES disability classification as the outcome of this "treatment". For individuals with $U = 1$, we observe $D(1)$ and for individuals with $U = 0$, $D(0)$ is observed.

The disability classifications can be thought of as consisting of two components, one deterministic and one stochastic, as specified below.

$$D_i(0) = \beta_0^{\ d} + \varepsilon_{0i}^{\ d} \text{ and } D_i(1) = \beta_1^{\ d} + \varepsilon_{1i}^{\ d} \, . \tag{2}$$

As evident in (2), additive separability between the deterministic and stochastic parts is assumed.

The deterministic parts $\beta_0^{\ d}$ and $\beta_1^{\ d}$ are the proportions of jobseekers at the PES classified as work disabled if unemployed and employed, respectively. Both components are assumed to be influenced by the unobserved "true" health among jobseekers, but also potentially by their subjective health. Allowing for the latter possibility seams reasonable, since the PES officials interact a great deal with the jobseekers, usually over a long period of time, and there is a regulation that the jobseeker should agree with the classification. It may also be the case that the PES official seeks to avoid conflict with the jobseeker, especially regarding classification of self-perceived diseases with vague symptoms.

[14] Note that jobseekers registered at the PES may be employed.

The stochastic parts $\varepsilon_{0i}{}^{d}$ and $\varepsilon_{1i}{}^{d}$ represent individual *i*'s difference (from the average of $\beta_0{}^{d}$ and $\beta_1{}^{d}$, respectively) in disability classification at the PES in the two states. These components, henceforth denoted "health differences", are similarly assumed to be influenced by both true and subjective health. Thus $\varepsilon_{0i}{}^{d}$ and $\varepsilon_{1i}{}^{d}$ is individual *i*'s potential health differences if unemployed or employed, respectively.

By plugging (2) into (1), we get

$$D_i = \beta_0{}^{d} + (\delta^{d} + \eta_i{}^{d})U_i + \varepsilon_{0i}{}^{d}, \qquad (3)$$

where $\delta^{d} = \beta_1{}^{d} - \beta_0{}^{d} \neq 0$ and $\eta_i{}^{d} = \varepsilon_{1i}{}^{d} - \varepsilon_{0i}{}^{d} \neq 0$ represent average and individual state dependence in disability classification, respectively.[15] This state dependence may be due to non-health considerations but may also be influenced by changes in true health, as unemployment in itself may affect health.[16,17] Note that (3) allows for heterogeneous treatment effects. An individual with a large $\eta_i{}^{d}$ is more likely to be classified as work disabled than an individual with a low $\eta_i{}^{d}$.

In the absence of an effect of unemployment on true health, δ^{d} is the average misreporting at the PES. For the moment, it is assumed that there are no such effects on true health and we proceed to discussing estimation of δ^{d} in this setting.

[15] We have imposed the super index *d* because the state-dependent error may differ in the PES and LFS disability classifications. In general, however, we would like to think that η_i is independent of the type of measurement.

[16] For evidence regarding effects of own unemployment on health, see, e.g., Björklund (1985), Gerdtham and Johannesson (2003) and Hamilton et al. (1997). Regarding health effects of economic conditions in general, see, e.g., Ruhm (2000, 2003).

[17] It is worth noting that not even random assignment to unemployment would necessarily enhance identification of potential misreporting in this context. Since unemployment may affect the individuals' future health, the probability of being classified as work disabled would be influenced in a way that is independent of misreporting.

3.1.1 Estimation and identification issues

In this section, we discuss estimation of δ^d using register data of PES classifications.

Observe that (3) can be rewritten as

$$D_i = \beta_0{}^d + \delta^d U_i + E(\eta_i{}^d \mid U_i = 1) + \varepsilon_{0i}{}^d + \omega_i{}^d , \tag{4}$$

where $\omega_i = \eta_i{}^d U_i - E(\eta_i{}^d \mid U_i = 1)$.

Equation (4) consists of one observed regressor, U_i , and three unobserved components. Note that the last term can be treated as an error, since both conditional and unconditional expectation are zero, thus $E(\omega_i{}^d \mid U_i) = E(\omega_i{}^d) = 0$. This means that if $\varepsilon_{0i}{}^d$ and $E(\eta_i{}^d \mid U_i)$ are both independent of the sample of unemployed and employed individuals, regressing D_i on U_i using an OLS estimator of δ^d provides a simple way to test for misclassification.

It is unlikely that $E(\eta_i{}^d \mid U_i)$ should depend on *U*. The argument for this is that we do not expect individuals to select into unemployment because of larger probability to be classified as disabled if unemployed than if employed. Still, there is one reason why the OLS estimator is likely to be biased. It is highly likely that individuals who have characteristics that increase the probability of unemployment, e.g., low education, also have worse health. Thus $\varepsilon_{0i}{}^d$ is likely to be larger for the sample of unemployed than for the employed. This "endogeneity" problem is likely to produce an upward-biased estimate of δ^d .

3.2 Framework for LFS classification

In this section, we discuss the self-reported work disability classification. Assume that the LFS classification is determined in the same way as the PES classification in the previous section. Then the corresponding equation to (3) becomes

$$S_i = \beta_0{}^s + (\delta^s + \eta_i{}^s) U_i + \varepsilon_{0i}{}^s , \tag{5}$$

where S_i is the discrete work disability classification. Here, parameters and errors with the superscript *s* correspond to those with superscript *d* in (3).

We allow the levels of work disability classification to differ in the LFS and the PES; thus it may well be the case that $\beta_0{}^s \neq \beta_0{}^d$, $\beta_1^s \neq \beta_1^d$, $\varepsilon_{0i}{}^s \neq \varepsilon_{0i}{}^d$ and $\varepsilon_{1i}{}^s \neq \varepsilon_{1i}{}^d$.

The equivalent to equation (4) is now

$$S_i = \beta_0{}^s + \delta^s U_i + E(\eta_i^s \mid U_i = 1) + \varepsilon_{0i}{}^s + \omega_i^s. \qquad (6)$$

Estimating (6), we encounter the same type of problems as when estimating (4).

3.3 Estimation of misreporting using both PES and LFS

We have noted in previous sections that estimating misreporting in the PES and LFS separately involves serious problems. In order to identify misclassification due to non-health considerations, it is necessary to assume that there is no effect of true health on unemployment. This is a highly restrictive assumption. Even under this under assumption, we noted that endogeneity problems may lead to biased estimates.

Using both classifications enables us to identify misreporting due to the incentives at the PES. However, δ^d and δ^s cannot be identified separately.

Taking the difference between D_{i} and S_i, in equations (4) and (6), respectively, we get

$$D_i - S_i = \Delta_i = \Delta\beta + \Delta\varepsilon_{0i} + \Delta\delta U_i + E(\Delta\eta_i \mid U_i = 1) + \Delta\omega_i, \qquad (7)$$

where $\Delta\beta = \beta_0{}^d - \beta_0{}^s$, $\Delta\delta = (\delta^d - \delta^s)$, $\Delta\varepsilon_{0i} = \varepsilon_{0i}{}^d - \varepsilon_{0i}{}^s$, $\Delta\eta_i = \eta_i{}^d - \eta_i{}^s$ and $\Delta\omega_i = \omega_i^d - \omega_i^s$.

There are various reasons why *S* and *D* may differ in levels: Different thresholds for assessing work capacity reduction (including the possibility of more fear of stigmatisation at the PES than in the LFS) and *S* being classified at three levels and *D* at two (see Section 2). Here, $\Delta\beta$ represents the average

PES-LFS difference in disability classifications for the population. Thus the probabilities to be classified as disabled at the PES and in the LFS may be different. The individual probability to be classified as disabled, if employed, may differ from the population average $\Delta\beta$, since $\Delta\varepsilon_{0i}$ may be non-zero. Note that the classification error stemming from different subjective thresholds across individuals is differenced out from $\Delta\varepsilon_{0i}$.

As discussed in Section 2, there may be incentives (both for jobseekers and officials) to overreport disability at the PES. These particular incentives should not exist in the LFS. Nevertheless δ^d and δ^s may both be distorted due to justification, i.e., jobseekers may, for psychological reasons, overreport disability in the LFS when unemployed and subjective health may also influence PES officials. It is assumed that such justification, if it exists, does not influence PES classifications more than reporting in the LFS. Furthermore, true health is assumed to have the same effect on both health measures. These two assumptions imply that $\delta^d > \delta^s$ and we interpret $\Delta\delta > 0$ as misreporting due to incentives at the PES. Observe that if self-assessed work disability, like the official measure, is affected by justification of unemployment, $\Delta\delta$ does not capture the full extent of systematic classification errors due to unemployment. In this case, the estimated effect rather represents a *lower bound* of this classification error.

3.3.1 Estimation of misreporting due to incentives at the PES

From (4) and (6), it is evident that both $\Delta\omega_i$ and $E(\Delta\eta_i \mid U_i)$ are mean independent of *U*, i.e., may be treated as regression errors. Thus the key to consistently estimate misreporting (due to incentives at the PES) is that $\Delta\varepsilon_{0i}$ is not systematically different for the employed and unemployed populations. $\Delta\varepsilon_{0i}$ is the individual PES-LFS difference to be classified as disabled if employed and it seems unlikely that this should be systematically different in the two populations.[18]

[18] The unemployed have less education and it is, at least theoretically, conceivable that this reduces their capacity to assess their own health. In order to account for this possibility, the empirical analysis includes background variables such as education and citizenship.

How would the estimation be affected if the PES officials were influenced solely by true health and not by the jobseekers' subjective assessment? Assume additive separability of the health differences into one (*s*)ubjective and one (*t*)rue health part, so that

$$\varepsilon_{ji}^{\ s} = t_{ji} + s_{ji}^{\ s},\ j = 0,1 \text{ and } \varepsilon_{ji}^{\ d} = t_{ji},\ j = 0,1.$$

If the PES officials' disability classifications are not influenced by the individuals' own assessment of health in equation (4), equation (7) is equal to

$$D_i - S_i = \Delta_i = \Delta\beta - s_{0i}^{\ s} + \Delta\delta U_i + E(\Delta\eta_i) + \Delta\omega_i^{*}. \quad (7')$$

It is likely that that the subjective health of the unemployed is worse than the subjective health of the employed, thus $E(s_{0i}^{\ s} \mid U = 1) > E(s_{0i}^{\ s} \mid U = 0)$ and this would bias the OLS estimator of $\Delta\delta$ downwards. Thus it will be more difficult to detect misreporting at the PES if self-reported health does not influence PES classifications.

As mentioned, the identification strategy builds on the assumption of additive separability of the potential disability classification if unemployed and employed at the PES and in the LFS (see equation 2). This assumption can of course be questioned, especially since *D* and *S* are both discrete variables, which puts restrictions on the unobserved health differences, $\varepsilon_{0i}^{\ d}$, $\varepsilon_{1i}^{\ d}$, $\varepsilon_{0i}^{\ s}$ and $\varepsilon_{0i}^{\ s}$. However, since we take the difference between two local approximations, the assumption of (local) additive separability is likely to be less of a problem in this application than in general.

We actually have more information on unemployment than just whether the individuals are unemployed or not: The length of *U* in months is observed. Thus "treatment" is observed at different "dosage" levels, which yields additional testable hypotheses and puts our theory to a stricter test. First, if there is a "treatment effect" it should be monotonic, i.e., a larger "dose" of unemployment (in months) causes the mean difference between the PES and LFS classifications to increase, for all values of unemployment. Arguably, the PES officials should have greater incentives to classify the long-term unemployed as disabled than those with less joblessness. The observed outcomes with unemployment measured in months can be written as

$$\Delta_i = \beta_0 + \Delta\delta_k I(U_i = k) + \psi_i, \quad k = 1,...,K, \tag{8}$$

where β_0 is the average difference in disability classification if employed, ψ_i is by (plausible) assumptions a regression error and $I(.)$ is the indicator function. From the monotonicity assumption, it follows that $\Delta\delta_k < \Delta\delta_{k+1}, \forall k$. Assuming constant marginal effects, we get

$$\Delta_i = \beta_0 + \Delta\delta U + \psi_i. \tag{9}$$

Here, $\Delta\delta$ is the average marginal effect of the incentives to exaggerate disability at the PES.

The differencing approach thus offers a clear advantage as it allows us to test for misreporting without having to assume that our chosen benchmark – self assessed health – is unbiased. This is achieved by using unemployment as the identifying "instrument".

4 Econometric results

In the following analyses we use the window sample, i.e., where health information in the PES and LFS is recorded within a period of 6 months. Unemployment is measured in months and includes participation in labour market programmes. The period of measurement is from 1991 up to, but not including, the current search category period. We start with a simple bivariate analysis, on aggregate as well as individual data. We then go on to estimate the misreporting effects on individual data, controlling for various personal characteristics.

In Figure 3, the bivariate relationships between accumulated unemployment and disability classifications in the data are presented. Panel a shows a simple scatter plot, where the individuals have been classified into groups depending on the number of months in unemployment.[19] Panel b is a bivariate regression

[19] The individuals in Figure 2.a are classified into K groups, depending on unemployment history, according to

$$U_k = u_k \mathrm{I}(a_k \le u_i < a_{k+1}), \; k = 1,\ldots, \mathrm{K},$$

of the same relationships on individual data, with unemployment smoothed instead of grouped into intervals and adding the aggregate disability classification in the LFS.

The two panels convey the same message. As expected, a strong positive relationship between accumulated unemployment and the probability to be classified as work disabled is visible. Obviously, this pattern may be due to lower job-finding probabilities among the disabled, but also, as discussed previously, state dependence (including adverse effects of unemployment on health) or stigmatisation, so we are not identifying any causal effects in the figures. However, their most interesting feature is that the probability to be classified as work disabled at the PES is increasing more strongly in months of unemployment than the corresponding probability in the LFS. This might indicate misreporting. It is also noteworthy that the slopes of the partially and highly disabled in the LFS do not differ significantly from each other, i.e., the individuals are not more likely to self-report a severe, rather than a less severe, disability as more unemployment is accumulated. We interpret this as mild evidence that unemployment does not contribute disproportionately to more severe health problems.

We now turn to the multivariate regressions. First, separate OLS regressions – corresponding to equations (4) and (6) – are run for the probability of being classified as work disabled at the PES or in the LFS (either partially or highly), respectively. Then regression models of the difference in classifications, i.e., equation (9), are estimated. Finally, additive regression models, which leave the functional form of the effects from the covariates unspecified, are estimated (see e.g. Hastie and Tibshirani, 1990). In addition to unemployment history,

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where u_k is accumulated unemployment in class *k*. The class interval is determined by a_k and a_{k+1}, where $a_1 = 0$. We calculate the proportion of work disabled in the sample according to the PES (P) and LFS (L) definitions for each interval, as follows

$$\pi^P{}_k = \frac{1}{n_k}\sum_{i=1}^{n_k} D_i \text{ and } \pi^L{}_k(s) = \frac{1}{n_k}\sum_{i=1}^{n_k} I(S_i = s_i)\text{ , } k = 1,\ldots,\mathrm{K}.$$

The number of classes, *K*, is 29. Unemployment is, up to 10 months of previous unemployment, grouped into intervals of one month. Then, in order to keep the subsamples of reasonable sizes, unemployment is grouped into larger intervals; first into two-month intervals, then into five-month and finally into ten-month intervals.

variables for age, gender, level of education, number of children, region of birth and the year in which the LFS was conducted are included in all models.

The results from the multivariate OLS estimations are displayed in Table 2. Let us first look at the coefficients of the control variables in the separate regressions for the PES and LFS. The probability of a disability classification increases with age, but at a decreasing rate. Individuals with more education are less likely to be classified as work disabled. Family attachments also seem to matter; being married or cohabitating and, mainly in the PES data, having children are associated with a lower probability of a disability classification. These results largely conform to findings in previous studies. Region of birth comes out insignificantly in most cases, with some exceptions, notably some non-European categories in the LFS. The negative coefficients for those individuals may be explained by, e.g., selection effects (having a disability makes migration difficult) or language difficulties.

What about unemployment, then? An increase in the number of months in unemployment is clearly associated with a higher probability to be classified as work disabled. The two coefficients – both strongly significant – are 0.0025 and 0.0013 in the PES and the LFS, respectively. An increase in unemployment of, say, 10 months is thus associated with an increase in the likelihood of a disability classification with 2.5 percentage points at the PES and 1.3 points in the LFS.

Our most interesting results are provided in the rightmost part of Table 2, which shows the regression with the PES-LFS difference in disability classifications. Here, the dependent variable takes on the values –1 (the individual is classified as work disabled in the LFS, but not at the PES), 0 (classifications agree) and 1 (no work disability classification in the LFS, but at the PES). Many of the coefficients that were significant in the separate regressions, e.g., for age, education and children, are now rendered insignificant. However, two of the coefficients for foreign-born individuals (Europe excluding EU 15 and Asia) remain significant and come out with a positive sign, i.e., a disability classification is more likely at the PES than in the LFS. Most importantly, unemployment retains strong significance, with a coefficient of 0.0012. So an individual with 10 months of previous unemployment is about 1 percentage point more likely to be classified as work disabled at the PES, but not in the LFS, than if the individual had no previous unemployment. This can be compared to the overall probability to be classified as work disabled at the PES, which is 5 per cent (see Table 1). Thus, on average, there is a 20 per cent increase in the likelihood of this type of classification error with each 10-month increase in unemployment. The misreporting we have detected in the data is thus not negligible.

The results in the PES-LFS regression in Table 2 lend support to the hypothesis that there are incentives to exaggerate disability at the PES. We argue that a causal interpretation of the relationship between unemployment and disability classification is justified here, unlike in the two separate regressions. The finding that most controls, including age, do not significantly contribute to explaining the difference in classifications also suggests that omitted variable bias is not likely to be a serious problem in our estimations.

We now turn to the more flexible specification, namely the additive regression model.[20] Unlike in the OLS regressions, the functional form of the continuous variables is not assumed to be known in advance. So the marginal effects of unemployment need not be constant, as assumed in equation (9). For the variables unemployment and age, loess smoothers (locally weighted running-line smoother with span 4/3) are used. The presentation of the regression results is limited to these two continuous variables and is in visual form only. For computational convenience, the relationships between the dependent and independent variables are evaluated with all other covariates, including the intercept, set to zero**.** As a consequence, the probability predictions in the figures may, without loss of generality, be negative.

Figures 4–7 show the additive regression results for PES and LFS separately. Figure 4 suggests a linear relationship between unemployment and work disability at the PES. A test indicates that linearity cannot be rejected (p-value 0.44). The relationship between age and work disability at the PES in Figure 5 is clearly non-linear (p-value < 0.01), i.e., increasing at first and then decreasing at around 50 years of age. The corresponding estimates for self-assessed work disability in the LFS are presented in Figures 6 and 7. Regarding unemployment, the relationship is less linear than in Figure 4. Although there is a tendency for a convex shape, linearity cannot be rejected at standard levels (p-value 0.054). This is due to the lack of precision at the right end in the graph. For age and the LFS classification we now find a consistently positive, and close to linear (p-value 0.075), association.

[20] The estimation is based on the local scoring algorithm, which iteratively fits weighted additive models by backfitting. The backfitting algorithm is a Gauss-Seidel method for fitting additive models, by iteratively smoothing partial residuals.

The results for age in the LFS data correspond more to what we expect than the findings for age in the PES, since it seems unlikely that health should improve as individuals get older. It is conceivable that the PES results are explained by the *prospect* of early retirement for elderly individuals (note that no early retirees are included in the sample). This may reduce the need for a disability classification at the PES and the associated special measures for the disabled, but should not affect LFS classifications.

Figures 8–10 show the additive regression results for the PES-LFS difference in work disability classifications. To begin with, Figure 8 displays a simple bivariate regression, where only previous unemployment is regressed on the PES-LFS difference. The gradient of unemployment is positive and almost linear. There is some concavity after 60 months of unemployment. However, the non-linearity is not statistically significant (p-value 0.14).

Figure 9 corresponds to Figure 8, with the controls added. The effect of unemployment on the dependent variable is basically the same as with no controls added (linearity is now rejected with an 18 per cent risk). Adding controls apparently does little to change the effect of unemployment on the PES–LFS difference. As in Table 2, the correlation between unemployment and the PES-LFS difference in Figure 9 clearly indicates that there is misclassification due to incentives to exaggerate disability at the PES. The difference is initially *negative* if being unemployed for less than 18 months and then positive. Under the extreme assumption that the unobserved thresholds[21] for work disability classification at the PES and in the LFS are the *same*, all of the initial negative effect, up to 18 months of unemployment, is attributable to stigmatisation (correlated with unemployment). Under the more realistic assumption that the threshold is *lower* for the self-reported measure than for PES classifications, this stigmatisation effect should be very small or absent.[22]

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[21] The average PES-LFS "classification error", using the overall work disability measure in the LFS, is –3.1 per cent = 4.7 – 7.8 per cent (see Table 1).

[22] The average PES-LFS "classification error" using the highly work disabled in the LFS is 2.6 per cent, according to Table 1. With the stricter LFS disability classification the resulting graph looks exactly the same as the one in Figure 9. However, the difference becomes strictly larger than zero, so if stigmatisation correlated with unemployment exists it is very low or non-existing for this sample.

Finally, in Figure 10 the results for age are shown, with controls added. Age has a negative impact on the difference around the age of 50 and linearity is rejected (p-value < 0.01).

What about the magnitude of the effects shown in Figures 8–10? An individual with 70 months of previous unemployment is about 7 percentage points more likely to be classified as work disabled at the PES, but not in the LFS, than an individual with no unemployment. The corresponding effect in Table 1 is about 8 percentage points, so, in this range of unemployment, the difference is not great across estimation methods. The magnitude of the age effects is, however, considerably smaller with both regression approaches and will not be discussed here.

We have performed various robustness tests of the PES-LFS difference regressions in Table 2 and Figures 9 and 10, the full details of which are available from the authors on request. See (i) – (vi) below.

(i) Municipal fixed effects were introduced in the regressions. This procedure is likely to pick up influences from the local labour market, since differences across regions in this respect tend to be permanent over time. The results from the fixed effects specification were very similar to previous findings.

(ii) We experimented with increasing the window length from 6 to 12 months. The number of observations increased to 23,178, but the results remained unchanged.

(iii) Non-Nordic-born individuals were excluded from the sample, in order to check whether the results regarding the unemployment effect are explained by language difficulties. It is conceivable that some non-Nordic-born do not fully understand the interview questions posed in the LFS and thus understate true health status, while this is less likely to occur at the PES, where contact is repeated and interpreter services may be available. We estimated the model excluding the 3,121 individuals born outside of the Nordic countries, but this did not change the results.

(iv) The additive regression results are robust with respect to the choice of span width. We have estimated all such models with spans ranging from ½ to 1½. We have also estimated generalised additive models, with a logit link**,** for the PES and LFS disability classifications (but not for PES-LFS difference). The results from these models are in agreement with the findings from the additive model.

(v) It may be the case that individuals condition survey responses on previous information from external sources and it was explored whether this affects the results. In our case, the responses in the LFS may be influenced by a PES classification occurring before the survey. In order to perform this test, it was necessary to redefine the sample, creating clear-cut limits between periods where the LFS and PES classifications, respectively, may have occurred. We thus used a sample of 7,026 individuals who have a spell of unemployment in the period 6 months before or after the LFS, but were not unemployed at all after or before the LFS. There are 5,191 individuals who have such a spell prior to the LFS and who were not unemployed post-LFS and there are 1,835 individuals who were not unemployed before the LFS but had an unemployment spell after the LFS. On this sample, of 7,026 individuals in total, an ordered logit regression model using the LFS classification ($S = 0,1,2$) as the dependent variable and the PES classification and a dummy variable for a spell prior to the LFS was estimated. The coefficient for the post-LFS dummy variable turned out to be insignificant (p-value 0.85), suggesting that conditioning of survey responses on official classifications is not a problem in our analysis.

(vi) Experiments were performed with more traditional non-linear models, with unemployment grouped into intervals as described in footnote 19. These logit and ordered logit regressions did not alter the basic conclusions of our previous exercises.

5 Conclusions

The issue considered in this study is whether objective, official, reports on disability status are reliable. While there is a rather large literature on the reliability of self-reported disability, evidence regarding objective data is scant. It seems to be widely believed among researchers that, since individuals out of work are inclined to respond towards poor health, it would be best to have official data provided by the relevant administrative bodies (like the Disability Insurance administration or the Public Employment Service).

The main message of our paper is that administrative data should be regarded with some suspicion, even if work capacity is taken into account in the data, since the administrators also have incentives to misreport. This is because the PES officials have quantitative targets regarding the placement of individuals in subsidised jobs and because the officials may be influenced by jobseekers who want to be labelled as disabled. Our findings should shed additional light on the distinction between, and usefulness of, subjective and more objective health measures as they are defined in the literature. The results suggest the presence of incentive problems in disability classification procedures at the PES and the sources of error we find are akin to the moral hazard effect in social insurance.

For a large sample of Swedish jobseekers, we have contrasted objective, official data with self-reported measures on health status, for the same individuals, from the Labour Force Surveys. The econometric analysis shows that the difference in the categorical disability classification between the PES and the self-reported LFS increases in accumulated unemployment of the individual. This result, which indicates misreporting in the official data, is robust to various experiments regarding estimation methods, control variables and subgroups. We also test whether misreporting increases monotonically in the length of "treatment", e.g., unemployment.

It should be noted that our definition of misreporting may be different from the one that is used internally at the PES. An internal document at the National Labour Market Board contains the following passage: "It is only after having mapped out and assessed the functional impairment *in relation to the labour market* and the *labour supply of the jobseeker* that one can determine whether a work disability exists" (Ams, 1999, p. 6, our translation and italics). A possible interpretation of these guidelines is that using unemployment in order to screen for health is permitted. Furthermore, the rules are very clear as regards the right of individuals to deny a disability classification, which, in contrast, leads to underreporting of impairments according to our definition. Rules and guidelines are not created in a vacuum, though, and may well be influenced by the incentive structures that we have discussed.

Unlike many other validation studies of economic data, we are not able to assess the magnitude of the error we find in the variable under consideration. This is due to our assumption that subjective health may be flawed in several respects, but that the difference in disability classifications should be independent of unemployment if there is no misreporting due to incentives to exaggerate disability at the PES**.** It is worth noting that, due to state dependence**,** our estimates rather are more likely to provide a *lower bound* of the misreporting of disability classifications at the PES offices. If self-assessed work disability, like the official measure, is (positively) correlated with unemployment given true health status, the effect of unemployment on PES disability classifications will be underestimated.

Although we use an objective, official measure of disability which is unusual in the literature and possibly not readily available in other countries, we believe that our results should have implications also for the validity of other official measures. If these measures are also influenced by the incentives of the persons making the classifications and the incentives of the individuals being classified, the validity of the measures should not be taken for granted. Institutional details of the classification procedures and empirical evidence supporting the validity need to be considered as well.

Our framework of analysis should be suitable also for studying the impact of various policy shifts, regarding, e.g., the generosity of benefits or screening procedures, in labour market programmes for the disabled. Do classification errors of the type we have considered here become more or less prevalent as a consequence of such shifts? To this and other related issues we intend to return in future research.

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Appendix A

Disability data in the HÄNDEL events database (PES) and in the Labour Force Surveys (LFS)

In the PES data, disabilities are classified into eight different categories: Heart and/or lung disease, hearing, vision or motion impairment, other somatic disabilities (including allergy, diabetes and stomach and intestinal diseases), and psychic, intellectual and socio-medicinal disabilities, the latter of which includes substance abuse. If an individual has more than one disability, only the main one is recorded, so it is not observed whether there are multiple disabilities.

In the LFS, there are questions concerning functional impairment, which is defined (and read aloud to the respondents) as "a physical, medical or psychic impairment, which may cause restrictions in daily life. The impairment may be congenital or developed later in life through sickness, accident or occupational injury. Examples of functional impairments are vision or hearing impairments, speech or voice disorders, motion impairment, allergy or other form of psychic impairments. It can also be dyslexia, epilepsy, diabetes, heart- and lung problems, and stomach and intestinal disease." The respondents are asked whether they have a functional impairment according to this definition.

If the answer is yes, there is follow-up question concerning the type of impairment. There are 16 categories (plus an open-ended alternative): Asthma/allergy or other type of hypersensitivity; DAMP/ADHD (neuropsychiatric children's diseases); diabetes; dyslexia; deafness; epilepsy; heart disease or vascular disorder; hearing impairment; stomach or intestinal disease; lung disease; psoriasis; psychic impairment; mental retardation; motion impairment; stammering, speech or voice disorders; and vision impairment/blindness. The respondents may choose more than one alternative from the list and are also asked whether they regard any one of them as the main impairment.

Those who have responded in the affirmative to the introductory question in the LFS and have also reported at least one impairment are requested to answer the query: "The following question is about work life, that is your situation at work and not at home. In your opinion, do(es) your functional impairment(s) reduce your work capacity?" The interviewees may reply "Yes, highly so", "Yes, partially so", "No, not at all" or "Do not know". The latter alternative is applicable for the unemployed or for persons who have not entered the labour market. The interviewers are instructed that the respondents themselves should decide what is meant by "much" and by "partly". Only one answer, applying to all impairments, is reported. To the extent that "Yes, much so" is given as an answer for one impairment and "Yes, partly" for another, the former alternative is reported. In addition, there are some questions intended for employed respondents only. These questions deal, *inter alia*, with the need for special aids, work tools or assistants at the workplace and whether such supportive measures have been undertaken.

We have no information on whether the disabilities are considered to be permanent in the self-reported data (although some of the impairments listed tend to be of a lasting nature, e.g., hearing impairment, epilepsy and mental retardation). Moreover, it is quite possible that respondents define the reduction of work capacity *only* in relation to a current and/or previous job and do not recognise the potential to adjust, with proper training and rehabilitation, to a new job. There are no questions concerning applications, rejections or awards of disability benefits in the LFS, nor in the PES data.

Respondents in the LFS are guaranteed a high degree of anonymity. According to the Secrecy Act (*Sekretesslagen*), strict confidentiality applies to information given by respondents in statistical surveys performed by the Government.

Appendix B

Table B: Sample characteristics. Cross-tabulations of types of work disability among individuals with contemporaneous information on work disability in the supplementary Labour Force Surveys (LFS) and in the unemployment register (PES). Number of individuals.

PES	None	A	D	HL	H	V	M	OS	P	I	OT	All
LFS												
None	**20,775**	2	3	15	22	10	227	126	64	34	80	21,358
A	257	**0**	1	3	0	0	6	43	0	0	2	312
D	23	0	**2**	0	1	0	0	6	1	2	0	36
HL	39	0	0	**10**	0	0	3	5	0	0	0	57
H	59	0	0	0	**12**	0	0	1	1	0	2	74
V	34	0	0	0	0	**6**	2	2	0	0	0	40
M	497	0	0	3	2	0	**205**	18	8	3	5	741
OS	101	0	0	2	1	0	10	**17**	1	2	1	135
P	65	0	1	0	0	0	3	3	**15**	0	3	90
I	6	0	0	0	0	0	0	0	0	**0**	0	6
OT	197	0	0	0	0	0	54	22	1	0	**2**	276
NS	33	0	0	1	1	0	12	5	0	0	1	53
All	22,086	2	7	35	39	16	520	246	90	41	96	23,178

Note: A = Asthma /allergy (PES) = Asthma/allergy (LFS)

D = Dyslexia (PES) = Dyslexia (LFS).

HL = Heart/and or lung disease (PES) = Heart disease/vascular disease + Lung disease (LFS).

H = Hearing impairment (PES) = Deafness + Hearing impairment (LFS).

V= Vision impairment (PES) = Vision impairment, blindness (LFS).

M = Motion impairment (PES) = Motion impairment (LFS).

OS = Other somatic disabilities (PES) = Diabetes + Epilepsy + Stomach or intestinal disease + Psoriasis + Stammering, speech and voice disorders (LFS).

P = Psychic disability (PES) = Psychic disability + DAMP/ADHD (LFS).

I = Intellectual disability (PES) = Mental retardation (LFS).

OT = Sociomedicinal disability (PES) = Other (LFS).

NS = Multiple disabilities, main one not stated (LFS only)

Disabilities of individuals in the LFS who have multiple disabilities and have reported a main one are included in the total and have been distributed according to type.

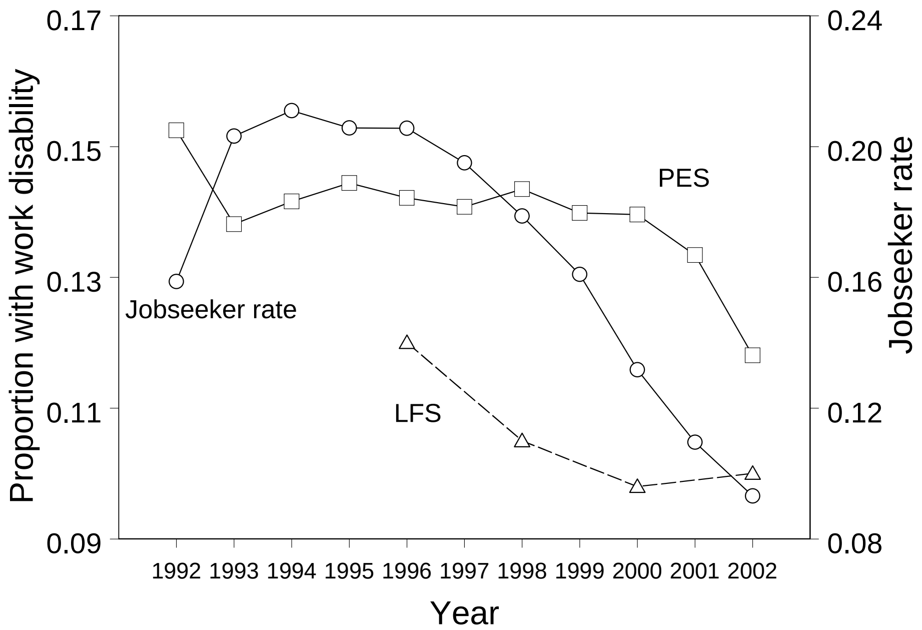


Figure 1: Work disability rates, at the PES and in the LFS, and the jobseeker rate at the PES, 1992–2002. Aggregate data from the PES and the LFS.

Note: The jobseeker rate is measured as the number of registered individuals looking for a job over the labour force. The proportion of registered (and disabled) individuals at the PES refers to October 15 each year.

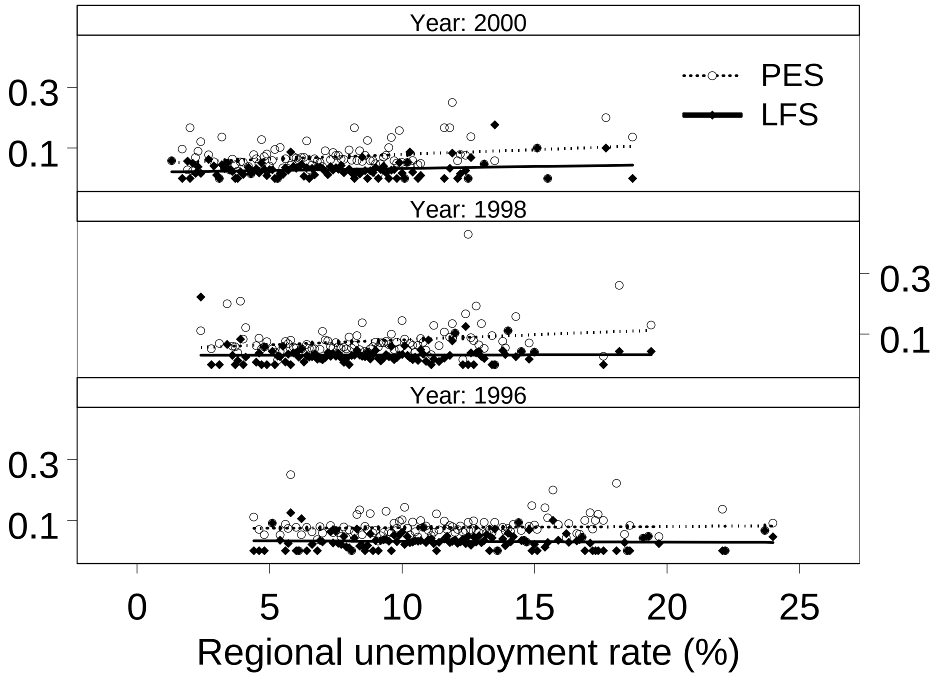


Figure 2: Work disability rates, at the PES and in the LFS, and the local unemployment rate, in 1996, 1998 and 2000. Aggregate data from the PES and LFS sample.

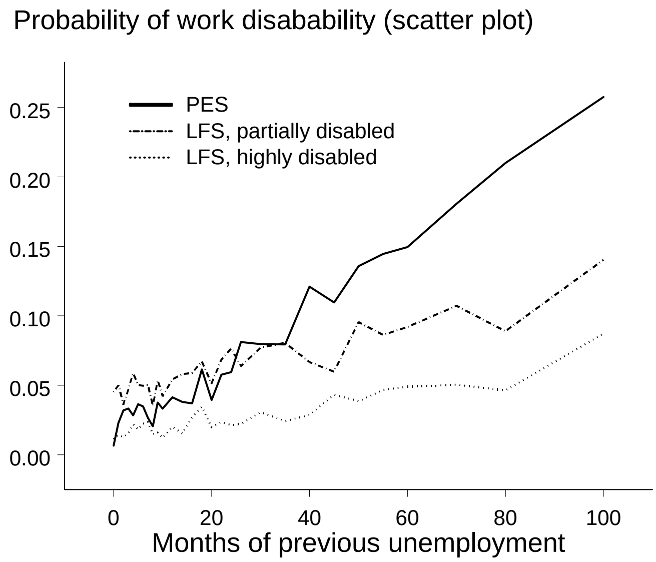
Table 1: Sample characteristics. Individuals in the supplementary Labour Force Surveys (LFS) 1996, 1998 and 2000. Means.

Characteristics	All years	1996	1998	2000
Disability characteristics:				
At all disabled	0.161	0.148	0.144	0.193
Work disabled	0.079	0.079	0.081	0.077
Partially	0.055	0.059	0.056	0.050
Highly	0.027	0.023	0.028	0.029
Subsample with contemporaneous information on work disability in unemployment register (PES)*	0.477	0.618	0.496	0.314
of which:				
Work disabled (LFS)	0.078	0.079	0.078	0.079
Partially	0.058	0.061	0.055	0.055
Highly	0.021	0.018	0.023	0.024
Work disabled (PES)	0.047	0.046	0.050	0.046
Work disabled (LFS) + Work disabled (PES)	0.022	0.021	0.022	0.023
Work disabled (LFS) + Not work disabled (PES)	0.057	0.058	0.056	0.056
Not work disabled (LFS) + Work disabled (PES)	0.025	0.025	0.027	0.022
Not work disabled (LFS) + Not work disabled (PES)	0.896	0.896	0.895	0.899
Months of previous unemployment (PES)	14.95	11.43	15.82	20.37
Other characteristics:				
Age	34.92	34.22	34.85	35.70
Female	0.515	0.513	0.514	0.518
Education:				
Primary	0.244	0.263	0.245	0.223
Upper secondary	0.517	0.523	0.518	0.510
University	0.231	0.205	0.228	0.260
Family status:				
Married or cohabitating	0.606	0.585	0.604	0.627
No. of children	0.794	0.778	0.783	0.823
Labour market status:				
Employed	0.692	0.637	0.684	0.756
Unemployed	0.085	0.121	0.079	0.053
Out of labour force	0.224	0.242	0.237	0.191
Region of birth:				
Sweden	0.857	0.857	0.858	0.856
Finland, Denmark and Norway	0.032	0.036	0.029	0.030
EU 15 (excluding the Nordic countries)	0.001	0.001	0.001	0.001
Europe excluding EU 15	0.037	0.036	0.037	0.038
Africa	0.001	0.001	0.001	0.001
North America	0.000	0.000	0.000	0.000
South America	0.001	0.001	0.001	0.001
Asia	0.043	0.040	0.043	0.045
Oceania	0.000	0.000	0.000	0.000
Former USSR	0.000	0.000	0.000	0.000
N	44,532	15,089	14,802	14,641

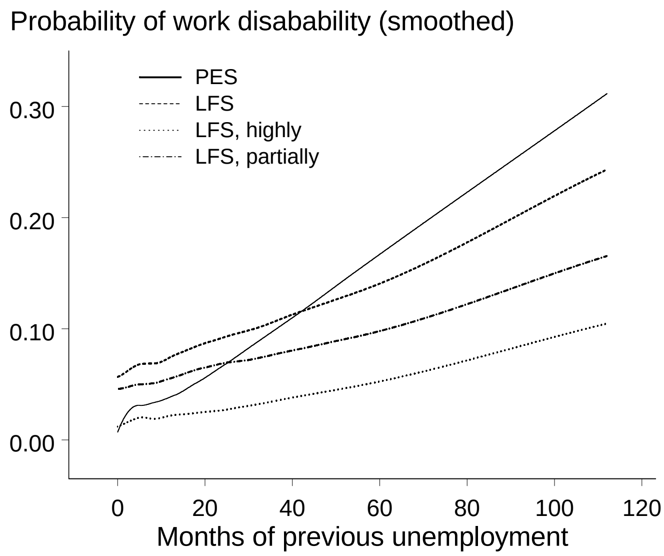
Note:* Information available within a period of 3 months before and after a Labour Force Survey.

Table 2: Regressions of PES, LFS and the difference in PES and LFS work disability classifications (Diff.). OLS. N= 21,249.

	PES		LFS		Diff.	
Variable/parameter	coefficient	| t-ratio |	coefficient	| t-ratio |	coefficient	| t-ratio |
Intercept	-0.0867	4.03	-0.0298	1.12	-0.0568	2.01
Unemployment	0.0025	22.59	0.0013	11.59	0.0012	9.15
Age	0.0067	6.26	0.0046	3.44	0.0020	1.36
Age squared x 100	-0.0068	4.89	-0.0032	1.81	-0.0036	1.83
Year of Labour Force Survey. Reference category: 1996						
1998	-0.0074	2.30	-0.0040	0.97	-0.0033	0.75
2000	-0.0223	6.00	-0.0108	2.26	-0.0115	2.25
Education. Reference category**:** unknown education						
Primary	-0.0068	0.49	-0.0046	0.28	-0.0022	0.13
Upper	-0.0247	1.78	-0.0193	1.17	-0.0053	0.33
University	-0.0545	3.91	-0.0551	3.30	0.0006	0.04
Family status. Reference categories: not married nor cohabiting, male and no children						
Married or cohabiting	-0.0154	4.13	-0.0081	1.75	-0.0073	1.50
Female	0.0043	1.49	0.0086	2.27	-0.0043	1.05
1 child	-0.0101	1.97	-0.0041	0.63	-0.0060	0.88
2 children	-0.0117	2.23	-0.0053	0.81	-0.0065	0.94
3 children	-0.0179	2.60	-0.0090	1.03	-0.0089	0.94
≥ 4 children	-0.0001	0.01	0.0272	1.82	-0.0273	1.73
Region of birth. Reference category**:** Sweden						
Finland, Denmark and Norway	0.0038	0.38	0.0131	1.03	-0.0093	0.71
EU 15 (excluding Nordic countries)	0.0135	0.74	0.0124	0.55	0.0011	0.05
Europe (excluding EU 15)	0.0025	0.33	-0.0293	3.69	0.0319	3.40
Africa	-0.0262	2.24	-0.0409	3.03	0.0147	1.07
North America	-0.0203	0.75	-0.0245	0.81	0.0042	0.10
South America	-0.0123	0.91	-0.0067	0.37	-0.0056	0.28
Asia	0.0026	0.34	-0.0243	3.14	0.0269	3.02
Oceania	0.0764	0.68	-0.0699	3.64	0.1465	1.23
Former USSR	-0.0152	0.39	-0.0006	0.01	-0.0145	0.39
R-square	0.0772		0.0274		0.0104	



a)



b)

Figure 3: The relationship between previous months of unemployment and the proportion of work disabled at the PES and LFS: a) Scatter plot and b) estimate by bivariate local regression (loess) smoothing using one degree polynomial, a symmetric distribution and cross validated span.

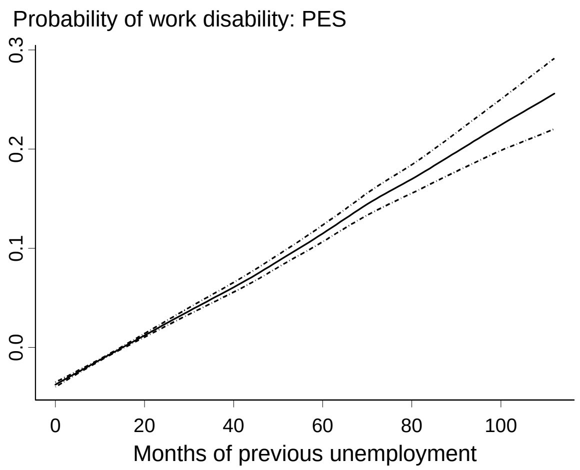


Figure 4: The estimated relationship between previous months of unemployment and PES work disability classification (95 per cent confidence interval).

Note: Multivariate regression based on the additive model with a one polynomial loess smoother with span ¾ and symmetric distribution.

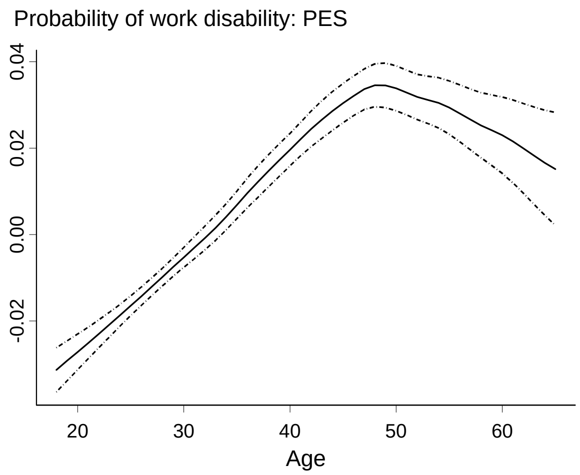


Figure 5: The estimated relationship between age and PES work disability classification (95 per cent confidence interval). See also note to Figure 4.

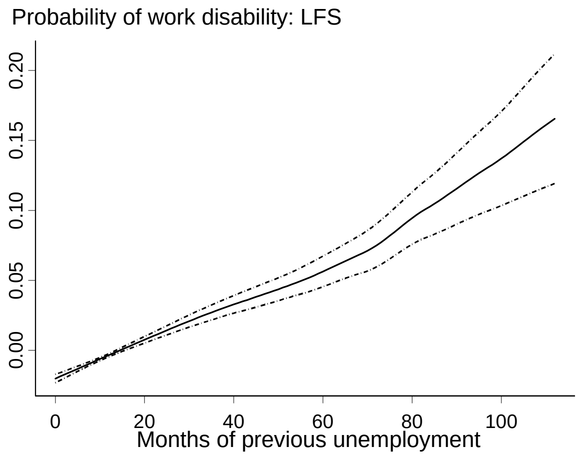


Figure 6: The estimated relationship between previous months of unemployment and LFS work disability classification (both partially and highly disabled, 95 per cent confidence interval).

Note: The LFS data refer to both partially and highly disabled. See also note to Figure 4.

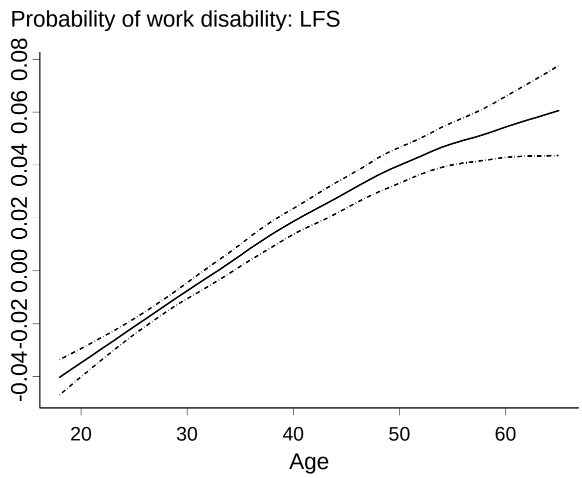


Figure 7: The estimated relationship between age and LFS work disability classification (95 per cent confidence interval). See also notes to Figures 4 and 6.

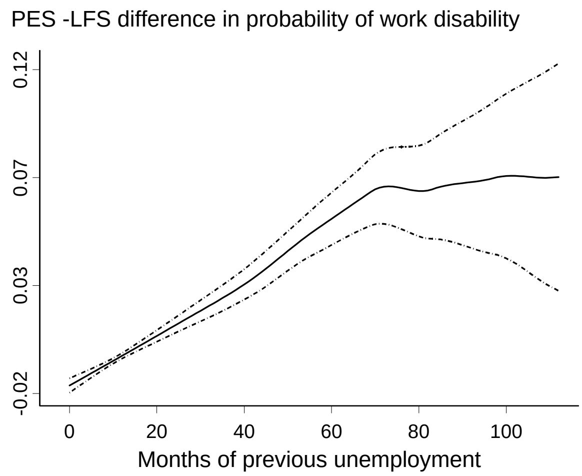


Figure 8: The estimated effect of previous months of unemployment on the PES-LFS difference in work disability classification (95 per cent confidence interval). Bivariate regression.

Note: Regression based on the additive model with a one polynomial loess smoother with span ¾ and symmetric distribution. See also note to Figure 6.

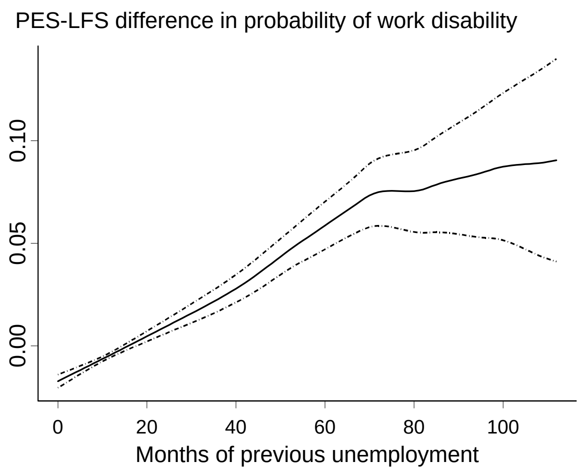


Figure 9: The estimated effect of previous months of unemployment on the PES-LFS difference in work disability classification (95 per cent confidence interval). Multivariate regression. See also notes to Figures 4 and 6.

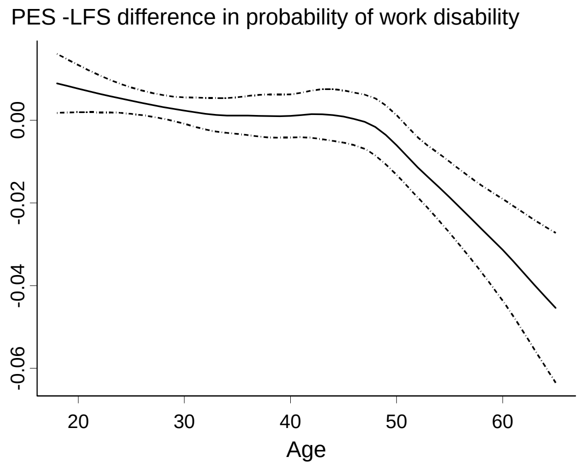


Figure 10: The estimated effect of age on the PES-LFS difference in work disability classification (95 per cent confidence interval). See also notes to Figures 4 and 6.