Unequal Risks on the Flexible Labor Market, The Case of the Netherlands

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Abstract

In accordance with the needs and preferences of both employers and employees, labor markets in Western countries became increasingly flexible. However, for workers such flexibility bears the risk of long-term exclusion. This paper deals with unequal exclusionary risks on contemporary labor markets, particularly for those who are inactive and have unfavorable endowments. The data used to reveal the risks are based on stock sampling. We estimate hazard rate models that account for both the stock-sampling and the possible maximum duration for the transitions from unemployment, household care and disability to employment. In our analyses we try to control for differences in human capital characteristics, using a decomposition method. The main result is that unequal risks exist, but to a different degree for the various groups and with variations per transition type. Transition skills seem to have some but not much effect on job chances.

JEL classification: C41, J64, J7.

Key words: Flexible labor market; duration; Oaxaca-Blinder decomposition.

1 Introduction

Ever since the seminal work of Atkinson (1984a,b) economists study labor market flexibilization. Originally, the employers' perspective dominated, as flexibilization was regarded as a necessary adaptation of the use of workers to increasingly turbulent consuming markets and fast-changing technologies. Research then focused on the *effects* on workers in different market segments. More recently, attention has also been paid to workers' needs and preferences. Certain types of flexibilization are now looked upon as *chosen* by employees who want to bring their working career in line with the requirements of their private life. Labor market flexibilization therefore seems to be advantageous for both employers and employees. It thus comes as no surprise that flexibilization is an ongoing process in today's Western labor markets. For some, flexibilization is even the core characteristic of such markets.

Among them is the German economist Schmid (1998, 2002) who typifies modern labor markets as 'transitional' markets. He found that employees experience a growing number of transitions during their working career as a result of increasing worker flexibility. Such transitions concern the domain of paid labor itself, e.g. transitions from one job to another, as well as transitions between work and other activities, such as family care, education, and unemployment. Since work became more variable and insecure, 'life-long tenures' are becoming a characteristic of the past. The standard biography (*education-work-inactivity* for males and *education-work-marriage/care-inactivity* for females) increasingly vanishes. It has gradually been replaced by a biography of choice, the more so since many transitions occur voluntarily from the workers' point of view. However, the situation of individual 'free choice' has a drawback. The new biography, which has been described as a 'do-it-yourself biography', in some instances turns out to be a 'breakdown biography' (Beck 1992, Giddens 1991). Current labor markets are therefore considered risky for many workers. The main risk being that interruptions of the working career that are meant to be temporary, become unintentionally permanent. For such cases Schmid uses the term 'exclusionary risks'. They occur particularly in transitions from work to unemployment, prolonged illness and household care.

Traditionally, workers with restricted human capital run the highest risk of prolonged non-working periods. However, as transitional labor markets are characterized by 'institutional arrangements' (Schmid, 1998) that are meant to facilitate returning to paid labor, workers' 'transition skills' have become increasingly important (Buitendam, 2001). The term refers to knowing the rules and regulations of the modern labor market, and to correctly applying these rules and regulations in their own situation. We may assume that individuals vary in the degree of *transition skills* just as they differ in human capital. This holds true even when protective institutional arrangements are available, as individuals also vary in 'institutional self-activity' (Dewey 1990) which means that people differ in the ability to understand and use provisions provided by public services.

Governments apply policy measures to further the return to work for those who experience a break in their working career. *Activating* labor market policies, supported by public and private arrangements stimulating labor market transitions, advance the efficient operation of the labor market as well as diminish the risks of long-term exclusion from paid labor. The Netherlands offers a good example in this respect (Schmid, 1998, 2002). The Dutch labor market can be characterized as *transitional*. It shows a high proportion of part-time work in newly created jobs. Furthermore, a large number of policy measures is directed at the placement of long-term unemployed with a vulnerable labor market position, while the government uses a 'flexicurity'-approach to optimize flexibility and work security (Wilthagen 1998).

Given the Dutch labor market situation, it is particularly interesting to choose the Netherlands as a case to investigate whether those out of work are able to find a job again and if so, at what pace. We therefore study the unemployed, the disabled to work and those who are in domestic care, and analyze their job chances. We are particularly interested whether groups with unfavorable characteristics still have larger *exclusionary risks*. We will control for human capital-characteristics to establish the importance of *transitional skills*. In this respect, the finding of Distelbrink and Pels (2002) is important. They established that immigrants in the Netherlands experience far more problems in relation to self-activity. The researchers found this to be a consequence of their upbringing which is more directed at compliance and respect than at autonomic thinking and acting. They furthermore explain these self-activity problems by the lower educational levels of immigrants. We thus expect immigrants to have less 'transition skills' in addition to impediments in their human capital, such as lower education and limited labor market experience (Veenman 1998). We will therefore focus on a comparison of the exclusionary risks of immigrants and Dutch natives.

As stated, we are interested in three transition types, namely from unemployment to work, from domestic care to work, and from prolonged illness (disability to work, to be more precise) to work.[1] The latter is of special interest for the Netherlands, where about 960,000 people received an allowance since they were officially registered as disabled to work in 2004 (Statistic Netherlands).[2] We will systematically *compare* the transition chances of immigrants and Dutch natives in these areas. To this end we estimate proportional hazard models for each group and for each transition from inactivity to work separately.

To *explain* the differences in exclusionary risks we calculate a decomposition of the differences in expected duration, implied by the hazard models, for each immigrant group and the native expected duration. This is a non-linear version of the well-known decomposition methodology of Oaxaca (1973) and Blinder (1973). Our methodology is an extension of the approach of Fairlie (2005) developed for the decomposition of logit and probit models. With this extension, being another contribution of this paper, we hope to gain insight into the importance of *transition skills*. In Section 2 we discuss our method and the data used. The empirical analyses and their results are presented in Section 3, where each of the three aforementioned transitions are elaborated on subsequently. Section 4 contains our conclusions and a short discussion of the main findings.

2 Data and method

With the exception of the year 1967, the Netherlands is a country of net immigration since the 1960s. From that time and until the 1990s, four immigrant groups dominated immigration. The majority, about 70 percent of the immigrants and their descendants, came from Turkey and Morocco (the Mediterraneans), and from Suriname and the Dutch Antilles (the Caribbeans). We will therefore focus on these four groups, also because they are the best documented immigrant groups in the Netherlands. Our data are from the nationwide survey 'Social Position and Use of Public Utilities by Migrants', more specifically from the survey's editions for the years 1998 and 2002.[3] The survey's main purposes are to gain insight into (the development of) the socio-

[1]The transition from education to work could have been added, but since we lack data on the duration of inactivity of those who left education, we are not able to estimate their hazard rates.

[2]Recently several measures were taken to diminish the number of those who are disable to work. The positive results show from the decline to about 880,000 people in 2005. To put this number in perspective, we add that the employed labor force in the Netherlands then counted about 6,9 million people.

[3] The 1998 survey was carried out by the Institute for Sociological and Economic Research (ISEO) from Erasmus University Rotterdam in cooperation with the Social and Cultural Planning Office of the Netherlands

economic position of the four largest immigrant groups in the Netherlands (Turks, Moroccans, Surinamese and Antilleans), in the variety in socio-economic position among these groups, as well as in differences in position compared to the native Dutch.[4] Because of the high degree of spatial concentration of immigrants in the larger cities, the survey is based on random sampling within the 13 largest Dutch cities. This procedure results in nationwide representativeness for the four immigrant groups.[5]

In each household, the head of household was asked to answer general questions on the composition of the household and (if relevant) on its migration history. All members of the household older than 11 years were asked to answer the other questions. Both the first generation of actual immigrants and the second generation (of descendants) are represented in the survey. Table 1 shows the number of respondents per group.

Table 1: Number of people in SPVA by ethnic origin and economic position.

	Turks	Moroccans	Surinamese	Antilleans	Natives	Total
*Economic position**						
Unemployed searching for job	575	489	361	271	140	1836
Domestic care	1309	1132	419	294	338	3492
Disability benefits	551	437	307	124	155	1574

* People aged 18 to 65 years. *Source:* SPVA (ISEO/SCP)

2.1 Duration analysis

The data used contain retrospective information on the length of the elapsed duration in the labor market situation at the time of the interview. These data on the duration in a particular state are based on stock sampling, because they are obtained by sampling from the stock in that state using a single interview.[6] Since for some individuals labor market transitions

(SCP). In 2002, ISEO cooperated with the SCP and, on specific items, with researchers from the Netherlands Organisation for Scientific Research (NWO)-Program Netherlands Kinship Panel Study (NKPS).

[4]To be considered as a member of one of the immigrant groups, the person, or at least one of his parents, should come from the country concerned.

[5]More detailed information on the survey can be found in Groeneveld and Weijers-Martens (2003).

[6]In fact some individuals are interviewed twice, both in 1998 and in 2002, in the SPVA. However, this occurs only for a very limited number of individuals. We therefore ignore the panel structure of the data.

occur at a very low rate, these individuals may stay in their current state until they reach the retirement age of 65. In the Netherlands, as in most European countries, unemployment benefits and disability benefits cease after retirement. In fact, everybody leaves the (potential) labor force when reaching the retirement age. This implies that every state has an upper bound of its duration until retirement. We will account for both the stock-sampling and the possible maximum duration.

In duration analysis the hazard rate or intensity is usually modelled. A common way to accommodate the presence of observed characteristics is to specify a proportional intensity model,

$$\lambda(t|x) = \lambda_0(t;\alpha)e^{\beta_0+\beta' x_i(t)}, \tag{1}$$

where $\lambda_0(t;\alpha)$ represents the baseline hazard, that is, the duration dependence of the intensity common to all individuals. The covariates affect the intensity proportionally, and the time-varying variables are external variables that change independently of the employment state, such as the age of a disabled individual that changes independently of the employment state. If the duration of individual i has an upper bound of $\bar{t}_i$, the time till retirement, the hazard of leaving unemployment at $\bar{t}_i$ is ∞. This implies that the probability to reach $\bar{t}_i$ for individual i is $S(\bar{t}_i|x_i) = \exp\bigl(-\int_0^{\bar{t}_i} \lambda_0(s;\alpha)e^{\beta_0+\beta' x_i(s)}\, ds\bigr)$.

If we sample from a stock of individuals at time 0 (in calendar time) in a particular state, e.g. from the stock of people on disability benefits, and observe the elapsed time e in that state, then the distribution of the observations of the elapsed time is a conditional distribution, see among others Heckman and Singer (1984). The condition is the presence of a particular individual in the stock. Let $r(-e|x_i)$ denote the entry rate, the probability to enter the state during $[e, e+de)$ in the past given observed characteristics x and assume, as Nickell (1979) does, that the entry of people with characteristics x is a constant fraction of the total entry, $r(-e|x) = r_1(-e)r_2(x)$. Then the density of the elapsed duration for individual i, adapted for the upper bound in the duration, is

$$h(e|\bar{t}_i, x_i) = \frac{r_1(-e)e^{-\Lambda(e|x_i)}}{\int_0^{\bar{t}_i} r_1(-\tau)e^{-\Lambda(\tau|x_i)}\, d\tau} \tag{2}$$

where $\Lambda(e|x_i) = \int_0^e \lambda_0(s;\alpha)\exp\bigl(\beta_0 + \beta' x_i(s)\bigr)\, ds$, the integrated hazard.

In practice it is hard to find a closed form solution to the integrals in the density. For example, the commonly applied proportional hazard model with Weibull baseline hazard leads to intractable integrals. Although these integrals may be approximated, the Weibull baseline is also very restrictive. A very flexible and tractable assumption is to use a piecewise constant baseline hazard. If the entry rate is also constant on intervals we have a closed form expression for the density of the elapsed duration, from which we can easily derive a maximum likelihood estimator for the parameters of the model. Let $I_m(t) = (t_{m-1} \leq t < t_m)$, for $m = 1, \ldots, M$ with $t_0 = 0$ and $t_M = \infty$, be the intervals on which we define the piecewise constant hazard. Then $\lambda_0(t) = \sum_{m=1}^{M} e^{\beta_0 + \alpha_m} I_m(t)$ with $\sum_{m=1}^{M} \alpha_m = 0$. Thus the α's only reflect the shape of the baseline hazard, while the level is captured in β_0, the intercept in the regression.

A well known issue in duration models is that neglecting unobserved heterogeneity in proportional hazards models leads to spurious negative duration dependence. In principle it is possible to allow for possible unobserved heterogeneity in our model through a multiplicative random error term in the hazard, $\lambda(t|x, v) = v\lambda_0(t; \alpha)e^{\beta' x_i(t)}$. Murphy (1996) shows how to include Gamma-distributed unobserved heterogeneity into the stock-sampled proportional hazards model. The adjustment to a possible upper bound on the duration is rather straightforward, as is the use of a discrete unobserved heterogeneity distribution. We attempted to fit models with a gamma or with a discrete unobserved heterogeneity distribution. However, none of these models have led to an indication of unobserved heterogeneity or a change in the parameters and, therefore, we do not present the details of the models with unobserved heterogeneity.

2.2 Decomposition of the difference in expected duration

Since we want to find out whether transition skills affect the differences in expected durations, we use a decomposition method. The standard wage decomposition methodology of Oaxaca (1973) and Blinder (1973) has been widely used to examine discrimination in the labor market. The technique decomposes the average difference in wages between two demographic groups into differences in observable characteristics (differences that the variables in the regression model can explain, mainly endowments), and differences in coefficient estimates (the structure of the model that cannot be explained).

Suppose we distinguish two groups $g = 1, 2$ and observe for each group $i = 1, \ldots, N_g$ individuals. Consider the following linear regression model, which is estimated separately for each group

$$Y_{ig} = X_{ig}\beta_g + \epsilon_{ig} \tag{3}$$

For such a linear model, the standard Oaxaca-Blinder decomposition of the average value of the dependent variable is

$$\bar{Y}_1 - \bar{Y}_2 = (\bar{X}_1 - \bar{X}_2)\hat{\beta}_1 + \bar{X}_2(\hat{\beta}_1 - \hat{\beta}_2) \tag{4}$$

where $\bar{Y}_g = N_g^{-1} \sum_{i=1}^{N_g} Y_{ig}$ and $\bar{X}_g = N_g^{-1} \sum_{i=1}^{N_g} X_{ig}$. The first term on the right-hand side of (4) represents the difference in the outcome variable between the groups due to differences in observable characteristics and the second term represents the differential due to differences in coefficient estimates. The second term also captures the portion of the differential due to group differences in unobserved characteristics.

However, in most models for duration outcomes the expectation is a non-linear function of the coefficients β and ancillary parameters α reflecting the shape of the baseline hazard. Additionally, duration data are usually censored and OLS estimation leads to biased estimation of the parameter vector and hence to misleading results of the decomposition. We follow Fairlie (2005) for the decomposition of the non-linear difference in expected duration. Let $E(X_i, \alpha, \beta)$ denote the expected duration for the individual with characteristics X_i given the coefficient vector β and the shape parameters of the baseline hazard α. Then the decomposition of the non-linear difference in expected duration $\bar{Y}_1 - \bar{Y}_2$ can be written as

$$\begin{aligned} D^1 &= \left[\sum_{i=1}^{N_1} \frac{E(X_{i1}, \hat{\alpha}_1, \hat{\beta}_1)}{N_1} - \sum_{i=1}^{N_2} \frac{E(X_{i2}, \hat{\alpha}_1, \hat{\beta}_1)}{N_2}\right] \\ &\quad + \left[\sum_{i=1}^{N_2} \frac{E(X_{i2}, \hat{\alpha}_1, \hat{\beta}_1)}{N_2} - \sum_{i=1}^{N_2} \frac{E(X_{i2}, \hat{\alpha}_2, \hat{\beta}_1)}{N_2}\right] \\ &\quad + \left[\sum_{i=1}^{N_2} \frac{E(X_{i2}, \hat{\alpha}_2, \hat{\beta}_1)}{N_2} - \sum_{i=1}^{N_2} \frac{E(X_{i2}, \hat{\alpha}_2, \hat{\beta}_2)}{N_2}\right] \end{aligned} \tag{5}$$

The first term in brackets on the right-hand side reflects the contribution of the observed characteristics, the second term in brackets reflects the contribution of the baseline hazard and the last term in brackets reflects the contribution of the coefficients to the difference in expected duration. Note that the decomposition also depends on the shape parameter(s), α. Consequently, there are three other equivalent possible decompositions of the difference in expected duration between the two groups on which α_g is used in the counterfactual parts of the decomposition equation (see Appendix A).

The alternative methods of calculating the decomposition provide different estimates, which is the familiar index problem with the Oaxaca-Blinder decomposition. Ham et al. (1998) suggest to average over the alternative decompositions to estimate the contribution of the coefficient estimates and of the coefficients. They did not consider the difference in the baseline hazard. Thus including the ancillary parameters, we propose to measure the contribution of the differences in the duration between the groups due to differences in observable characteristics in a similar way (see Appendix A).

Note that the three components add to the difference in mean. However, this holds only for uncensored data. For censored data (and also for stock-sampled data) the average observed duration is not equal to the true underlying expected duration. Therefore, we decompose the expected durations implied by the proportional hazards model in section 2.1, instead of the observed mean durations. By doing this, we are able to find out whether there is room for the explanatory variable *transition skills* in addition to the observed characteristics in the model.

Many articles only report the size of each of the components of the difference in the mean between the two groups. Without knowing the significance of these components, this is of little value. However, for our nonlinear decomposition method (and because it is an average of four alternative decompositions) it is very hard to calculate the exact variance. We therefore rely on a bootstrap method to calculate the approximate variances of each of the components (see Appendix A).

3 Differences in exclusionary risks

In this section we attempt to establish whether the contemporary flexible labor market in the Netherlands implies higher risks of 'exclusionary' transitions for immigrants than for Dutch natives, and if so, why. We will subsequently focus on three transition types: from unemployment, domestic care and prolonged illness (disability to work) to paid work.

3.1 From unemployment to work

The unemployment rate among immigrant groups 'officially' registered by the Employment Office is four to five times higher than among Dutch natives, with the most disadvantageous figures for the Mediterraneans.[7] These differences in employment rate are reflected in data on

[7]The 'registered' unemployment figures are: Dutch natives 2%, Surinamese: 7%, Antilleans 8%, Moroccans 9% and Turks 10%. (source: SPVA-2002 and survey Labor Force 2002)

the unemployment duration. Looking at the 'registered' unemployment again, we find that the Turks have, on average, the longest duration, followed by (in this order) Antilleans, Moroccans and Surinamese.

As stated before, the described data on the unemployment duration are based on stock sampling which leads to a distortion as a consequence of 'length-biased sampling'.[8] This means that both unemployed from a period with high unemployment and long-term unemployed are overrepresented in the data. We adjust for such overrepresentation by assuming that the national inflow in the unemployment in the past is proportional to the observed characteristics of the unemployed.[9] These inflow figures give the weights $r_1(-e)$ in equation (2). The inclusion of two time-varying covariates, age and presence of young children, deserve additional explanation. The age of the unemployed at the moment of the interview is calculated back to the age at the moment their unemployment spell begun. The presence of young children (under twelve) in the household is also calculated back through the information on the age of all the children now present in the household.

For this stock based sample of unemployment durations (in months) we apply a proportional hazards model with a piecewise constant baseline hazard on six intervals: 0 to 2 months; 2 to 6 months; 6 months to 1 year; 1 to 2 years; 2 to 5 years and 5 years or over.[10] The estimation results are given in Table 6 in Appendix B. From the parameters of the piecewise constant baseline hazard we can estimate the implied baseline survival functions for each ethnic group. This is the survival function for the reference individual, an individual with all covariates at zero, that is a single male aged 35, with primary education, good health, and with no children under 12 years of age at home. This baseline survival function (taking the changing age into account) is depicted for each ethnic group in Figure 1. We see that a native reference individual leaves unemployment the fastest and a Turkish reference individual the slowest.

[Place Figure 1 here]

[8] Another problem with stock-sampled data is that we do not observe one single transition, hence we can only identify the transition rate out of unemployment. However, from national figure from Statistics Netherlands, `http://statline.cbs.nl/`, we know that in 2004-2005 87% of the transition out of unemployment was into employment (excluding retirement), and 11% into disability. Thus, most of the unemployed make a transition to work.

[9] See UWV, `http://www.uwv.nl/overuwv/kennis-publicaties/index.aspx` (only in Dutch)

[10] Due to limited observations in particular in duration intervals for some ethnic groups we had to combine the baseline intervals for those groups.

The impact of observed characteristics on the outflow into employment differs substantially among the ethnic groups. We see from Table 6 (in Appendix B) that the education level plays an important role. High educated individuals leave unemployment faster than low educated individuals. Married Turks and Moroccans have a higher reemployment rate. The presence of young children reduces the reemployment rate. Surinamese and Antillean women have a slower departure from unemployment. For Turks health problems lead to lower reemployment rate.

To measure the possible effect of the unobserved transition skills on the exclusionary risks, we applied the decomposition method explained in section 2.2. For each immigrant group we calculate the expected unemployment duration implied by parameter estimates and compare it with the expected duration of Dutch natives. The decomposition allows us to calculate the portion of the difference that arises from differences in coefficients, the portion of the difference that arises from differences in the baseline hazard (different survival rates for the reference individual) and the portion of the difference that arises from differences in explanatory variables.

Table 2: Decomposition of differences in expected UNEMPLOYMENT duration (in months)

	Turks	Moroccans	Surinamese	Antilleans
Expected duration immigrant group	38.2	40.0	24.9	19.3
immigrant group - natives (4.5)	33.6**	35.5**	19.5**	14.8**
	(6.7)	(8.0)	(5.5)	(6.0)
Difference due to:				
Explanatory variables	9.0**	11.6**	3.8**	5.0**
	(2.4)	(2.8)	(1.6)	(2.1)
Coefficients	17.3*	15.8	8.0	1.8
	(8.3)	(8.8)	(8.3)	(6.3)
Baseline hazard	7.3	8.1	7.6	7.9
	(6.0)	(6.2)	(7.0)	(5.1)

Notes: Standard errors are shown in parentheses. $^{*}p < 0.05$;$^{**}p < 0.01$. *Source:* SPVA (ISEO/SCP)

The results in Table 2 show that Turks and Moroccans have by far the longest expected unemployment duration (more three years) and Dutch natives by far the shortest (about 5 months). The difference in the expected unemployment duration is mainly attributable to the fact that the variables in our model turn out to be unfavorable for the job chances of Turks and Moroccans. The difference in coefficients only for Turks leads to a significant difference in the expected unemployment duration. The difference in the baseline duration dependence does not have a significant impact on the difference in expected unemployment duration. These findings imply that the observed human capital characteristics and demographic characteristics seem more important than the unobserved transition skills when explaining differences in exclusionary risks among the unemployed.

3.2 From domestic care to work

Since domestic care is still predominantly a female activity, even in 'modern' Western societies (Hofmeister et al. 2003), we focus on women in this section. Looking at the labor market participation in 2002, we find the highest rates among Surinamese females (64%), followed by Antillean and native Dutch females (59%). A large gap exists with Mediterranean females: 32% labor market participation among Turkish women and 30% among Moroccan women.

When estimating the hazard rates for the time spent in domestic care (in years), we again use the model with maximum duration for stock-sampled data that accounts for varying entry.[11] Women often stay at home for a long period. Thus the domestic care duration can easily be of 20 years. This implies that many women do not participate in the labor market until their retirement age. The upper bound on the duration therefore has an important impact on the estimation results. The participation rate of women in the Netherlands increased only recently. In the late 70s less than 20% of the women were participating in the labor market. This implies an overrepresentation of women who began their domestic care in the 70s or earlier. We adjust for this overrepresentation by assuming that the national inflow in domestic care in the past is proportional to the number of non-participating women 20 years of age.[12] We also assume that this inflow is proportional to the observed characteristics of the women.

We estimate a proportional hazards model with a piecewise constant baseline hazard on five intervals: 0 till 10 years; 10 till 15 years; 15 till 20 years; 20 till 25 years and 25 years and beyond.[13] The estimation results are given in Table 7 in Appendix B. Again, the parameters

[11] For the time spent in domestic care we are also not sure that these women get employed, see footnote 8. They might get unemployed first. De Koning et al. (2005) find for Dutch panel data that 95% of the women left the non-participation state for employment.

[12] See the public statistics site of Statistics Netherlands, `http://statline.cbs.nl/` for the numbers.

[13] See note 10.

estimates differ among the ethnic groups. We estimate the implied survival rate for the reference female, that is a single female, aged 45, with no employment experience, with primary education, with no children under 12 years of age living at home. This baseline survival function (taking the changing age into account) is depicted for each ethnic group in Figure 2. A Dutch native (reference) female in domestic care has the slowest outflow till age 60, from age 60 an Antillean female has the slowest outflow, while a Moroccan female has the fastest. Note the drop to zero in the baseline survival functions after 20 years in domestic care, when the retirement age of 65 is reached.

[**Place Figure 2 here**]

The impact of observed characteristics on the reemployment rate out of domestic care differs substantially among the ethnic groups. Table 7 shows that previous employment experience has a large impact on the outflow from domestic care for Turkish, Surinamese and Antillean women. Education is also an important factor in explaining the outflow. Non-native women without education leave much slower. For Moroccan women the effect of the presence of children is very pronounced, leading to a virtual stop of the outflow. Marital status is important for Turkish and Moroccan women. Within both groups, married/cohabiting women leave domestic care faster. To find out to what extent transition skills may affect the expected duration of domestic care, we apply the decomposition method explained in section 2.2.

The results in Table 3 show that Moroccan women have the longest expected domestic care duration (33 years) and native women the shortest (13 years). The difference in the expected domestic care duration for Moroccan women is attributable to the fact that the variables in our model are unfavorable for their chances to leave domestic care. These variables are also disadvantageous for Turkish women, and to a lesser extent, for Surinamese and Antillean women. Neither the differences in coefficients nor the differences in the shape of the baseline hazard leads to significant differences in the expected domestic care duration. Thus, the difference in unobserved transition skills does not seem to be important for explaining the difference in exclusionary risks among the women in domestic care.

3.3 From prolonged illness to work

The last transition type to be discussed here is between prolonged illness and paid work. Disability to work is a clear social and economic problem in the Netherlands. That is why we

Table 3: Decomposition of differences in expected DOMESTIC CARE duration (in years)

	Turks	Moroccans	Surinamese	Antilleans
Expected duration immigrant group	27.8	33.0	14.3	20.1
immigrant group - natives (12.8)	15.0**	20.2**	1.5	7.3
	(2.9)	(4.8)	(3.7)	(4.1)
Difference due to:				
Explanatory variables	9.7**	10.3**	6.7**	7.3**
	(2.4)	(5.0)	(1.9)	(2.5)
Coefficients	5.2	10.7	−5.0	2.8
	(6.0)	(5.5)	(7.6)	(8.3)
Baseline hazard	0.1	−0.8	−0.3	−2.8
	(3.5)	(1.7)	(7.5)	(6.2)

Notes: Standard errors are shown in parentheses. $^{*}p < 0.05$;$^{**}p < 0.01$. *Source:* SPVA (ISEO/SCP)

focus on this form of prolonged illness. The SPVA-2002 contains data on self-reported disability to work and on receiving a disability allowance. Combining these two variables, we find highly varying proportions of disabled persons per ethnic group, as shown in Table 4.

Table 4: Percentage disabled persons in the total population (15-65 years) and in the labor force by ethnic group

	Turks		Moroccans		Surinamese		Antilleans		Dutch	
	M	F	M	F	M	F	M	F	M	F
Total Population	11	8	11	4	5	7	4	4	9	8
Labor force	17	25	17	12	7	11	5	6	12	14

Source: SPVA (ISEO/SCP)

Looking at the total population (15-65 years of age), we find the proportion of disabled persons to be the highest among Mediterranean males, followed by native Dutch males. The proportion of disabled persons among Caribbean males is much lower. Among females, the Turks and the Dutch natives show the highest proportion of disabled persons, followed by the Surinamese. The proportion is low among Moroccan and Antillean women. The proportion of disabled persons in the labor force (those working for at least 12 hours per week or actively looking for work for at least 12 hours per week) is the highest among Turkish females (25%). This is the result of a combination of relatively many disabled persons and a relatively small labor force. Mediterranean males also show a high proportion of disabled persons in the labor force (17%), followed at some distance by the native Dutch males (12%). A much lower proportion is found among the Antilleans, males and females alike.

Again we estimate the hazard rate for the transition from disability to work (in years).[14] To this end, we apply the model described in section 2.1. Since the duration on disability benefits can exceed 20 years, the maximum duration implied by the retirement age also plays an important role in the analysis of the return to work after disability. Because the inflow into disability has changed over time, we use the national inflow figures to adjust for the changing inflow in the past.[15] We assume a piecewise constant baseline hazard on three intervals: aged 0 to 10 years; 10 to 20 years and 20 years and over.[16] The estimated survival functions for the reference individual, a single forty-eight year old male with primary education, are depicted in Figure 3. Note the drop to zero in the baseline survival functions after 17 years in disability, when the retirement age of 65 is reached. An Antillean (reference) individual in disability has the fastest outflow into employment. Turks and Moroccans have a very low rate of leaving disability.

[**Place Figure 3 here**]

The estimation results in Table 8 (in Appendix B) indicate that the impact of observed characteristics on the reemployment rate differs substantially among the ethnic groups. Gender is important for Turks and Moroccans. For both groups a disabled woman returns to work faster than a disabled man. Married Surinamese have a higher reemployment rate. Due to limited observations we could not include marital status in the model for Antilleans and the low education categories in the model for natives. The education level of the individuals has a large impact on the chance to leave disability.

[14] In our stock-sampled data we also do not observe any transition for the people in disability, see footnote 8. From national figures from Statistics Netherlands we know that in 2004-2005 73% of the transition out of disability was into employment (excluding retirement), while 26% became unemployed. Thus, a substantial share of the disabled do make a direct transition to work.

[15] See note 9

[16] See note 10.

Table 5: Decomposition of differences in expected DISABILITY duration (in years)

	Turks	Moroccans	Surinamese	Antilleans
Expected duration immigrant group	12.3	14.6	12.7	8.5
immigrant group - natives (16.7)	-4.3	-2.0	-3.9	-8.1
	(3.7)	(3.7)	(3.8)	(4.2)
Difference due to:				
Explanatory variables	4.8**	3.7**	3.0**	1.9**
	(1.1)	(1.6)	(0.9)	(0.8)
Coefficients	-9.4	-6.6	-6.4	-7.4
	(5.2)	(4.7)	(4.9)	(5.0)
Baseline hazard	0.3	0.9	-0.5	−2.6
	(2.6)	(1.9)	(2.7)	(3.3)

Notes: Standard errors are shown in parentheses. $^{*}p < 0.05$;$^{**}p < 0.01$. *Source:* SPVA (ISEO/SCP)

We apply the decomposition method to reveal the possible effect of transition skills on the expected disability duration. The results in Table 5 show that Dutch natives have the longest expected disability duration (17 years) and Antilleans the shortest (9 years). This is a surprisingly short period when compared to the expected disability duration of Dutch natives. For Turks, Moroccans and Surinamese the high expected disability durations are attributable to unfavorable observed characteristics, which leaves hardly any room for an explanation from transition skills.

4 Summary and conclusions

Contemporary labor markets are characterized by such a high degree of flexibility that a new type of labor market is emerging. This market features a large number of transitions during the working career. The so-called transitional labor market offers new chances to both employers and employees, but at the same time increases the risk of long-term exclusion for the latter. The Netherlands offers a good example of a transitional labor market with institutional arrangements to mitigate the risk of exclusionary transitions.

We investigated whether the contemporary flexible labor market in the Netherlands implies higher risks of such transitions for groups which, for human capital reasons, are already vulnerable in the labor market. We added the criterion of restricted transition skills to select the groups under study. This led us to compare immigrants to Dutch natives. We subsequently focused on the transitions from (a) unemployment, (b) domestic care, and (c) prolonged illness to work. We applied a duration analysis to estimate the chance of a transition from inactivity to work for each group.

For the duration analysis we used proportional hazards models with maximum duration for stock-sampled data that account for varying entry. We assumed a piecewise constant baseline hazard on different intervals (calculated in months for unemployment and in years for both domestic care and prolonged illness). Looking at the baseline survival function, we find that in the case of unemployment the native Dutch reference individual leaves unemployment the fastest, while Turks leave unemployment the slowest. The analysis of the departure from domestic care, which is restricted to women, establishes that among the reference women Moroccans clearly have the fastest outflow, while the Antilleans and Turks, Dutch native women till the age of 60, have the slowest outflow. In the case of leaving disability, the departure is the fastest for the Antillean reference individual. More generally, Moroccans diverge remarkably from all other groups that show very low outflows, especially in the first ten years of disability. However, Moroccan women with young children, more than half of those women, have a virtually zero departure rate from domestic rate.

Our analyses thus show that unequal exclusionary risks exist, but to a different degree for the various groups and with variations per transition type. Turks and Moroccans have the longest expected unemployment duration. Among the Moroccans and the Turks, women also have the longest expected home care duration. Native Dutch furthermore have the longest disability duration. While the expected unemployment duration among Antilleans is longer than among Dutch natives, their expected disability duration is the shortest. Surinamese and Antilleans have similar expected durations for unemployment and domestic care (among women), which are both longer than the respective expected durations for Dutch natives.

To find out whether transition skills really affect the transition chances, we used decomposition analyses on the expected durations estimated by the proportional hazards model. In the case of unemployment, we first established that the impact of the observed characteristics on the outflow differs among the various groups. We then showed that the higher exclusionary risks for the Turks and Moroccans are mainly attributable to their unfavorable observed characteristics. These characteristics concern both endowments and demographic features, such as marital status, gender and age.

In the case of domestic care, we again found fairly large differences in the impact of the observed characteristics on the exclusionary risks of the immigrant groups. The decomposition of the expected home care durations shows that the observed characteristics are particularly unfavorable for Moroccan and Turkish women.

In the case of disability to work, the impact of the observed characteristics differs as well among the various groups. The low outflow of Turks, Moroccans and Surinamese seems to be primarily related to the observed characteristics. The coefficients do not add significantly to the explanation, although recent research shows that miscommunication between immigrant clients on the one hand, and civil servants from the agency responsible for the disability benefits on the other hand, helps to explain the disadvantaged outflow chances of the first (Veenman 2006).

The short discussion of the results from the decomposition analyses shows that transition skills are not dominant in the explanation of exclusionary risks. Human capital characteristics and demographic features turn out to be far more important. On the basis of our analyses it seems that the transitional labor markets do not pose new problems to those groups who already had a vulnerable labor market position. One condition may be added to this condition. If transitional skills are related to education, which is not an odd assumption, the actual meaning of these skills could be 'hidden' in the significance of education that we established.

Generally speaking, our analyses show that duration analyses combined with decomposition analyses reveal a lot about exclusionary risks. They are however not conclusive with respect to the explanatory variables. That is why we plead for more labor market research, preferably using panel data. This is probably a far more superior method in trying to achieve a real comprehension of exclusionary labor market processes.

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A Decomposition

Let $E(X_i, \alpha, \beta)$ denote the expected duration for the individual with characteristics X_i given the coefficient vector β and the shape parameters of the baseline hazard α. Then the decomposition of the non-linear difference in expected duration $\bar{Y}_1 - \bar{Y}_2$ can be obtained in the following four equivalent ways

$$\begin{aligned}
D^1 &= D\big(X_1, 1, 1, X_2, 1, 1\big) + D\big(X_2, 1, 1, X_2, 2, 1\big) + D\big(X_2, 2, 1, X_2, 2, 2\big) \\
D^2 &= D\big(X_1, 1, 1, X_2, 1, 1\big) + D\big(X_2, 1, 2, X_2, 2, 2\big) + D\big(X_2, 1, 1, X_2, 1, 2\big) \\
D^3 &= D\big(X_1, 2, 2, X_2, 2, 2\big) + D\big(X_1, 1, 1, X_1, 2, 1\big) + D\big(X_1, 2, 1, X_1, 2, 2\big) \\
D^4 &= D\big(X_1, 2, 2, X_2, 2, 2\big) + D\big(X_1, 1, 2, X_1, 2, 2\big) + D\big(X_1, 1, 1, X_1, 1, 2\big)
\end{aligned}$$

where

$$D\big(X_m, a^1, b^1, X_n, a^2, b^2\big) = \sum_{i=1}^{N_m} \frac{\mathrm{E}(X_{im}, \hat{\alpha}_{a^1}, \hat{\beta}_{b^1})}{N_m} - \sum_{i=1}^{N_n} \frac{\mathrm{E}(X_{in}, \hat{\alpha}_{a^2}, \hat{\beta}_{b^2})}{N_n}$$

Note that D^1 is the decomposition in (5). The alternative methods of calculating the decomposition provide different estimates, which is the familiar index problem with the Oaxaca-Blinder decomposition. Ham et al. (1998) suggest to average over the alternative decompositions to estimate the contribution of the coefficient estimates and of the coefficients. They did not consider the difference in the baseline hazard. Thus including the ancillary parameters, we propose to measure the contribution of the difference in the duration between the groups due to differences in observable characteristics by

$$D(X) = \frac{1}{2} \sum_{k=1}^{2} D\big(X_1, k, k, X_2, k, k\big) \tag{A.1}$$

The contribution of the coefficient estimates to the differential is measured by

$$D(\beta) = \frac{1}{4} \sum_{g=1}^{2} \Big[D\big(X_g, 2, 1, X_g, 2, 2\big) + D\big(X_g, 1, 1, X_g, 1, 2\big) \Big] \tag{A.2}$$

The contribution of the baseline hazard to the differential is measured by

$$D(\alpha) = \frac{1}{4} \sum_{g=1}^{2} \Big[D\big(X_g, 1, 2, X_g, 2, 2\big) + D\big(X_g, 1, 1, X_g, 2, 1\big) \Big] \tag{A.3}$$

Note that $D(X) + D(\beta) + D(\alpha) = D\big(X_1, 1, 1, X_2, 2, 2\big) = \bar{Y}_1 - \bar{Y}_2$, as should be.

In principle the standard errors could be approximated using the delta method, see Oaxaca and Ransom (1998) and Fairlie (2005). We choose to approximate the standard errors by a bootstrap method. For each transition type we sample with replacement from each ethnic group the same number of observations as in the true sample. We then estimate for each ethnic group the duration model described in Section 2.1. Based on the sampled observations and the parameter estimates for that sample we estimate the decompositions. With each decomposition we repeat this 100 times. The bootstrap standard errors are the standard errors of these 100 decompositions.

A.1 A note on identification of the decomposition

It is well known that the standard Oaxaca-Blinder decomposition cannot separate out the contribution of the constant term in the presence of dummy variables, see Jones (1983) and Oaxaca and Ransom (1999). A first glance we face the same problem when separating out the contribution of the shape of the baseline hazard in the presence of dummy variables. However, for the decomposition of the, non-linear, expected duration in a proportional hazard model with a piecewise constant baseline hazard we can distinguish between the contibution of the coefficients and the shape of the baseline hazard.[17] An example will illustrate this.

Consider a proportional hazard model with one variable X and a piecewise constant baseline hazard on three intervals,

$$\lambda_0(t) = \begin{cases} e^{\beta_0+\alpha_a} & t < t_a \\ e^{\beta_0+\alpha_b} & t_a \leq t < t_b \\ e^{\beta_0+\alpha_c} & t \geq t_b \end{cases}$$

with $\sum_{m=1}^{3} \alpha_m = 0$. Then the expected duration (obtained by maximum likelihood estimation)

[17] In fact this holds for any baseline hazard with separate shape parameter(s), like the Weibull model.

for group g is

$$
\begin{aligned}
\bar{Y}_g &= \frac{1}{N_g}\sum_{i=1}^{N_g} \mathrm{E}\Big(X_{ig}, \hat{\alpha}_g, \hat{\beta}_g\Big) \\
&= \frac{1}{N_g}\sum_{i=1}^{N_g} \Big\{ e^{-\beta_{0g}-\hat{\alpha}_{ag}-\hat{\beta}_{1g}X_{ig}} \Big[1-\exp\Big(-e^{\hat{\beta}_{0g}+\hat{\alpha}_{ag}+\hat{\beta}_{1g}X_{ig}} t_a\Big)\Big] \\
&\quad + e^{-\hat{\beta}_{0g}-\hat{\alpha}_{bg}-\hat{\beta}_{1g}X_{ig}} \exp\Big(-e^{\hat{\beta}_{0g}+\hat{\alpha}_{ag}+\hat{\beta}_{1g}X_{ig}} t_a\Big)\Big[1-\exp\Big(-e^{\hat{\beta}_{0g}+\hat{\alpha}_{bg}+\hat{\beta}_{1g}X_{ig}}(t_b-t_a)\Big)\Big] \\
&\quad + e^{-\hat{\beta}_{0g}-\hat{\alpha}_{cg}-\hat{\beta}_{1g}X_{ig}} \exp\Big(-e^{\hat{\beta}_{0g}+\hat{\alpha}_{ag}+\hat{\beta}_{1g}X_{ig}} t_a - e^{\hat{\beta}_{0g}+\hat{\alpha}_{bg}+\hat{\beta}_{1g}X_{ig}}(t_b-t_a)\Big)\Big\}
\end{aligned}
\tag{A.4}
$$

The resulting decomposition is given by $\bar{Y}_1 - \bar{Y}_2 = D(X) + D(\beta) + D(\alpha)$ with

$$
\begin{aligned}
D(X) &= \frac{1}{2}\Bigg[\frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_1,\hat{\beta}_1\Big) - \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_1,\hat{\beta}_1\Big) \\
&\quad + \frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_2,\hat{\beta}_2\Big) - \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_2,\hat{\beta}_2\Big)\Bigg]
\end{aligned}
\tag{A.5}
$$

$$
\begin{aligned}
D(\beta) &= \frac{1}{4}\Bigg[\frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_1,\hat{\beta}_1\Big) - \frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_1,\hat{\beta}_2\Big) \\
&\quad + \frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_2,\hat{\beta}_1\Big) - \frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_2,\hat{\beta}_2\Big) \\
&\quad + \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_1,\hat{\beta}_1\Big) - \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_1,\hat{\beta}_2\Big) \\
&\quad + \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_2,\hat{\beta}_1\Big) - \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_2,\hat{\beta}_2\Big)\Bigg]
\end{aligned}
\tag{A.6}
$$

$$
\begin{aligned}
D(\alpha) &= \frac{1}{4}\Bigg[\frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_1,\hat{\beta}_1\Big) - \frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_2,\hat{\beta}_1\Big) \\
&\quad + \frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_1,\hat{\beta}_2\Big) - \frac{1}{N_1}\sum_{i=1}^{N_1}\mathrm{E}\Big(X_{i1},\hat{\alpha}_2,\hat{\beta}_2\Big) \\
&\quad + \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_1,\hat{\beta}_1\Big) - \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_2,\hat{\beta}_1\Big) \\
&\quad + \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_1,\hat{\beta}_2\Big) - \frac{1}{N_2}\sum_{i=1}^{N_2}\mathrm{E}\Big(X_{i2},\hat{\alpha}_2,\hat{\beta}_2\Big)\Bigg]
\end{aligned}
\tag{A.7}
$$

Now consider a simple transformation of X given by $\tilde{X} = \theta X + \gamma$. Then the expected duration (obtained by maximum likelihood estimation) for group g is

$$
\begin{aligned}
\bar{Y}_g &= \frac{1}{N_g}\sum_{i=1}^{N_g} \mathrm{E}\Big(\tilde{X}_{ig}, \tilde{\alpha}_g, \tilde{\beta}_g\Big) \\
&= \frac{1}{N_g}\sum_{i=1}^{N_g}\Big\{ e^{-\tilde{\beta}_{0g}-\tilde{\alpha}_{ag}-\tilde{\beta}_{1g}\tilde{X}_{ig}}\Big[1-\exp\Big(-e^{\tilde{\beta}_{0g}+\tilde{\alpha}_{ag}+\tilde{\beta}_{1g}\tilde{X}_{ig}}t_a\Big)\Big] \\
&\quad + e^{-\tilde{\beta}_{0g}-\tilde{\alpha}_{bg}-\tilde{\beta}_{1g}\tilde{X}_{ig}}\exp\Big(-e^{\tilde{\beta}_{0g}+\tilde{\alpha}_{ag}+\tilde{\beta}_{1g}\tilde{X}_{ig}}t_a\Big)\Big[1-\exp\Big(-e^{\tilde{\beta}_{0g}+\tilde{\alpha}_{bg}+\tilde{\beta}_{1g}\tilde{X}_{ig}}(t_b-t_a)\Big)\Big] \\
&\quad + e^{-\tilde{\beta}_{0g}-\tilde{\alpha}_{cg}-\tilde{\beta}_{1g}\tilde{X}_{ig}}\exp\Big(-e^{\tilde{\beta}_{0g}+\tilde{\alpha}_{ag}+\tilde{\beta}_{1g}\tilde{X}_{ig}}t_a - e^{\tilde{\beta}_{0g}+\tilde{\alpha}_{bg}+\tilde{\beta}_{1g}\tilde{X}_{ig}}(t_b-t_a)\Big)\Big\} \qquad \text{(A.8)}
\end{aligned}
$$

with $\tilde{\beta}_{1g} = \hat{\beta}_{1g}/\theta$, $\tilde{\beta}_{0g} = \hat{\beta}_{0g} - \frac{\gamma}{\theta}\hat{\beta}_{1g}$ and $\tilde{\alpha}_{mg} = \hat{\alpha}_{mg}$ for $m = 1, 2, 3$. It is straightforward to show that, because

$$\tilde{\beta}_{0g} + \tilde{\beta}_{1g}\tilde{X}_{ik} = \hat{\beta}_{0g} + \hat{\beta}_{1g}X_{ik} \qquad \text{for } k = 1, \ldots, 3$$

none of the expected durations in (A.5), (A.6) or (A.7) change. Thus, the decomposition is invariant to affine transformations. Note that a change of the reference category of a dummy variable in included in the transformation when $\theta = -1$ and $\gamma = 1$.

B Estimation results

Table 6: Parameter estimates of hazard model with maximum duration for time in UNEMPLOYMENT (in months)

	Turks	Moroccans	Surinamese	Antilleans	Natives
Regression coefficients					
Female	0.063	0.067	−0.155*	−0.336**	−0.085
	(0.080)	(0.101)	(0.078)	(0.099)	(0.104)
Married/Cohabiting	0.286**	0.207	0.345**	0.187	0.041
	(0.099)	(0.107)	(0.106)	(0.136)	(0.106)
No education	−0.591**	−0.409**	−0.332*	−0.207	−0.041
	(0.114)	(0.114)	(0.131)	(0.141)	(0.303)
Basic education	−0.292**	−0.110	0.148	−0.159	−0.041
	(0.113)	(0.142)	(0.137)	(0.160)	(0.303)
Low Secondary educ.	−0.033	0.466**	0.317*	0.095	0.099
	(0.135)	(0.179)	(0.125)	(0.164)	(0.184)
High Secondary educ.	0.161	0.557**	0.233*	0.158	0.264
	(0.148)	(0.168)	(0.115)	(0.144)	(0.168)
High education	0.161	0.557**	0.233*	0.158	0.531**
	(0.148)	(0.168)	(0.115)	(0.144)	(0.185)
bad health	−0.359**	−0.215	−0.141	−0.028	0.072
	(0.117)	(0.120)	(0.129)	(0.158)	(0.130)
age[a]	−0.016	−0.008	−0.035	0.062	−0.001
	(0.057)	(0.072)	(0.049)	(0.062)	(0.070)
age-squared	−0.095*	−0.238**	−0.021	−0.049	−0.008
	(0.044)	(0.060)	(0.039)	(0.047)	(0.051)
Children (< 12)	−0.646**	−0.649**	−0.713**	−0.216	−0.042
	(0.146)	(0.164)	(0.157)	(0.147)	(0.140)
Constant	−3.053**	−2.833**	−3.138**	−2.808**	−2.739**
	(0.199)	(0.141)	(0.158)	(0.134)	(0.186)
duration dependence[b]					
α_1 (0 to 2 months)	0.331	0.614	0.558	1.216**	2.477**
	(0.616)	(0.441)	(0.407)	(0.257)	(0.284)
α_2 (2 to 6 months)	0.331	0.614	0.558	1.216**	0.801
	(0.616)	(0.441)	(0.407)	(0.257)	(0.600)
α_3 (6 month to 1 year)	0.423	0.737*	0.686**	0.201	−0.788
	(0.321)	(0.372)	(0.243)	(0.288)	(0.582)
α_4 (1 to 2 years)	0.423	−0.699**	0.686**	0.201	−0.788
	(0.321)	(0.193)	(0.243)	(0.288)	(0.582)
α_5 (2 to 5 years)	−0.211	−0.699**	−0.412	−0.636*	−0.598**
	(0.228)	(0.193)	(0.228)	(0.262)	(0.271)
α_6 (> 5 years)	−0.543**	−0.653**	−0.832**	−0.780**	−1.891**
	(0.205)	(0.137)	(0.172)	(0.133)	(0.193)
Log-likelihood	-3052.5	-2606.8	-1820.3	-1379.0	-666.5
N	575	489	361	271	140

[a] Age is the (time-varying) age at each year of unemployment, starting from the year the individual entered unemployment, centered at the mean age of 35 years.
[b] Some intervals are combined. Turks: 1 and 2, 3 and 4; Moroccans: 1 and 2, 4 and 5; Surinamese: 1, 2 and 3; Antilleans: 1 and 2, 3 and 4; Natives: 3, 4 and 5.
Notes: Standard errors are shown in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$. *Source:* SPVA (ISEO/SCP)

Table 7: Parameter estimates of hazard model with maximum duration for time in DOMESTIC CARE (in years) for women

	Turks	Moroccans	Surinamese	Antilleans	Natives
Regression coefficients					
Employment experience	1.029**	0.324	1.142**	1.688**	0.248
	(0.158)	(0.252)	(0.343)	(0.565)	(0.614)
Married/Cohabiting	0.843**	0.676**	0.407	−0.231	0.262
	(0.141)	(0.176)	(0.208)	(0.231)	(0.552)
No education	−1.215**	−1.526**	−1.530**	−0.571	0.815
	(0.162)	(0.231)	(0.410)	(0.318)	(1.472)
Basic education	−0.423*	−0.077	−0.916**	−0.427	0.815
	(0.173)	(0.265)	(0.356)	(0.307)	(1.472)
Low Secondary educ.	−0.326	−0.686*	0.064	−0.213	−0.021
	(0.239)	(0.300)	(0.269)	(0.242)	(0.531)
High Secondary educ.	0.269	0.195	−0.250	−0.282	0.721
	(0.266)	(0.294)	(0.312)	(0.253)	(0.543)
High education	0.269	0.195	−0.250	−0.073	0.976
	(0.266)	(0.294)	(0.312)	(0.412)	(0.783)
age[a]	−0.773	0.575	0.732**	−0.385	1.972*
	(0.492)	(0.305)	(0.188)	(0.340)	(0.953)
age-squared	−1.119*	−0.879*	0.155	−0.557*	0.781
	(0.449)	(0.385)	(0.161)	(0.232)	(0.587)
Children (< 12)	−1.236**	−12.003**	−0.027	−0.060	0.106
	(0.353)	(2.184)	(0.370)	(0.276)	(1.003)
Constant	−2.419**	−1.566**	−3.243**	−3.003**	−6.027**
	(0.238)	(0.271)	(0.448)	(0.654)	(1.814)
duration dependence[b]					
α_1 (0 to 10 years)	0.029	0.319*	0.162	0.647**	0.115
	(0.101)	(0.153)	(0.154)	(0.148)	(0.241)
α_2 (10 to 15 years)	0.029	0.319*	0.162	−0.647**	0.115
	(0.101)	(0.153)	(0.154)	(0.148)	(0.241)
α_3 (15 to 20 years)	−0.029	0.319*	−0.162	−0.647**	0.115
	(0.101)	(0.153)	(0.154)	(0.148)	(0.241)
α_4 (20 to 25 years)	−0.029	−0.319*	−0.162	−0.647**	0.115
	(0.101)	(0.153)	(0.154)	(0.148)	(0.241)
α_5 (> 25 years)	−0.029	−0.319*	−0.162	−0.647**	−0.115
	(0.101)	(0.153)	(0.154)	(0.148)	(0.241)
Log-likelihood	−4611.0	−4140.0	−1424.0	−992.2	-1145.6
N	1309	1132	419	294	338

[a] Age is the (time-varying) age at each year of domestic care, starting from the year the individual entered domestic care, centered at the mean age of 45 years. [b] Some intervals are combined. Turks: 1–2, 3–5; Moroccans: 1–3, 4–5; Surinamese: 1–2, 3–5; Antilleans: 2–5; Natives: 1–4.
Notes: Standard errors are shown in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$. *Source:* SPVA (ISEO/SCP)

Table 8: Parameter estimates of hazard model with maximum duration for time in DISABILITY (in years)

	Turks	Moroccans	Surinamese	Antilleans	Natives
Regression coefficients					
female	0.680**	1.323**	0.413	0.461	0.839
	(0.222)	(0.420)	(0.295)	(0.341)	(0.663)
Married/Cohabiting	0.346	−0.217	0.656*	–	1.042
	(0.203)	(0.375)	(0.282)		(0.647)
No education	−0.306	0.054	−0.078	−0.650	–
	(0.319)	(0.449)	(0.402)	(0.615)	
Basic education	0.538	1.499*	−0.034	−0.429	–
	(0.340)	(0.591)	(0.428)	(0.519)	
Low Secondary educ.	0.796	−0.194	0.861	−0.291	1.167
	(0.416)	(0.751)	(0.464)	(0.420)	(0.996)
High Secondary educ.	1.179**	0.770	0.904	0.165	1.680*
	(0.450)	(0.767)	(0.480)	(0.328)	(0.840)
High education	1.179**	0.770	0.904	0.165	2.307
	(0.450)	(0.767)	(0.480)	(0.328)	(1.207)
age[a]	0.173	0.188	0.740**	0.359	0.842**
	(0.183)	(0.240)	(0.192)	(0.255)	(0.339)
age-squared	0.007	0.149	0.257	0.327*	0.567**
	(0.129)	(0.165)	(0.180)	(0.147)	(0.222)
Constant	−2.778**	−3.133**	−3.417**	−2.917**	−5.797**
	(0.355)	(0.596)	(0.455)	(0.469)	(1.482)
duration dependence[b]					
α_1 (0 to 10 years)	−0.459*	−0.815**	−0.095	0.469	−0.636
	(0.234)	(0.367)	(0.257)	(0.462)	(0.647)
α_2 (10 to 20 years)	−0.594	−0.740	−0.153	−0.669	0.524
	(0.312)	(0.430)	(0.289)	(0.814)	(0.530)
α_3 (> 20 years)	1.053**	1.555**	0.249	0.201	0.111
	(0.213)	(0.269)	(0.262)	(0.573)	(0.548)
Log-likelihood	-1684.4	-1331.2	-943.2	-364.5	-488.7
N	551	437	307	124	155

[a] Age is the (time-varying) age at each year of disability, starting from the year the individual entered disability, centered at the mean age of 48 years. *Notes:* Standard errors are shown in parentheses. $^{*}p < 0.05$; $^{**}p < 0.01$. *Source:* SPVA (ISEO/SCP)

C Figures

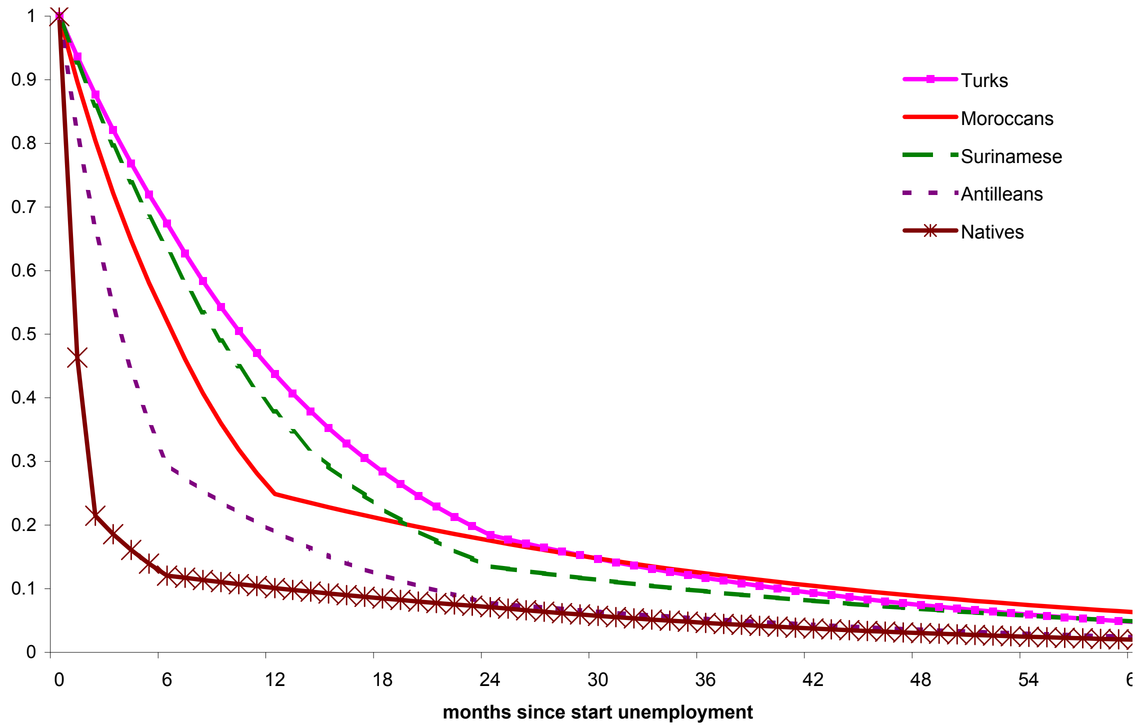

Figure 1: Estimated survival rate in UNEMPLOYMENT for a reference individual.
A reference individual is a single male with primary education, good health, no children and aged 35.

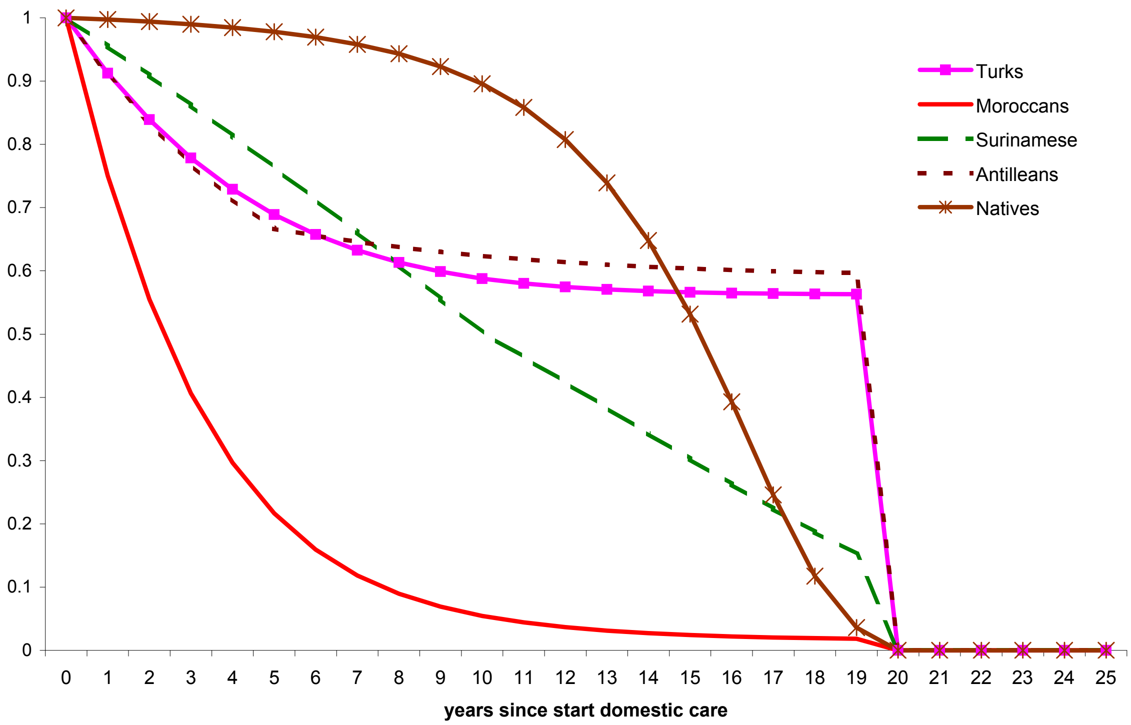

Figure 2: Estimated survival rate in DOMESTIC CARE for a reference female.
A reference female is a single female with primary education, no employment experience, no children and aged 45.

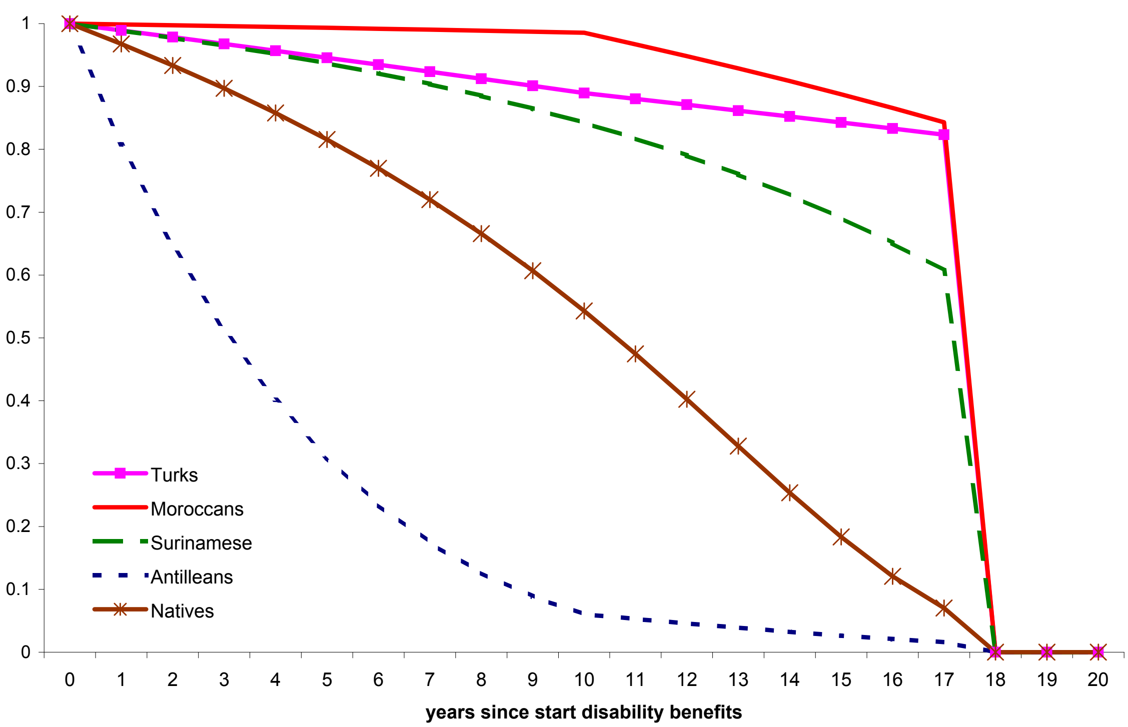

Figure 3: Estimated survival rate in DISABILITY for a reference individual.
A reference individual is a single male with no high education, no children and aged 48.