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* Views expressed are those of the authors and do not necessarily reflect official positions of De Nederlandsche Bank.

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Abstract

Using administrative data between 2006 and 2020, I analyze interregional migration in the Netherlands. In theory, individuals move out of regions with high unemployment rates, but most empirical research does not strongly support this prediction. Likewise, I only find a small effect of regional unemployment on interregional migration. Furthermore, I find that the unemployed are more mobile during the first three months of unemployment. In addition, my results suggest that renters in the private sector are much more mobile than homeowners or renters in the social housing sector. Finally, I find that commuters are much more likely to migrate, despite good infrastructure and relative short distances in The Netherlands.

Keywords: Migration; Regional Labor Markets; Unemployment; Commuting; Duration; Cox; Netherlands
JEL classification: J61; R23

1 Introduction

Geographical mobility is an important economic adjustment mechanism in response to local labor market shocks (Arpaia et al., 2016; Blanchard et al., 1992). Workers move from regions with high unemployment to regions with better job opportunities. Moreover, interregional migration helps reallocating production factors to regions where they are more efficient; migration raises the aggregate employment rate (David et al., 2010) and reduces education-job mismatches.

The level of migration within Europe is lower than in the United States, despite larger variation in unemployment levels across European regions (Bentivogli & Pagano, 1999). Interregional migration in Europe is more important than cross country mobility, since the latter is hampered by language and cultural differences (Broersma & Van Dijk, 2002). Moreover, European labor markets are less flexible than those in the US. In that case, interregional migration is even more important in case of wage rigidity (Arpaia et al., 2016).

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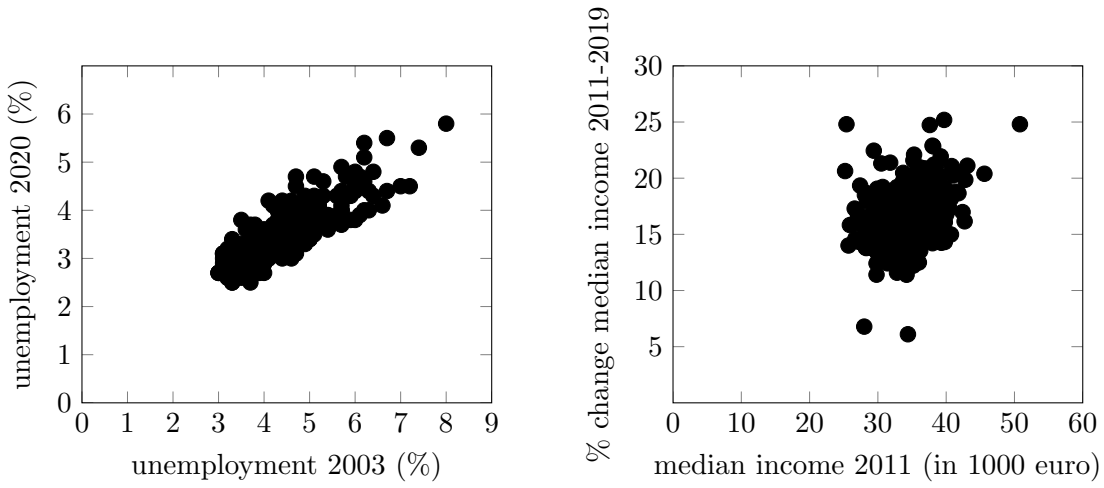
It is interesting to study interregional migration in the Netherlands for a number of reasons. The Dutch labor market is characterized by high participation rates, high labor productivity levels, and low unemployment rates relative to other European countries (Hoeberichts et al., 2021). This indicates a well functioning labor market. At the same time, nominal wage rigidities are widespread in The Netherlands, due to long duration of contracts and the large coverage of collective agreements (Caloia et al., 2021). Therefore, the Netherlands relies even more on interregional migration as an adjustment mechanism. However, labor market indicators in the Netherlands suggest persistence. Figure 1 (left panel) shows that there is a strong correlation between municipal unemployment levels in 2003 and 2020. Figure 1 (right panel) shows that there is little convergence in income levels between municipalities as well. Municipalities with high income levels in 2011 tend to have above median income growth rates between 2011 and 2019.

Figure 1: Persistent income and unemployment differences across municipalities



Source: CBS Statline, own computations. The unemployment rate is the percentage of the labor force without paid work. The unemployed labor force includes all individuals in The Netherlands between 15 and 75 years who do not live in an institution and are available and searching for paid work. Median income is the median of household disposable income (excluding students).

In this paper, I examine interregional migration in the Netherlands. I use the Human Capital Theory (HCT) to select potential determinants of interregional migration: the regional unemployment rate, the duration of individual unemployment, commuting distance, and housing tenure (Section 2). Individuals might also move for non-economic reasons; this is beyond the scope of this paper[1].

[1]For example, Smits (2010) shows that parents of young children move near their own parents after a recent divorce, Van Ham and Clark (2009) find that the composition of the neighbourhood population and housing stock drive migration to another neighbourhood, and Bijker et al. (2012) show that people move to rural areas

The following research questions will be addressed: 1) Does living in a region with a higher unemployment rate increase the probability of interregional migration?, 2) Are homeowners less likely to migrate to a different region than renters?, 3) What is the effect of the duration of individual unemployment on the probability to move to a different region? and 4) Are long distance commuters more likely to move?

The dataset used to answer these research questions is a random sample of the Dutch population between 25 and 65, which contains more than 700,000 individuals. The dataset is highly granular: it contains multiple address spells per individual, including the date of moving to a new address, and multiple unemployment spells if applicable, including the start and end date of unemployment.

This research contributes to the literature by including variables that have not been studied before. The theoretical effect of these variables is underpinned by the HCT. First, my paper is the first to use time-varying unemployment rates by region and by level of education. Unemployment rates differ substantially by level of education and individuals with different levels of education may respond differently to changes in unemployment rates. Second, I evaluate the effect of homeownership, renting in the social sector, and renting in the private sector on interregional mobility. Most scholars combine the two types of rental housing and find that homeownership reduces mobility and the functioning of the labor market. However, I show that renters in the private sector are much more mobile than those in social housing. Third, my paper is the first that evaluates the effect of the duration of individual unemployment on mobility. The HCT suggests that the effect of unemployment on mobility changes with the duration of unemployment: human capital declines during unemployment. Moreover, unemployment benefits and hence the expected returns of migration change with the duration of unemployment. I find that in particular individuals who are less than three months unemployed and individuals who are near the end of their unemployment benefit entitlement are more likely to migrate to a different region than the employed and those not available for work. Fourth, I evaluate the effect of commuting distance on interregional migration, which has not yet been studied in the Netherlands. Commuting can be an alternative to migration. I find that commuting distance has a strong effect on the probability to migrate. This finding suggests that commuting is a stepping stone to migration rather than a long-term alternative (Melzer & Hinz, 2019).

This paper is structured as follows. Section 2 explains the theoretical effect of the deter-

to live close to family and friends, for housing characteristics, physical environment, and low house prices.

minants on migration. Section 3 presents the empirical method and Section 4 describes the dataset. Section 5 offers the results. Finally, Section 6 concludes.

2 Theoretical framework

Individual interregional migration decisions can be explained by the Human Capital Theory (HCT). Under the HCT, an individual moves to a different region if the expected returns exceed the costs associated with relocation. The returns of relocation are equal to the difference in the net present value of the expected returns in the region of destination and the region of origin (Sjaastad, 1962)[2].

2.1 Regional unemployment rate

High regional unemployment rates reduce the net present value of the expected income in the region of origin. Recent graduates or unemployed individuals tend to move to a region with better probabilities to find a job, even before receiving a job offer. This is also known as speculative migration (Molho, 1986). Regional unemployment rates are also reflected in the net present value of expected returns of employed individuals. In case of high regional unemployment, the probability to become unemployed increases and the probability to find a new job in case of unemployment decreases.

There is some evidence that interregional migration reduces regional unemployment disparities in Germany, although regional wage disparities remain (Niebuhr et al., 2012). Furthermore, Andrews et al. (2011) finds that regional differences in real wages and labor market tightness do not have a strong influence on the level of interregional migration in the United Kingdom. Likewise, Palomares-Linares and Van Ham (2020) report that regional unemployment hardly impacts interregional migration in Spain, while Broersma and Van Dijk (2002) show that interregional migration only plays a limited role as adjustment mechanism to regional labor market shocks in the Netherlands.

Unemployment rates do not only vary by regions, but also by level of education. The unemployment rate of lower-educated persons was almost three times as high as that of persons

[2]A large strand of literature is based on the conceptual framework by Sjaastad (1962). See Mincer (1978) for an evaluation of the effect of family ties on the costs and benefits of migration, Carlsen et al. (2006) for an overview of empirical studies of interregional migration motivated by the HCT approach, Kennan and Walker (2011) for a structural model on the effect of expected income on individual migration decisions and Saks (2008) for an evaluation of the effect of housing supply on local labor markets.

with a bachelor's or master's degree in The Netherlands in 2020[3]. Moreover, previous research suggests that migration of lower-educated individuals responds less to regional unemployment shocks than that of higher-educated individuals (Carlsen et al., 2013). Therefore, I use regional unemployment rates by level of education. To my best knowledge, this is the first paper that uses unemployment rates by level of education to estimate the probability of interregional migration.

2.2 Housing tenure

Housing tenure may have an effect on the decision to move to a different region via the costs or the returns of such a move. The costs associated with relocation are higher for homeowners than for renters (Oswald, 1997)[4]. This finding has been confirmed in the empirical literature (Dietz & Haurin, 2003). Homeowners with negative house equity are even less mobile. House prices declined sharply between 2008 and 2012 in the Netherlands, and Van Veldhuizen et al. (2020) find that homeowners with negative home equity are 21% less likely to move than homeowners with positive home equity.

The costs of housing are included in the expected returns of migration. The majority of the rental housing market in the Netherlands is regulated. Social housing is only available for individuals below a certain income threshold and waiting lists apply. The regulated housing sector is subsidized and rents are lower than rents in the unregulated sector. Migration to a different region implies an increase in rents or a loss in housing quality and reduces the expected returns. Munch and Svarer (2002) find that tenants in more regulated houses are less likely to move to a different region.

There is evidence of a negative relationship between homeownership and unemployment, or job mobility, in the Netherlands (Van Leuvensteijn & Koning, 2004; Van Vuuren, 2017). Moreover, Helderman et al. (2004) find that homeowners are less likely to move than renters. However, the effect of renting in the private sector versus the social housing sector has not yet been studies for the Netherlands. I evaluate the effect of housing tenure on the probability of interregional migration, and consider three types of housing tenure: homeownership, renting in the social sector, and renting in the private sector.

[3]The unemployment rate in the Netherlands was 7.0% for lower-educated and 2.6% for the higher-educated individuals between 15 and 65 years old (Statistics Netherlands [CBS], 2022).

[4]An overview of transaction costs is provided by Quigley (2004). They include financial costs such as notary fees and financing costs, as well as non-financial costs such as search time.

2.3 Individual unemployment

Theoretically, the effect of individual unemployment on migration decisions is ambiguous. The return of migration to a region with better job perspectives is larger. The net present value in the region of origin is lower in the absence of a job. On the other hand, the HCT predicts a deterioration of human capital that increases the longer someone is unemployed, because the unemployed have limited possibilities to update their skills (Blanchard & Summers, 1986; Moeller, 1989). A lower level of human capital might not only reduce the possibilities to find a new job, but also reduces the probability of interregional migration, since the expected returns decrease. The probability of migration might increase near the end of the unemployment benefit entitlement, because the net present value of the expected income in the region of origin decreases.

The effect of the duration of individual unemployment on the probability to move to a different region has not been studied yet. Broersma and Van Dijk (2002) and Niebuhr et al. (2012) evaluate the effect of unemployment at the macro level. Other studies include a dummy for individual unemployment, but do not control for the duration of individual employment (Andrews et al., 2011; Palomares-Linares & Van Ham, 2020). This is usually because a lack of data. Kettunen (2002) estimates the probability of the unemployed to become employed by moving to a different region. The author finds a decline in the probability to become unemployed by moving to another area of residence over time. This finding may be caused by a decline in the probability of someone who is unemployed to become employed or by a decline in the probability to move to a different region. In this paper, I disentangle these two effects.

2.4 Commuting distance

It is important to study commuting and migration together, because the two are alternatives (Melzer & Hinz, 2019). Expected income decreases with commuting costs (Morrison, 2005). Even if travel expenses are covered by the employer, commuting involves costs in terms of time. In the HCT, individuals compare the returns of migrating to a region with a smaller commuting distance against the costs associated with relocation. They might, however, accept jobs with longer commuting distance if there is a possibility to move closer to the job in the future (Van Ommeren et al., 1999).

The empirical literature confirms that commuting distance has a positive impact on the probability to move. Van Ham and Clark (2009) show that Dutch households with a long

commuting distance are more likely to have the intention to move for job-related reasons. Roberts and Taylor (2017) find that workers in the United Kingdom are more willing to commute if the unemployment rate increases, in particular male workers. Van Ommeren et al. (1999) find that an increase of 10 kilometers in commuting distance reduces the expected stay in the same residence by approximately one year in The Netherlands. However, the effect of commuting distance on interregional migration has not yet been studied. I use an approach similar to Van Ommeren et al. (1999), but use migration to a different region instead of any move as dependent variable.

Figure 2 shows the median commuting distance by region in the Netherlands. The median commuting distance is less than 10 kilometers in the region of Amsterdam and surroundings, Groningen and The Hague (Agglomeratie 's Gravenhage in Dutch). The median commuting distance is the largest in Flevoland: 26 kilometres. This COROP region includes Almere, a city with many inhabitants who commute to Amsterdam.

3 Method

To estimate the effect of unemployment on the probability of interregional migration in the Netherlands, I use a duration model. Andrews et al. (2011) show that the probability of inter-regional migration decreases with the number of years spent in a region, as individuals become attached to the region: there is negative duration dependence. Cross-sectional models do not take this effect into account and therefore might lead to biased coefficient estimates (Andrews et al., 2011).

Like Andrews et al. (2011), I estimate a mixed proportional hazard model, where the hazard rate is a migration to a different region. The duration model is:

$$h_i(t) = h_0(t) \cdot \exp(\alpha U_{r,e} + \beta' X_{i,t} + \gamma' F_r) \tag{1}$$

with $h_0(t)$ the baseline hazard rate, t elapsed duration, $U_{r,e}$ the unemployment rate by region r and level of education e, $X_{i,t}$ a vector of time-varying individual characteristics, and F_r a vector of region dummies. Section 4.3 provides an overview of individual characteristics included in the model. The model does not include individual fixed effects, because this may lead to incidental parameter bias.

Andrews et al. (2011) estimate a competing risk model with two possible outcomes: moving

Figure 2: Median commuting distance in sample by COROP region

Source: CBS Microdata, own computations

to a region with higher or lower labor market tightness. In this paper, I consider one type of risk: moving to a different region. An advantage of using a single outcome variable is that one can allow for time-varying regional unemployment rates. Andrews et al. (2011) use a labor market variable that does not vary over time. I extend on Andrews et al. (2011) by including additional variables: a time-varying regional unemployment rate by level of education, the duration of individual unemployment, and commuting distance. Housing tenure is included in my model as well as in Andrews et al. (2011).

While Andrews et al. (2011) use a fully parametric duration model, I use a semi-parametric Cox Proportional Hazard model. This model does not require any assumptions about the distribution of the baseline hazard function, and is hence less sensitive to misspecification (Van den Berg, 2001).

4 Data

The dataset consists of individual address spells for inhabitants of the Netherlands including the date of moving to a different address. It is a subset of the dataset used in Biesenbeek et al. (2022) with some extensions. A spell is defined as a period between migration from one region to another. An individual can live on multiple addresses within a spell, as long as those addresses are in the same region. Individuals remain in the sample after migration to another region; interregional migration is not an absorbing state and multiple spells per individual may exist. Every spell includes an anonymized person ID, one or more address ID('s), and the beginning and end date of the period that the individual lives on this address.

4.1 Sample selection

The starting point of my dataset is the Municipal Records Database (Gemeentelijke Basisadministratie, GBA). It contains every inhabitant in the Netherlands as of 1995 (25.9 million). My sample is a subset of this dataset. First, I remove individuals who live for one or more years in an institutional household, such as a psychiatric hospital, because they are unlikely to move for labor market reasons[5]. Next, I take a 10% random sample of the remaining dataset. It is possible that two individuals from the same household are both selected in the sample. I remove individuals without address information available from the sample, including those who moved abroad, have died, or became homeless before 2005. Finally, because I am interested in migrations for job opportunities only, I remove all address spells that end before an individual turns 25 or begin after an individual turns 65[6]. A deviation from Andrews et al. (2011) is that I keep those without a job in the dataset and do not remove individuals in the armed forces from the dataset. Both groups of individuals might migrate to a different region to find a different job or to become employed.

My sample contains 1,493,614 individuals after taking a 10% random sample and removing individuals in institutional households, individuals with unknown address information, and individuals outside the 25-65 age range. The regressors are available for 773,081 individuals

[5]Statistics Netherlands defines institutional households as "One or more individuals living together in a residential unit where their livelihood needs are met by professional care workers".

[6]The statutory retirement age has become age-dependent and gradually increased from 2012 on. For simplicity, I remove all individuals from the sample at age 65.
Both selections require address information, that is available after merging address spells to the dataset. For computational reasons, I take a 10% random sample first and remove individuals who no longer live in the Netherlands or are outside working age thereafter.

(Table 1). They include the regional unemployment rate by level of education, household composition, gender, age, level of education, gross household income, household net wealth, housing type, and the duration of individual unemployment, if applicable.

I use a sub-sample of wage employees to assess the effect of commuting distance. This variable is available as of 2014. Moreover, I exclude interns and employees in sheltered jobs from the sample of employees, because they are not representative and unlikely to move because of local labor market circumstances. The sub-sample of wage employees includes 344,070 individuals. Section 4.3 provides further details.

Table 1: Sample size after selections (left) and number of migrations (right), ×1000

	Individuals		**Migrations**
Total sample	25,919	Total	720
No institutional households	25,130	Within same region	550
Random sample 10%	2513	To other region	170
Address information available	2095		
Age 25-65	1494		
Main sample, regressors available	774		
Sub-sample of employees, regressors available	344		

Source: CBS Microdata, own computations

I observe in total 719,911 moves to a different address for the individuals in the sample (1.1 moves on average per individual, or 2.1 address spells). Approximately three quarters of those moves are within the same region, and one quarter to a different region (170,193 migrations). Individuals become at risk when they become 25 and are right censored when they become 65. There is no left censoring in the data: I observe the beginning date of residence of every address spell. In case of middle censoring, for example, when an individual lives abroad for a period, individuals remain in the sample. Moving to a different region after middle censoring does not count as a migration.

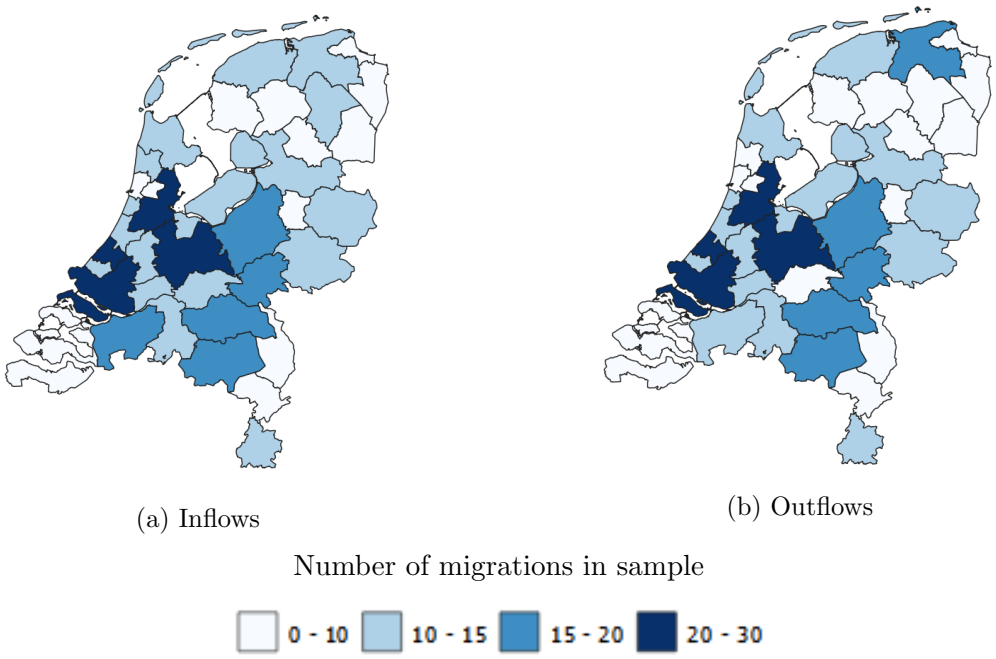
4.2 Definition of a region

The region is defined as a COROP region or commuting zone. COROP is the Dutch equivalent of the European NUTS3 level and it is an approximation of labor market regions (Vermeulen & van Ommeren, 2009)[7]. There are 40 COROP regions in the Netherlands.

[7]I use COROP regions, because the labor market conditions are similar within a COROP regions and because the majority the Dutch population works and resides in the same COROP region (64%, own calculation based on CBS data). Alternatively, provinces or municipalities can be used as regional classifications. However, substantial labor market differences exist within provinces and only 40 percent of the Dutch population works and resides

Figure 3 shows the number of migrations by COROP regions in the sample. The number of migrations is larger in regions with more inhabitants. This is not a problem in my empirical model, because I estimate the probability of migration rather than the number of migrations by region. In- and outflows are quite similar in most regions. However, the outflows are larger than the inflows in the region of Groningen. This probably reflects that students often leave the region after graduating.

Figure 3: Number of migrations in sample by COROP region



(a) Inflows (b) Outflows

Source: CBS Microdata, own computations

4.3 Regressors

All regressors except gender are time-varying variables in the duration model. The regional unemployment rate is available by year and level of education[8]. Andrews et al. (2011) define a regional labor market tightness indicator as the logarithm of the ratio of job centre vacancies to unemployment levels, both in 2009. Unfortunately the number of vacancies is not available at the regional level for the Netherlands.

I merge several other data from Statistics Netherlands (CBS) to the dataset to obtain

in the same municipality.

[8]The unemployment rate is available at Statistics Netherlands for low, medium, and higher levels of education. Lower level of education: early childhood education, primary education and lower. Medium level of education: upper secondary education, post-secondary non-tertiary education, and short cycle tertiary education. Higher level of education: bachelor's or master's degree.

information about individual and job characteristics. The variable household type is constructed by CBS, based on the Municipal Records Database (GBA, Gemeentelijke Basisadministratie), rent allowance applicants, and the Labor Force Survey (EBB). The composition of a household may change within a year; I use January 1^{st} as reference date. Gender and age are available from the GBA. The highest level of education achieved is derived by CBS from registers. I classify the level of education following the ISCED definition in lower level of education, medium level of education, bachelor degree, and master degree. Level of education is available for 53% of the sample. I control for sample selection by estimating the same model on a sample of all employees and a sample of employees for whom their level of education is available.

Household income is derived from multiple sources, including the Dutch Tax Authority. It is the quantile of gross household income from labor, business and social benefits in the distribution of household income within a year. Table 2 shows that households in the highest income quantile are over-represented in the sample. This is because high-income households are more often couples and hence have a larger probability to be included in the sample than singles. Household wealth refers to the quantile of total net household assets (i.e., assets net of debts), including net housing wealth in the distribution of household wealth within a year. Table 2 shows that the lowest quantile in the household wealth distribution has negative wealth. The distribution of household in wealth quantiles in the sample is quite close to the distribution in the Netherlands.

Housing type (rental or owner-occupied) is available for every individual in the sample. A further breakdown of rental properties in social housing and private housing is available as of 2012. I consider all properties rented by social housing associations and municipalities as social housing. This is a rough approximation: social housing associations are allowed to let approximately 10% of dwellings in the unregulated sector. 63.9% of my sample was owner-occupant in 2020 (Table 2).

Individual data on unemployment is available in the sample period from the Netherlands Employees Insurance Agency (UWV). I refer to individuals who receive an unemployment benefit as unemployed in this paper. Multiple spells can exist for an individual within one year. The unemployment data contains the beginning of the period of unemployment. This allows me to calculate the unemployment duration (in weeks). 96.2% of the sample was not unemployed during the last observation (Table 2).

Job information is available from registration data for the sub-sample of wage employees.

Table 2: Summary statistics: main sample

	%		%
Observations	773,081	*Household income*	
Household type		(Median value of quantile, ×1000)	
Single, no children	21.3	0% -20% (20)	10.4
Unmarried couple, no children	11.1	20%-40% (34)	12.7
Married couple, no children	17.5	40%-60% (55)	18.4
Unmarried couple with children	9.6	60%-80% (86)	26.0
Married couple with children	32.8	80%-100% (141)	32.5
Single parent	7.6	*Household net wealth*	
Gender		(Median value of quantile, ×1000)	
Female	49.9	0%-20% (-11)	20.5
Age		20%-40% (4)	16.5
25-35	27.3	40%-60% (59)	22.4
35-45	21.8	60%-80% (177)	21.3
45-55	21.7	80%-100% (465)	19.4
≥55	29.3	*Housing type*	
Level of education		Owner	63.9
Lower	20.9	Rental, social sector	24.3
Medium	39.1	Rental, private sector	10.8
Bachelor	24.6	Rental, sector unknown	1.0
Master	15.4	*Unemployment duration*	
		Not applicable	96.2
		<3 months	1.0
		3-6 months	0.6
		6 months-1 year	0.9
		1-2 year	0.8
		≥2 years	0.5

Source: CBS Microdata, own computations. Median household income and median household net wealth are in 1000 euro. Household income and household wealth refer to the quantile of the gross household income and total household net wealth within a year. All regressors except gender are time-varying; this table presents the latest available information.

If an individual has multiple jobs, I select the job with the highest gross annual wage within a year, excluding paid overwork and special remunerations. An estimate of the commuting distance is provided by CBS for a subset of the employees (346,421 individuals, Table 1). It is estimated by CBS as follows. If a firm has only one location, the location of work is directly observed. For firms with multiple locations, CBS receives the number of employees for each location from a survey. Next, CBS assigns individual employees to the location closest to their district of residence, which is retrieved from registration data. Finally, CBS calculates commuting distance as the distance between the district of the work location and the district of residence. This implies that the commuting distance equals zero for workers who live and work in the same district. This is the case for 9.7% of the sample (Table 3).

Contract type, the number of hours worked per week, and the sector of employment are included as additional regressors in a model including commuting distance. Temporary contracts are quite common in the Netherlands (28.5% in the sample, Table 3). Flexible hour jobs can be permanent or temporary; the number of working hours varies. The abbreviation DGA stands for director shareholder (Directeur Grootaandeelhouder in Dutch). A DGA receives tax benefits, but is in general not entitled to unemployment benefits.

Part time work is common in the Netherlands as well. Almost half of the sample works less than 35 hours per week. The number of hours worked excludes overwork. Company sectors are classified using the Standard Industrial Classifications (Standaard Bedrijfsindeling in Dutch, based on the European NACE classification). The full set of summary statistics for the sample of employees can be found in Table 6 in Appendix A.

Table 3: Selection of summary statistics: sample of employees

	%		%
Observations	346,421	*Sector*	
Commuting distance		Agriculture	0.8
0 (same district)	9.7	Manufacturing	7.7
<5km	16.6	Electricity, gas, water supply	0.7
5 -10km	15.5	Construction	3.8
10-20km	18.8	Wholesale and retail trade	13.6
20-50km	24.3	Transportation and storage	4.5
≥ 50km	15.1	Accommodation and food service	3.5
Contract type		Information en communication	4.5
Permanent	56.6	Financial and insurance activities	3.5
Temporary	28.5	Business services	24.0
Agency work	7.4	Public administration	4.9
Flexible hours	5.0	Education	6.5
DGA	2.6	Human health and social work	18.2
		Other service activities	3.9
Hours per week			
<12	4.7		
12-20	7.0		
20-25	11.1		
25-30	8.8		
30-35	14.1		
≥35	54.2		

Source: CBS Microdata, own computations. All regressors are time-varying; this table presents the latest available information. Summary statistics not presented here are reported in Appendix A.

5 Results

This section presents results of Cox duration models, with the probability to migrate to a different COROP region as the dependent variable. All results are reported as hazard ratios. A hazard ratio is the ratio of the hazard rates, or the probability to move to a different region, corresponding to two different values of a regressor. A hazard ratio of 1 implies that the regressor does not have an effect on the hazard rates. Standard errors are clustered by COROP region in all models. Ignoring clustering by region leads to a downward bias in the standard errors (Andrews et al., 2011; Moulton, 1986).

5.1 Regional unemployment rate

For the first research question, I evaluate the effect of the regional unemployment rate on the probability of interregional migration. I find that every percentage point increase in the unemployment rate in the region of origin reduces the probability to migrate by 4% (see Table 4). Sample selection does not drive my results. I estimate the same models for samples including and excluding individuals for whom their level of education is unavailable and find similar hazard ratios for the effect of the regional unemployment rate (see Table 7 in Appendix A).

I use a set of observed characteristics as regressors: household type, gender, age, level of education, household income, household wealth, housing tenure, and individual unemployment duration. Couples, in particular couples with children, are less likely to move to a different region than singles without children (Table 4). This result is in line with the HCT: families are less mobile because the returns from migration increase less than costs as household size increases (Mincer, 1978). It is in line with the empirical literature as well; Huttunen et al. (2018) find that workers with a spouse and with school-aged children are less likely to move after a job displacement.

I find that men are approximately 7% more likely to move than women. Moreover, I find a strong negative relation between age and the probability to move, and a positive relation between the level of education and the probability to move (Table 4). Both findings are in line with the HCT: the returns of migration in terms of expected income decrease with age and increase with level of education. The lowest quantile within the household income distribution is the most likely to migrate to a different region. This is in line with the HCT if current income is related to expected income in the region of origin. Finally, the probability to move

to a different region is the highest for the highest household wealth quantile. This cannot be explained by the HCT. An alternative explanation could be that wealthier households are more mobile, because the transaction costs associated with moving are lower. They might be able to buy a house without a mortgage and do not face financing costs.

Table 4: Cox proportional hazard model: main sample

	Hazard ratio	**Standard error (robust)**
Regional unemployment rate (by level of education)	1.040***	(0.005)
Household type reference: single without children)		
Unmarried couple without children	0.766***	(0.007)
Married couple without children	0.684***	(0.008)
Unmarried couple with children	0.592***	(0.007)
Married couple with children	0.590***	(0.005)
Single parent	0.821***	(0.009)
Gender		
Male	1.067***	(0.006)
Age (reference: 25-35)		
35-45	0.481***	(0.004)
45-55	0.282***	(0.003)
≥55	0.217***	(0.003)
Level of education (reference: lower)		
Medium	1.358***	(0.027)
Bachelor	1.845***	(0.048)
Master	2.423***	(0.065)
Household income		
20%-40%	0.820***	(0.009)
40%-60%	0.813***	(0.008)
60%-80%	0.776***	(0.009)
80%-100%	0.944***	(0.012)
Household wealth (reference: <20%)		
20%-40%	0.874***	(0.007)
40%-60%	0.851***	(0.007)
60%-80%	0.991	(0.009)
80%-100%	1.237***	(0.012)
Housing type (reference = owner occupant)		
Rental, social sector	1.364***	(0.012)

Continued on next page

Cox proportional hazard model: main sample (continued)

	Hazard ratio	**Standard error (robust)**
Rental, private sector	2.499***	(0.019)
Rental, sector unknown	1.671***	(0.021)
Unemployment duration (reference = not applicable)		
<3 months	1.445***	(0.030)
3-6 months	1.137***	(0.034)
6 months-1 year	1.121***	(0.033)
1-2 year	1.189***	(0.042)
≥2 years	1.078	(0.059)
Region fixed effects	Yes	
Clustered standard errors	Yes	
N (1000 obs)	773	

Source: CBS Microdata, own computations. * = 1%, ** = 5%, *** = 10% significance level. Standard errors are robust for clustering by 40 COROP regions.

5.2 Housing tenure

I find that renters are more likely to migrate to a different region than homeowners. This finding confirms Oswald's theory and is in line with the empirical literature (Dietz & Haurin, 2003; Oswald, 1997). This could be the result of higher transaction costs for homeowners.

I also find a substantial difference in mobility within the rental housing sector. Renters in the private sector are 2.5 more mobile than homeowners; renters in the social sector are only 1.4 times more likely to move to a different region than homeowners (Table 4). Renters in the social sector face smaller transaction costs, but may be unable to find another house in the social sector in a different region as a result of waiting lists. This "loss" reduces the expected returns of migration to a different region and may explain why renters in the social sector are hesitant to move to another region, even if job perspectives in the region of destination are better. Andrews et al. (2011) report similar results for the United Kingdom: they find that private sector tenants are the most mobile, but there is little difference in the propensity to migrate between homeowners and tenants renting houses from local authorities.

5.3 Individual unemployment

I find that those who are unemployed are more likely to migrate, in particular during the first three months of unemployment. Those being unemployed for less than three months are 1.5 times more likely to migrate to a different region than individuals who are not unemployed

(including wage employees), the self employed and those who are not available for work, see Table 4). A potential explanation could be that the unemployed are more willing to migrate, because a current job loss might reduce future income expectations of staying in the current region.

The effect of individual unemployment on migration decreases to 1.1 after three months of unemployment. This decrease can be explained by the HCT: human capital deteriorates during unemployment, because the unemployed have limited possibilities to update their skills (Blanchard & Summers, 1986; Moeller, 1989). Unobserved personal characteristics, such as flexibility, may have an effect on mobility as well as the probability to find a job. The most flexible unemployed workers leave unemployment first.

During one to two years of unemployment duration, the probability to migrate to a different region increases slightly to 1.2. This may reflect that the duration of unemployment benefits is maximized at two years[9]. After the unemployment benefit entitlement ends, those without a substantial income receive social assistance. This usually leads to a sharp income decline, because social assistance is less generous than unemployment benefits[10]. This expected income decline may increase the willingness to migrate.

5.4 Commuting distance

Table 5 presents the key results of a duration model on the sample of employees. It shows that commuting distance has a strong and positive effect on the probability to migrate. Employees with a commuting distance between 10 and 20 kilometres are 1.5 times more likely to migrate to a different region than employees who do not commute. Those with a commuting distance of 50 kilometres or more are 2.5 times more likely to migrate. The finding that commuting distance increases is in line with the results of previous studies (Roberts & Taylor, 2017; Van Ham & Clark, 2009; Van Ommeren et al., 1999). It suggests that long distance commuting is a stepping stone to migration rather than a long-term alternative to migration to a different region (Melzer & Hinz, 2019). However, commuters might migrate for non-job-related reasons. This argument might in particular hold for part time employees. However, after restricting the sample to employees working at least 25 hours per week, I find similar results (see Model ≥ 25

[9]Unemployment benefit entitlements depend on work history: one month per year worked. The duration of unemployment benefits was maximized at two years in 2019. Unemployment benefit durations longer than two years may exists for those who became unemployed before 2019.

[10]Those with wealth above a certain threshold are not eligible to social assistance. This threshold was 6,225 euro for singles without children and 12,450 euro for couples and single parents in 2020.

hours in Table 9 in Appendix A).

In this model, every percentage point increase in the regional unemployment rate increases the probability to migrate to a different region by 11.5%. The effect of regional unemployment on mobility is thus slightly larger than in the model for the full sample. This reflects sample selection; similar results as in the main model are found when I estimate a duration model without job characteristics on the sample of employees only (see Model No job vars in Table 8 in Appendix A).

Employees with a temporary contract are more likely to migrate than those with a permanent contract. This could reflect that these contracts imply job insecurity and thus reduce the expected income in the current region. Employees working more hours per week are more likely to migrate to a different region, probably because the returns of migration are greater for full time jobs than for part time jobs[11]. Moreover, I find that employees in the food and accommodation, information and communication, human health and social work and other service activities (such as hairdressers) are more mobile. On the other hand, employees in the construction sector have a lower probability of interregional migration. The full results of the duration model on the sample of employees can be found in Model Baseline in Table 9 in Appendix A.

6 Conclusion

After controlling for individual characteristics, the regional unemployment rate has a small but significant and positive effect on the probability to migrate to a different region. Every percentage point increase in the unemployment rate in the country of origin increases the probability to migrate to a different region by approximately 4%. The positive relation between regional unemployment and mobility is in line with the Human Capital Theory (Mincer, 1978; Sjaastad, 1962) and confirms the concept of speculative migration (Molho, 1986). A positive, but small impact of regional unemployment on regional mobility was found in previous papers as well (Andrews et al., 2011; Broersma & Van Dijk, 2002; Palomares-Linares & Van Ham, 2020).

A potential explanation for the limited effect of regional unemployment on mobility could be the housing market in The Netherlands. I find that renters in the private sector are ap-

[11] A job of 35 hours or more per week is considered as a full time job in the Netherlands.

Table 5: Cox proportional hazard model, sample of employees only

	Hazard ratio	**Standard error (robust)**
Regional unemployment rate (by level of education)	1.115***	(0.028)
Commuting distance (reference = 0, same district)		
0-5km	1.073	(0.135)
5-10km	1.226	(0.190)
10-20km	1.527***	(0.085)
20-50km	1.981***	(0.160)
≥50km	2.452***	(0.196)
Contract type (reference = permanent)		
Temporary	1.330***	(0.055)
Agency work	1.052	(0.040)
Flexible hours	1.136**	(0.056)
DGA	1.214***	(0.052)
Hours per week (reference: <12)		
12-20	0.991	(0.048)
20-25	1.040	(0.037)
25-30	1.234***	(0.046)
30-35	1.386***	(0.053)
≥35	1.659**	(0.096)
Sector (reference = financial services)		
Agriculture	0.957	(0.112)
Manufacturing	0.930	(0.046)
Electricity, gas, water supply	1.046	(0.061)
Construction	0.814***	(0.037)
Wholesale and retail trade	1.016	(0.043)
Transportation and storage	1.087	(0.058)
Accommodation and food service	1.150***	(0.035)
Information en communication	1.143***	(0.035)
Business services	1.066**	(0.025)
Public administration	1.086	(0.048)
Education	1.115*	(0.060)
Human health and social work	1.125**	(0.048)
Other service activities	1.160***	(0.043)
Region fixed effects	Yes	
Clustered standard errors	Yes	
N (1000 obs)	344	

Source: CBS Microdata, own computations. * = 1%, ** = 5%, *** = 10% significance level. Standard errors are robust for clustering by 40 COROP regions. The sample of employees does not include self-employed, interns and workers in sheltered jobs.

proximately 2.5 more likely to move to a different region than homeowners, while renters in the social sector are 1.4 more likely to migrate to a different region. This is in line with previous research for the United Kingdom (Andrews et al., 2011) and Denmark (Munch & Svarer, 2002). Approximately 12% of the housing stock in The Netherlands consisted of rental houses not owned by corporations in 2020. The relative small size of the private housing market may partly explain the limited effect of regional unemployment on interregional mobility.

I find that unemployed individuals are more likely to move, particularly during the first three months of unemployment. This could be a result of expected income losses related to unemployment benefit entitlements and depreciation of human capital, or a selection effect. Unobserved individual characteristics such as flexibility may have a positive effect on the probability to move to another region as well as the probability to find a job after a short period of unemployment. Finally, it appears that commuting distance has a strong effect on the probability of interregional migration, much stronger than the effect of regional unemployment.

It can be argued that interregional mobility is not important in The Netherlands, because distances are short from an international perspective, because working from home is more common since the Corona pandemic, or because unemployment rates are currently low in all regions in The Netherlands. However, my results suggest that employees prefer living closer to their current job, than to find a new job. This may imply that commuting distance does matter to employees, and that commuting is not a long-term alternative to interregional migration, in line with Melzer and Hinz (2019). Working from home has become more common since the Corona pandemic, but some jobs cannot be performed from home, and the distance between the region of residence and region of work remains relevant. Although unemployment levels in The Netherlands are currently very low, interregional migration remains an important channel for the functioning of the labour market. It may help to reduce local labor supply shortages and reduce education-job mismatches. Interregional mobility thus remains an important channel for the proper functioning of the labour market.

My findings suggest policy directions to enhance interregional mobility. For example, as to the housing market, employers may provide relocation services to new employees, to help reduce housing search time for employees. Local social housing corporations could work together, to enhance mobility of renters with low incomes across regions. Another policy direction is the design of the social security system, as my paper suggests that unemployed are more mobile during the first three months of unemployment and near the end of their unemployment benefit

entitlement.

This paper indicates potential determinants of interregional migration, including housing tenure and individual unemployment duration. Future research could identify the causal effect of these determinants on mobility. For example, a suggestion for the identification of the causal effect of individual unemployment duration would be to exploit exogenous variation in the maximum unemployment benefit duration, resulting from a policy reform in 2019. This type of research helps to disentangle the policy effect of unemployment benefits from other factors, such as selection or human capital depreciation, on mobility.

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A Additional Tables

Table 6: Summary statistics: sample of employees

	%		%
Observations	334,070	*Unemployment duration*	
Household type		Not applicable	96.8
Single, no children	20.9	<3 months	0.9
Unmarried couple, no children	14,8	3-6 months	0.4
Married couple, no children	10.7	6 months-1 year	0.8
Unmarried couple with children	11.2	1-2 year	0.9
Married couple with children	34.6	≥2 years	0.3
Single parent	7.9	*Commuting distance*	
Gender		0 (same district)	9.7
Female	49.7	<5km	16.6
Age		5 -10km	15.5
25-35	41.5	10-20km	18.8
35-45	24.8	20-50km	24.3
45-55	20.5	≥ 50km	15.1
≥55	13.2	*Contract type*	
Level of education		Permanent	56.6
Lower	13.1	Temporary	28.5
Medium	40.4	Agency work	7.4
Bachelor	27.8	Flexible hours	5.0
Master	18.7	DGA	2.6
Household income		*Hours per week*	
(Median value of quantile, ×1000)		<12	4.7
0% -20% (20)	5.3	12-20	7.0
20%-40% (35)	10.9	20-25	11.1
40%-60% (56)	18.6	25-30	8.8
60%-80% (86)	29.0	30-35	14.1
80%-100% (141)	36.1	≥35	54.2
Household wealth		*Sector*	
(Median value of quantile, ×1000)		Agriculture	0.8
0%-20% (-15)	24.2	Manufacturing	7.7
20%-40% (5)	16.0	Electricity, gas, water supply	0.7
40%-60% (57)	25.0	Construction	3.8
60%-80% (174)	19.9	Wholesale and retail trade	13.6
80%-100% (463)	15.0	Transportation and storage	4.5
Housing type		Accommodation and food service	3.5
Owner	64.4	Information en communication	4.5
Rental, social sector	21.6	Financial and insurance activities	3.5
Rental, private sector	14.0	Business services	24.0
Rental, sector unknown	0.0	Public administration	4.9
		Education	6.5
		Human health and social work	18.2
		Other service activities	3.9

Source: CBS Microdata, own computations. A subset of this table is presented in Table 3. Median household income and median household net wealth are in 1000 euro. Household income and household wealth refer to the quantile of the gross household income and total household net wealth within a year. All regressors except gender are time-varying; this table presents the latest available information.

Table 7: Cox proportional hazard model: main sample, and main sample plus individuals for whom level of education is unavailable

	Main sample		**With individuals for whom level of education unavailable**	
	HR	SE	HR	SE
Regional unemployment rate (not adjusted by level of education)	0.980	(0.013)	0.983	(0.016)
Household type (reference: single without children)				
Unmarried couple without children	0.758***	(0.029)	0.728***	(0.030)
Married couple without children	0.635***	(0.034)	0.625***	(0.041)
Unmarried couple with children	0.538***	(0.051)	0.527***	(0.056)
Married couple with children	0.468***	(0.021)	0.521***	(0.026)
Single parent	0.743***	(0.025)	0.729***	(0.026)
Gender				
Male	1.055***	(0.007)	1.032***	(0.009)
Age (reference: 25-35)				
35-45	0.478***	(0.020)	0.480***	(0.023)
45-55	0.261***	(0.007)	0.269***	(0.007)
≥55	0.192***	(0.006)	0.198***	(0.006)
Household income (reference: <20%)				
20%-40%	0.821***	(0.018)	0.835***	(0.018)
40%-60%	0.854***	(0.026)	0.882***	(0.023)
60%-80%	0.846***	(0.031)	0.880***	(0.031)
80%-100%	1.147***	(0.034)	1.184***	(0.040)
Household wealth (reference: <20%)				
20%-40%	0.850***	(0.011)	0.853***	(0.008)
40%-60%	0.849***	(0.014)	0.872***	(0.016)
60%-80%	0.943*	(0.023)	1.018	(0.021)
80%-100%	1.108***	(0.029)	1.300***	(0.028)
Housing type (reference: owner occupant)				
Rental, social sector	1.282***	(0.038)	1.296***	(0.039)
Rental, private sector	2.669***	(0.123)	2.594***	(0.091)
Rental, sector unknown	1.600***	(0.043)	1.647***	(0.043)
Unemployment duration (reference: not applicable)				
<3 months	1.515***	(0.033)	1.415***	(0.033)***
3-6 months	1.204***	(0.037)	1.109***	(0.033)
6 months-1 year	1.196***	(0.033)	1.093	(0.029)

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Cox proportional hazard model (continued)

	Main sample		**With individuals for whom level of education unavailable**	
	HR	SE	HR	SE
1-2 year	1.291***	(0.039)	1.164***	(0.035)
≥2 years	1.191***	(0.060)	1.055	(0.059)
Region fixed effects	Yes		Yes	
Clustered standard errors	Yes		Yes	
N (1000 obs)	1,252		773	

Source: CBS Microdata, own computations. * = 1%, ** = 5%, *** = 10% significance level. Standard errors are robust for clustering by 40 COROP regions. Both models includes the same regressors as the baseline model on the main sample presented in Table 4, except for level of education, and the regional unemployment rate is not adjusted by level of education in this model.

Table 8: Cox proportional hazard model: sample of employees, model with and without job characteristics

	Baseline		**No job vars**	
	HR	SE	HR	SE
Regional unemployment rate (by level of education)	1.115***	(0.028)	1.130***	(0.029)
Household type (reference: single without children)				
Unmarried couple without children	0.703***	(0.031)	0.681***	(0.031)
Married couple without children	0.684***	(0.045)	0.651***	(0.048)
Unmarried couple with children	0.619***	(0.075)	0.550***	(0.070)
Married couple with children	0.675***	(0.033)	0.596***	(0.032)
Single parent	0.911*	(0.034)	0.842***	(0.031)
Gender				
Male	0.939***	(0.013)	1.070***	(0.015)
Age (reference: 25-35)				
35-45	0.524***	(0.028)	0.523***	(0.032)
45-55	0.313***	(0.011)	0.315***	(0.012)
≥55	0.264***	(0.010)	0.257***	(0.010)
Level of education (reference: lower)				
Medium	1.548***	(0.141)	1.618***	(0.153)
Bachelor	2.269***	(0.281)	2.267**	(0.281)
Master	2.766***	(0.364)	2.806***	(0.367)
Household income (reference: <20%)				
20%-40%	0.670***	(0.029)	0.800***	(0.037)
40%-60%	0.633***	(0.029)	0.793***	(0.039)
60%-80%	0.624***	(0.036)	0.799***	(0.046)
80%-100%	0.781***	(0.041)	1.045	(0.060)
Household net wealth (reference: <20%)				
20%-40%	0.830***	(0.014)	0.816***	(0.014)
40%-60%	0.792***	(0.021)	0.764***	(0.024)
60%-80%	0.979	(0.028)	0.930*	(0.031)
80%-100%	1.312***	(0.039)	1.211***	(0.033)
Housing type (reference: owner occupant)				
Rental, social sector	1.351***	(0.053)	1.364***	(0.051)
Rental, private sector	2.106***	(0.040)	2.110***	(0.046)
Rental, sector unknown	3.211***	(0.765)	3.267***	(0.790)
Unemployment duration (reference: not applicable)				

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Cox proportional hazard model: sample of employees (continued)

	Baseline		**No job vars**	
	HR	SE	HR	SE
<3 months	1.240***	(0.070)	1.476***	(0.080)
3-6 months	0.827**	(0.059)	0.969*	(0.071)
6 months-1 year	0.907	(0.046)	1.021	(0.053)
1-2 year	0.957	(0.066)	1.026	(0.074)
≥2 years	0.602***	(0.084)	0.618***	(0.088)
Commuting distance				
(reference: 0, same district)				
0-5km	1.073	(0.135)		
5-10km	1.226	(0.190)		
10-20km	1.528***	(0.085)		
20-50km	1.981***	(0.160)		
≥50km	2.452***	(0.196)		
Contract type				
(reference: permanent)				
Temporary	1.330***	(0.055)		
Agency work	1.052	(0.040)		
Flexible hours	1.136**	(0.056)		
DGA	1.214***	(0.052)		
Hours per week				
(reference: <12)				
12-20	0.991	(0.048)		
20-25	1.040	(0.037)		
25-30	1.234***	(0.046)		
30-35	1.386***	(0.053)		
≥35	1.659**	(0.096)		
Sector				
(reference: financial services)				
Agriculture	0.957	(0.112)		
Manufacturing	0.930	(0.046)		
Electricity, gas, water supply	1.047	(0.061)		
Construction	0.814***	(0.037)		
Wholesale and retail trade	1.016	(0.043)		
Transportation and storage	1.087	(0.058)		
Accommodation and food service	1.150***	(0.035)		
Information en communication	1.143***	(0.035)		
Business services	1.066**	(0.025)		
Public administration	1.086	(0.048)		
Education	1.115*	(0.060)		
Human health and social work	1.125**	(0.048)		
Other service activities	1.160***	(0.043)		
Region fixed effects	Yes		Yes	
Clustered standard errors	Yes		Yes	
N (1000 obs)	344		344	

Source: CBS Microdata, own computations. * = 1%, ** = 5%, *** = 10% significance level. Standard errors are robust for clustering by 40 COROP regions. A subset of this table is presented in Table 5. The

sample of employees does not include self-employed, interns and workers in sheltered jobs. The model $\geq$25 hours includes only jobs for 25 weekly working hours or more.

Table 9: Cox proportional hazard model: sample of employees, full sample and restricted sample of employees working 25 hours per week or more

	Baseline		**≥25 hours**	
	HR	SE	HR	SE
Regional unemployment rate (by level of education)	1.115***	(0.028)	1.124***	(0.030)
Household type (reference: single without children)				
Unmarried couple without children	0.703***	(0.031)	0.692***	(0.032)
Married couple without children	0.684***	(0.045)	0.688***	(0.048)
Unmarried couple with children	0.619***	(0.075)	0.625***	(0.079)
Married couple with children	0.675***	(0.033)	0.685***	(0.033)
Single parent	0.911*	(0.034)	0.932	(0.041)
Gender				
Male	0.939***	(0.013)	0.915***	(0.014)
Age (reference: 25-35)				
35-45	0.524***	(0.028)	0.562***	(0.029)
45-55	0.313***	(0.011)	0.329***	(0.011)
≥55	0.264***	(0.010)	0.274***	(0.013)
Level of education (reference: lower)				
Medium	1.548***	(0.141)	1.513***	(0.144)
Bachelor	2.269***	(0.281)	2.267**	(0.281)
Master	2.766***	(0.364)	2.806***	(0.367)
Household income (reference: <20%)				
20%-40%	0.670***	(0.029)	0.671***	(0.036)
40%-60%	0.633***	(0.029)	0.632***	(0.034)
60%-80%	0.624***	(0.036)	0.634***	(0.040)
80%-100%	0.781***	(0.041)	0.790***	(0.048)
Household wealth (reference: <20%)				
20%-40%	0.830***	(0.014)	0.835***	(0.017)
40%-60%	0.792***	(0.021)	0.782***	(0.024)
60%-80%	0.979	(0.028)	0.966	(0.033)
80%-100%	1.312***	(0.039)	1.294***	(0.034)
Housing type (reference: owner occupant)				
Rental, social sector	1.351***	(0.053)	1.398***	(0.056)
Rental, private sector	2.106***	(0.040)	2.086***	(0.045)
Rental, sector unknown	3.211***	(0.765)	3.077***	(0.746)
Unemployment duration (reference: not applicable)				

Continued on next page

Cox proportional hazard model: sample of employees (continued)

	Baseline		**≥25 hours**	
	HR	SE	HR	SE
<3 months	1.240***	(0.070)	1.318***	(0.079)***
3-6 months	0.827**	(0.059)	0.839*	(0.071)
6 months-1 year	0.907	(0.046)	0.933	(0.050)
1-2 year	0.957	(0.066)	1.010	(0.090)
≥2 years	0.602***	(0.084)	0.602*	(0.124)
Commuting distance				
(reference: 0, same district)				
0-5km	1.073	(0.135)	1.068	(0.138)
5-10km	1.226	(0.190)	1.186	(0.197)
10-20km	1.528***	(0.085)	1.484***	(0.087)
20-50km	1.981***	(0.160)	1.896***	(0.161)
≥50km	2.452***	(0.196)	2.318***	(0.182)
Contract type				
(reference: permanent)				
Temporary	1.330***	(0.055)	1.300***	(0.057)
Agency work	1.052	(0.040)	0.972	(0.040)
Flexible hours	1.136**	(0.056)	1.029	(0.054)
DGA	1.214***	(0.052)	1.156**	(0.052)
Hours per week				
(reference: <12)				
12-20	0.991	(0.048)		
20-25	1.040	(0.037)		
25-30	1.234***	(0.046)	reference	
30-35	1.386***	(0.053)	1.129***	(0.024)
≥35	1.659**	(0.096)	1.373***	(0.054)
Sector				
(reference: financial services)				
Agriculture	0.957	(0.112)	0.940	(0.111)
Manufacturing	0.930	(0.046)	0.924	(0.046)
Electricity, gas, water supply	1.047	(0.061)	1.050	(0.063)
Construction	0.814***	(0.037)	0.812***	(0.038)
Wholesale and retail trade	1.016	(0.043)	1.005	(0.042)
Transportation and storage	1.087	(0.058)	1.091	(0.057)
Accommodation and food service	1.150***	(0.035)	1.127**	(0.042)
Information en communication	1.143***	(0.035)	1.143***	(0.039)
Business services	1.066**	(0.025)	1.075**	(0.026)
Public administration	1.086	(0.048)	1.084	(0.048)
Education	1.115*	(0.060)	1.077	(0.056)
Human health and social work	1.125**	(0.048)	1.126**	(0.052)
Other service activities	1.160***	(0.043)	1.160**	(0.054)
Region fixed effects	Yes		Yes	
Clustered standard errors	Yes		Yes	
N (1000 obs)	344		288	

Source: CBS Microdata, own computations. * = 1%, ** = 5%, *** = 10% significance level. Standard

errors are robust for clustering by 40 COROP regions. A subset of this table is presented in Table 5. The sample of employees does not include self-employed, interns and workers in sheltered jobs. The model $\geq$25 hours includes only jobs for 25 weekly working hours or more.

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