From Welfare to Work: Does the Neighborhood Matter?

Bas van der Klaauw*
Jan C. van Ours †

May 2001

Abstract

This paper investigates whether individual transition rates from welfare to work are influenced by neighborhood effects. We use a unique administrative database on welfare recipients in Rotterdam, the second largest city of The Netherlands. We find that conditional on personal characteristics there is a negative relationship between the neighborhood unemployment rate and the transition rate from welfare to work of young Dutch welfare recipients. We do not find any neighborhood effects for older Dutch welfare recipients and non-Dutch welfare recipients. When performing some sensitivity analyses this result is robust to different specifications.

*Free University Amsterdam and Scholar.
Address: Department of Economics, Free University Amsterdam, De Boelelaan 1105, NL–1081 HV Amsterdam, The Netherlands.
†CentER for Economic Research, Tilburg University, Institute for Labor Studies (OSA), IZA and CEPR.
Address: Department of Economics, Tilburg University, P.O.Box 90153, NL–5000 LE Tilburg, The Netherlands.

Keywords: welfare to work, unemployment duration, spillover effects, selection effects.

We are grateful to the Welfare Agency (Dienst Sociale Zaken en Werkgelegenheid) of Rotterdam, and Daan Spannenberg in particular, for kindly providing the individual data and to the Center of Research and Statistics (Centrum voor Onderzoek en Statistiek) of Rotterdam for providing the neighborhood statistics. We thank two anonymous referees for useful comments.

1 Introduction

In many OECD countries, the rate at which welfare recipients leave welfare is very low, even though welfare programs differ substantially between countries. In the U.S. welfare is typically used to support single-parent households, whereas in European countries welfare is also used to support long-term unemployed workers.[1] Welfare (or "social assistance") then acts as a safety net for those unemployed workers who are not entitled (anymore) to any other benefits system such as unemployment insurance (UI) benefits or disability benefits.

Welfare recipients on average have low skills, i.e. low skilled unemployed workers are not only overrepresented in the inflow into welfare, but also have on average longer durations of collecting welfare benefits. Often low skilled workers live concentrated in poor areas of the city. Topa (2001) shows that unemployment in Chicago is geographically concentrated in a few areas and that the individual employment status not only depends on individual characteristics but also on the characteristics of neighbors. These spillover effects seem to be stronger for more disadvantaged workers, which suggests that neighborhood effects are particular relevant for welfare recipients as this group of workers is typically thought to contain the most disadvantaged workers. Similar results for the U.S. are found by Cutler and Glaeser (1997) who study the consequences of racial segregation.

This paper investigates the individual transition rate from welfare to work using micro data on Rotterdam, the second largest city in The Netherlands. We are not only interested in individual characteristics that determine the exit rate to work, but we also analyze the relevance of neighborhood effects. Although not as striking as in the U.S., in The Netherlands the long-term unemployed workers are not equally distributed over all neighborhoods of the city. Welfare recipients with identical observed characteristics living in different neighborhoods may have different individual transition rates due to demand and supply side conditions related to the neighborhood. Rotterdam is divided into around 80 neighborhoods with most of the economic activity concentrated in a small number of sparsely populated neighborhoods around the harbor area. The densely populated neighborhoods are all in the inner-city of Rotterdam, which is a relatively small area of around 100 square kilometers. There are substantial differences between neigh-

[1]European labor markets are characterized by a low inflow into unemployment, a high average duration of unemployment and long benefits entitlement (see Bean, 1994; and Layard, Nickell and Jackman, 1991; for surveys).

borhoods in the inner-city. The neighborhood unemployment rate ranges from slightly over 0% to around 20% (see Figure 1). Whereas in less than 30% of the neighborhoods the unemployment rate is larger than 15%, more than 50% of the welfare recipients lives in such a neighborhood.

Demand side conditions like local labor market conditions are not very likely to affect the individual transition rates from welfare to work. The geographical distances between the densely populated neighborhoods and the areas with most of the economic activity are small, i.e. commuting costs are low. It seems more likely that neighborhood effects are caused by the supply side. Supply side differences between neighborhoods exist if individuals with similar characteristics prefer to live in the same neighborhood or if the individual job search behavior is affected by neighbors. In economic literature two main explanations are given for the latter point. First, individuals may imitate the behavior of successful or better informed neighbors (Bala and Goyal, 1998; Eshel, Samuelson and Shaked, 1998). And second, individuals may transmit information on vacancies to each other, i.e. referral or informal job search (Holzer, 1988; Koning, Van den Berg and Ridder, 1997; Montgomery, 1991; Topa, 2001).

The relevant empirical literature can be divided into literature on neighborhood effects and literature on referral job search. The study most similar to ours is Hoynes (2000), who uses micro duration data to show that the role of the local labor market is particular important with respect to the duration that families receive AFDC (Aid to Families with Dependent Children) benefits. Another study on how the neighborhood affects the individual employment status is by Topa (2001) who analyzes data on tracts in Chicago and finds that spillovers are stronger for areas with more disadvantaged workers. Case and Katz (1991) and O'Regan and Quigley (1998) show that the neighborhood composition matters when determining the youth employment status. A higher unemployment rate decreases the individual employment probabilities. Mayer and Jencks (1989) give an overview of the literature on how the neighborhood affects the inhabitant's behavior, for example in case of school achievement, crime, success in the labor market, etcetera.

Holzer (1988) finds that job referral is the most frequent used and most efficient search method of youth unemployed workers. An opposite result is found by Blau and Robbins (1990), who suggest that referral job search is particular relevant to employed job searchers, but almost negligible to unemployed workers. Koning, Van den Berg and Ridder (1997) who analyze Dutch data find that the distinction between formal and informal job search is largely irrelevant. Similar results on The Netherlands are found by Lindeboom and Van Ours (1993).

In the empirical analysis of this paper we use a Mixed Proportional Hazard specification. The exit rate out of welfare into employment is allowed to depend on observed explanatory variables, both individual characteristics and neighborhood characteristics, on the elapsed unemployment duration, and on unobserved determinants. For the duration dependence we take a flexible piecewise constant specification. To estimate the model we use three different subsamples of welfare recipients; Dutch job losers, non-Dutch job losers and Dutch school leavers.

Manski (1993, 1995, 2000) stresses the problems arising with identifying neighborhood effects. Only in case the researcher has prior information specifying the composition of a reference group inference on the mechanisms through which the neighborhood affects labor market outcomes is possible. Using a reduced-form empirical analysis of single-spell micro duration data it is not possible to make a direct distinction between the above mentioned neighborhood effects. However, we argue that an indirect distinction between the relevant types of neighborhood effects can be made. First, due to the small geographical distances between the neighborhoods in our case local labor market effects are irrelevant. What remains are spillover effects and selection effects. To make a distinction between these effects, we consider the local unemployment rate to be a measure of spillover effects and the average housing prices in the neighborhood to be related to selection effects. For justification we use the following line of reasoning. Expenditures on housing are a very important part of the total expenditures of low income households. Individuals who anticipate a long period of low income will choose to live in a neighborhood where housing expenditures are low. Due to rent regulation rents are constant over long periods of time.[2] Therefore, welfare recipients who want to have low housing expenditures will select themselves into neighborhoods where housing prices are low. The local unemployment rate does not affect the (expected) expenditures of the low income households. Therefore, this is not an indicator for selection into neighborhoods. Instead, a high local unemployment

[2]The Dutch housing market is highly regulated, which means that there are social rental housing projects in almost all neighborhoods of the city. The amount of (government) rent subsidies only depends on household income and the rent (see Koning and Ridder, 1997). The rent subsidy only compensates a part of the difference between a low and a high rent. So, conditional on the rent there are no financial incentives for welfare recipients to prefer living in certain neighborhoods over other neighborhoods.

rate may have negative spillover effects on job finding rates. We do not claim that this argumentation is a strict identification. We return in Subsection 3.1 to the issue of identification.

Our empirical results show that for young Dutch welfare recipients the local unemployment rate does matter and the average housing prices do not. It should be stressed that young individuals are the most mobile. The argumentation given above should thus be most valid for this group of welfare recipients. This implies that spillover effects are important and selection effects are irrelevant. The nature of the spillover effects is unclear. On the one hand in a neighborhood with high unemployment, there might be less (informal) information about jobs available, i.e. social networks in these neighborhoods are less valuable when searching for a job. On the other hand, the attitude towards joblessness and the social norms concerning work may differ between low and high unemployment neighborhoods. We do not find any significant neighborhood effects for the groups of older Dutch welfare recipients and non-Dutch welfare recipients. We present various types of sensitivity analyses, including allowing for other observed and also unobserved neighborhood characteristics, but the basic results remain the same.

The outline of this paper is as follows. Section 2 gives a short description of the Dutch welfare system. In Section 3 we discuss some theoretical background on how the neighborhood might affect the individual transition rate from welfare to work and we present our statistical model. Section 4 discusses the unique database we use to estimate the model. This database covers all unemployed individuals who started to collect welfare benefits in Rotterdam in 1994 and contains information about them until they left the welfare system or until October 1996, whichever occurred first. Except for individual characteristics we also observe the welfare recipient's neighborhood, which is linked to a separate database containing information on statistics of each neighborhood in Rotterdam. In Section 5 we present the estimation results. Section 6 concludes.

2 Welfare recipients in The Netherlands

In this section we describe some institutional aspects of the Dutch welfare (or "social assistance") system in the mid-1990s. It is not our intention to give an exhaustive description of the system. Instead, we explain the basic structure.[3]

The Netherlands has about 16 million inhabitants of which 6 million are employed workers. Welfare benefits support people without income who are not entitled to any other benefits scheme. In addition, the individual must (*i*) be legally allowed to stay in The Netherlands, and (*ii*) be over 18 years. In 1994, 485.000 individuals without work received welfare benefits. Of these, 320,000 are counted as unemployed, which means that they are obliged to search for a job. The remaining 165,000 individuals received welfare benefits without an obligation to search for a job. Of the latter group, 55% belongs to a single-parent household with children aged below 12 years (welfare for the latter type of individuals is similar to AFDC in the U.S.). In the sequel we ignore the recipients who do not have an obligation to search for a job, since their job finding rate is determined in a very different way than for the other recipients. For simplicity we will use the term "welfare recipient" to denote recipients that have an obligation to search for a job.

Welfare benefits are means-tested (the means-test also relates to income of a partner and ownership of assets like a house). Concerning the level of benefits there are four household categories.[4] In 1995, the net benefits level for a two-parent family (i.e., a married couple with or without children) was about 1800 Dutch guilders per month.[5] For a single-parent family, this was about 1600 guilders. Finally, for a single individual aged over 23 it was about 1250 guilders, whereas for a single individual aged below 23 it was about 900 guilders. Municipalities have power to provide bonuses on top of the basic benefits level.

In 1994, about 35% of the welfare recipients had been collecting welfare benefits for an uninterrupted duration of more than 3 years. Of the welfare recipients, 68% is single, 25% is married and only 7% belongs to a single-parent family. Welfare recipients often have low skills. The fraction of individuals with primary education is 15% for the whole labor force but 35% for the welfare recipients. The age structure of the population of welfare recipients is about the same in the labor force.

In terms of inflow one may distinguish between two types of welfare recipients.

[3]A more extensive discussion can be found in Van den Berg, Van der Klaauw and Van Ours (1998). Our description is based on some publications in Dutch on welfare in The Netherlands (Angenent, Bommeljé and Schep, 1993, 1994; Angenent and Den Heeten, 1995).

[4]There are a few other cases that are less common; see e.g. Van Andel and Bommeljé (1996).

[5]One guilder is about 0.45 Euro.

The first type concerns school leavers, i.e. workers who enter unemployment after leaving full-time education. The second type concerns job losers, i.e. workers with a history of labor force attachment. The workers in this group have either run out of eligibility for UI benefits or never collected UI benefits because they did not meet eligibility criteria at the start of their unemployment spell. The maximum duration of UI benefits depends on the employment history of the individual and ranges from 6 months to 4.5 years. Note that the individuals entering welfare from UI are a selective sample of the inflow into UI. On average, the more disadvantaged workers eventually move to welfare. In the inflow into welfare, the group of school leavers is much smaller than the group of job losers (10% versus 90%). There is also a large difference between the exit rates of the two groups (65% and 35% within a year, respectively[6]).

A welfare recipient has several obligations in order to remain eligible for a benefit: he has to (*i*) prevent unnecessary job loss, (*ii*) take actions to prevent him from staying unemployed, so he has to search for a job and accept appropriate job offers, register at the public employment office, participate in education and training, etcetera, and (*iii*) keep the welfare agency informed about everything that is relevant to the payment of welfare benefits. A welfare recipient who does not comply with these guidelines may be confronted with a sanction in the form of a punitive temporary reduction of the welfare benefits (see Van den Berg, Van der Klaauw and Van Ours, 1998).

3 Specification of the statistical model

3.1 Theoretical background

In this section we present the Mixed Proportional Hazard model that we use in the empirical analysis. Before giving the outline of this model we first discuss some hypotheses that may explain why neighborhoods affect the individual transition rate from welfare to work. At the end of this section we consider the parameterization of our model.

The neighborhood may affect the behavior of individuals in many ways. We focus on three main effects, local labor market effects, spillover effects and selec-

[6]Note that most welfare recipients under 21 years participate in youth job guarantee programs after having been on welfare for 6 months.

tion effects.[7] At the end of this subsection we discuss the identification of these effects.

Labor markets in different regions may be independent even if they are characterized by different demand side conditions in terms of wages and available job opportunities. A low geographical worker mobility, most likely caused by high cost of commuting faced by the workers, is often responsible for this. Workers that live far from areas with a high economic activity may face high commuting costs, which increases their reservation wage. Then, local labor market conditions are an important determinant of local unemployment. For the U.S. Hoynes (2000) finds that local labor market conditions have an important effect on the transition rate from welfare (AFDC) to work.

Within a structural job search framework Van den Berg and Gorter (1997) study the willingness to pay for commuting time in The Netherlands. Their empirical results show that the disutility of commuting time is low for workers living in highly urbanized areas as compared to rural areas and particularly high for females with dependent children. This indicates that in our setting it is very unlikely that local labor market conditions affect individual transition rates from welfare to work. First, our database contains welfare recipients in Rotterdam, which is a highly urbanized area. Most of the economic activity in and around Rotterdam is concentrated is a small number of sparsely populated neighborhoods. Because the distance between these areas and the densely populated areas is small, commuting times are short and therefore the disutility of commuting is low. And second, recall from Section 2 our database only contains welfare recipients with an obligation to search for a job. Females with dependent children, which is the group of workers with the highest disutility of commuting, are not in our database. Single females with dependent children do not have the obligation to search for a job and when females are not single, most often the husband works or is the household member eligible for collecting unemployment benefits.

In economic literature many studies address the importance of distinguishing between various job search methods. Holzer (1988) introduced a discrete time model which involves the choice of the job search method by the unemployed worker. As the unemployed worker determines the effort denoted to each job

[7] Manski (1993) refers to these effects as exogenous effects, endogenous effects and correlated effects, respectively. Manski (2000) distinguishes contextual interactions endogenous interactions and correlated effects.

search method, job offer arrival rates are endogenous (see also Blau and Robins, 1990). The most frequently used distinction is between formal and informal job search (Koning, Van den Berg and Ridder, 1997; Montgomery, 1991). Job search is considered as formal in case the worker applies for a job using formalized search methods like personnel advertisements and the public employment office. Informal search occurs when for example unemployed workers receive job offers through referral by an employed worker, a friend or a relative. An essential requirement to use informal job search is an extensive network of employed relatives and friends. Informal search channels are less costly in time and money than formal search channels. Furthermore, firms consider referrals from their employees as more informative and more reliable. Montgomery (1991) argues that informal job search allows firms to generate more profit. And workers with a large social network use informal job search because it generates more income. Topa (2001) suggests that due to basic insurance motives optimally behaving individuals share information concerning vacancies within their social network. It is in the interest of employed workers to tell relatives and friends about job opportunities, so that if the worker becomes unemployed these relatives and friends will in turn help him find a job.

In case welfare recipients actually use informal job search methods, neighborhood effects are only observed if the social networks largely coincide with the neighborhood. Using data on The Netherlands Koning, Van den Berg and Ridder (1997) find no evidence that the choice of search channels is endogenous and they do not find a wage advantage of informal job search over formal job search. Because having a large social network does not increase the rate at which job offers arrive, they suggest that the distinction between formal and informal job search is largely irrelevant. In their empirical analysis, the size of network is a subjective measure of the number of friends and acquaintances. Koning, Van den Berg and Ridder (1997) distinguish between two types of individuals, i.e. individuals who have larger than normal social network and individuals who have a normal or smaller social network. The quality of the social network is thus not taken into account. Also using data on The Netherlands Lindeboom and Van Ours (1993) find that informal job search is not very relevant to unemployed workers.

Similar kind of neighborhood effects exist if individuals imitate the behavior of their neighbors. Within the neighborhood spillovers arise if individuals copy behavior of successful or better informed neighbors. Some studies refer to this as positive role models within neighborhoods. In a theoretical local interaction model Eshel, Samuelson and Shaked (1998) show that in equilibrium different types of areas exist. In some areas altruistic behavior dominates, in other areas egoistic behavior. In their model agents need to learn which actions work well. Then, imitation may be an important tool. Agents copy the neighbors' behavior in case the neighbors on average generate better outcomes.[8] Eshel, Samuelson and Shaked (1998) study individuals investing in a public good, but some of the results may also hold for the labor market. An application to the labor market is possible if for example individual outcomes refer to wages or unemployment duration and investing in a public good refers to the amount of search effort.

The final possible neighborhood effect we discuss results from the endogeneity of location choice. Individuals may prefer to live in neighborhoods where people have a similar attitude towards joblessness or have similar job search behavior. This may lead to segregation (Schelling, 1971). Neighborhood effects are then observed as a consequence of segregation. An alternative explanation for this type of neighborhood effects originates when individuals choosing a neighborhood to live anticipate on future earnings. Individuals with bad labor market characteristics expect long unemployment durations and low future incomes. Therefore, these individuals probably prefer to live in cheap houses. If cheap housing is concentrated in certain neighborhoods of the city then a high proportion of individuals with bad labor market positions lives in these neighborhoods. The neighborhood effects observed in this case are not merely the result of interaction between individuals, but are rather caused by independent behavior of similar individuals. Cutler and Claeser (1997) correct for endogeneity of location choice by comparing the aggregated outcomes of different cities. Their empirical results show that a higher degree of racial segregation leads to substantially worse outcomes for blacks.

In our study we use cross-neighborhood differences to identify neighborhood effects. Manski (1993) stresses the limitations of studying the nature of these effects (see Manski, 1995, 2000, for a more extensive discussion on the subject of identification problems within these frameworks). Without having a control group of individuals, it is formally not possible to distinguish between the different hypotheses to explain why neighborhoods affect the individual transition rate from welfare to work. However, above we argued that differences in local labor

[8]Bala and Goyal (1998) suggest that also to utility maximizing agents it can be optimal to imitate the behavior of others, for example if decision making is costly or agents do not possess the computational capacity for complex decision making.

market conditions are very unlikely the cause of differences in individual exit rates to work. Therefore, in particular, we are left with distinguishing between (*i*) the effect of neighborhoods on the behavior of individuals (e.g. informal job search, copying neighbors' behavior) and (*ii*) the individual selection of the neighborhood. In our empirical analysis we can not make a direct distinction between the competing hypotheses. To illustrate this consider a certain neighborhood in which housing is cheap and the individual transition rate from welfare to work is low. In case not all relevant individual characteristics are observed, it is easy to show that both earlier stated hypotheses may be valid. Assume for example that motivation to search for a job is an unobserved individual characteristic. On the one hand, the individuals living in the same neighborhood may affect each others motivation and therefore most of the individuals living in this neighborhood have a low motivation. On the other hand, less motivated individuals know that they face long unemployment spells and low expected future earning. If individuals take their expected future earnings into account many less motivated individuals live in neighborhoods where housing is cheap. Although we cannot make a direct distinction between the alternative hypotheses we can do it indirectly by investigating whether conditional on observed characteristics and elapsed duration of the welfare spell unobserved characteristics are present. Furthermore, we relate differences in exit rates out of welfare to differences in neighborhood characteristics. More specifically, if the choice of location is relevant we expect the average price of housing in the neighborhood to matter and if spillover effects are relevant we expect the neighborhood unemployment rate to be important.

Finally, it may be the case that individuals with similar observed individual characteristics live concentrated in a few neighborhoods of the city. Then after correcting for observed individual heterogeneity we would not find any neighborhood effects due to selection anymore. Therefore, in the empirical analyses we will investigate the sensitivity of the estimated neighborhood effects with respect to generating additional observed heterogeneity. In particular, we will drop individual characteristics from the empirical analysis that are related to past labor market behavior.

3.2 The empirical model

Before discussing our empirical model it is useful to first give a brief outline of our data where the next section gives more detailed information. Our database consists of all individuals who started collecting welfare benefits in 1994 in Rotterdam. For each individual we know the precise duration of welfare, unless there was right-censoring at the end of the observation period, which is October 1996. We also observe the exit destination, which is usually employment. Other possibilities are: leaving the city, getting married or stopping to apply for welfare benefits for unknown reasons. Exit to such destinations is treated as independent right-censoring of the duration until exit to work. We do not have information about what happens afterwards.

The empirical model we use is similar to the common used Hazard rate models (see e.g. Lancaster, 1990). Consider individuals receiving welfare benefits for t units of time. We assume that differences in transition rates from welfare to work can be characterized by the observed individual characteristics x, the observed neighborhood characteristics z, the unobserved characteristics v and the elapsed welfare duration itself. We assume x and z to be constant and v to be independent of x and z.

The transition rate from welfare to work at t conditional on x, z and v is denoted by $\theta(t|x,z,v)$ and is assumed to have the familiar Mixed Proportional Hazard (MPH) specification

$$\theta(t|x,z,v) = \lambda(t)\psi(x,z)\exp(v) \tag{1}$$

in which $\lambda(t)$ represents the individual duration dependence. Let t be the realized duration when leaving to employment. The conditional density function of $t|x,z,v$ can be written as

$$f(t|x,z,v) = \theta(t|x,z,v)\exp\left(-\int_0^t \theta(s|x,z,v)ds\right)$$

Let $G(v)$ be the distribution function of the unobserved characteristic v. The density function of t conditional on x and z equals

$$f(t|x,z) = \int_v f(t|x,z,v)dG(v)$$

It is straightforward to derive the individual contributions to the likelihood function from this density function. The use of a flow sample of welfare spells means that all spells are observed from the start, so that we do not have any problems with initial conditions. The right-censoring in the data is exogenous and is therefore solved in a straightforward manner within the hazard rate framework.

For the duration dependence function we take the most flexible specification used to date. We take $\lambda(t)$ to have a piecewise constant specification,

$$\lambda(t) = \exp\left(\sum_{j=1,2,\ldots} \lambda_j I_j\left(t\right)\right)$$

where j is a subscript for time intervals and $I_j(t)$ are time-varying dummy variables that are one in consecutive time intervals. Note that with an increasing number of time intervals any duration dependence pattern can be approximated arbitrarily closely. By now it is well known that duration dependence specifications with only one parameter (like a Weibull specification) are overly restrictive (see e.g. Lancaster, 1990). We come back to the specification of the function $\psi(x, z)$ and the distribution of the unobserved heterogeneity term v in Section 5 when we discuss the estimation results.

4 Data

Our database concerns welfare recipients in Rotterdam, which is the second largest city of The Netherlands. At the end of 1995 Rotterdam had almost 600,000 inhabitants of which approximately 260,000 were employed workers. About 40% of the Rotterdam population consists of immigrants or their children. There were around 35,000 unemployed workers, which is 15% of the labor force. About 61,000 individuals were receiving some kind of unemployment benefit. Of these, 78% had received this benefit already for more than one year.

The database contains administrative information on all unemployed individuals who started to collect welfare benefits in Rotterdam in 1994 and who were obliged to search for a job. The advantage of using an administrative database is that the data do not suffer from selective nonresponse or attrition from the database. The full database consists of 11350 individuals. We exclude from the data individuals who became eligible for welfare before 1994 but did not start to collect benefits until 1994, individuals for which the moment of inflow into welfare equals the moment of outflow, individuals for which the location of the neighborhood is missing and individuals living in neighborhoods not belonging to the inner-city of Rotterdam. As a result, the final data set consists of 7519 job losers and 1150 school leavers. As explained in Section 2 job losers and school leavers have very different characteristics and it is obvious that the behavior of these two groups can not be captured within a single model. Therefore, we analyze these groups separately. We distinguish not only between job losers and school leavers, but within these groups we also distinguish between Dutch and non-Dutch welfare recipients. The final database only contains only 205 non-Dutch school leavers, which is insufficient for an empirical analysis. Consequently, we estimate the empirical model using the three separate data sets consisting of Dutch job losers, non-Dutch job losers and Dutch school leavers. All information on events is daily.

In the empirical analyses we use the values of the explanatory variables x and z at the moment of inflow. In addition to standard personal characteristics, we include in x a variable indicating whether the individual has ever received welfare benefits before. It may be clear that this variable is only relevant to job losers, school leavers come from full-time education and hence face their first spell of collecting welfare benefits. In case of marriage or concubinage the individual is classified as being "married". To allow for interaction between marriage and children, we consider four different household types, (*i*) single without children, (*ii*) single with children, (*iii*) married without children, and (*iv*) married with children. Recall that single parents with children under 12 years old are not in our database as they do not have an obligation to search for a job. Because school leavers are of low age, we do not consider "age" as an explanatory variable for this group. For the same reason, single parents hardly appear in our database. However, because this is a special subsample we should not ignore "single with children" as explanatory variable. It should be stressed that variables that are not relevant for the welfare agency are not included in the database. This means that we do not have information on the profession and the level of education of the welfare recipients.

Finally, the database identifies the neighborhood of the welfare recipient which is used to assign neighborhood characteristics using summaries from the Center of Research and Statistics of Rotterdam. The neighborhood statistics are recorded in 1994, which is the year that the welfare recipients in the database started collecting welfare benefits. As mentioned in the introduction some industrialized neighborhoods are very sparsely populated and often no welfare recipients live in these neighborhoods. Rotterdam is divided into approximately 80 neighborhoods of which 66 belong to the inner-city. The total area of the inner-city is approximately 100 square kilometers, which means that a neighborhood on average is 1.5 square kilometers. The average number of inhabitants in the neighborhoods in the inner-city is approximately 8000. The distance to the center of Rotterdam from any neighborhood is at most 6 kilometers (which is less than 4 miles), while the harbor area can always be reached within at most 10 kilometers. Furthermore, Rotterdam has a well organized public transport consisting of trams, busses and a subway network.[9] The additional database on neighborhood statistics includes for each neighborhood a number of economic, social and demographic characteristics z, such as the unemployment rate, share of Non-Dutch inhabitants, average price of houses, geographical mobility and crime rate.

The empirical survival rates (Kaplan-Meier estimates) of the four above defined samples of welfare recipients are given in Figure 2. As expected, school leavers have higher exit rates than job losers and Dutch welfare recipients have higher exit rates than their counterparts. The differences between the groups are rather large. While after 8 months 50% of the Dutch school leavers found work, around 75% of the Dutch job losers and non-Dutch school leavers is still on welfare and more than 85% of the non-Dutch job losers still receives welfare benefits.

Table 1 provides some statistics of the data set of 5653 Dutch job losers, 1866 non-Dutch job losers and 945 Dutch school leavers. There are big differences in the percentages of individuals that leave the welfare system before October 1996. School leavers are observed to exit welfare to work more often than job losers and within this group the exit probability of Dutch welfare recipients is higher than the non-Dutch welfare recipients. Since some of the welfare recipients were "exposed to the risk" of leaving the welfare system since January 1994, while others entered in December 1994, it is difficult to draw conclusions from these numbers. Nevertheless, we can get a first impression of differences between individuals by comparing such probabilities for different subsamples. Within all subsamples male, married and childless welfare recipients have a slightly higher exit probability than their counterparts. Furthermore, for the subsamples of job losers the exit probabilities of older recipients are much smaller than of young recipients, recurrent recipients have a slightly lower exit probability for the group of non-Dutch and higher exit probability for the group of Dutch recipients. Finally, single welfare recipients without kids are more often observed to exit to work than their counterparts. Within the above mentioned groups the neighborhood statistics do differ between welfare recipients who are observed to exit before October 1996 and welfare recipients who do not exit to work. However, there are

[9] The distances also imply that a 30-40 minutes bicycle ride would be sufficient to cover the city.

differences between the subsamples of welfare recipients. Dutch welfare recipients tend to live more often than non-Dutch welfare recipients in neighborhoods with more expensive houses, a higher crime rate, lower geographical mobility and a less non-Dutch inhabitants. The unemployment rate does not seem to differ very much.

5 Estimation results

5.1 The baseline model

In this section we discuss the results of our empirical analyses. We start with discussing a model that only allows for heterogeneity through variation in individual characteristics. In Subsection 5.2 we extend this model by including neighborhood effects. The parameter estimates of all model specifications are obtained by using the method of Maximum Likelihood. We take the unit of time to be a month. Furthermore, we specify the piecewise constant duration dependence in terms of quarters and normalize by taking $\lambda_1 = 0$. To perform the estimations we have to specify the unobserved heterogeneity distribution, decide which neighborhood characteristics to include and specify $\psi(x, z)$ in equation (1). We estimate the model separately for the subsamples of Dutch job losers, non-Dutch job losers and Dutch school leavers.

In our "baseline" model the individual transition rate from welfare to work depends only on the elapsed duration of the welfare spell and observed individual characteristics, such that $\psi(x, z) = \exp(x'\beta)$. And the parameter v is an intercept, i.e. $G(v)$ is concentrated at a single (unknown) point of support. We estimate the parameters λ_t $(t = 1, \ldots, 11)$, v and β, where β is a vector of 9 parameters for the subsamples of job losers and 4 parameters for the subsample of school leavers.[10] For the subsample of non-Dutch job losers we do not observe any recipients with the age above 56 finding a job, therefore the maximum likelihood estimate corresponding to the covariate "Age 56–65" equals $-\infty$. Table 2 presents the estimation results for the three specified subsamples.

The estimated intercept v has the highest value for the Dutch school leavers, implying that conditional on the observed characteristics school leavers have a higher transition rate from welfare to work than job losers. For this latter group

[10] Because we do not observe any transition from welfare to work in the subsamples of job losers during the 11th quarter we can not estimate λ_{11}.

individuals with the Dutch nationality have higher exit rates than non-Dutch individuals. The estimates of the duration dependence λ_t indicate that overall the individual transition rate from welfare to work decreases as the duration of collecting welfare benefits increases. Apparently, stigmatization and discouraged worker effects play a significant role. The covariate effects on the exit rates to work are almost all significantly different from 0. In all three groups of individuals females, single welfare recipients and welfare recipients with children have lower probabilities to find work than their counterparts. It is interesting to pay some attention to the household characteristics, as they are closely related to the welfare benefits level. Recall that a couple without children receives benefits that are much lower per person than what a single individual receives, so one may expect someone in the former household to have a higher probability to find a job (note that someone who is married to a full-time employed worker is in general not entitled to welfare, so he would not be in our data). Irrespective of whether or not there are children in the household the individual in the "married" household has a higher exit rate than the single individual. Now consider the effect of children. Having children increases the benefits level of unmarried recipients, so one may expect this to decrease the exit rate (of course, having children may also increase the non-pecuniary utility of being unemployed, and this is an additional reason to expect a lower exit rate). It turns out that children do have a negative effect on the exit rate, whether one is married or not. Note that if the individual is a single parent and one of the children is below 12 years then he is not obliged to search for a job, so then he is not in our data. Finally, age seems to be the most important covariate in the transition rate for job losers. The job finding rate is lower for older job losers.

So far we did not correct for possible unobserved heterogeneity. It is well known that neglecting unobserved heterogeneity may lead to biased parameter estimates, both in duration dependence and observed heterogeneity. In particular, estimated duration dependence decreases slower and the estimated covariate effects are biased toward 0 when the hazard rate does not involve an unobserved component.[11] We take the distribution of the unobserved heterogeneity to be discrete with two unrestricted points of support (v^a, v^b) with associated probabilities $\Pr(v = v^a) = p = 1 - \Pr(v = v^b)$, where $0 \leq p \leq 1$. However, for none of the

[11]These results only hold in case of large samples and no right-censoring (see e.g. Lancaster, 1990).

subsamples of individuals we observe any significant unobserved heterogeneity. When optimizing the loglikelihood function of the model containing unobserved heterogeneity the locations of both mass points converge to each other during the iterations, i.e. the optimal value of the loglikelihood function does not improve compared to the model not containing unobserved heterogeneity.

5.2 Allowing for neighborhood effects

Now let us turn to the way in which the neighborhood may affect the individual transition rate from welfare to work. The available neighborhood statistics suffer from two problems. First, the neighborhood statistics describe the situation at the beginning of the welfare spell in 1994 and therefore are not time varying. This is a serious limitation as it does not allow us to include both the neighborhood characteristics and dummy variables for each neighborhood (fixed effects). The second problem concerns the high correlation between some of the neighborhood characteristics.[12] A high correlation between regressors causes some problems in the empirical analyses, in particular the standard errors of the parameter estimates are large. We return to this issue below. In the remainder of this section we focus only on the covariate effects of neighborhood characteristics.[13]

We start the neighborhood analysis with extending the "baseline" model by allowing for fixed neighborhood effects, i.e. for each neighborhood an indicator function for living in this neighborhood is included. Within each subsample there are some neighborhoods for which there are no welfare recipients observed and some neighborhoods for which we only observe welfare recipients with right-censored unemployment spells. Obviously, in the former case we are unable to estimate a fixed neighborhood effect, while in the latter case the estimated values of the fixed effects equal $-\infty$. Estimated standard errors are computed conditional on these values. In Table 3 we only report the estimated effect of the neighborhood with the highest exit rate and of the neighborhood with the lowest exit rate, ignoring neighborhoods for which we do not observe any outflow to work. For each subsample the differences between these values are larger than 4, implying

[12] On the level of the neighborhoods the correlations between the unemployment rate and other characteristics are: share of non-Dutch inhabitants 0.83, average house price -0.68, geographical mobility 0.23, crime rate -0.24.

[13] The estimated individual duration dependence and the estimated covariate effects do not change much as compared to the previous discussed "baseline" model. Therefore, these parameter estimates are not given in the tables providing the estimated neighborhood effects.

extremely large differences in transition rates between welfare recipients living in the neighborhood with the highest exit rate and identical welfare recipients living in the neighborhood with the lowest exit rate. We test whether all fixed effects are equal, i.e. we test the "baseline" model against this "fixed effect" model. The Likelihood Ratio (LR) statistic has a chi-square distribution with respectively 63, 54 and 59 degrees of freedom for the Dutch job losers, non-Dutch job losers and the Dutch school leavers. The LR test statistics equal 152.7, 65.5 and 100.2 indicating that for the both groups of Dutch welfare recipients indeed the neighborhood affects individual transition rates, while we can not reject the null hypothesis for the group of non-Dutch job losers ($\chi^2_{63;0.95} = 95.65$, $\chi^2_{54;0.95} = 72.2$ and $\chi^2_{59;0.95} = 78.8$).[14] The group of Non-Dutch welfare recipients is a quit heterogenous group. The largest groups come from Morocco (10% of the non-Dutch population in Rotterdam in 1994), Turkey (15%) and the former Dutch colony Surinam (19%). And these percentages vary also between neighborhoods. While in some neighborhoods the population from Morocco exceeds the population of Surinam, in other neighborhoods the population from Surinam is more than 10 times bigger. If there would be differences in re-employment rates between ethnic groups, the large fluctuations in ethnic composition between neighborhoods and the fact that we do not observe the exact nationality would cause neighborhood effects (due to selection). Since we do not find significant neighborhood effects for this group, the country of origin is not a very relevant indicator in explaining re-employment probabilities. Furthermore, it may be the case that non-Dutch individuals are involved in cross-neighborhood social networks that are either multi-ethnic or not very concerned with job search. It would be interesting to see whether this is also the case for young non-Dutch school leaver welfare recipients. However, as indicated before we lack a sufficient number of observations for this category of welfare recipients.

We have established that for Dutch welfare recipients the neighborhood af-

[14]We also perform the test for the existence of neighborhood effects given in Ridder and Tunalı(1999). This test is based on Stratified Partial Likelihood Estimation and allows for more general neighborhood effects including differences in duration dependence. This test shows that neighborhood effects exist for Dutch school leavers, but not for both groups of job losers. The values of the test statistics are 11.85, 4.92 and 12.59 for the groups of Dutch job losers, non-Dutch job losers and Dutch school leavers, respectively. The test statistics have a χ^2-distribution with 9, 8 and 4 degrees of freedom. The parameter estimates of the covariate effects obtained by Stratified Partial Likelihood Estimation are very close to the earlier presented covariate effects.

fects individual exit rates. To get an indication what drives these neighborhood effects, we replace the fixed effects by neighborhood characteristics (z) according to the multiplicative specification $\psi(x, z) = \exp(x'\beta + z'\gamma)$.[15] We have already argued in Subsection 3.1, that in our opinion the unemployment rate and the average price of houses are particularly important neighborhood characteristics. The unemployment rate within the neighborhood is interpreted as an indicator for spillover effects between unemployed workers searching for work. And we consider the average price of houses as an indicator for selection effects. If any selection effects exist, these are most likely to be represented by average housing price on young welfare recipients. Young welfare recipients have most likely just left their parental house. The price of a house is the most important variable when finding a new house. The selection effect then implies that individuals with bad labor market prospects, i.e. long expected durations of unemployment and low expected future income, select them self into the neighborhoods with cheap housing. Therefore, we first include the unemployment rate and the average price of houses separately, and then simultaneously. Later on we also investigate whether other neighborhood characteristics have any explanatory power concerning differences in the job finding rates. Additionally, we allow for unobserved neighborhood effects, which means that we exploit the "knowledge" that all individuals within a neighborhood have a similar unobserved heterogeneity component. The welfare spells of individuals living in the same neighborhood are treated as being multiple spells.[16] Again we choose a discrete distribution with two unrestricted points of support.

Table 4 presents the estimation results of the models including the unemployment rate, the average price of houses, and unobserved neighborhood effects. Only in case of the Dutch job losers we observe some dispersed unobserved heterogeneity at the "neighborhood level". The presence of unobserved neighborhood effects can either imply the presence of selection effects as individuals with a similar unobserved individual characteristic live in the same neighborhood or imply that other neighborhood characteristics than the unemployment rate and the av-

[15]As an additional test we also do this for the group of non-Dutch job losers, for which we can not reject the hypothesis that there are no neighborhood effects.

[16]In general, the standard errors of the estimated neighborhood effects are downward biased if we treat welfare recipients living in the same neighborhood as independent observations. This approach solves for this bias. However, in our empirical analyses this bias turned out to be almost 0.

erage housing prices are important for the exit rate to work. We investigate the latter possibility below. Unobserved neighborhood effects are absent for the group of Dutch school leavers and non-Dutch job losers. Only for both subsamples of Dutch welfare recipients we find significant covariate effects of the unemployment rate and the average price of housing when including these separately. However, for both groups of welfare recipients when including both the unemployment rate and the average price of house the covariate effect of the average prices of houses is insignificant while the unemployment rate still has a significant impact on the job finding rates. More precise adding the average price of houses to the model that already contains the unemployment rate does not improve the model, while adding the unemployment rate to a model containing the average housing price significantly improves the model and makes the covariate effect of the average price of houses disappear. The parameter estimates of the unemployment rate equals -4.92 for Dutch school leavers and -3.40 for Dutch job losers. To illustrate the magnitude of this neighborhood effect, we compare the exit rate to work of a welfare recipient living in a neighborhood with a relatively low unemployment rate (5%) with a welfare recipient with identical individual characteristics living in a neighborhood with a relatively high unemployment rate (15%). For a Dutch school leaver the exit rate is 1.64 times larger when living in the neighborhood with the low unemployment rate as compared to the neighborhood with the high unemployment rate, while this ratio is 1.41 for Dutch job losers. Additional to this neighborhood effect we observe only for Dutch job losers a second neighborhood effect, as we find dispersed unobserved heterogeneity at a neighborhood level. The estimation results show that within 28% of the neighborhoods welfare recipients have a higher exit rate than in the other 72% of the neighborhoods. The individual exit rates in the neighborhoods with a high exit rate are 1.31 times higher.

So far we only included the unemployment rate and the average price of houses as measures of the neighborhood. It may be the case that other characteristics are relevant to the individual exit rate to work. We add to the model the percentage inhabitants with a non-Dutch nationality, the geographical mobility and the crime rate. The geographical mobility and the crime rate are considered to represent negative stigma effects. The percentage of inhabitant with a non-Dutch nationality is also a measure of selection effects, particularly for non-Dutch welfare recipients who may prefer to live in neighborhood with a high percentage of non-Dutch inhabitants. The estimation results of this model extension are presented in Table 5. For none of the subsamples adding these neighborhood characteristics improved the model significantly. Furthermore, all estimated neighborhood effects are insignificant. However, if we remove the unemployment rate from the models for Dutch welfare recipients, the loglikelihood function decreases with 2.06 for the job losers and 1.33 for the school leavers, which is according to a Likelihood Ratio test significant for the Dutch job losers. Since this shows the importance of the unemployment rate as explanatory variables for differences between neighborhood, we also estimate a model with a more flexible specification for the unemployment rate. We categorize the unemployment rate into four intervals, 0%–5%, 6%–10%, 11%–15% and 16%–20% (see also Figure 1). For the last three intervals we include a dummy variable. As can be seen from Table 6 the estimated covariate effects of the dummy variables decrease almost linearly in the unemployment rate for the both groups of Dutch welfare recipients.

When including neighborhood characteristics, we also tried dropping some of the individual characteristics from the model. The underlying idea is that when the results are driven by selection and selection on the observables is similar to selection on unobservables, the estimation results of the neighborhood effects will be affected. The prime candidate individual characteristic for being excluded from the model is "new client". This variable is more than the other individual characteristics the result of the individual behavior. However, we also tried dropping "age" from the model. Excluding these individual characteristics hardly affects the parameter estimates corresponding to the neighborhood characteristics. This confirms that selection effects are not very important in explaining differences in exit rates to employment between similar individuals living in different neighborhoods.

Until now, the specification of the statistical model is restrictive in the sense that it assumes that the neighborhood affects the behavior of all welfare recipients within a subsample in the same way. Empirical studies show however that spillover effects differ between individuals (Hoynes, 2000; Topa, 2001). To account for differences in effect between individuals we allow for interaction terms within the hazard rate, $\psi(x,z) = \exp(\beta' x + \gamma' z + \sum_{i,j} \alpha_{ij}(x_i \cdot z_j))$. Since from the analyses above follows that only the unemployment rate within the neighborhood is relevant, we only include interaction effects between the unemployment rate and the individual characteristics. We do not find any significant interaction effects for the subsamples of non-Dutch job losers and Dutch school leavers.

However, for the Dutch job losers the interaction with "age" is significant, as can be seen from Table 7 (for completeness the table also shows the same estimation results for the non-Dutch job losers). In particular, Dutch job losers with an age between 18 and 25 are more sensitive to the unemployment rate than older welfare recipients. This result is consistent with the effect we find for the school leavers.[17]

Finally, we perform some simulations to investigate the size of the impact of the unemployment rate on the transition rates from welfare to work. We focus on the probability of leaving welfare to work within one year after the start of collecting welfare benefit and distinguish between two types of individuals. Individual J is 25 years old and individual K is 50 years old. Both individuals are single men without children who never collected welfare benefits before. For each of the three subsamples we compute the exit probability of individuals J and K conditional on living in a neighborhood with a low unemployment rate (5%) or with a high unemployment rate (15%). Because for the Dutch job losers we found some dispersed unobserved heterogeneity on a neighborhood level we also condition on living in a neighborhood with high and low job finding rates due to unobserved characteristics. To compute the estimated exit probabilities we use for the Dutch job losers the parameter estimates of the model that allows for interaction effects between the unemployment rate and "age". For the non-Dutch job losers and the Dutch school leavers we use the parameter estimates of the model that only includes the unemployment rate as neighborhood characteristic.

The estimated exit probabilities are presented in Table 8. As noted earlier exit probabilities are much lower for non-Dutch individuals than for Dutch individuals. It is clear that the neighborhood does not affect the probability of job finding for non-Dutch job losers. The neighborhood effects are largest for the young Dutch welfare recipients. Consider individual J in the group of Dutch job losers, who is living in a neighborhood with a low unemployment rate and a high job finding rate due to unobserved neighborhood characteristics. This individual has an exit probability of 0.65 as compared to 0.39 for an identical individual living in a neighborhood with a high unemployment rate and a low job finding

[17] As a final check on the existence of neighborhood effects for young job losers (age under 26 years) we performed the test by Ridder and Tunalı(1999) on a subsample of young job losers finding that indeed such effects exist. The value of the test statistic is 1.44. Since, the test statistic has a χ^2-distribution with 5 degrees of freedom, we can not reject the null hypothesis that there do not exist any neighborhood effects.

rate due to unobserved neighborhood characteristics. If this individual J is a school leaver the exit probabilities are 0.72 when living in a neighborhood with a low unemployment rate and 0.54 when living in a neighborhood with a high unemployment rate. While for young Dutch job losers the exit rates are the most affected by the unemployment rate within the neighborhood, the exit rates of older Dutch job losers are equally affected by the unobserved neighborhood characteristics and the unemployment rate in the neighborhood.

In most literature on neighborhood effects in the U.S. results similar to ours are found (see Case and Katz, 1991; O'Regan and Quigley, 1998; Topa, 2001). Our results are easiest to compare with the results found by Hoynes (2000), as she also focuses on the re-employment of welfare recipients. Of course, when comparing the results we must keep in mind that the welfare program differs substantially between the U.S. and The Netherlands as does the population of unemployed workers collecting welfare benefits. The results found by Hoynes (2000) do not coincide completely with our results. There are two main differences. First, Hoynes (2000) finds that also neighborhood characteristics other than the unemployment rate and the educational level, such as for example median income, are relevant. And second, Hoynes (2000) finds that minorities are more sensitive to the neighborhood composition, whereas we find the opposite result that the neighborhood does not affect the job finding rate of non-Dutch welfare recipients

6 Conclusions

In this paper we have investigated to what extent the transition from welfare to work of individual welfare recipients is influenced by characteristics of the neighborhood they live in. We analyzed a sample of welfare recipients in Rotterdam, which is the second largest city of The Netherlands. In particular, we distinguished three groups of welfare recipients, Dutch job losers, non-Dutch job losers and Dutch school leavers. For non-Dutch job losers we did not find any evidence that neighborhood characteristics determine their exit rate to a job. This does not necessarily mean that the job search behavior of non-Dutch welfare recipients is insensitive to social interaction. The social network of non-Dutch welfare recipients may not coincide with the neighborhood, but it can be organized according to cross-neighborhood social networks.

Our empirical results show that the neighborhood affects the individual transition rates from welfare to work of young Dutch welfare recipients. These transition rates are lower if the unemployment rate within the neighborhood is higher. Other neighborhood characteristics, in particular housing prices do not have any effect.

Like most empirical analyses on neighborhood effects our empirical analysis also suffers from identification problems. We are unable to make a distinction between the case in which individual job search behavior is affected by the neighborhood and the case in which individuals choose to live in neighborhoods with similar behaving inhabitants. We do not claim to have formally solved this identification issue. However, we made indirectly a distinction between the nature of the neighborhood effects by examining which characteristics matter and which characteristics are irrelevant. We argued that housing prices are a measure for selection effects and the local unemployment rate an indicator for spillover effects. Expenditures on rent are the largest share of the total expenditures of a low income household and due to government regulation housing prices remain constant over long periods. Welfare recipients who anticipate on low income for a relatively long period, prefer to live in neighborhoods with cheap housing. Since local unemployment rates do not affect (expected) expenditures of low income groups, unemployment rates are no indicators for selection of neighborhoods.

Since the unemployment rate within the neighborhood appears to have a negative effect on the exit rate to work of young Dutch welfare recipients, spillover effects drive the neighborhood effects. It is not surprising that we find spillover effect to be important for young welfare recipients, this group is particularly vulnerable for social interaction. From a policy point of view this implies that when it comes to youth unemployment policy special attention should be given to young welfare recipients in high unemployment neighborhoods. The nature of the spillover effects is not clear and it is obvious that this would determine the required type of policy. For example, if high unemployment rates have a negative effect on individual transition rates from welfare to work because they cause a negative attitude towards work then a policy of strict monitoring is useful. If the spillover effects are due to the lack of efficient search networks intensive counseling is more relevant.

References

Angenent, F.J.A., Y.B. Bommeljé and G.J. Schep (1993), *Incentives for welfare recipients (in Dutch: prikkels in de bijstand)*, VUGA Uitgeverij, 's-Gravenhage.

Angenent, F.J.A., Y.B. Bommeljé and G.J. Schep (1994), *From welfare to job; about the position in the labor market and the outflow to work of welfare recipients (in Dutch: Van bijstand naar baan; over de positie op de arbeidsmarkt en de uitstroom van werk van clienten in de ABW-sec/RWW)*, VUGA Uitgeverij, 's-Gravenhage.

Angenent, F.J.A. and J. den Heeten (1995), *Punishment or incentive? The application of sanctions as labor market instrument in welfare (in Dutch: Straf of stimulans? Het toepassen van sancties als arbeidsmarktinstrument in de RWW)*, VUGA Uitgeverij, 's-Gravenhage.

Bala, V. and S. Goyal (1998), Learning from neighbours, *Review of Economic Studies* 65, 595–621.

Bean, C.R. (1994), European unemployment: A survey, *Journal of Economic Literature* 32, 573–619.

Blau, D.M. and P.K. Robins (1990), Job search outcomes for the employed and unemployed, *Journal of Political Economy* 98, 637–655.

Case, A.C. and L.F. Katz (1991), The company you keep: The effects of family and neighborhood on disadvantaged youth, NBER working paper no. 3705.

Cutler, D.M. and E.L. Glaeser (1997), Are ghettos good or bad?, *Quarterly Journal of Economics* 112, 827–872.

Eshel, I., L. Samuelson and A. Shaked (1998), Altruists, egoists and hooligans in a local interaction model, *American Economic Review* 88, 157–179.

Holzer, H. (1988), Search method use by the unemployed youth, *Journal of Labor Economics* 6, 1–20.

Hoynes, H.W. (2000), Local labor markets and welfare spells: Do demand conditions matter?, *Review of Economics and Statistics* 82, 351–368.

Koning, P., G.J. van den Berg and G. Ridder (1997), A structural analysis of job search methods and subsequent wages, Working Paper, Tinbergen Institute, Amsterdam.

Koning, R.H. and G. Ridder (1997), Rent assistance and housing demand, *Journal of Public Economics* 66, 1–31.

Lancaster, T. (1990), *The Econometric analysis of transition data*, Cambridge University Press, Cambridge.

Layard, R., S. Nickell and R. Jackman (1991), *Unemployment: Macroeconomic performance on the labour market*, Oxford University Press, Oxford.

Lindeboom, M. and J.C. van Ours (1993), Macro matching and micro search durations looking inside the black box of job formation, in H. Bunzel, P. Jensen and N. Westergård-Nielsen (eds.), *Panel data and labour market dynamics*, Elsevier Science Publishers, Amsterdam.

Manski, C.F. (1993), Identification of endogenous social effects: The reflection problem, *Review of Economic Studies* 60, 531–542.

Manski, C.F. (1995), *Identification problems in the social sciences*, Harvard University Press, Cambridge.

Manski, C.F. (2000), Economic analysis of social interactions, *Journal of Economic Perspectives* 14, 115–136.

Mayer, S.E. and C. Jencks (1989), Growing up in poor neighborhoods: How much does it matter, *Science* 243, 1441–1445.

Montgomery, J.D. (1991), Social networks and labor-market outcomes: Towards an economic analysis, *American Economic Review* 81, 1408–1418.

O'Regan, K.M. and J.M. Quigley (1998), Spatial effects upon employment outcomes: The case of New Jersey teenagers, Working Paper, University of California, Berkeley.

Ridder, G. and İ. Tunalı(1999), Stratified partial likelihood estimation, *Journal of Econometrics* 92, 193-232.

Schelling, T.C. (1971), Dynamic models of segregation, *Journal of Mathematical Sociology* 1, 143–186.

Topa, G. (2001), Social interactions, local spillovers and unemployment, *Review of Economic Studies* forthcoming.

Van Andel, H.G. and Y.B. Bommeljé (1996), *Into and out of welfare* (In Dutch: In en uit de bijstand), VUGA Uitgeverij, 's-Gravenhage.

Van den Berg, G.J. and C. Gorter (1997), Job search and commuting time, *Journal of Business and Economic Statistics* 15, 269–281.

Van den Berg, G.J., B. van der Klaauw and J.C. van Ours (1998), Punitive sanctions and the transition rate from welfare to work, Working Paper, Tinbergen Institute, Amsterdam and CentER Discussion Paper, Tilburg University.

	Job losers						School leavers		
	Dutch			Non-Dutch			Dutch		
Exit	**Obs**	**Cen**	**Tot**	**Obs**	**Cen**	**Tot**	**Obs**	**Cen**	**Tot**
Individual characteristics									
Age 18–25	51%	49%	2298	38%	62%	770	63%	37%	838
Age 26–35	42%	58%	2018	27%	73%	711	68%	32%	107
Age 36–45	31%	69%	867	22%	78%	253	–	–	0
Age 46–55	26%	74%	391	15%	85%	110	–	–	0
Age 56–65	11%	89%	79	0%	100%	22	–	–	0
Male	45%	55%	3446	31%	69%	1452	68%	32%	507
Female	38%	62%	2207	23%	77%	414	59%	41%	438
Collected welfare before	40%	60%	3125	30%	70%	1055	–	–	0
New client	46%	54%	2528	29%	71%	811	64%	36%	945
Single, no kids	44%	56%	4406	31%	69%	1010	64%	36%	884
Single, kids	25%	75%	602	16%	84%	148	17%	83%	12
Married, no kids	53%	47%	289	37%	63%	191	79%	21%	42
Married, kids	42%	58%	356	27%	73%	517	71%	29%	7
Neighborhood characteristics									
Unemployment rate	0.12	0.13	0.13	0.14	0.14	0.14	0.12	0.13	0.12
Average price of houses ($\times$ 10,000)	7.45	7.07	7.23	6.40	6.43	6.42	7.83	7.21	7.60
Non-Dutch inhabitants	0.47	0.50	0.49	0.56	0.56	0.56	0.46	0.52	0.49
Geographical mobility	0.20	0.20	0.20	0.21	0.21	0.21	0.20	0.21	0.20
Crime rate	0.15	0.15	0.15	0.13	0.13	0.13	0.19	0.17	0.19
Total	42%	58%	5653	30%	70%	1866	64%	36%	945

Explanatory note: The upper half of the table shows how welfare recipients with a certain individual characteristic are distributed over the subsamples defined by whether a transition from welfare to work is observed (Obs) or not (Cen). The last column (Tot) gives the total number of welfare recipients in the subsamples. The lower half of the table shows averages of the neighborhood characteristics over the above defined groups of welfare recipients. The last column (Tot) gives the full sample averages. The unemployment rate is the fraction of the neighborhood population that receives some type of unemployment benefits, house prices are in 10,000 Dutch guilders (1 guilder = 0.45 Euro), geographical mobility is the number of individuals flowing in or out the neighborhood as a fraction of the neighborhood population, crime rate is the number of crimes reported at the police also as a fraction of the neighborhood population.

Table 1: Some characteristics of the data set.

	Dutch job losers		Non-Dutch job losers		Dutch school leavers	
Intercept						
v	-3.06	(0.055)	-3.64	(0.12)	-2.44	(0.082)
Duration dependence						
λ_1	0		0		0	
λ_2	0.044	(0.061)	0.28	(0.14)	0.026	(0.11)
λ_3	-0.17	(0.068)	0.17	(0.15)	-0.18	(0.13)
λ_4	-0.33	(0.076)	-0.16	(0.17)	-0.59	(0.16)
λ_5	-0.39	(0.081)	-0.34	(0.18)	-0.42	(0.17)
λ_6	-0.47	(0.087)	-0.43	(0.19)	-1.16	(0.25)
λ_7	-0.55	(0.094)	0.081	(0.17)	-0.91	(0.24)
λ_8	-0.95	(0.12)	-0.55	(0.22)	-1.26	(0.30)
λ_9	-1.00	(0.14)	-0.57	(0.26)	-1.57	(0.43)
λ_{10}	-1.49	(0.23)	-1.54	(0.51)	-2.06	(0.71)
λ_{11}	–		–		-2.08	(1.00)
Individual characteristics						
Age 26–35	-0.27	(0.047)	-0.39	(0.098)	–	
Age 36–45	-0.66	(0.072)	-0.56	(0.15)	–	
Age 46–55	-0.97	(0.10)	-1.11	(0.25)	–	
Age 56–65	-1.98	(0.34)	$-\infty$		–	
Female	-0.084	(0.045)	-0.38	(0.12)	-0.14	(0.084)
New client	0.18	(0.042)	-0.016	(0.087)	–	
Single, kids	-0.66	(0.093)	-0.48	(0.23)	-1.84	(0.75)
Married, no kids	0.29	(0.084)	0.12	(0.14)	0.50	(0.19)
Married, kids	0.0083	(0.087)	-0.21	(0.11)	-0.28	(0.51)
$\log \mathcal{L}$	-10731.35		-2771.39		-2220.08	
N	5653		1866		945	

Explanatory note: Standard errors in parentheses.

Table 2: Estimation results of the "baseline" model for the subsamples of Dutch job losers, non-Dutch job losers and Dutch school leavers.

	Dutch job losers	Non-Dutch job losers	Dutch school leavers
Fixed effects			
Maximum	0.16	0.95	0.22
Minimum	-4.06	-4.64	-4.75
$\log \mathcal{L}$	-10654.98	-2738.64	-2170.08

Table 3: Estimated neighborhood effects in the model specification that extends "baseline" model by allowing for fixed effects for each neighborhood.

	Dutch job losers		Non-Dutch job losers		Dutch school leavers	
Specification A						
Unobserved heterogeneity (on neighborhood level)						
v^a	-2.46	(0.19)				
v^b	-2.71	(0.16)				
p^a	0.28	(0.31)				
p^b	0.72	(0.79)				
Neighborhood characteristics						
Unemployment rate	-3.40	(0.94)	-0.20	(1.16)	-4.92	(0.84)
$\log \mathcal{L}$	-10700.52		-2771.38		-2203.32	
Specification B						
Unobserved heterogeneity (on neighborhood level)						
v^a	-3.15	(0.19)				
v^b	-3.45	(0.16)				
p^a	0.48	(0.38)				
p^b	0.52	(0.41)				
Neighborhood characteristics						
Average price of houses	0.035	(0.015)	0.0034	(0.021)	0.037	(0.010)
$\log \mathcal{L}$	-10706.18		-2771.38		-2214.66	
Specification C						
Unobserved heterogeneity (on neighborhood level)						
v^a	-2.53	(0.29)				
v^b	-2.80	(0.28)				
p^a	0.27	(0.22)				
p^b	0.73	(0.60)				
Neighborhood characteristics						
Unemployment rate	-3.06	(1.25)	-0.14	(1.37)	-5.78	(1.23)
Average price of houses	0.0070	(0.018)	0.0020	(0.026)	-0.016	(0.016)
$\log \mathcal{L}$	-10700.31		-2771.37		-2202.78	

Explanatory note: Standard errors in parentheses. The "baseline" model is extended by allowing for unobserved heterogeneity on the neighborhood level (random effects). The distribution of the unobserved neighborhood characteristics is only dispersed for the subsample of Dutch job losers. In Specification A we also take into account the unemployment rate within the neighborhood. In Specification B we replace the unemployment rate by the average price of houses within the neighborhood. And, in Specification C we include both the unemployment rate and the average price of houses within the neighborhood.

Table 4: Estimation results for the neighborhood characteristics in a model specification that extends the "baseline" model by allowing for the unemployment rate, the average price of houses and unobserved neighborhood characteristics.

	Dutch job losers		Non-Dutch job losers		Dutch school leavers	
Unobserved heterogeneity (on neighborhood level)						
v^a	−2.57	(0.39)				
v^b	−2.85	(0.39)				
p^a	0.30	(0.31)				
p^b	0.70	(0.74)				
Neighborhood characteristics						
Unemployment rate	−2.36	(2.73)	2.17	(3.00)	−3.52	(2.72)
Average price of houses	0.0091	(0.022)	0.0024	(0.027)	−0.013	(0.017)
Non-Dutch inhabitants	−0.27	(0.59)	−0.45	(0.64)	−0.51	(0.65)
Geographical mobility	0.39	(0.88)	−0.57	(1.05)	−0.31	(1.02)
Crime rate	−0.037	(0.10)	0.051	(0.41)	0.27	(0.18)
$\log \mathcal{L}$	-10700.01		-2770.93		-2200.95	

Explanatory note: Standard errors in parentheses.

Table 5: Estimation results for the neighborhood characteristics in a model specification that extends the "baseline" model by allowing for all observed (and unobserved) neighborhood characteristics.

	Dutch job losers		Non-Dutch job losers		Dutch school leavers	
Unobserved heterogeneity (on neighborhood level)						
v^a	−2.54	(0.17)				
v^b	−2.82	(0.13)				
p^a	0.27	(0.28)				
p^b	0.73	(0.77)				
Unemployment rate (dummy-specification)						
0%–5%	0		0		0	
6%–10%	−0.18	(0.15)	−0.10	(0.23)	−0.19	(0.13)
11%–15%	−0.35	(0.12)	−0.17	(0.22)	−0.53	(0.13)
16%–20%	−0.48	(0.12)	−0.089	(0.21)	−0.63	(0.12)
$\log \mathcal{L}$	-10701.11		-2770.91		-2203.17	

Explanatory note: Standard errors in parentheses.

Table 6: Estimation results of model specifications that categorizes the neighborhoods into four groups based on the unemployment rate and includes dummy-variables for these categories.

	Dutch job losers		Non-Dutch job losers	
Unobserved heterogeneity (on neighborhood level)				
v^a	-2.27	(0.19)		
v^b	-2.55	(0.16)		
p^a	0.28	(0.31)		
p^b	0.72	(0.78)		
Interaction unemployment rate $\times$ age				
Age 18–25	-4.75	(0.99)	0.17	(1.66)
Age 26–35	-2.22	(1.68)	-1.59	(1.93)
Age 36–45	-1.32	(2.41)	3.65	(3.43)
Age 46–55	-2.69	(2.82)	-5.05	(5.54)
Age 56–65	-6.51	(11.81)	–	
$\log \mathcal{L}$	-10695.68		-2770.13	

Explanatory note: Standard errors in parentheses. Since we only found significant interaction between the unemployment rate and age, we do not have any estimation results for the Dutch school leavers. All individuals in this subsample are young.

Table 7: Estimation results of model specifications that allow for interaction between the unemployment rate and individual characteristics.

Unempl. rate	Unobs. charac.	Individual J	Individual K
Dutch job loser			
5%	v^a	0.65	0.28
15%	v^a	0.48	0.22
5%	v^b	0.54	0.22
15%	v^b	0.39	0.17
Non-Dutch job loser			
5%	v	0.29	0.11
15%	v	0.29	0.11
Dutch school leavers			
5%	v	0.72	-
15%	v	0.54	-

Explanatory note: Individual J is single living, 25 years old man without children who never collected welfare benefits before. Individual K is identical to individual J except that he is 50 years old. It might be clear that Individual K can not be a school leaver. For both types of welfare recipients we computed the probability of leaving welfare to work within one year conditional on living in a neighborhood with a high unemployment rate (15%) or in a neighborhood with a low unemployment rate (5%). Furthermore, if the individual is a Dutch job losers we also take the dispersed unobserved heterogeneity on neighborhood level into account (for the other subsamples we did not find dispersed unobserved heterogeneity).

Table 8: Estimated probabilities to find a job within one year after entering the welfare benefit system; three groups of welfare recipients.

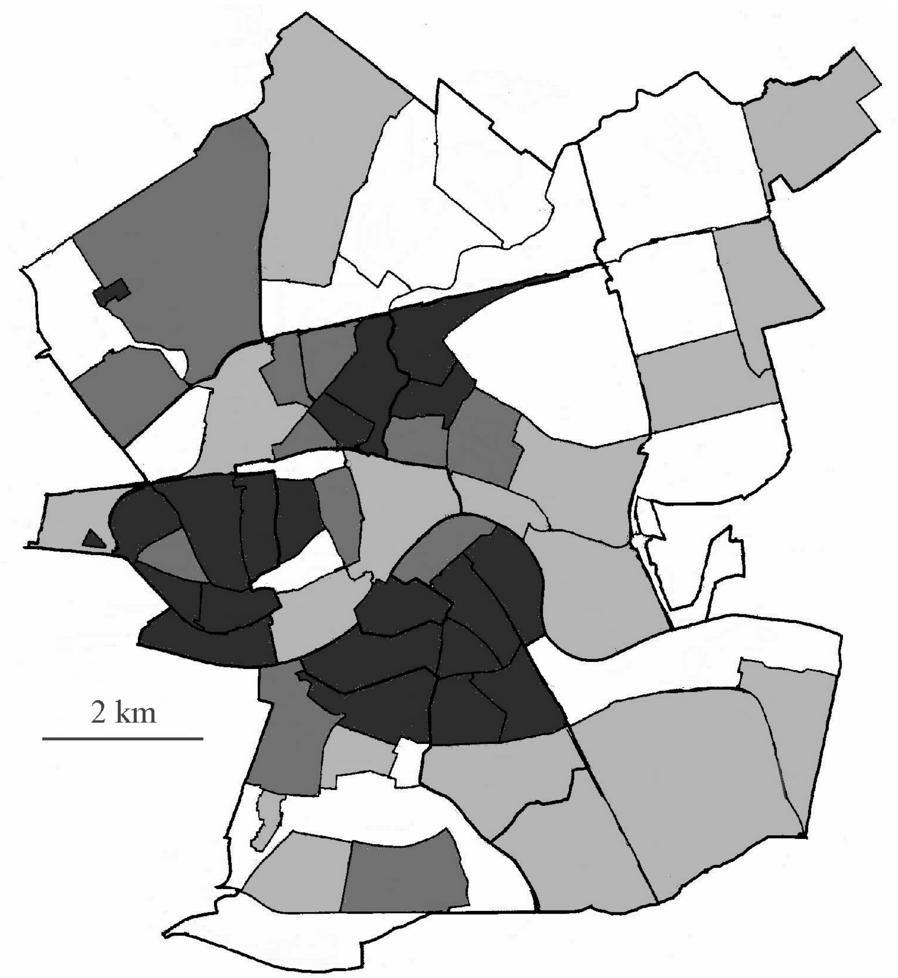

Figure 1: The unemployment rate within the neighborhoods of Rotterdam (from light to dark 0%–5%, 6%–10%, 11%–15% and 16%–20%).

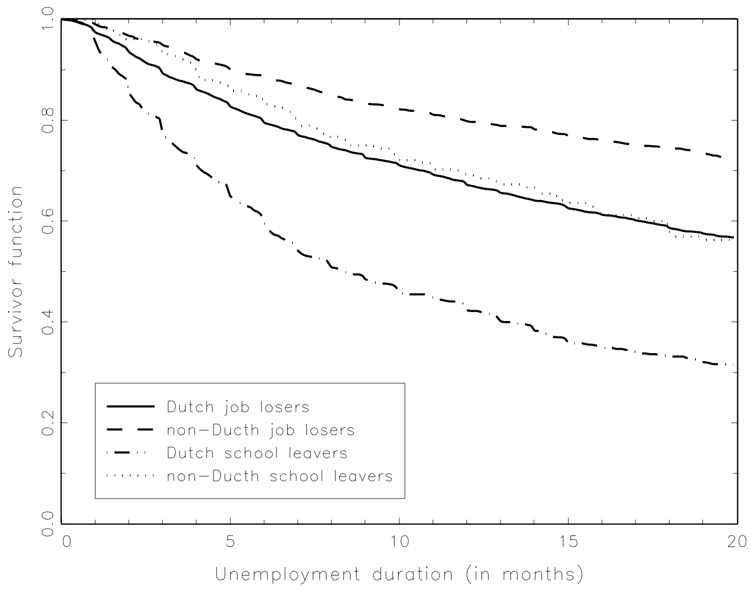

Figure 2: Kaplan-Meier estimate of the transition from welfare to work of the four subsamples of the database.