

**Unemployment Persistence in Belgium: An In-depth
Econometric Analysis of the Flows out of Unemployment**

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Acknowledgements

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Chapter 1

General Introduction

Finding an explanation for the rise and persistence of European unemployment has been one of the main research programmes of labour economists during the last decade. In this doctoral thesis, we contribute to this literature by questioning the causes of unemployment persistence in Belgium, more specifically in Wallonia, the French speaking region in the South¹. To that purpose, we conduct an in-depth econometric analysis of the flows out of unemployment in this country. The case of Belgium is particularly interesting, since its share of long-term unemployment is one of the highest in Europe. By refining the causes of unemployment persistence in Belgium, our doctoral research may also contribute to the design of more effective labour market policies.

The outline of this introduction is as follows. We first present some stylised facts about unemployment in Belgium and in its regions². We then give three possible explanations of unemployment persistence and the existing evidence for Belgium. Finally, we present in details the motivations and the content of our doctoral research. In particular, we show how it may improve both the diagnosis of unemployment persistence and the design of active labour market policies in Belgium.

¹Belgium is divided into three regions: Wallonia, Flanders and Brussels.

²We only focus on the two main regions of Belgium, Flanders and Wallonia.

1.1 Stylised facts

To describe the pattern of unemployment in Belgium, we focus on administrative data, which are also used in our empirical analysis. In these data, workers are defined to be unemployed if they are officially registered as full-time unemployed, are entitled to unemployment benefits and are actively looking for a job. This definition of unemployment is likely to give a fair view of unemployment in Belgium since the period of entitlement to benefits is in principle indefinite³. However, the benefits entitlement is conditional on a sufficiently long employment record⁴.

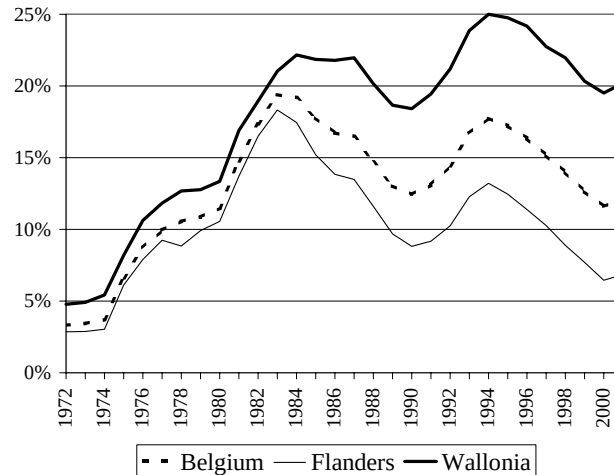


Figure 1.1: Unemployment rate in Belgium, Flanders and Wallonia

The unemployment rate⁵ increased steadily in Belgium after the first and the second oil price shocks: From 3% in 1973 to 19% in 1983. This evolution is illustrated in Figure 1.1. With the economic recovery of the mid eighties, the unemployment rate decreased to a level of

³One exception to this rule concerns the cohabitants, e.g. living with a working partner or with their parents. They can loose entitlements on grounds of ‘excessive’ unemployment duration.

⁴Graduated students who never worked can also be eligible after some waiting period.

⁵The unemployment rate is the ratio between the full-time registered unemployed people, entitled to unemployment benefits and actively looking for a job, and the population insured against unemployment.

12%, which still lied far above the level reached in 1973. From 1990, the economic downturn pushed the unemployment rate up again. This evolution masks an important disparity between the two main regions of Belgium: Flanders and Wallonia. Up to 1983, the two regions had roughly the same performance in terms of unemployment, worse than in our bordering countries (Germany, France and the Netherlands). From 1983, a diverging evolution seems to show up: The unemployment rate decreased markedly in Flanders, while unemployment remained at a high level in Wallonia. In 2000, the unemployment rate was 20% in Wallonia and 6% in Flanders⁶. According to Binon *et al.* (1998), the diverging evolution in the unemployment rate across Belgian regions cannot be attributed to a different growth in the active population.

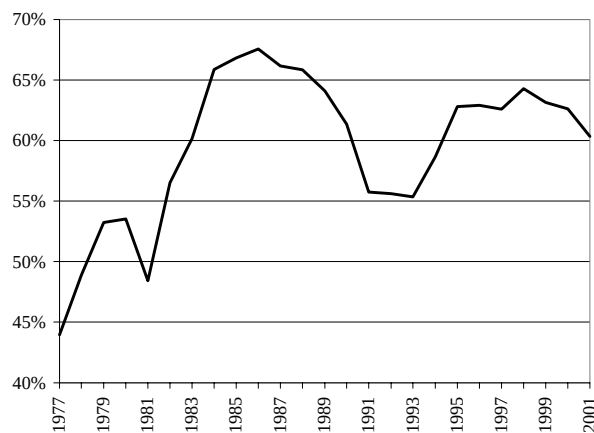


Figure 1.2: Incidence of long-term unemployment in Belgium

The rise in the level of unemployment came with an increase in the incidence of long-term unemployment (proportion of the unemployed workers who have been unemployed more than one year), as depicted in Figure 1.2. During the 1983-1996 period this share has peaked to a level of 68% in 1986 and has only been slightly below 60% during the

⁶The size of the gap between Flanders and Wallonia is sensitive to the definition of unemployment (see Binon *et al.* 1998). If one includes other categories of unemployed workers, like the old insured unemployed people who are no more looking for a job, the difference between the unemployment rates in the two main regions of Belgium reduces, but remains at a relatively high level though.

1991-1993 recession. These figures are somewhat higher in Wallonia. According to survey data, the incidence of long-term unemployment in Belgium was, in 1995, one of the highest in Europe⁷ (see Machin and Manning 1999).

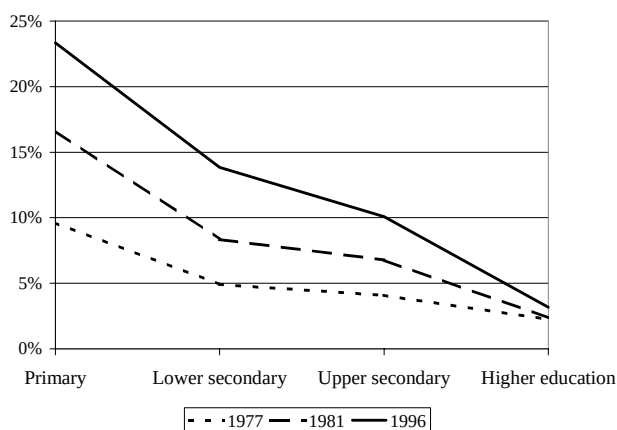


Figure 1.3: Unemployment rate by level of education in Belgium

The rising unemployment was not evenly spread across all groups of unemployed. The risk of unemployment increased more markedly for the lowest skilled workers. Figure 1.3 depicts the unemployment rate by level of educational attainment in 1977, 1981 and 1996⁸. Given the lack of more accurate data, the skill level is measured by the educational degree. From the late seventies, unemployment increased for all schooling groups, but at quite different rates. In 1996, the unemployment rate of the less educated workers (with at most a lower secondary degree⁹) increased by a factor of 2.6 as compared to its level in 1977 while this factor only amounts to 1.4 for workers who completed higher education. The Belgian ratio between the unemployment rate of these two school-

⁷Belgium comes in third, after Ireland and Italy.

⁸In Belgium, there is not time-series on the working population by level of educational attainment. This information is available on an annual basis in the labour force surveys since 1989 only. In Figures 1.3, 1.4 and 1.5, unemployment rates by schooling level are calculated on the basis of a socio-economic survey in 1977 and the population census in 1981.

⁹A lower (resp. upper) secondary degree corresponds to 9 (resp. 12) years of education.

ing groups was, in 1995, one of the largest among 15 OECD countries¹⁰ (see OECD 1997a).

It should however be noted that the rising disparities in the unemployment rate by level of education is more a feature of the Walloon labour market than the Flemish one, as illustrated in Figures 1.4 and 1.5.

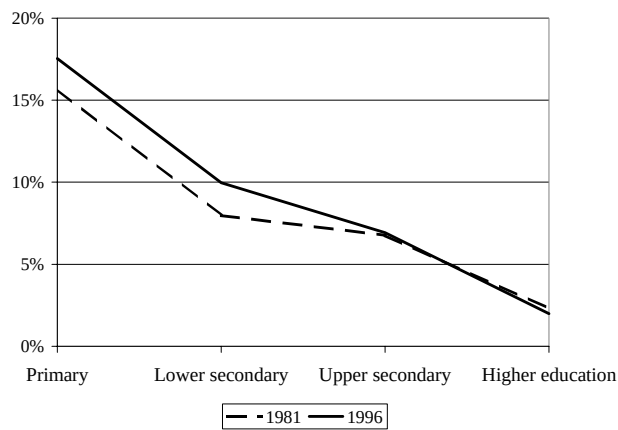


Figure 1.4: Unemployment rate by level of education in Flanders

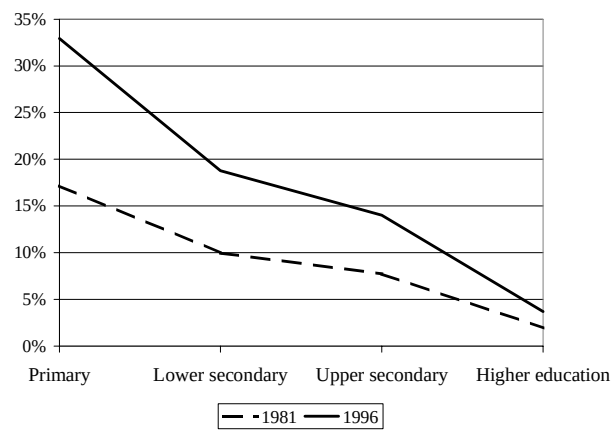


Figure 1.5: Unemployment rate by level of education in Wallonia

¹⁰Belgium comes in fourth, after the United States, Ireland and Luxemburg.

Figure 1.6 also indicates that the relative rise in the unemployment rate of the lowest educated workers took place despite a growing share of high educated workers in the labour force¹¹.

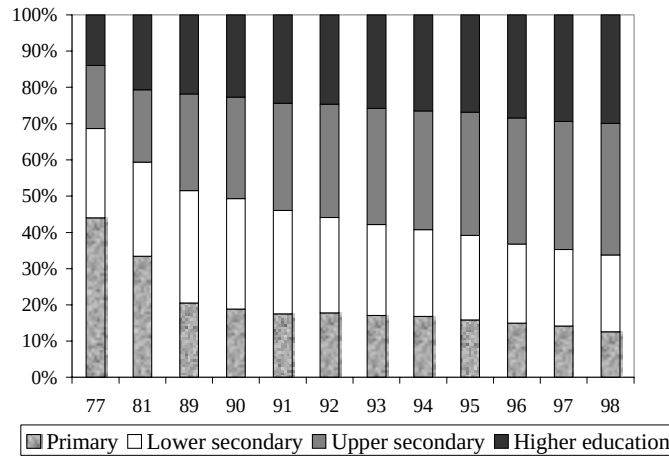


Figure 1.6: Labour force by level of education in Belgium

The reviewed evolutions concern both male and female unemployment. Nevertheless, we only focus on male workers in our doctoral research. The main reason for this choice is that our data sets do not allow us to distinguish between unemployment spells ending in employment, participation in labour market programmes or withdrawal from the labour force. This is not likely to bias our results given that employment is the most frequent state of exit for the male unemployed workers: About 77% of them leave for employment, against 47% for the women (see FOREM 1995). Although the male unemployment rate is lower than the female one, its evolution is similar to what the aggregate statistics suggest (see Binon *et al.* 1998). In particular, the gap between the unemployment rates in Flanders and Wallonia is the largest for the male workers.

¹¹This information comes from the labour force surveys since 1989, from a socio-economic survey in 1977 and from the population census in 1981.

1.2 Possible diagnosis and evidence for Belgium

In the previous section, we described the main pattern of unemployment in Belgium. This country is characterised by a high degree of unemployment persistence and a very large share of long-term unemployment, more particularly in Wallonia. Moreover, there is a high incidence of unemployment among the less educated workers, which is also a feature of the Walloon labour market. Below, we review three possible explanations of unemployment persistence and the existing empirical evidence for Belgium. These explanations do not exhaust the list of possible causes of unemployment persistence in this country. We only review the main explanations which can be compatible with the pattern of unemployment in Belgium. The focus is also on the explanations which can be supported by the findings of our doctoral thesis.

The first explanation attributes the persistence of unemployment to the existence of disemployability effects, whereby prolonged unemployment induces a process of skill deterioration, demotivation and habituation (see e.g. Layard *et al.* 1991). According to this view, the succession of negative economic shocks in the late seventies and early eighties, combined with the negative effect of duration on the employability of unemployed workers, contributed to the rise of persistent and long-term unemployment. Disemployability effects prevent the unemployment rate from returning to its initial equilibrium level through two channels¹². First, unemployment dependency leads to labour shortages in case of economic recovery, although unemployment stays high. Second, it reinforces the bargaining power of insiders with respect to wage demands, tempering by this way employment growth. In the literature, this explanation is often referred to the *hysteresis diagnosis* of unemployment persistence. How this explanation could account for the larger increase in the unemployment rate of the lower skilled workers? Given the existence of rigidities at the bottom of the wage distribution (due to the existence of a legal or bargained minimum wage), the impact of the initial shocks on the level of unemployment is likely to be stronger for the

¹²Notice that the rules governing the unemployment benefit system, like the level of unemployment benefits and their time profile, can play an important role in explaining disemployability effects.

low skilled workers, reinforcing disemployability effects, and thereby the persistence of unemployment for this group of workers¹³.

Most of the empirical evidence on the hysteresis diagnosis of unemployment persistence relies on the analysis of the relationship between the aggregate exit rate out of unemployment and the duration of unemployment. This relationship is generally found to be decreasing. Figure 1.7 depicts the exit rate which is observed for any cohort of workers entering unemployment in Wallonia¹⁴. In order to focus on the dependency question, the exit rate is normalised to one at the first duration quarter. Its strong decline over duration seems to support the existence of disemployability effects in Wallonia. However, this conclusion is misleading if the unemployed population is heterogeneous. In that case, the individuals with the most favourable characteristics flow from unemployment rapidly leaving behind the lowest skilled workers. This sorting process causes the aggregate exit rate to decrease *spuriously* with duration even if the individual probability of leaving unemployment is constant over duration, i.e. even in the absence of disemployability effects.

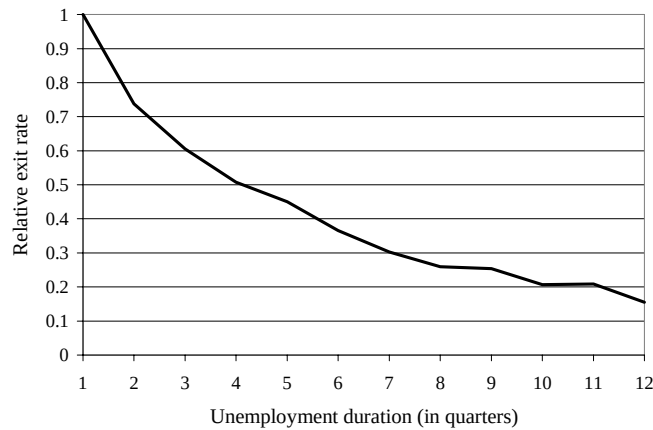


Figure 1.7: Observed duration dependence in the exit rate out of unemployment in Wallonia

¹³The higher replacement rate for the low skilled workers can also contribute to a more rapid demotivation and habituation to unemployment.

¹⁴We do not have a similar picture for Flanders.

A number of researchers (see Spinnewyn 1982, Plasman 1993 and Mahy 1994) have studied the duration dependence of the outflow rate for Belgium¹⁵. They find that the negative duration dependence is completely spurious. The exit rate out of unemployment increases significantly once heterogeneity in the unemployed population is taken into account. However, in view of the strong parametric assumptions regarding both the pattern of the true duration dependence (Weibull) and the heterogeneity distribution (Gamma), these results are likely to be biased. The evidence from other European studies on duration dependence and heterogeneity seems to converge to the same conclusion (for a recent review, see Machin and Manning 1999): Once controlling for (observed and unobserved) heterogeneity in the unemployed population, there is no marked evidence of true negative duration dependence in most European countries, like France, the Netherlands, Germany, Austria, Spain, Denmark and the Scandinavian countries. One exception to this conclusion is the United Kingdom where the individual exit rate from unemployment displays strong negative duration dependence.

According to the second diagnosis, the persistence of unemployment at a high level comes from a general slowdown of the economic growth which reduces the demand for both skilled and unskilled workers. The slowdown of economic growth could reflect a depressed capital accumulation due to excessively high labour costs (see Daveri and Tabellini 1997) or coordination failures (see Drèze 1997; Shadman-Mehta and Sneessens 1998). In such a context, more educated workers tried to compensate the decreased demand by extending job search on the skill segment below their own. Adopting this search behaviour, they crowded out lower educated unemployed in their segment. At the bottom of the skill ladder, the lowest educated were condemned to unemployment or inactivity. The crowding out process was even reinforced by a rise in the supply of highly educated workers. In the literature, this process is also called *job competition*, bumping down or ladder effect, and is used as a possible cause of the relative rise in the unemployment rate of the low educated workers (see, e.g., Green *et al.* 1999; Dolado *et al.* 2000; Gautier 2001).

Up to now, most of the empirical evidence on job competition relies on measures of *overeducation*, which give the share of workers with a

¹⁵None studies have separately analysed Flanders and Wallonia.

higher schooling level than the one required to perform the job. There is a growing interest in the overeducation literature, witness the special issue of the *Economics of Education Review* (19, April 2000) on this question. Since definition and measurement issues (see below) make comparisons across countries difficult, we only report that the incidence of overeducation ranges between 10% and 35% in European countries (see Green *et al.* 1999 and Hartog 2000). Besides, there is some evidence of increasing overeducation over the seventies and early eighties in the United Kingdom, the Netherlands, Portugal and Spain. A limited number of studies tried to evaluate the incidence of overeducation for Belgium (see Van Hoof 1996 and Denolf *et al.* 1999). Based on a vacancy survey to employers, Denolf *et al.* (1999) conclude that 32% of the newly hired workers were overeducated¹⁶ in 1997 and that this proportion is countercyclical¹⁷. This fraction must, however, be largely overestimated. The authors associate vacancies for which the employers have no preference regarding the required level of education to those requiring at most an elementary degree. Unsurprisingly, the proportion of overeducated workers is 70% for these job offers while this fraction turns around 20% only for the other levels of education.

There is a more important measurement issue in the literature on overeducation though: The results are sensitive to the classification of jobs according to the required schooling level, which is often asked to the workers themselves. When this information comes from the employers or external experts, reports are also likely to be biased. For instance, employers can increase their educational requirements in order to attract the best candidates for the job or simply because they know that there is a large number of highly educated job seekers (see Green *et al.* 1999). If the schooling profile of the job is evaluated through external experts, the information must be frequently updated since the job content may change with the introduction of new technologies.

The third diagnosis attributes the persistence of unemployment to a structural *skill mismatch* between the demand and the supply of skills. According to this view, the economic growth came with a change in the composition of labour demand biased against the low skilled workers

¹⁶26% in Wallonia and Brussels, 35% in Flanders.

¹⁷This vacancy survey has been conducted since 1995.

(by the introduction of new technologies, de-industrialisation and/or international competition), without an equivalent adjustment in the composition of labour supply (see, for example, Drèze and Sneessens 1997; Autor *et al.* 1998; Berman *et al.* 1998; Machin and Van Reenen 1998; Acemoglu 2001). These structural evolutions, together with a downward rigid wage structure, led to a growing skill mismatch between the demand and the supply of labour: An excess demand of high skilled workers coexists with an excess supply of low skilled workers. Skill mismatch can therefore also account for the relative rise in the incidence of unemployment among the less educated workers.

A number of studies tried to evaluate the extent of skill mismatch by computing mismatch indicators (see for Belgium, Binon *et al.* 1998, Sneessens *et al.* 1999; for France, Sneessens and Shadman-Mehta 1995; for the United Kingdom, Jackman and Roper 1987 and Jackman *et al.* 1990; for other countries, including the UK, Manacorda and Petrongolo 1999). According to the indicator constructed for Belgium, there has been a growing imbalance between the demand and the supply of skills in this country from the late seventies and up to the mid eighties, more particularly in Wallonia. For the other countries, results are rather mixed. Although the definition of the mismatch index differs across studies, there is some evidence of increasing skill mismatch in France, the United Kingdom, Italy and Germany, but not in the Netherlands and the Scandinavian countries.

However, all measures of mismatch are built on models which ignore the mobility of workers between segments of the labour market, so that they *exclude* the job competition process. If such a process takes place, the mismatch indicators are biased. As an example, the mismatch indicator of Sneessens *et al.* (1999) is the ratio of skilled to total employment rates. Skilled employment is measured by the share of highly educated¹⁸ people in the working population. Therefore, the increase in the mismatch indicator for Belgium could partly reflect a more intense crowding out of lower educated workers by higher educated ones. Other indicators suffer from the same type of measurement problem.

Notice that skill mismatch and job competition are *not mutually ex-*

¹⁸Highly educated workers are those who at least completed an upper secondary degree.

clusive. The first explanation emphasises the role of the *composition* of employment growth and labour supply on the observed evolutions while the second stresses the importance of the *level* of employment growth.

1.3 Objective and motivation of the doctoral research

This thesis consists of an in-depth econometric analysis of the flows out of unemployment in Belgium. Based on administrative data, we conduct three empirical researches on the determinants of the exit rate out of unemployment in this country (see Figure 1.8). In Chapters 2 and 3, we study the behaviour of the exit rate out of unemployment over duration and calendar time. In Chapter 3, we investigate whether this behaviour differs according to the place of living and the skill level, as measured by the level of education. Finally, in Chapter 4, we determine to what extent the divergences in the rate of flowing from unemployment between workers with different levels of education can be explained by a skill mismatch phenomenon and/or by a job competition story.

The first motivation of our doctoral research is to improve the diagnosis of unemployment persistence in Belgium, more particularly in Wallonia, by analysing the transition rate out of unemployment in various dimensions. Refining the causes of unemployment persistence in Belgium may then be a step towards the design of more efficient labour market policies in this country. The second motivation is to contribute to the existing literature by providing new methodological developments. In particular, we address some of the methodological issues which have been raised in the literature on skill mismatch and job competition.

Below, we describe the objectives of the three chapters of our doctoral thesis. We also stress the way they interact to each other, such as depicted in Figure 1.8. For each chapter, we then show how their findings may improve both the diagnosis of unemployment persistence and the design of active labour market policies in Belgium. A more detailed discussion on the policy implications of our results is provided in the general conclusion. Finally, we briefly give the main methodological contributions of the three chapters.

Figure 1.8: Outline of the doctoral research

1.3.1 Objective of the three chapters

In **Chapter 2**, we focus on the flows out of unemployment in Wallonia. We observe the *quarterly* exit rates of male workers flowing into unemployment between June 1989 and February 1994. The first objective of this chapter is to investigate what causes the aggregate exit rate out of unemployment in Wallonia to decline strongly over duration (see Figure 1.7). Is this negative duration dependence ‘true’, i.e. induced by a process of demotivation and skill deterioration, or ‘spurious’, i.e. generated by heterogeneity in the unemployed population? We also investigate whether the true duration dependence of the outflow rate is compatible with the *ranking* hypothesis, a recruitment rule which consists in hiring the unemployed candidate with the shortest unemployment duration. Since our data are only stratified by the age group, we control for the (unobserved) heterogeneity in the unemployed population by estimating its distribution. Contrary to the existing studies on duration dependence and heterogeneity in Belgium, the duration dependence of the outflow rate is specified in a flexible way. In the benchmark model, the heterogeneity distribution is parametrised (Gamma). We then compare our findings with those found with a non-parametric specification. Notice that we estimate the extent of duration dependence and heterogeneity for the young and prime aged men separately.

The second objective of Chapter 2 is to study the cyclical and the seasonal behaviour of the exit rate out of unemployment in Wallonia. The aggregate exit rate out of unemployment is generally found to be procyclical. In this chapter, we try to determine the part of this cyclical variation which is explained by a *general effect*, i.e. by changes in the exit rate of all currently unemployed workers with the business cycle, and by a *composition effect*, i.e. by fluctuations in the average quality of entrants into unemployment leaving the individual exit rates constant. For instance, if workers with more favourable labour market characteristics, say ‘high skilled’ workers, were less (more) likely to enter unemployment in a downturn (upturn), while the ‘low skilled’ workers face always the same risk of losing their job, then this change in the composition of the unemployed could partly drive the procyclical variation in the aggregate outflow rate: The average quality of entrants would deteriorate in

downturn and improve in upturn. In order to disentangle composition from general effects of the calendar time on the outflow rate, we allow the mean of the heterogeneity distribution to vary over seasons and the business cycle. Since we do not observe any personal characteristics of the unemployed workers (except the age), we can only compute an *unobserved composition effect*.

In **Chapter 3**, we focus on the flows *in and out of* unemployment in the two main regions of Belgium, Flanders and Wallonia, over a longer timespan. We observe the *yearly* exit rates of male workers aged 25-44 and flowing into unemployment in the month of June, each year from 1972 to 1992. These data also contain a number of personal characteristics of the unemployed people. The latter include the age (measured in months), the level of education, the province of living and the sector occupied before becoming unemployed. The objective of this chapter is to investigate whether the diverging evolution in the unemployment stock in Flanders and Wallonia is driven by different evolutions in their average unemployment *duration* and/or their unemployment *incidence*. To that purpose, we proceed in two stages.

In the first stage, the average unemployment duration is modelled through the specification of the exit rate out of unemployment¹⁹. As in Chapter 2, we decompose variations in the aggregate outflow rate over calendar time in each region between a *general effect* and a *composition effect*. We also evaluate the extent of duration dependence and heterogeneity in each region. However, Chapter 3 contains three novelties as compared to the analysis conducted in Chapter 2. On the one hand, the timespan covered by the data is sufficiently long to investigate both cyclical and structural evolutions in the aggregate outflow rate. On the other hand, the composition effect is made of variations in both the *observed* and *unobserved* characteristics of those flowing into unemployment. The use of aggregate data covering 21 years and stratified by a set of relevant characteristics allows us to control for changes in the inflow composition without relying (completely) on functional form assumptions. Finally, the richness of the data set allows us to test whether the general effect of the calendar time is the same for unemployed workers

¹⁹In a steady-state environment, there is a one-to-one relationship between the average unemployment duration and the exit rate out of unemployment.

with different levels of education and province of living, in each region. In the second stage, we decompose variations of the unemployment stock in Flanders and Wallonia into an *incidence* effect and the *duration* effect estimated in the first stage²⁰.

The findings of Chapter 3 reveal that the outflow rate of low educated unemployed workers in Belgium deteriorated by 30% more than the exit rate of the highest educated workers over the period 1973-1993. In **Chapter 4**, we investigate to which extent disparities in the exit rate between workers with different levels of education can be explained by *job competition* and/or *skill mismatch* in Wallonia. To that purpose, we use administrative data on the flows from unemployment by level of education. As in Chapter 2, we observe the *quarterly* exit rates of male workers flowing into unemployment between June 1989 and February 1994. However, these data are now stratified according to the educational attainment of the individual. Our analysis also exploits the number of job vacancies registered at the public employment agency. These job offers are *not* classified according to the required level of education.

The exit rate out of unemployment is modelled in a matching function framework in which the job market is segmented by schooling level. In the presence of job competition, all unemployed workers search for jobs in their own segment and some fraction search simultaneously in the segment just below their own. Under this assumption, the probability of flowing out of unemployment by level of education is made of two components: The probability of finding a job corresponding to his schooling profile and the probability of finding a downgrading job. We then estimate the structural form of the outflow probability by schooling level. The parameters of interest are the extent of job competition at each schooling level (except the lowest level) as well as the distribution of job offers according to the required level of education.

Estimating the distribution of job offers by schooling level allows us to calculate unbiased mismatch indicators, which will measure the dispersion in the vacancy-unemployment (V-U) ratio by level of education. It should however be stressed that we only observe, in our data set, un-

²⁰In a steady-state environment, the stock of unemployed workers is simply the product of the number of workers flowing into unemployment (incidence) and their average unemployment duration.

employed workers who separated from their employers and who did not directly find a new job (i.e. dismissed workers). As a consequence, our estimation of vacancies by schooling level concerns *only those intended to this selective population*, which *excludes* young school leavers and employed job seekers. So we can only evaluate the extent of skill mismatch (and job competition) *within* this selective population.

1.3.2 How may this doctoral research improve the diagnosis of unemployment persistence and the design of active labour market policies in Belgium ?

How can the empirical analysis of our doctoral thesis improve the diagnosis of unemployment persistence in Belgium, more particularly in Wallonia, and therefore be a step towards the design of more efficient labour market policies?

In **Chapter 2**, we investigate the relative importance of true and spurious negative duration dependence of the aggregate exit rate out of unemployment in Wallonia. We can therefore evaluate whether skill deterioration and demotivation can be the main channels of unemployment persistence in this region. This question is also highly relevant from a policy perspective. If unemployment duration is of little importance to explain the low employability of the long-term unemployed in comparison with the role of their intrinsic skills (interpreted in a very broad sense), then public outlays to labour market policies should not primarily focus on temporary work experience schemes with little training content. While these programmes can help to maintain skills and work habits if unemployment leads to deterioration of skills and loss of work experience, they are unlikely to be by themselves effective if unemployment merely reveals the individuals with low skill attributes²¹.

In **Chapter 3**, we can also evaluate whether disemployability effects may have driven unemployment persistence in Flanders and in Wallonia. A corollary of the hysteresis diagnosis of unemployment persistence is that the duration of unemployment should drive its persistence. By determining the relative role of duration and incidence in the structural

²¹Except for those for whom the ‘low skill attributes’ means the lack of work experience, as the young school leavers for instance.

rise of unemployment in the two main regions of Belgium, we can see whether the hysteresis diagnosis can explain the diverging evolution of unemployment in these regions. Some of the policy recommendations that we can put forward in this chapter are therefore similar to those proposed in Chapter 2.

Some authors also argue that if variations in the duration of unemployment are mainly driven by a general effect, targeted policies are unlikely to be useful. In Chapter 3, we show that even if composition effects play an unimportant role, there is a scope for labour market policies aimed at specific groups of unemployed workers. For, the general effect of the calendar time on the exit rate is not necessarily the same for all groups of unemployed workers.

Chapter 4 aims to determine the relative importance of job competition and skill mismatch for a population of unemployed workers in Wallonia. This question is also crucial from a policy perspective. For instance, it is often argued that training programmes should be encouraged in case of skill mismatch while they would be inefficient in case of job competition: They would only reinforce the job competition process and merely redistribute unemployment between different groups of workers. If job competition exists, an economic growth rich in employment is sufficient to improve the relative position of the less-skilled workers in the labour market.

We should however be *extremely cautious* with this type of policy recommendations in this chapter, for two reasons. First, the available data allow us to evaluate the extent of job competition and skill mismatch *only for a selective population of unemployed workers*, which excludes young school leavers and on-the-job searchers. Second, in the conclusion of Chapter 4, we emphasise that education and training programmes can help to reduce the extent of job competition, and thereby unemployment, contrary to what the typical view on job competition suggests.

1.3.3 What are the main methodological contributions of this doctoral research?

Finally, what are the main methodological contributions of the three chapters of our doctoral thesis?

In **Chapter 2**, we depart from mixed proportional hazard (MPH) models²² to disentangle true from spurious duration dependence: We allow the true duration dependence of the outflow rate to vary between a boom and a recession in order to test the ranking hypothesis. We show that the MPH assumption may result in an underestimation of the extent of spurious negative duration dependence. In **Chapter 3**, we propose a complete and formal decomposition of the variations in the aggregate outflow rate over time, focusing on both cyclical and structural variations. Besides, we choose to parametrise the time dependence of the distribution of unobserved characteristics by the number of entrants into unemployment (as in Chapter 2). If variations in the composition of inflow closely follow variations in the number of entrants into unemployment, our specification turns out to be a better alternative than a non-parametric specification. For, our parametric specification allows the unobserved composition effect to follow a trend (i.e. the trend in incidence), separately from the trend in the general effect. In **Chapter 4**, we estimate the structural form of the outflow rate by level of education in the presence of job competition, without relying on a reduced form specification. This estimation approach conducts to a better interpretation of our parameter estimates. In addition, we estimate the distribution of job offers according to the required level of education. Our empirical framework does not need to rely on the reports of employers or workers concerning the skill requirements of a job, contrary to most of the empirical research on skill mismatch and job competition.

The plan of our doctoral thesis is as follows. The three empirical researches conducted in our doctoral thesis are the focus of the next three chapters. Although these chapters bring similarities concerning the data, the model specification and the estimation approach, each chapter can be read independently of the other chapters. The conclusion summarises the main results and discusses policy implications.

²²In a mixed proportional hazard model both the observed and unobserved explanatory variables enter the hazard multiplicatively. The distribution of the unobserved variable is called the mixture (heterogeneity) distribution.

Chapter 2

Duration and Calendar Time Dependence of the Exit Rate out of Unemployment in Belgium. Is it True or Spurious?

2.1 Introduction

Finding an explanation for the rise and persistence of European unemployment has been one of the main research programmes of labour economists the last decennia. This study aims at contributing to this literature by questioning the causes of unemployment dependency in Belgium, more specifically in Wallonia, the French speaking region in the South¹. The case of Belgium is particularly interesting, since the share of long-term unemployment in this country is one of the highest in Europe. During the 1983-1996 period this share has peaked to a level of 68% in 1986² and has only been slightly below 60% during the recession

¹Belgium is divided into three regions: Wallonia, Flanders and Brussels.

²This figure gives the share of the unemployed workers who have been unemployed more than one year. Workers are here defined to be unemployed if they are full-time registered, are entitled to unemployment benefits and are actively looking for a job.

of the early nineties³.

It is particularly important to understand what drives this dependence. Does unemployment dependency by itself increase the likelihood of future dependency? Prolonged unemployment may induce a process of skill deterioration and demotivation or may be used as a recruitment criteria by the employers (for a survey of the ‘true’ negative duration dependence explanations, see Machin and Manning 1999). Or is the negative duration dependence that we observe for any cohort of unemployed spurious, i.e. generated by a process of sorting? The individuals with the most favourable characteristics flow from unemployment rapidly leaving behind the ‘low skilled’ workers. This sorting process causes the aggregate exit rate to decrease spuriously with duration, as the aggregate exit rate is simply equal to the average exit rate of those remaining unemployed. Although these questions are old (see Salant 1977, Nickell 1979, Lancaster 1979), disentangling true from spurious duration dependence remains highly relevant from a policy point of view.

The first aim of this chapter is to investigate what causes the aggregate hazard estimated in Wallonia to decline over duration. A number of researchers have studied this question for Belgium (see Spinnewyn 1982, Plasman 1993 and Mahy 1994). They find that the negative duration dependence is completely spurious. The hazard rate increases significantly once unobserved heterogeneity is taken into account. However, in view of the strong parametric assumptions regarding both the baseline hazard (Weibull) and the mixing distribution (Gamma), these results are likely to be biased. The evidence from other European studies on duration dependence and heterogeneity seems to converge to the same conclusion (for a recent review, see Machin and Manning 1999): Once controlling for (observed and unobserved) heterogeneity, there is no marked evidence of true negative duration dependence of the exit rate out of unemployment in most European countries, like France, the Netherlands, Germany, Austria, Spain, Denmark and the Scandinavian countries. One exception to this conclusion is the United Kingdom where the conditional hazard displays strong negative duration dependence.

The second aim of this chapter is to study the cyclical and the seasonal behaviour of the exit rate out of unemployment in Wallonia. The

³Note that these figures are somewhat higher in Wallonia.

hazard rate out of unemployment is generally found to be procyclical. This dynamic fluctuation in the average unemployment duration can be explained by variations in the quality of entrants into unemployment rather than by the effect of the business cycle on the exit rate of all currently unemployed workers. For instance, if workers with more favourable labour market characteristics, say ‘high skilled’ workers, are less (more) likely to enter unemployment in a downturn (upturn), while the ‘low skilled’ workers face always the same risk of losing their job, then this change in the composition of the unemployed could partly explain the procyclical variation in the hazard rate⁴. If this compositional effect is important, then the ‘low skilled’ workers benefit less from an economic recovery than what aggregate statistics on the cyclical evolution of the hazard rate out of unemployment suggest. In order to answer this question we try to disentangle the general effect of the business cycle (and the seasons) on the hazard, affecting all unemployed workers in the same proportion, from its compositional effect. Given the recent interest of European researchers in this question, there are few studies on the business cycle effect on unemployment duration in Europe⁵. Abbring *et al.* (2001a) and Rosholm (2001), respectively for France and Denmark, conclude that compositional effects are of minor importance. On the other hand, Kalwij (2001) finds that cyclical fluctuations in the quality of entrants account for a significant part of the cyclical variation in the aggregate outflow rate for the United-Kingdom.

The analysis of this study is based on aggregate data. We observe the quarterly exit rates of male workers flowing into unemployment between June 1989 and December 1993. Using this type of aggregate data, Abbring, Van den Berg and Van Ours (2001a) developed an estimation method allowing for a non-parametric specification of both the distribution of duration and of unobserved individual characteristics. They prove that the model is identified if the underlying data are generated by a discrete time process and if the hazard is specified as a Mixed

⁴Darby *et al.* (1985) and Rosholm (2001) refer to changing proportions of voluntary quitters (‘job shoppers’) and laid off workers (‘career makers’) over the cycle rather than to proportions of ‘high’ and ‘low skilled’ workers.

⁵However, this question has puzzled American researchers since the mid 1980s already (see e.g. Darby *et al.* 1985, Sider 1985, Dynarski and Sheffrin 1990, Baker 1992, Imbens *et al.* 1993).

Proportional Hazard (MPH) model⁶. In this study, we choose both to depart from their modeling assumptions and to apply another method of estimation.

Abbring, Van den Berg and Van Ours (2001a) assume that the data are generated by a discrete time process. It is well known (see e.g. Flinn and Heckman 1982, p.53-56) that such assumption implies that the parameters are not invariant to the time unit chosen. Consequently, consistency requires that the timing of the underlying stochastic duration process coincides with the actual grouping of the data⁷. In order to avoid this problem, we specify the discrete-time process as a continuous-time model (see e.g. Van den Berg and Van der Klaauw 2001).

The MPH specification is standard in the literature. We relax it in two ways. First, we allow the hazard to vary non-proportionally between two sub-periods, i.e. between a boom and a recession. The reason for doing so, is that if true negative duration dependence is caused by ranking, a recruitment rule which consists in hiring the (unemployed) candidate with the shortest unemployment duration, the individual exit rate is predicted to vary non-proportionally over the business cycle: It will decline more rapidly the more depressed is the labour market (see Blanchard 1991, Blanchard and Diamond 1994, and Abbring *et al.* 1997). By considering an interaction effect between the duration and the cyclical dependence of the hazard, we can test the ranking hypothesis. Moreover, we show that ignoring such a non-proportionality may lead to an underestimation of the unobserved heterogeneity. For this model to be non-parametrically identified, we impose two essential assumptions: (i) The model is assumed to be MPH *within* the two sub-periods (boom and recession) and (ii) we assume that one regressor, an indicator of the business cycle at the time of inflow, varies continuously over the set of real numbers. The latter is required, since the data are grouped over duration (see Ridder 1990).

Second, the MPH specification assumes that the business cycle at the time of exit influences the hazard of all cohorts, that is of all duration

⁶In a MPH model both the observed and unobserved explanatory variables enter the hazard multiplicatively (see e.g. Ridder 1990).

⁷The authors are aware of this problem and test the validity of this assumption (see e.g. Van den Berg and Van Ours 1994, p.437).

classes at this instant, with the same factor of proportionality. We generalise by allowing for random deviations from this specification, i.e. by introducing cohort-specific random business cycle effects at the time of exit. Moreover, if one suppose that cohorts are each other's imperfect substitutes, then an increase (decrease) in the hazard of one particular cohort spills over to the other cohorts. If we assume that the degree of substitutability decreases with the difference of the elapsed duration between the affected and non-affected cohorts, then this substitution induces, for any fixed exit time, the model residuals to be positively autocorrelated with duration. We will show below that for our data the correlation structure of the residuals is compatible with this type of specification error.

Our modeling assumptions also differ for another reason. We allow the observed exit probability⁸ to deviate randomly from its theoretical counterpart in the population since this fraction is calculated on the basis of a finite population. As the size of this population varies over the observations, this induces an heteroskedastic error term. This is neglected by Abbring *et al.* (2001a). Their approach can be justified in two ways. First, they choose to evaluate the extent of duration dependence and heterogeneity *for the population they observe*. In our study, we make inference for an *hypothetical super-population* which encompasses our observed population. Second, if there are many unemployed in each duration interval, the sampling (approximation) errors will be small. Since Abbring *et al.* (2001a) use data on larger countries (as compared to Wallonia) and for only the first duration quarters or months (up to at most one year), their modeling assumption can be justified. The approximation errors are likely to be larger in our study since we analyse a smaller population of unemployed workers and we consider up to 18 quarters of unemployment⁹.

Since the distribution of the aggregate exit probabilities is known, Maximum Likelihood (ML) seems to be the most appropriate estimation method. Nevertheless, we choose instead the Minimum Chi-Square method (Berkson 1944, Amemiya 1981; for an application on transition

⁸The fraction of individuals with a given unemployment duration at a particular calendar time who leave unemployment in the next period.

⁹The size of the groups decreases sharply with duration.

data, see Cockx 1997). In a nutshell, this method consists in regressing the observed exit probabilities to their theoretical counterparts in the population. This method has two main advantages. First, it is more robust. Second, it can more easily accommodate random specification or measurement errors (see Amemiya and Nold 1975, Cockx and Ridder 2001)¹⁰.

The baseline hazard is specified as piecewise-constant. Related to our objective to disentangle compositional from general effects of the calendar time on the outflow rate, we allow the mean and the variance of the mixing distribution to vary (proportionally) over seasons and the business cycle. In the benchmark model the mixing distribution is assumed to be Gamma. We compare our findings with those found with a non-parametric specification of the mixing distribution, as approximated by one with a discrete number of points of support (see Heckman and Singer 1984, Baker and Melino 2000).

The plan of the chapter is as follows. The next section describes the data and introduces the main notations and assumptions. In a third section we test whether the MPH specification is compatible with our data. The fourth section is devoted to the derivation of our generalisation of the MPH model. The estimation results are discussed in Section 2.5. The concluding part summarises our findings.

2.2 Data, notations and assumptions

Our analysis exploits quarterly census data relative to the male unemployed in Wallonia and stratified by a limited number of characteristics: The quarter of inflow, the unemployment duration and the age group (less than 29 years old, and between 29 and 44 years old).

Workers are defined to be unemployed if they are officially registered as full-time unemployed and if a sufficiently long employment record entitles them to unemployment benefits. The inflow in a given quarter is equal to the number of workers who entered unemployment for the first time or after an exit of at least three months and who are still unem-

¹⁰A third reason to prefer the estimation method proposed in this study is that in contrast to the one proposed by Van den Berg and Van Ours (1994), its computational complexity does not increase with the number of duration intervals.

employed at the end of the quarter in which they enter¹¹. The observation period consists of 19 quarterly intervals¹², the first interval starting on the 1th of June 1989, the last one ending on the 28th of February 1994. So there are 18 cohorts of unemployed¹³ (a cohort being defined by its quarter of inflow), stratified by age group. For each cohort, the outflows out of unemployment are counted on a quarterly basis, from the time of inflow until the end of February 1994, the date at which all spells are right censored. For each age group, the data are therefore grouped into $N = \sum_{n=1}^{18} n = 171$ homogeneous cells.

The data do not allow us to distinguish between unemployment spells ending in employment, participation in labour market programmes or withdrawal from the labour force. This is not likely to bias our results for two reasons. First, employment is the most frequent state of exit for the male unemployed workers: About 77% of them become employed, against 47% for the women (see FOREM 1995). In our sample, the fraction of men flowing to employment must be larger. For, the reported figure includes unemployed workers older than 44 years. These workers often enter a kind of early-retirement scheme, a policy heavily used after the mid eighties in Belgium for older workers. Second, the period of entitlement to benefits is in principle indefinite in Belgium. One exception to this rule concerns the cohabitants (e.g. living with a working partner or with their parents). They can lose entitlements on grounds of ‘excessive’ unemployment duration. However the duration threshold is beyond the maximum unemployment duration in our data set (18 quarters), so that this sanction is not likely to influence the pattern of the duration dependence of the outflow rate in our analysis.

In the sequel, the variables l and t denote respectively the calendar time at the moment of inflow and unemployment duration. These variables are measured in quarters. The way the inflow is constructed in our data requires us to model calendar time at the moment of inflow, l , as a

¹¹These restrictions allow to neglect temporary exits (for administrative reasons for example).

¹²Four quarters are defined: (Jun,Jul,Aug); (Sep,Oct,Nov); (Dec,Jan,Feb); (Mar,Apr,May).

¹³There are 18 cohorts instead of 19 as there is, by definition, no exit defined for those entering the unemployment pool in the 19th quarter.

discrete time process. We have that $l \in \{0, 1, \dots, 17\}$ and by definition, that $t \equiv 0$ at the moment of inflow l .

Although we analyse discrete data, we treat unemployment duration, t , as a continuous-time process. So, $t \in R^+$. Otherwise, the specification would be sensitive to the chosen duration interval (see Flinn and Heckman 1982). Misspecified duration intervals, i.e. not consistent with the unemployed behaviour, would then lead to non-proportionality, violating the MPH specification imposed below¹⁴.

We then denote the hazard of an individual unemployed for t quarters and at risk of leaving unemployment at calendar time $l + t$, conditional on unmeasured characteristics v , by:

$$h(t | l + t, v) \quad (2.1)$$

and the survivor function at unemployment duration t by:

$$S(t | v) = \exp \left[- \int_0^t h(s | l + s, v) ds \right] \quad (2.2)$$

Here and in the sequel, the calendar time dependence is implicit in the notation of the survivor function.

We then specify a mixed proportional hazard (MPH) model in which we impose a continuous baseline hazard and constant calendar time effects within quarterly intervals:

$$\forall t \in [k - 1, k) : h(t | l + t, v) = \exp [\varphi_1(k) + \varphi_2(l + k)] v \equiv h_{kl} v \quad (2.3)$$

where $v > 0$, $k \in \{1, \dots, 18\}$, $\varphi_1(k) = \int_{k-1}^k \varphi_1(t) dt$ and the functions $\varphi_1(\cdot)$ and $\varphi_2(\cdot)$ represent respectively the duration and calendar time dependence of the conditional hazard.

¹⁴Note that the process is continuous except from conditioning on survival through the quarter of entry into unemployment. A ‘genuine’ continuous time process would require modeling spells that start and end within the same quarter. This would substantially complicate our specification.

We assume that calendar time at the moment of inflow affects the shape of the mixing distribution (see Abbring *et al.* 2001a). Using (2.2) and (2.3), the mixture survivor function at the end of quarter k can then be found to be:

$$S^m(k|l) = \int_0^\infty \exp \left[-v \sum_{j=1}^k h_{jl} \right] dF_l(v) \quad (2.4)$$

where $F_l(\cdot)$ is the heterogeneity distribution. Below, we will specify this distribution as well as how it depends on calendar time at the inflow.

We parametrise $\varphi_1(k)$ as a piecewise-constant function:

$$\varphi_1(k) = c + \sum_{j=2}^{18} (\gamma_j - c) \delta_{jk} \quad (2.5)$$

where δ_{jk} is the Kronecker delta and where we impose that $\forall j \geq 12$: $\gamma_j = \gamma_{12}$. The latter restriction is imposed to avoid erratic behaviour of the parameters induced by a too small number of observations at the tail of the duration distribution.

In the line of Abbring *et al.* (2001b), we represent the calendar time dependence of the hazard, $\varphi_2(l+k)$, by the following flexible parametric specification, where we decompose $\varphi_2(l+k)$ into a cyclical part, $\varphi_{2c}(l+k)$, and a seasonal part, $\varphi_{2s}(l+k)$:

$$\begin{aligned} \varphi_{2c}(l+k) &= \sum_{i=1}^5 \beta_{ci} p_i(l+k) \\ \varphi_{2s}(l+k) &= \sum_{a=2}^4 (\beta_{sa} - c) s(l+k) \end{aligned} \quad (2.6)$$

The effect of calendar time at the outflow on the hazard is represented by a flexible fifth degree polynomial in calendar time, $p_i(l+k)$, capturing business cycle effects¹⁵, and by dummy variables, $s(l+k)$, capturing seasonal effects. To avoid multi-collinearity problems, we follow Abbring

¹⁵A fifth degree polynomial should track the business cycle dependence of the hazard in a flexible way. Note, in order to avoid the incidental parameter problem, the number of degrees should be constant or at least increase at a slower rate than the

et al. (2001b) and use the orthogonal Chebyshev polynomial instead of an ordinary polynomial¹⁶.

2.3 Testing the proportionality assumption

2.3.1 Statistical model

Intuitively, the presence of heterogeneity in a proportional hazard model, such as defined in (2.3), implies a decrease in the aggregate hazard (i.e. unconditional on v) with duration which is slower for low value of $\varphi_2(l+k)$ (e.g. in downturn) and faster for high value of $\varphi_2(l+k)$ (e.g. in upturn). In a tight labour market, the individuals with a high value of v leave unemployment at a very fast rate. So the group of survivors is rapidly made of ‘low skilled’ individuals, inducing a strong negative duration dependence of the aggregate hazard. However, in a depressed labour market, even the unemployed with the best characteristics are likely to stay some time in that state. The aggregate exit rate declines only slowly over duration.

Formally, this intuition is, however, only correct if the duration is small (see Van den Berg 2001). For larger durations, the sign of this interaction depends on the form of the heterogeneity distribution. For instance, Lancaster (1979) shows that if the unobserved heterogeneity is distributed Gamma, the interaction remains always negative. On the other hand, for a discrete distribution with a finite number of points of

number of calendar time points. In the latter case, the ‘good’ asymptotic properties of the estimator cannot be guaranteed (see Gourieroux and Monfort 1995, p.189). However, this does not imply that the number of parameters should necessarily be fixed, such as Merz (1999, p.333) claims in her critique on Van den Berg and Van der Klaauw (2001).

¹⁶The series of Chebyshev polynomials is obtained as follows (see Abramowitz and Stegun 1970, Table 22.3). First, linearly transform the domain of calendar time to the domain of orthogonality of the Chebyshev Polynomial, $[-1, 1]$, by means of $(x = l+k$ and $x_0 = 1)$:

$\hat{x}(x) = 2\frac{x-x_0}{n-1} - 1$, where n ($= 18$) is the number of calendar time intervals considered.

Then generate the series of orthogonal polynomials, $p_i(\hat{x})$, by means of:

$$p_i(\hat{x}) = \frac{i}{2} \sum_{j=0}^{\lfloor \frac{i}{2} \rfloor} (-1)^j \frac{(i-j-1)!}{j!(i-2j)!} (2\hat{x})^{i-2j}, \text{ for } i = 1, 2, \dots, 5 \text{ and for } j \in R^+.$$

support, it is clear that the interaction must be positive on some range, since, as $t \rightarrow \infty$, the group of survivors becomes homogenous¹⁷ and the interaction goes back to its value at $t = 0$.

The MPH model implies, however, that the cumulative interaction of the aggregate hazard over the duration interval $[0, t]$ is always negative (see Van den Berg 2001). In our notation, $\forall k \in \{2, 3, \dots, 17\}$ ¹⁸, we must have that:

$$\frac{\partial}{\partial \varphi_{2i}(l+k)} \left(\log \frac{h_{kl}^a}{h_{1(k+l-1)}^a} \right) < 0 \quad \text{for } i = c, s \quad (2.7)$$

where $h_{1(k+l-1)}^a$ is the aggregate hazard in the first duration quarter at calendar time $l+k$.

We can therefore test whether the MPH assumption is compatible with our data by testing whether such a cumulative interaction effect is negative. This amounts to adding an interaction effect, $\varphi_3(k, l+k)$, to a proportional specification of the aggregate hazard, h_{kl}^a :

$$\log(h_{kl}^a) = \varphi_1(k) + \varphi_2(l+k) + \varphi_3(k, l+k) \quad (2.8)$$

where $\varphi_3(k, l+k)$ is specified in the following way:

$$\varphi_{3i}(k, l+k) = \left(\psi_i \log(k) \sum_{j=2}^{18} \delta_{jk} \right) \varphi_{2i}(l+k) \quad \text{for } i = c, s \quad (2.9)$$

Note that the interaction with the cyclical component, c , is defined separately from the seasonal component, s . We test whether $\psi_i < 0$ ¹⁹.

¹⁷All survivors having the lowest value v of the points of support.

¹⁸The derivative is not defined for $k = 18$ as there is only one observation for this duration quarter.

¹⁹The specification of the time-duration interaction in (2.9) imposes that the cumulative interaction effect is monotonically decreasing in duration. As already stated, this is compatible with a Gamma, but not with a discrete heterogeneity distribution. A specification that allows the interaction to vary non-monotonically with duration could therefore guide us with respect to the specification of the heterogeneity distribution. We therefore also estimated a model in which we include a second interaction parameter in $\log^2(k)$. The coefficient of this second term is, however, always very imprecisely estimated.

There are theoretical reasons to believe that the proportionality assumption stated in (2.3) does not hold. The ranking model (see Blanchard 1991, Blanchard and Diamond 1994) implies that the effects of duration on the conditional exit rate are stronger the more depressed is the labour market. As the state of the labour market deteriorates, the employers posting vacancies receive many applications of unemployed workers. If employers rank applicant according to their elapsed unemployment duration, competition among the long-term unemployed to occupy a vacancy is increased as compared to the situation in a tight labour market. Formally, Abbring *et al.* (1997) show that, contrary to the MPH model, the ranking model implies a *positive* cumulative interaction effect, i.e. $\psi_i > 0$ in (2.9).

The sign of ψ_i can therefore only be informative on the *relative* importance of unobserved heterogeneity as compared to ranking. If it is significantly negative, unobserved heterogeneity dominates and the data are compatible with a MPH specification. However, it does not exclude that ranking is at work simultaneously. In such circumstances, a MPH specification, even if it will identify some spurious negative duration dependence, will underestimate the extent to which the duration dependence is spurious. We illustrate this in the next section by introducing an interaction term between duration and two sub-periods, one covering an upturn and the other a downturn of the business cycle.

The ranking model of Blanchard and Diamond (1994) is built on the assumption that workers have no, or only observed, quality differences. However, their prediction on the time-duration interaction implied by ranking may not hold in a model in which employers observe the skill profile of workers incompletely. In that case, Lockwood (1991) predicts a *negative* interaction between the duration dependence of the conditional exit rate and the state of the labour market. In his framework, the employers rank applicants according to their elapsed duration because a long unemployment spell signals low productivity. Since the weeding out of high productive individuals is faster in a boom than in a recession (see above in the text), the employers will decrease the length of acceptable period of unemployment in a boom since the risk of having a low productive worker is reduced. This recruitment behaviour induces the conditional hazard to decline faster in a boom than in a re-

cession²⁰. As a result, the prediction of Blanchard and Diamond could be reversed if the extent of unobserved heterogeneity (from the employer's perspective) was large in the unemployed population. For identification purposes, we will, however, assume that ranking is associated with a *positive* time-duration interaction in the conditional hazard. This assumption is actually supported by the findings of Chapter 3 which show that the remaining disparity in the quality of the unemployed workers is weak when one accounts for observed differences in their characteristics (such as the level of education and the age).

We now turn to a description of the estimation procedure, which we choose to be Minimum Chi-Square (see Berkson 1944, Amemiya 1981, Cockx 1997). In a nutshell, this method consists in regressing for each cohort a transformation of the observed exit probability, i.e. the fraction of workers that leave unemployment within a particular duration interval given that they did not leave earlier, to its theoretical counterpart. The theoretical probability at the k^{th} duration interval for a worker who is at risk of leaving unemployment within the $(l + k)^{th}$ quarter is:

$$P_{kl} \equiv \Pr(k - 1 \leq T < k | T \geq k - 1, l + k) \quad (2.10)$$

Using (2.2), we then link this probability to the aggregate hazard rate defined in (2.8):

$$P_{kl} = \frac{S^u(k - 1) - S^u(k)}{S^u(k - 1)} = 1 - \exp[-h_{kl}^a] \quad (2.11)$$

where $S^u(\cdot)$ is the unconditional survivor function. Inverting this relationship gives us:

$$z_{kl} = \log[-\log(1 - P_{kl})] = \log(h_{kl}^a) \quad (2.12)$$

We now relate the theoretical probability to the empirical probability. Let u_{kl} be the number of individuals who entered into unemployment at l , are still in that state at the start of the k^{th} duration interval and are therefore at risk of leaving unemployment within the $(l + k)^{th}$ quarter.

²⁰In a different model, Lebon (1993) also predicts a negative interaction between the duration dependence of the conditional hazard and the state of the business cycle.

Let f_{kl} be the number of these individuals who leaves unemployment within the k^{th} duration interval. We can then estimate the probability of leaving unemployment, P_{kl} , by the Kaplan-Meier estimator of the hazard adapted to grouped data:

$$\hat{P}_{kl} = \frac{f_{kl}}{u_{kl}} \quad (2.13)$$

If we replace the probability of leaving unemployment by its estimate, $\hat{P}_{kl}$, in (2.12), the equality of this equation does no longer hold exactly, since the observed aggregate exit probability is calculated on the basis of a finite sample. We follow Cockx (1997) and expand $\log \left[-\log \left(1 - \hat{P}_{kl} \right) \right]$ in a Taylor series around P_{kl} :

$$\hat{z}_{kl} = \varphi_1(k) + \varphi_2(l+k) + \varphi_3(k, l+k) + \omega_{kl} \quad (2.14)$$

$$\text{with the approximation error } \omega_{kl} = \frac{\hat{P}_{kl} - P_{kl}}{(1 - P_{kl}) \log(1 - P_{kl})}$$

There is an additional term, but since it is of order less or equal than u_{kl}^{-1} , it can be ignored for large u_{kl} ²¹ (see Amemiya 1985, pp.276-77). Since conditional on the number of individuals at risk, u_{kl} , the number of outflows, F_{kl} , in the empirical estimator (2.13) has a binomial distribution with a probability of ‘success’ P_{kl} , Cockx (1997) shows that $E(\omega_{kl}) = 0$ and that a consistent estimate of the variance of ω_{kl} is²²:

$$\hat{s}_{kl}^2 = \hat{P}_{kl} \left[\left(1 - \hat{P}_{kl} \right) \left[\log \left(1 - \hat{P}_{kl} \right) \right]^2 \right]^{-1} \frac{1}{u_{kl}} \quad (2.15)$$

The Minimum Chi-square estimator is then defined as the weighted least squares estimator as applied to (2.14).

²¹The size of our cells is indeed quite large. The lowest and the average u_{kl} are respectively 266 and 1649 for the men aged between 29 and 44 years old, and respectively 155 and 1973 for the men aged less than 29 years old.

²²The covariance is zero.

2.3.2 Empirical results

The estimation results for the model specified in (2.14) are reported in the first column of Table 2.1 and Table 2.2 of Appendix 4, respectively for men aged 29-44 and for men aged less than 29 years old. For both demographic groups, the interaction parameters, ψ_c and ψ_s , are negative: Duration dependence of the aggregate hazard is steeper for high value of $\varphi_2(l+k)$ than for low value of $\varphi_2(l+k)$. This result is consistent with the presence of heterogeneity in a MPH model such as specified in (2.3). This finding implies that we can identify heterogeneity within a proportional framework in the next stage.

Note that for the men aged between 29 and 44 years old, the parameter ψ_c is small in absolute value and insignificant. One possible reason of this finding is that ranking according to unemployment duration is present for the prime aged men. As mentioned above, the interaction parameter ψ_c would then ‘underestimate’ the importance of heterogeneity in the data, unlike the parameter ψ_s . In the next stage, we therefore relax the proportionality assumption between two calendar time sub-periods (a boom and a recession), but maintain it within these two sub-periods. We maintain the proportionality in the seasonal component.

2.4 The mixture models

2.4.1 A mixed non-proportional hazard model

Insofar as we showed that the proportionality assumption of the hazard in duration and the state of the business cycle might be too restrictive for the oldest men, we decide to relax this assumption between two calendar time sub-periods. In order to contrast the two periods considered, we retain for the first sub-period calendar time intervals relative to the peak, i.e. between September 1989 and November 1990, and for the second sub-period, those relative to the slack period starting in December 1990 and continuing up to February 1994. This amounts to add in the conditional hazard (2.3) an interaction term $\tilde{\varphi}_3(k, l+k)$:

$$\begin{aligned} \forall t \in [k-1, k) : h(t | l+t, v) &= \exp [\varphi_1(k) + \varphi_2(l+k) + \tilde{\varphi}_3(k, l+k)] v \\ &\equiv h_{kl} v \end{aligned} \quad (2.16)$$

which is specified as follows:

$$\tilde{\varphi}_3(k, l+k) = \phi I_{\{1,2,3,4,5\}}(l+k) \sum_{j=2}^{18} |\gamma_j - c| \delta_{jk} \quad (2.17)$$

The interaction parameter, ϕ , is only defined for the boom period (i.e. the first five calendar time intervals) and is assumed to affect the logarithm of the baseline hazard in absolute value multiplicatively. We take the absolute value to avoid that the sign of the duration dependence affects the sign of the interaction term. Ranking implies that $\phi > 0$.

One could propose alternative specifications of the cumulative interaction effect, in our notation: $\phi |\gamma_j - c|$. Since the boom period spans only 5 quarters, a separate piecewise-constant specification of the baseline hazard in upturn yields too imprecise estimates. Other parsimonious specifications of the interaction term exist such as $\phi \log(k)$ or as $\phi_1 \log(k) + \phi_2 \log^2(k)$. However, the latter yield much less precise parameter estimates than our chosen specification (not reported²³).

When unobserved heterogeneity is taken into account, we have to replace the survivor function in (2.11) by the mixture survivor function as defined in (2.4), yielding:

$$P_{kl} = \frac{S^m(k-1 | l) - S^m(k | l)}{S^m(k-1 | l)} = 1 - \frac{\int_0^\infty \exp \left[-v \sum_{j=1}^k h_{jl} \right] dF_l(v)}{\int_0^\infty \exp \left[-v \sum_{j=1}^{k-1} h_{jl} \right] dF_l(v)} \quad (2.18)$$

In the sequel, we choose two specifications for the mixing distribution, $F(v)$. In principle, a non-parametric specification of the mixing distribution would be the best choice. However, recent Monte Carlo analysis of Baker and Melino (2000) reveals that a non-parametric specification

²³These estimation results can be obtained from the authors on request.

of both the distribution of duration and of unobserved heterogeneity can result in large and systematic bias in the parameters of these components, if estimated by maximum likelihood. Baker and Melino show that the bias can be reduced by modifying the objective function such that specifications with many points of support are penalised. We will follow a similar procedure below, based on the Schwarz (1978) information criterion.

The findings of Baker and Melino suggest that a parametric specification of the mixing distribution could improve upon a non-parametric one. Recently, Abbring and Van den Berg (2001) justify the choice of a Gamma distribution for $F(v)$. For, they show that for a continuous v and under mild regularity conditions, the unobserved heterogeneity distribution among survivors at t converges to a Gamma distribution if $t \rightarrow \infty$. In the benchmark model the mixing distribution is therefore assumed to be Gamma. We then compare our findings with those found with a non-parametric specification of the mixing distribution, as approximated by one with a discrete number of mass points.

The Gamma mixing distribution

We assume that V (random variable) is a Gamma variate of mean, $\mu_l = \frac{\lambda}{\delta_l}$, and variance, $\sigma_l^2 = \frac{\lambda}{\delta_l^2}$. As such, we allow the mean and the variance of V to vary proportionally over calendar time at the moment of inflow, l . The mean of the mixing distribution needs to fluctuate proportionally to its variance for purposes of identification (see below). By normalisation, the mean is equal to one for $l = 0$. We therefore impose $\lambda = \delta_0$. Since the moment generating function of this Gamma variate is (see Lancaster 1990, p.328):

$$M_v \equiv E(e^{sV}) = \left(1 - \frac{s}{\delta_l}\right)^{-\lambda} \quad (2.19)$$

we are able to simplify greatly the last expression in (2.18).

Before deriving the mixture regression model, we specify how the variable δ_l depends on calendar time at the inflow. We first introduce the following notation: $\delta_l = \exp[-\varphi_4(l)]$ where we decompose $\varphi_4(l)$ into a cyclical (c) and a seasonal component (s): $\varphi_4(l) = \varphi_{4c}(l) + \varphi_{4s}(l)$.

Unlike for the effect of calendar time on the hazard at the moment of exit, we choose to characterise the effect of calendar time at the moment of inflow by a business cycle indicator and by the season at inflow. This leads us to specify $\varphi_{4c}(l)$ and $\varphi_{4s}(l)$ as follows:

$$\begin{aligned}\varphi_{4c}(l) &= \eta_c b(l) \\ \varphi_{4s}(l) &= \eta_{s1} + \sum_{a=2}^4 (\eta_{sa} - \eta_{s1}) s(l)\end{aligned}\quad (2.20)$$

The business cycle indicator, $b(l)$, is the de-seasonalised logarithm of the number of quarterly flows into unemployment²⁴, and $s(l)$ are the seasonal dummies at the time of inflow. We impose $b(0) = 0$, so that $\lambda = \exp(-\eta_{s1})$.

Combining (2.18), (2.19) and (2.20), we then obtain the following non-linear heteroskedastic regression model:

$$1 - \hat{P}_{kl} = \left[1 - \frac{\sigma_0^2 \mu_l \exp[\varphi_1(k) + \varphi_2(l+k) + \tilde{\varphi}_3(k, l+k)]}{1 + \sigma_0^2 \mu_l \sum_{j=1}^k \exp[\varphi_1(j) + \varphi_2(l+j) + \tilde{\varphi}_3(j, l+j)]} \right]^{\frac{1}{\sigma_0^2}} + \omega_{kl} + \varepsilon_{kl} \quad (2.21)$$

where $\sigma_0^2 = \exp[\eta_{s1}]$, $\mu_l = \exp[\varphi_4(l) - \eta_{s1}]$ and $\omega_{kl} = \hat{P}_{kl} - P_{kl} - \varepsilon_{kl}$ is the approximation error. The errors ε_{kl} are specification errors which allows for random deviation from the true specification of the hazard rate. We assume that they have a distribution such that $E(\varepsilon_{kl}) = 0$ and $E(\varepsilon_{kl}^2) = s_\varepsilon^2$. We have that $E(\omega_{kl}) = 0$ and its variance can be consistently estimated by (see Cockx 1997):

$$\hat{s}_{kl}^2 = \left[\left(\hat{P}_{kl} \right) \left(1 - \hat{P}_{kl} \right) \right] \frac{1}{u_{kl}} \quad (2.22)$$

²⁴The inflow rate would be a more appropriate indicator. This statistic is not available on a quarterly basis. However, if the number of employed workers remains approximately constant over the observation period, we can approximate it by the number of workers flowing into unemployment.

We now show that the correlation structure of the specification errors is informative about the type of misspecification. We find that the empirical correlation between the residuals of adjacent duration classes for any fixed calendar time at the outflow, i.e. the correlation between ε_{kl} and ε_{k-l+1} , denoted by ρ_{l+k} , is significantly positive according to the LM-test statistic (see Godfrey 1978 and Breusch and Pagan 1980) for both the men aged 29-44 and those aged ≤ 28 : Respectively, 0.65 and 0.77. We explain below how we calculate such a statistic. These results suggest to interpret the model residuals as cohort-specific random business cycle effects at the time of exit. On average these random deviations from the MPH specification cancel out. However, to the extent that cohorts with a different elapsed duration are imperfect substitutes, then an increase (decrease) in the hazard of one particular cohort will spill over to the other cohorts. If we assume that the degree of substitutability decreases with the difference of the elapsed duration between the affected and non-affected cohorts, then this substitution induces, for any fixed exit time, the model residuals to be positively autocorrelated with duration. If cohorts were not substitutable, then the coefficient of autocorrelation would be zero. On the other hand, if substitution was perfect, the cohort-specific business cycle effect would affect each cohort by a common factor.

Note that ε_{kl} could also have been interpreted as a measurement error in the line of Abbring *et al.* (2001a) and Van den Berg and Van der Klaauw (2001). In this interpretation, the errors are made in counting the number of unemployed at a particular duration and/or calendar time interval. Consequently, they introduce a difference between the true and the observed value of u_{kl} in (2.13) and, indirectly, between P_{kl} and $\hat{P}_{kl}$. Measurement errors of this type, whether they are independent or not, always imply that the correlation between the residuals of adjacent duration classes for any fixed calendar time at the inflow, i.e. the correlation between ε_{kl} and ε_{k-1l} , denoted by ρ_l , is equal to $-\frac{1}{2}$. For our data, the correlation structure of the residuals is however not compatible with this type of measurement error: The empirical correlation between ε_{kl} and ε_{k-1l} is not significantly different from zero according to the LM-test statistic whatever the age group.

A this stage, it is important to notice that the approximation errors,

ω_{kl} , do not correspond to the measurement errors such as introduced by Abbring *et al.* (2001a) nor to specification errors. They reflect the stochastic nature of the empirical exit rates, $\hat{P}_{kl}$. Taking the heteroskedastic approximation errors into account improves the efficiency of the estimator and yields consistent estimators of the parameter variance-covariance matrix.

We might depart from our general mixture model in (2.21) by testing two restrictions on the parameters:

$$R1 : \phi = 0 \quad (2.23)$$

$$R2 : \eta_c = 0 \quad (2.24)$$

$R1$ restricts the pattern of duration dependence not to vary over the business cycle. $R2$ imposes a fixed heterogeneity distribution over the business cycle: The mean and the variance of the unmeasured characteristics, v , of those entering unemployment are constant over the cycle.

The estimation procedure consists in two-steps (see Amemiya and Nold 1975). In a first step we estimate the model (2.21) by Ordinary Least Squares (OLS). On the basis of the OLS residuals ($\hat{v}_{kl}$) and of the estimated variance of the approximation error ($\hat{s}_{kl}^2$), we can calculate a consistent estimate of s_ε^2 :

$$\hat{s}_\varepsilon^2 = \frac{1}{N} \left\{ \sum_{l=0}^{17} \sum_{k=1}^{18-l} \left[(\hat{v}_{kl})^2 - \hat{s}_{kl}^2 \right] \right\} \quad (2.25)$$

Using this statistic and the empirical autocovariance of the OLS residuals, we can also calculate a consistent estimate of the autocorrelation coefficients, ρ_{l+k} and ρ_l , of the higher mentioned specification errors, ε_{kl} (see Appendix 1). In a second step, we estimate the statistical model (3.14) by Generalised Least Squares (GLS), explicitly allowing for the AR(1) disturbances (ε_{kl}) over k , for any fixed $l+k$ (see Appendix 2).

Because we have grouped data, we can use a χ^2 -goodness-of-fit test to evaluate the model specification. The weighted sum of squared residuals ($WSSR$) is distributed $\chi_{N-N_\theta}^2$ if the model is correctly specified,

where N denotes the number of cells and N_θ is the number of parameters. Moreover, we can test the acceptability of the higher mentioned restrictions, $R1$ and $R2$. The difference between the weighted sum of squared residuals of the constrained and the unconstrained model ($WRSS_0 - WRSS$) is distributed $\chi^2_{(N_\theta - N_{\theta_0})}$ ²⁵.

A non-parametric specification of the mixing distribution

A non-parametric mixing distribution can be specified as a discrete one with unknown support and an unknown number of mass points. Heckman and Singer (1984) propose a procedure to estimate such a distribution by maximum likelihood. Baker and Melino (2000) supply an heuristic interpretation and adjust this procedure to reduce the bias of the estimator in finite samples. To that purpose, they propose to maximise the Hannan-Quinn or the Schwartz Information Criterion rather than the log-likelihood function (see also Leroux 1992). They report (footnote 14, p.376) that results are virtually identical for these two criteria. We choose the Schwartz criterion (see also Chow 1985, pp.300-305, for a justification).

To make the above mentioned procedure applicable, we need to modify the objective function, i.e. we minimise the weighted sum of squared residuals ($WSSR$) rather than maximise a loglikelihood function. How this modifies the rule is discussed in Appendix 3. In the Schwartz criterion, the $WSSR$ replaces minus twice the loglikelihood value (see Amemiya 1981). According to this criterion, the preferred model is therefore the one that minimises the following statistic:

$$WSSR + N_\theta \ln(N) \quad (2.26)$$

We will not only evaluate the mixture models with a different number of mass points according to this criterion, but also the non-parametric to the Gamma mixture models.

Finally, we write down the expression for the non-linear heteroskedastic regression model with a discrete mixing distribution with S points of support:

²⁵For the purpose of this test statistic, the constrained model is estimated with the estimated variance matrix of the specification errors in the unconstrained model.

$$1 - \hat{P}_{kl} = \frac{\sum_{s=1}^S \pi_s \exp \left[-v_s \exp [\tilde{\varphi}_4(l)] \sum_{j=1}^k h_{jl} \right]}{\sum_{s=1}^S \pi_s \exp \left[-v_s \exp [\tilde{\varphi}_4(l)] \sum_{j=1}^{k-1} h_{jl} \right]} + \omega_{kl} + \varepsilon_{kl} \quad (2.27)$$

where $\forall s \in \{1, 2, \dots, S\} : v_s > 0, 0 \leq \pi_s \leq 1$, and where we normalise the mean of the mixture at calendar time $l = 0$ to one, i.e. $v_1 = \frac{1 - \sum_{s=2}^S \pi_s v_s}{\pi_1}$. The function $\tilde{\varphi}_4(l)$ is equal to $\varphi_4(l)$ for $\eta_{s1} = 0$ ²⁶. The function $\tilde{\varphi}_4(l)$ is interpreted as a composition effect, affecting the shape of the mixing distribution.

2.4.2 Identification

The MPH specification ensures that the conditional hazard is non-parametrically identified from a large number of observations on two conditions. First, the mean of the mixing distribution has to be finite. The second condition depends on the nature of the data and on the way in which they are modeled. If duration data are continuous, the regressor function needs to take on at least two values (see Elbers and Ridder 1982). If duration data are grouped, we need to distinguish between two cases. If duration is modeled as a continuous time process, as it is done in this study, Ridder (1990) proves that the presence of a continuous explanatory variable, varying over the whole set of real numbers, is sufficient. If duration is modeled as a discrete time process, the mixing distribution is identified up to its moments, in so far as the support of the heterogeneity distribution is bounded²⁷ and the regressor function is non-constant (see Van den Berg and Van Ours 1994, 1996 and Abbring *et al.* 2001a).

If we impose *R1* on our specification (2.21), we obtain, apart from the random specification errors, the standard MPH model. To see this, note that *R1* implies that calendar time at the outflow influences the baseline

²⁶We can normalise $\eta_{s1} = 0$, since this parameter determines the value of the variance in the Gamma mixture model. The variance is no longer a separate parameter if the mixing distribution is discrete.

²⁷The finite mean is implied by this condition.

hazard proportionally throughout the observation period. However, even with such assumption, an exponential trend in the inflow cannot be identified from an exponential trend in the outflow (see Abbring *et al.* 2001a). We avoid this problem because entry effects are assumed to be completely captured by seasonal effects and a business cycle indicator at the time of entry, i.e. the logarithm of the number of entrants. If this indicator does *not* vary *only* according to an exponential trend, identification is assured.

Nevertheless, entry effects still have two indistinguishable interpretations, i.e. either compositional or competition effects (see Abbring *et al.* 2001a). Until now, we interpreted them as compositional effects, by assuming that calendar time at the moment of inflow affects the shape of the distribution of v in the inflow. Calendar time at the inflow could, however, also influence the individual exit rate directly, leaving the composition of inflow constant over time. In such an interpretation, seasonal and cyclical fluctuations in the number of workers entering the unemployment pool may alter the intensity of the job-search competition faced by the newly unemployed and, therefore, their exit rate. So, the inflow into unemployment creates a negative intra-group externality corresponding to congestion effects. In that case, the multiplicative effect of the indicators at the time of inflow should be taken to affect the conditional hazard rather than the form of the mixing distribution (see De Toldi *et al.* 1992). We rule this out by assumption. The reader can, however, validly interpret the empirical findings below differently, in terms of competition rather than compositional effects. Note, moreover, that in such an interpretation, the competition effects would be captured by the variables specified in $\varphi_4(l)$ ²⁸ that affect the conditional hazard multiplicatively. This implies that the conditional hazard is of the MPH form in the variables capturing the effect of calendar time at the inflow.

If restriction *R1* (i.e. MPH) is imposed, we can rely on the non-parametric identification results of Ridder (1990). The mean of the

²⁸The parameter η_{s1} would then be (a transformation of) the variance of the mixing distribution, while the parameters η_c and η_{sa} would represent the effect of calendar time at the inflow on the conditional hazard rather than on the shape of the mixing distribution.

mixing distribution is assumed to be finite and normalised to one in the quarter beginning in June 1989. For each duration interval, the business cycle indicator affects the baseline hazard proportionally and varies continuously over the set of real numbers as the number of workers entering unemployment increases over our observation period.

If we restriction $R1$ is not imposed, the specification is no longer MPH. The baseline hazard is then allowed to vary non-proportionally between two calendar time sub-periods at the time of exit. However, as long as the number of sub-periods does not increase with the number of observations²⁹, identification is assured by the MPH assumption within each sub-period. Kalwij (2001) and Rosholm (2001) allow for a full interaction between the baseline hazard and the business cycle. Since they observe multiple spells for a given individual, identification of unobserved heterogeneity is ensured without imposing restrictions on the time-duration interaction.

2.5 Empirical results

2.5.1 Specification tests

In Appendix 4, we report the estimation results of the mixture regression models, respectively for men aged between 29 and 44 years old (see Table 2.1) and for those aged less than 29 years old (see Table 2.2). We estimate for both age groups a Gamma and a non-parametric mixture model (see, respectively, the second and the last column). For the young age group, we also report the Gamma mixture with a constant baseline hazard and restriction $R1$ (see the third column of Table 2.2). According to the χ^2 -test, this specification is not rejected at a significance level of 5% (P-value= 36%) for the young people while it is for the prime aged group. For the young group, we therefore estimate the non-parametric mixture model on which we impose a constant baseline hazard and $R1$ (see the last column of Table 2.2). The constant term is, after an exponential transformation, the estimated hazard of a reference individual with average unmeasured characteristics (i.e. $v = 1$). All models fit

²⁹This is feasible if observations are classified to one of the subperiods according to whether they are realised in an upturn or a downturn.

the data reasonably well: According to the goodness-of-fit statistic, no model can be rejected against the saturated model at a significance level of 5%.

In the procedure allowing to select the number of mass points of the non-parametric mixing distribution (see Section 2.4.1 and Appendix 3), we can decrease the $WSSR$ marginally by increasing this number from, two to three. The probability assigned to the third mass point is very small for the prime aged men while it is significantly positive for the young men. However, on the basis of the Schwartz criterion, the models with two points of support are preferred for both age groups.

If we now compare the Gamma mixture to the non-parametric mixture model, the Schwartz criterion selects the Gamma for the age group 29-44, but the non-parametric mixture for the other group. This is in line with the Monte Carlo findings of Baker and Melino (2000). For the young workers, a constant baseline hazard is preferred. In that case, Baker and Melino report that the non-parametric mixture performs well. If the true mixing distribution is not Gamma, the non-parametric mixture model should be selected. This is precisely what the Schwartz information criterion does. On the other hand, for the older workers, a constant baseline hazard is rejected. In that case, Baker and Melino report that parameter estimators are biased in finite samples. Even if their modified estimation procedure based on the Schwartz criterion leads to a dramatic improvement, it does not guarantee a better performance as compared to a parametric choice of the mixing distribution. In this application, the Gamma mixture indeed performs better than the non-parametric one. In the subsequent discussion, we retain the preferred model, i.e. the discrete mixture for the younger workers and the Gamma for the older workers.

Before entering into a more detailed interpretation of the estimation results with respect to duration and calendar time dependence, we first question whether we can impose the two restrictions proposed in Section 2.4.1.

According to the χ^2 -test, the estimated interaction parameter, ϕ , is significantly positive for men aged between 29 and 44 years old ($\phi = 1.99$). Consequently, restriction $R1$ is rejected. This result means that duration dependence becomes more negative when the labour market state

deteriorates (i.e. after 1990). This provides evidence in favour of the ranking model of Blanchard and Diamond (1994). It also explains why the interaction effect ψ_c estimated in the first stage (see the first column of Table 2.1 in Appendix 4), although negative and thereby suggesting the presence of heterogeneity, is small in absolute value: Ranking has an opposite effect than unobserved heterogeneity on the duration dependence of the aggregate outflow rate within the business cycle. As expected, we underestimate the variance of the Gamma distribution in a model ignoring this interaction³⁰. On the other hand, restriction $R1$ cannot be rejected for the youngest men with a close to one P-value, as suggested by the proportionality test conducted in Section 2.3.

For the prime aged men, neither the mean nor the variance of the mixing distribution varies significantly over the cycle: According to the χ^2 -test, $R2$ cannot be rejected at a significance level of 5%. But it is rejected for the young men (P-value= 0.5%). The average quality of the young male entrants (and its dispersion) increases significantly over our observation period. Unlike cyclical effects, seasonal effects induce significant fluctuations of the mean and the variance of the mixing distribution for both age groups.

Finally, note that standard deviation of the specification errors is small: of the order of .01 and .02 respectively for the prime aged and the young group. For the adult population, the specification error accounts only for 1.2% of the variation in the dependent variable while it is somewhat larger for the young unemployed workers (3%). Cohort specific calendar time effects are thus unimportant.

To conclude, for the prime aged men, cyclical variations in the hazard rate is general and cannot be due to compositional effects. On the other hand, cyclical changes in the quality of young entrants into unemployment explain part of the fluctuations in their aggregate hazard rate. Seasonal changes in the composition of entrants into unemployment drive some seasonal variations in the hazard for both age groups. Ranking can partly explain the negative unemployment duration of prime aged unemployed workers. A neglect of this phenomenon causes the variance of the mixing distribution to be underestimated. Ranking is not important for young unemployed workers.

³⁰These estimation results can be obtained from the authors on request.

2.5.2 True versus spurious duration dependence

The results for the estimated variance of the mixing distribution indicate an important disparity between the characteristics of those flowing into unemployment. For prime aged men, the estimated variance of the Gamma distribution is significantly positive at the reference calendar time of inflow (0.89). The dispersion of the two mass points is lower for the young unemployed workers, although significantly different from zero (0.26)³¹.

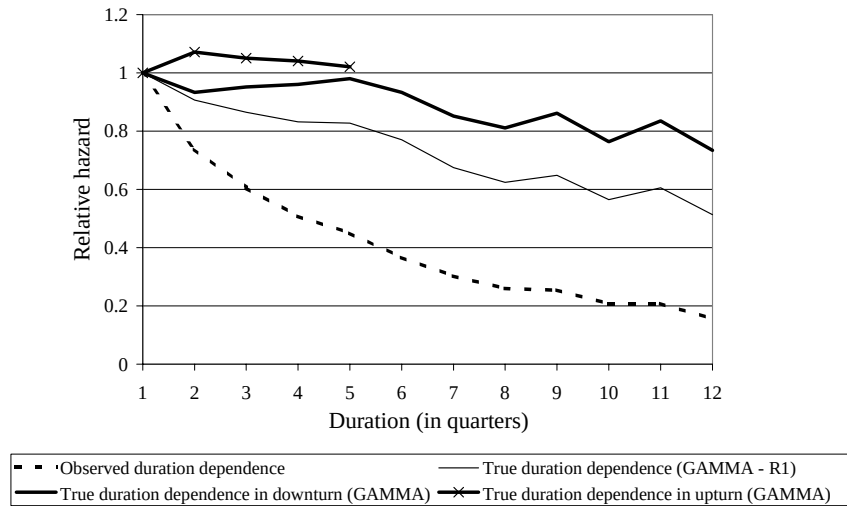


Figure 2.1: Baseline hazard - Men aged 29-44

Figure 2.1 shows, for men aged 29-44, the duration pattern of the hazard resulting from three different model specifications: A model with neither unmeasured heterogeneity nor a time-duration interaction³², the mixture model (2.21) under *R1*, i.e. without interaction, and the general mixture model (2.21). In the general model, the duration dependence in the upturn is positive while it is negative in the downturn. We attribute

³¹Note however that the variances of the two age groups are not readily comparable as they come from different distributions. The estimated variance of the Gamma distribution is 0.55 for the young men.

³²In order to take into account inflow effects in this model, we assume that the conditional hazard is multiplicative in calendar time at the moment of inflow.

this to the theoretical prediction that in the hiring process, ranking according to unemployment duration is less important or is even absent in upturn. Notice that the ‘true’ negative duration dependence is overestimated (and the variance of the mixing distribution underestimated) when ignoring the interaction.

Since the cumulative interaction is specified proportional to the baseline hazard (in absolute value), it increases between the first and the second duration quarter, and then decreases. This means that the marginal interaction effect becomes negative from the second quarter of unemployment. This result can be understood in a context where the employers rank candidates according to their unemployment duration but optimally choose a duration threshold beyond which no unemployed workers are hired. With the same argument as used in the ranking model, this threshold should depend positively on the labour market tightness. From two duration quarters, the baseline hazard would be no more decreasing in downturn while it would continue to do so in upturn, inducing the cumulative interaction effect to decline. However, we cannot check whether this prediction holds for larger durations as the boom period spans only 5 quarters. Moreover, the small number of observations during the boom period required us to impose a parsimonious specification of the interaction term. The negative marginal interaction effect may disappear if more data are available.

If we focus on the duration dependence pattern estimated in downturn, the nature of the negative duration dependence of the aggregate hazard in Wallonia is largely spurious: The sorting process due to unobserved heterogeneity explains most of the sharp decline in the aggregate exit rate with unemployment duration for the men aged 29-44. There is a 7% decrease in the individual hazard between the first and the second quarter of unemployment, and then a slight increase up to fifth quarter where the hazard nearly reaches its initial level. Given the level of parameters significance, we can argue that individual exit probabilities are, if anything, slightly decreasing over the first 1.5 years of unemployment and exhibit significant negative duration dependence afterwards. After two years and a half of unemployment the conditional hazard has dropped by 20%.

We now turn to the estimated duration dependence pattern for the

young unemployed workers. As the interaction parameter is insignificantly different from zero, the estimated duration dependence of the exit rate does not vary over the business cycle. After correcting for unobserved heterogeneity, the estimated duration dependence is strongly positive. The baseline hazard is, however, very imprecisely estimated. As stated above, we cannot reject duration to follow an exponential distribution at a significance level of 5%. We can therefore conclude that the observed negative duration dependence of the aggregate hazard is completely spurious for the young group.

How to explain the differences in the duration pattern between the distinct age groups? First, unlike for the adult unemployed workers, there is no evidence of ranking for the young people. Why is the ranking rule not relevant for the young workers? The depreciation of human capital during unemployment is likely to be more important for the older workers than for younger. This is because the skills that older workers have acquired on their previous job may require more maintenance than the general skills learnt at school. The employer can therefore increase the productivity of his recruits by ranking the older workers according to unemployment duration. The reliability of the ranking rule for the prime-aged men is reinforced, because their conditional hazard exhibits true negative duration dependence after 1.5 years that is unlikely to be completely explained by the ranking in the recruitment procedure³³. For the young men, the conditional hazard is not decreasing.

The higher rate of human capital depreciation can also lead to a more rapid ‘demotivation’ of older workers in their search for a job. Observe that the net expected returns to the on-the-job investments required in a new job are lower for older than for younger workers, simply because older workers face a shorter horizon. This may not only affect the search intensity level, but also its pattern over duration. The more human capital depreciates, the larger the on-the-job investments required in the new job.

Differential participation in active labour market programmes (ALMPs)

³³We cannot infer this from our data, because the observation period in the upturn is too short, i.e. only 5 quarters. If the negative duration dependence of the conditional hazard would not be observed in the upturn, the negative duration dependence would be completely induced by ranking.

can also explain the different pattern of duration dependence between the two age groups. For, participation in ALMPs in Belgium is often targeted to young and long-term unemployed workers. Besides, young people are likely to be more involved in ALMPs given that they expect a higher return of these programs than older people who have a lower timespan to amortise their investment. However, we do not have any figures to corroborate the fact that the young unemployed participate more to ALMPs than the prime-aged unemployed in Belgium. If it is actually the case, this may induce the baseline hazard of the younger workers to increase with unemployment duration since in our data set participants in these programmes are recorded to leave unemployment³⁴ if they do not return within the next quarter³⁵.

Finally, the rules governing the unemployment benefit scheme may induce younger workers to search more intensively as they are longer on the dole. For, the likelihood that young male workers are head of a family is lower than for the older age group. Since unemployment benefits for those who are not head of a family drop after 1 year and once more after 18 months if one is cohabitant, e.g. living with one's parents, the young will decrease their reservation wage and increase their search intensity gradually with unemployment duration (see Van den Berg 1990). By contrast, the heads of households are entitled to a constant unemployment benefit for an indefinite duration. Moreover, since the drop in the level of unemployment benefits after 18 months can be postponed with a factor that is proportional to past work experience, the more experienced and therefore older cohabiting workers will also be less affected by the declining profile of unemployment benefits³⁶.

³⁴An exception to this rule is the participation in counseling programmes: The worker remains registered as unemployed.

³⁵This is the so-called 'tautological' effect of ALMPs (see Calmfors 1994).

³⁶Another reason to explain the different pattern of duration dependence between the two age groups is related to temporary exits to employment. In our data set, an exit should last at least three months to be recorded as such. As a consequence, the measure of the elapsed duration into unemployment will not be affected by short exits to employment. Since young workers are over-represented in temporary contracts (in 1998, 34% of these were held by workers aged less than 25 years old while these workers represent only 10% of salaried employment, see Van Haeperen 2000), they are likely to accumulate short stays into employment during their unemployment spell, thereby maintaining skills and work habits. We might therefore underestimate the extent of true negative duration dependence for the young men.

We finish the discussion of our estimation results on duration dependence and heterogeneity by comparing them to those obtained in other studies. For purpose of comparison with our analysis, we restrict our discussion to recent European studies on unemployment duration applying a MPH framework and a flexible functional form for the duration dependence (for a more complete survey, see Machin and Manning 1999).

In view of our results Belgium belongs to the large pool of European countries where there is both no marked evidence of ‘true’ negative duration dependence of the exit rate out of unemployment and important ‘spurious’ dependence. So the United Kingdom seems to remain the exception, with individual unemployment duration distributions exhibiting strong negative duration dependence and not being significantly heterogeneous (see Nickell 1979, Van den Berg and Van Ours 1994, Kalwij 2001).

With respect to the prime aged men, the duration dependence of the conditional hazard in Wallonia resembles much the one that is found for the Netherlands and France, where there is evidence of non-monotonic true duration dependence, first constant, or even slightly increasing, then decreasing. Using a non-parametric specification of the mixing distribution, Van den Berg *et al.* (1998) estimate a slightly increasing trend of the individual outflow probabilities over the first year of unemployment for the men aged 25-49, while these exhibit significant negative duration dependence onwards³⁷. Although they treat the population of male unemployed globally, Van den Berg and Van Ours (1994) and Kerckhoffs *et al.* (1994) obtain the same kind of non-monotonicity in the Netherlands, using a discrete mixing distribution. Yet, the estimated hazard is overall constant over the first year of unemployment (first increasing, then decreasing) and declines very mildly onwards. Notice that unlike Belgium, France and the Netherlands, there is a slight positive dependence of the exit rate over all durations in Germany (see Steiner 2001), Spain (see

³⁷Only the first four quarters of unemployment are explicitly introduced in their empirical analysis. They use an informal procedure to deduce the duration dependence pattern beyond. They estimate non-parametrically the moments of the mixing distribution, and show that these are compatible with a two points of support distribution. The estimate of this mixing distribution on data regarding the first four quarters only and the aggregate observed exit rates are then used to infer the duration dependence of the conditional exit rate for the intervals beyond one year.

Bover *et al.* 1996) and Norway (see Hernaes and Strom 1996).

Concerning the young job-seekers, most of the studies tend to estimate a constant, or weakly negative (after some quarters of inactivity), duration dependence of the exit rate. Van den Berg and Van Ours (1999) as well as Van den Berg *et al.* (1998) found that young unemployment duration distributions in France exhibit no significant duration dependence during the first year of unemployment and a moderate negative duration dependence thereafter³⁸. Specifying a Gamma mixing distribution, D'Addio (1998) found no evidence of negative true duration dependence of the exit rate of young French workers unlike the preceding authors. Besides, an exponential distribution for the duration dependence pattern cannot be rejected as in our analysis.

We should, however, keep in mind that most of the reviewed studies do not allow the pattern of the duration dependence to vary over the business cycle. As is shown in this study, this potentially biases their findings regarding duration dependence downwards. Two exceptions are the studies of Kalwij (2001) and Rosholm (2001), which allow for a full interaction between duration dependence and the business cycle. Rosholm (2001) estimated that the duration dependence of the hazard becomes less negative, but insignificantly so, when unemployment increases for adult male workers³⁹, even after controlling for unobserved heterogeneity. He interprets this as evidence against the ranking model. On the contrary, Kalwij (2001) found evidence of ranking for men unemployed workers aged 18-59: The baseline hazard decreases faster in a times of low economic growth than in times of high economic growth. However, the difference between the slopes of the baseline hazard across the business cycle is very thin, particularly at short durations.

Note that our study does not only indicate that ignoring an interaction between the duration dependence and the business cycle may bias the estimations. It also suggests that the duration dependence, and so ranking, may not be similar across age groups. The common⁴⁰ assumption that age affects the baseline hazard proportionally, may accordingly lead

³⁸See the preceding footnote.

³⁹The interaction between the baseline hazard and the unemployment rate is not significant for the young men.

⁴⁰Rosholm (2001) and van den Berg *et al.* (1998) deviate from this common rule and specify a distinct baseline hazard by age groups.

to incorrect conclusions.

Our findings cast serious doubt on the reliability of some studies attempting to disentangle true from spurious duration dependence in Belgium (see Spinnewyn 1982 and Mahy 1994). Using strong parametric assumptions (Weibull) regarding the baseline hazard, they estimate a significant positive duration dependence of the conditional baseline hazard. Note that, assuming a Gamma mixing distribution, Kerckhoffs *et al.* (1994) estimate for the Netherlands a strong positive duration dependence with a Weibull baseline hazard specification while they obtain a similar result as ours when allowing for a flexible duration dependence pattern. These findings confirm that the importance of specifying the baseline hazard with sufficient flexibility (see also Heckman and Singer 1984). Finally, note that the positive duration dependence found by Plasman (1993) is not inconsistent with our findings. For, he restricts his analysis to young school leavers, excluded from our study.

2.5.3 Decomposition of the aggregate hazard over calendar time

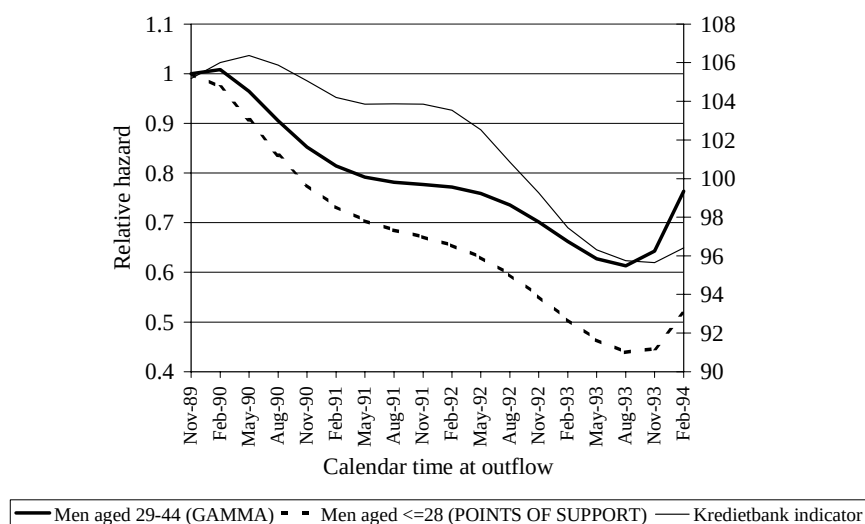


Figure 2.2: Cyclical dependence of the conditional hazard and the Kredietbank indicator (right scale)

The outflow rate from unemployment appears to be procyclical for men in Wallonia, as observed in comparing a Belgian business cycle indicator (the Kredietbank indicator, see Kredietbank 1997) and the estimated five degrees polynomial function in Figure 2.2.

The exit rate of the young unemployed is more heavily hit by the recession in 1993 than the one of the adult unemployed: There is a nearly 40% (resp. 60%) drop in the conditional hazard in August 1993 compared to its level in November 1989 for the men aged 29-44 (resp. men aged ≤ 28). This is consistent with the lower turnover costs for younger workers. It contrasts, however, with the findings of Van den Berg *et al.* (1998) who estimated that the exit rate of young workers is less affected by the cycle than the one of the adult workers in France.

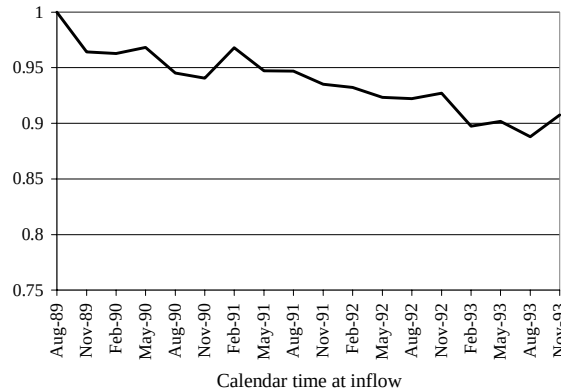


Figure 2.3: Mean of the mixing distribution (Gamma) over the cycle - Men aged 29-44

Figures 2.3 and 2.4 show the estimated de-seasonalised mean of the mixing distribution at each calendar time of our observation period for both age groups⁴¹. We observe that the quality of prime-aged male entrants has declined, although not significantly, from the cyclical peak at the end of 1989 to the downturn in 1993, while the number of inflows into unemployment was increasing. However, since this effect is small

⁴¹Here, we do not represent the estimated calendar time dependence of the variance, which is simply twice the evolution of the mean (both in the Gamma and the non-parametric distribution).

and insignificant, we conclude that compositional variation cannot explain any cyclical variation of the aggregate hazard for the prime-aged unemployed workers. During the same period, the quality of young male entrants significantly improved, which suggests a rising share of young entrants with good re-employment prospects as labour market conditions deteriorate in Wallonia. Apparently, employers fire the most able workers only if they have no alternative, i.e. in a recession. Less able workers are made redundant all the time. Note that we do not capture voluntary quits here, since these workers are not eligible for unemployment benefits.

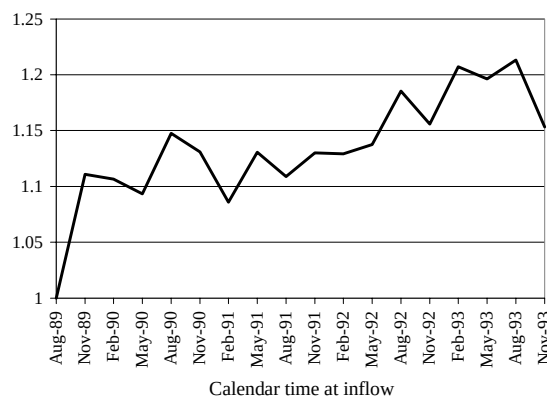


Figure 2.4: Mean of the mixing distribution (Points of support) over the cycle - Men aged ≤ 28

Although he treats the population of male workers globally, Kalwij (2001) found that the quality of entrants improved significantly in times of low economic growth, for the United Kingdom. With respect to the prime aged men, our findings are in line with the results obtained with French data by Abbring *et al.* (2001a) and Van den Berg and Van der Klaauw (2001). They conclude that compositional effects are of minor importance to explain variations in the outflow rate over time. Notice that Van den Berg *et al.* (1998) did not account for cyclical composition effects. We can therefore explain the divergence between their results and ours as regards to the cyclical pattern in the exit rate of young men.

For, the strong decline in their outflow rate in recession (see Figure 2.2) would be mitigated if we did not account for the increase in their average quality at entry into unemployment. Finally, note that we only observe data in the descending phase of a business cycle. We should therefore be cautious when generalising our findings to the complete cycle. For instance, Rosholm (2001) finds for Danish data that the compositional effect varies across the cycle.

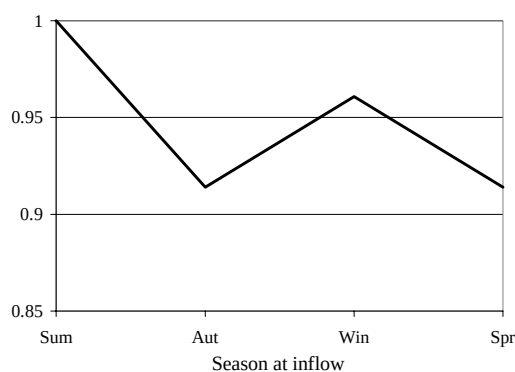


Figure 2.5: Mean of the mixing distribution (Gamma) over seasons - Men aged 29-44

There is also some seasonal variation in the average quality of the inflow as we observe in Figures 2.5 and 2.6. For the oldest men, the average characteristics of new entrants slightly worsen in autumn and spring compared to those observed in the other seasons. The quality of the young entrants is far better in the summer time than in all other seasons.

We also find significant seasonal variations in the outflow rate that remain unexplained by the seasonal variation in the quality of the inflow (see Tables 2.1 and 2.2 in Appendix 4). These are about the same for both age groups. As expected, the summer and the winter time seems to impede a lot the exit from unemployment, while the labour market conditions are more favourable in the autumn and in the spring.

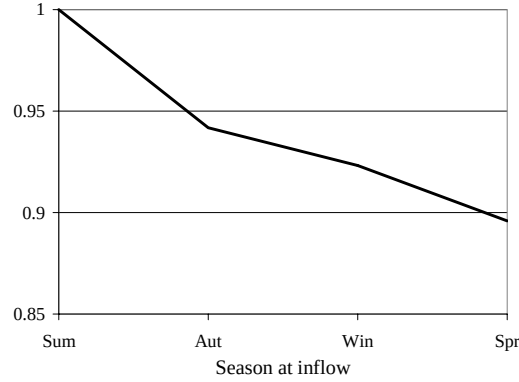


Figure 2.6: Mean of the mixing distribution (Points of support) over seasons - Men aged ≤ 28

2.6 Conclusion

In this chapter, we investigated what causes the aggregate exit rate out of unemployment estimated in Wallonia to decline strongly over duration and to vary over calendar time. To that purpose, we proposed to relax the commonly used MPH specification in two ways. First, we allowed the individual hazard to vary non-proportionally between two sub-periods, i.e. a boom and a recession, in order to test the ranking hypothesis. Second, we allowed for random deviations from the MPH framework by introducing cohort-specific random business cycle effects at the time of exit.

We estimated our model by Minimum Chi-Squares on quarterly data of male workers entering unemployment between June 1989 and February 1994. We distinguished between two age groups, those aged less than 29 and workers between 29 and 44 years old. For both age groups, we found that heterogeneity induces significant spurious negative duration dependence of the aggregate hazard. During a recession, the conditional hazard of prime-aged men is, if anything, slightly decreasing over the first 1.5 years of unemployment, and exhibits significant negative duration dependence onwards. When the labour market conditions ameliorate, duration dependence is slightly positive. So, there is evidence of ranking

for the adult unemployed. For the young men, the individual exit rate cannot be rejected to be constant over all durations, whatever the state of the business cycle. Ranking is therefore not important for the young unemployed workers.

On the basis of these results, we conclude that deterioration of skills and demotivation during unemployment, even if they play a role, cannot be the main channel of unemployment persistence in Wallonia. The hysteresis diagnosis of unemployment persistence originates from the United Kingdom (see e.g. Layard *et al.* 1991), where individual exit rates exhibit strong negative duration dependence. Empirical studies on unemployment duration and heterogeneity in Europe have proven that the United Kingdom remains the exception in a large pool of countries where there is no marked evidence of true negative duration dependence. Among this group, the duration dependence of the conditional hazard in Wallonia resembles much to the one that is found in the Netherlands and in France.

For the men aged between 29 and 44 years old, the procyclical variation of the aggregate exit rate in Wallonia is driven by a cyclical fluctuation in the individual exit rate of all currently unemployed rather than by a change in the average quality of the new entrants within the economic cycle. This finding is in line with the results obtained with French data. On the other hand, the strong decline in the individual outflow rate of the young workers in recession seems to be mitigate at the aggregate level by a significant increase in the quality of those flowing into unemployment. As we only observe data in the descending phase of a business cycle, we should, however, be cautious when generalising our findings to the complete cycle. Seasonal fluctuations in the aggregate exit rate are the result of large seasonal variations both in the individual exit rate and in the average characteristics of the inflow.

As to the estimation of mixture models, our analysis is in line with the recent Monte Carlo evidence of Baker and Melino (2000). For the young workers, we could not reject the hypothesis of a constant baseline hazard. In this case, Baker and Melino report that the estimator of non-parametric mixture is well behaved. According to the Schwartz Information Criterion, we indeed reject the parametric Gamma mixture against the non-parametric. However, if the hazard displays duration de-

pendence and both the baseline hazard and the mixing distribution are specified non-parametrically, Baker and Melino provide evidence of a significant bias. Even if this bias can be significantly reduced by their modified estimation procedure, they cannot preclude a better performance for a parametric mixing distribution. For the workers aged between 29 and 44 years old, the Gamma mixture performs indeed better according to the Schwartz Information Criterion than the non-parametric mixture model.

For the prime aged group, we significantly improve the fit of our statistical model in departing from the ‘pure’ proportionality assumption. We show that the variance of the mixing distribution can be underestimated in a model ignoring the non-proportionality of the hazard in duration and calendar time at the outflow, i.e. the ranking hypothesis. However, we are aware that the time-duration interaction implied by ranking is specified in an imperfect way. For identification purposes, we cannot allow for non-proportionality within the two sub-periods, but only between two sub-periods. Moreover the timespan covered by our data is too short for conducting a proper sensitivity analysis by considering different sub-periods. Further research is therefore called for. Both a longer observation period and additional continuous regressors could help better identifying the interaction generated by ranking. However, one should also be aware that assuming proportionality in other continuous regressors could be as imperfect as assuming the absence of time-duration interaction within sub-periods.

2.7 Appendix

2.7.1 Appendix 1: Empirical autocorrelation coefficient

In this appendix, we derive the empirical correlation coefficients between ε_{kl} and, respectively, ε_{k-1l+1} and ε_{k-1l} .

Let us define the total errors v_{kl} as the sum of the approximation errors and the specification (or measurement) errors:

$$v_{kl} = \omega_{kl} + \varepsilon_{kl} \quad (\text{a1})$$

and make the following assumptions on the covariance structure of these errors:

$$\begin{aligned} E(\omega_{kl}\omega_{k-sl+s}) &= E(\omega_{kl}\omega_{k-sl}) = E(\omega_{kl}\varepsilon_{kl}) \\ &= E(\omega_{k-sl+s}\varepsilon_{kl}) = E(\omega_{k-sl}\varepsilon_{kl}) = 0 \quad \forall s \neq 0 \quad (\text{b1}) \end{aligned}$$

First, consider that in (a1), ε_{kl} follows an AR(1) process over k and for $l+k$ fixed:

$$\varepsilon_{kl} = \rho_{l+k}\varepsilon_{k-1l+1} + \xi_{kl}, \text{ where } |\rho_{l+k}| < 1 \quad (\text{c1})$$

where it is assumed that:

$$E(\varepsilon_{k-1l+1}\xi_{kl}) = 0 \quad (\text{d1})$$

Upon substitution of (c1) in (a1) and expressing ε_{k-1l+1} as a function of v_{kl} and ω_{kl} , we obtain:

$$v_{kl} = \rho_{l+k}v_{k-1l+1} + \xi_{kl} + \omega_{kl} - \rho_{l+k}\omega_{k-1l+1} \quad (\text{e1})$$

Multiplying both sides by v_{k-1l+1} and taking the expectation give:

$$\begin{aligned} E(v_{kl}v_{k-1l+1}) &= \rho_{l+k}E(v_{k-1l+1}^2) + E(\xi_{kl}v_{k-1l+1}) + E(\omega_{kl}v_{k-1l+1}) \\ &\quad - \rho_{l+k}[E(\omega_{k-1l+1}\varepsilon_{k-1l+1}) + E(\omega_{k-1l+1}^2)] \quad (\text{f1}) \end{aligned}$$

By using the assumptions stated in (b1) and in (d1), we then find that the covariance of v_{kl} in the dimension $l+k$ and for varying k is given by:

$$E(v_{kl}v_{k-1l+1}) = \rho_{l+k}s_\varepsilon^2 \quad (\text{g1})$$

From (g1), we can finally derive a consistent estimate of ρ_{l+k} :

$$\hat{\rho}_{l+k} = \frac{\frac{1}{N} \sum_{l=0}^{16} \sum_{k=2}^{18-l} \hat{v}_{kl} \hat{v}_{k-1l+1}}{\hat{s}_\varepsilon^2} \quad (\text{h1})$$

where $\hat{v}_{kl}$ is the OLS residual of the regression (2.21) and $\hat{s}_\varepsilon^2$ is the estimate of s_ε^2 given in (2.25). In fact, $\hat{\rho}_{l+k}$ is a generalisation of the empirical autocorrelation coefficient found in the literature to the case of two errors terms, one of them following an AR(1) process. The LM-test statistics for $\hat{\rho}_{l+k}$ takes the form (see Godfrey 1978 and Breusch and Pagan 1980):

$$LM = N (\hat{\rho}_{l+k})^2 \underset{\alpha}{\sim}^{H_0} \chi^2(1) \quad (\text{i1})$$

where the null hypothesis is $H_0 : \rho_{l+k} = 0$ against $H_1 : \rho_{l+k} \neq 0$ and α is the significance level of the test.

If in (a1), ε_{kl} follows an AR(1) process over k and in the dimension l :

$$\varepsilon_{kl} = \rho_l \varepsilon_{k-1l} + \zeta_{kl}, \text{ where } |\rho_l| < 1 \quad (\text{j1})$$

where it is assumed that:

$$E(\varepsilon_{k-1l} \zeta_{kl}) = 0 \quad (\text{k1})$$

we can similarly find a consistent estimate of $\hat{\rho}_l$:

$$\hat{\rho}_l = \frac{\frac{1}{N} \sum_{l=0}^{17} \sum_{k=2}^{18-l} \hat{v}_{kl} \hat{v}_{k-1l}}{\hat{s}_\varepsilon^2} \quad (\text{l1})$$

and apply the same LM-test statistic than in (i1).

2.7.2 Appendix 2: Two-step estimation procedure

In this appendix, we give the estimation procedure of the mixture model (2.21) where the disturbances, e_{kl} , follow an AR(1) process over k and in the dimension $l + k$.

When ε_{kl} follows an AR(1) process across k and for $l + k$ fixed such that:

$$\varepsilon_{kl} = \rho \varepsilon_{k-1l+1} + \xi_{kl} \quad (\text{a2})$$

the mixture model in (2.21) becomes a non-linear regression model with heteroskedastic and correlated disturbances. Assuming that $E(\omega_{kl} \varepsilon_{kl}) = 0$, the variance-covariance matrix of the N total disturbances, v_{kl} , is then block-diagonal. The block-matrix, idempotent and of dimension $l + k$ (for simplicity, we denote $l + k$ by c), takes the following form:

$$\begin{bmatrix} s_{1c-1}^2 + s_\varepsilon^2 & \rho s_\varepsilon^2 & \rho^2 s_\varepsilon^2 & \dots & \rho^{c-1} s_\varepsilon^2 \\ \rho s_\varepsilon^2 & s_{2c-2}^2 + s_\varepsilon^2 & \rho s_\varepsilon^2 & \dots & \rho^{c-2} s_\varepsilon^2 \\ \rho^2 s_\varepsilon^2 & \rho s_\varepsilon^2 & s_{3c-3}^2 + s_\varepsilon^2 & \dots & \rho^{c-3} s_\varepsilon^2 \\ \dots & \dots & \dots & \dots & \dots \\ \rho^{c-1} s_\varepsilon^2 & \rho^{c-2} s_\varepsilon^2 & \rho^{c-3} s_\varepsilon^2 & \dots & s_{c0}^2 + s_\varepsilon^2 \end{bmatrix} \quad (\text{b2})$$

(c, c)

The estimation procedure consists then in two-steps. The first step consists in using OLS to estimate the residuals $\hat{v}_{kl}$. These allow us to construct a consistent estimate of the specification errors, $\hat{s}_\varepsilon^2$, (see (2.25)) and to calculate the empirical correlation coefficient ρ (see (h1) in Appendix 1). In a second step, we estimate the variance-covariance matrix in (b2) and estimate the parameters of the mixture model (2.21) by GLS.

2.7.3 Appendix 3: Baker and Melino procedure

In this appendix, we give the estimation procedure of the mixture model (2.27) where the heterogeneity distribution is specified as discrete with unknown support and an unknown number of mass points. We follow the estimation method proposed by Heckman and Singer (1984) as adjusted by Baker and Melino (2000). To make their procedure applicable, we need to modify the objective function, i.e. we minimise the weighted sum of squared residuals ($WSSR$) rather than maximise a loglikelihood function.

The approach to identify the optimal number of mass points proceeds as follows (see Baker and Melino 2000, pp.360-361). Suppose that we have the Weighted Least Square (WLS) estimator $\{\hat{\theta}, \hat{v}_s, \hat{\pi}_s; s = 1, 2, \dots, S\}$, where θ are the other parameters, conditional on having S points of support. The approach consists in checking whether the $WSSR$ can be decreased by adding an additional point of support to the S existing ones. Let $v_{S+1} = \bar{v}$ be a candidate for such an additional mass point. Formally, the problem is to minimise the $WSSR$ over $(\pi_1, \pi_2, \dots, \pi_{S+1})$, given $\{\hat{\theta}, \hat{v}_s; s = 1, 2, \dots, S\}$ and $v_{S+1} = \bar{v}$:

$$\min_{\{\pi_1, \dots, \pi_{S+1}\}} WSSR =$$

$$\sum_{l=0}^{17} \sum_{k=1}^{18-l} \left[\frac{1}{\hat{s}_{kl}^2 + \hat{s}_\varepsilon^2} \left(\left(1 - \hat{P}_{kl} \right) - \frac{\sum_{s=1}^{S+1} \pi_s \exp \left[-v_s \sum_{j=1}^k h_{jl} \right]}{\sum_{s=1}^{S+1} \pi_s \exp \left[-v_s \sum_{j=1}^{k-1} h_{jl} \right]} \right)^2 \right]$$

$$+ \lambda \left(\sum_{s=1}^{S+1} \pi_s - 1 \right) + \delta \left(\sum_{s=1}^{S+1} \pi_s v_s - 1 \right) + \sum_{s=1}^{S+1} \mu_s \pi_s$$

for which the Kuhn-Tucker first-order conditions (FOCs) are:

$$\frac{dWSSR}{d\pi_s} = A + \lambda + \mu_s = 0 \quad (\text{a3})$$

$$\frac{dWSSR}{d\lambda} = \left(\sum_{s=1}^{S+1} \pi_s - 1 \right) = 0 \quad (\text{b3})$$

$$\frac{dWSSR}{d\delta} = \left(\sum_{s=1}^{S+1} \pi_s v_s - 1 \right) = 0 \quad (\text{c3})$$

$$\text{and } \pi_s \geq 0; \mu_s \geq 0; \mu_s \pi_s = 0 \quad (\text{d3})$$

$$\text{where } A = \sum_{l=0}^{17} \sum_{k=1}^{18-l} \frac{2}{\hat{s}_{kl}^2 + \hat{s}_e^2} \left(\left(1 - \hat{P}_{kl} \right) - \frac{\sum_{s=1}^{S+1} \pi_s \exp \left[-v_s \sum_{j=1}^k h_{jl} \right]}{\sum_{s=1}^{S+1} \pi_s \exp \left[-v_s \sum_{j=1}^{k-1} h_{jl} \right]} \right) \\ \cdot \left(\frac{\exp \left[-v_s \sum_{j=1}^k h_{jl} \right] \sum_{s=1}^{S+1} \pi_s \exp \left[-v_s \sum_{j=1}^{k-1} h_{jl} \right] - \exp \left[-v_s \sum_{j=1}^{k-1} h_{jl} \right] \sum_{s=1}^{S+1} \pi_s \exp \left[-v_s \sum_{j=1}^k h_{jl} \right]}{\left(\sum_{s=1}^{S+1} \pi_s \exp \left[-v_s \sum_{j=1}^{k-1} h_{jl} \right] \right)^2} \right)$$

The idea then consists in evaluating the Kuhn-Tucker multiplier of the candidate additional mass point, μ_{S+1} , at $\pi_{S+1} = 0$ and for a grid of values of $\bar{v} \in [v_L, v_H]$, given the parameter estimates of the mixture model with S points of support, i.e. given $\{\hat{\theta}, \hat{v}_s, \hat{\pi}_s; s = 1, 2, \dots, S\}$. If $\mu_{S+1} \geq 0$, the last constraint of (d3) is binding, so adding a point of support at $\bar{v}$ cannot decrease the $WSSR$. If this is true for all $\bar{v} \in [v_L, v_H]$, then $\{\hat{\theta}, \hat{v}_s, \hat{\pi}_s; s = 1, 2, \dots, S\}$ is the non-parametric WLS estimator. If instead $\mu_{S+1} < 0$ for some $\bar{v}$, then it is possible to decrease the $WSSR$ by adding a point of support at $\bar{v}$. This additional mass point will however not be retained if the Schwartz information criterion of the mixture model with $S + 1$ mass points (see (2.26) in Section 2.4.1) is above the one with S mass points (see Baker and Melino 2000, p.376).

If we multiply (a3) by π_s , sum over s , and use (b3), (c3) and (d3), we obtain $\lambda + \delta = 0$. The Kuhn-Tucker multiplier, μ_s , is therefore the (negative of the) derivative of the $WSSR$ with respect to π_s :

$$\mu_s = -A \quad (\text{e3})$$

Applying this approach in a systematic way from the outset, the estimation of the non-parametric mixture model (2.27) can be summarised as follows (see Baker and Melino 2000, pp.361-362):

Step 0: Set $S = 1$ and $\pi_1 = 1$. Choose initial value for θ and v_1 .

Step 1: Given the current value of S ,

minimise the Schwartz Information Criterion (SIC),

i.e. minimise the $WSSR$, over θ and $(v_s, \pi_s; s = 1, 2, \dots, S)$.

a. If $SIC_S > SIC_{S-1}$, then **STOP**.

b. Else, **Step 2**.

Step 2: Evaluate μ_{S+1} for a grid value of $\bar{v} \in [v_L, v_H]$ such that P_{kl} is restricted to the set $[\varepsilon, 1 - \varepsilon]$ where ε is set to 10^{-5} .

a. If $\mu_{S+1} \geq 0 \quad \forall \bar{v} \in [v_L, v_H]$, then **STOP**.

b. Else, set v_{S+1} to the value of $\bar{v}$ that yield the smallest value for μ_{S+1} .

Step 3: Given the current value of θ , $(v_s; s = 1, 2, \dots, S)$ and v_{S+1} , increase the value of S by 1 and minimise the $WSSR$ to obtain new initial values for $(\pi_s; s = 1, 2, \dots, S)$. Return to **Step 1**.

2.7.4 Appendix 4: Estimation results

Table 2.1: Hazard model estimates - Men aged 29-44

Variables	TEST Ranking vs Sorting		GAMMA		POINTS OF SUPPORT	
		SD		SD		SD
c	-0.85	0.02	-0.59	0.08	-0.71	0.06
1. Duration (in quarters)						
2 (γ_2-c)	-0.32	0.02	-0.07	0.03	-0.15	0.03
3 (γ_3-c)	-0.53	0.03	-0.05	0.03	-0.16	0.05
4 (γ_4-c)	-0.71	0.04	-0.04	0.04	-0.15	0.07
5 (γ_5-c)	-0.84	0.04	-0.02	0.05	-0.11	0.08
6 (γ_6-c)	-1.05	0.05	-0.07	0.06	-0.16	0.10
7 (γ_7-c)	-1.24	0.06	-0.16	0.07	-0.26	0.11
8 (γ_8-c)	-1.40	0.07	-0.21	0.08	-0.34	0.12
9 (γ_9-c)	-1.43	0.08	-0.15	0.08	-0.32	0.12
10 $(\gamma_{10}-c)$	-1.63	0.10	-0.27	0.10	-0.49	0.14
11 $(\gamma_{11}-c)$	-1.63	0.11	-0.18	0.10	-0.46	0.14
12 $(\gamma_{12}-c)^*$	-1.91	0.09	-0.31	0.11	-0.70	0.15
2. Calendar time at outflow						
Cycle						
β_{c1}	-0.21	0.02	-0.22	0.05	-0.22	0.05
β_{c2}	0.08	0.02	0.06	0.02	0.06	0.02
β_{c3}	0.01	0.01	0.03	0.02	0.02	0.02
β_{c4}	0.03	0.01	0.04	0.02	0.04	0.02
β_{c5}	0.04	0.01	0.05	0.02	0.04	0.02
Seasons						
Winter ($\beta_{s2}-c$)	-0.35	0.03	-0.31	0.03	-0.30	0.03
Spring ($\beta_{s3}-c$)	0.00	0.02	0.01	0.03	0.02	0.03
Summer ($\beta_{s4}-c$)	-0.36	0.03	-0.31	0.03	-0.31	0.03
3. Interaction terms						
ψ_c	-0.11	0.12				
ψ_s	-0.14	0.06				
ϕ			1.99	0.81	0.87	0.35
4. Variance of the Gamma at $l=0$						
η_{s1}			-0.12	0.06		
$\sigma_0^2 = \exp(\eta_{s1})$			0.89	0.05		
4'. Points of support						
π					0.55	0.05
v_1					1.60	0.09
$v_2 = (1 - \pi v_1) / (1 - \pi)$					0.26	0.05
$\text{var}[v] = \pi(v_1 - 1)^2 / (1 - \pi)$					0.44	0.05

* $\gamma_{18} = \dots = \gamma_{12}$

(Table continued on next page)

Table 2.1: (Continued)

5. Calendar time at inflow			
Cycle			
η_{cl}		-0.18	0.18
Seasons			
Autumn ($\eta_{s2}-\eta_{s1}$)**		-0.09	0.03
Winter ($\eta_{s3}-\eta_{s1}$)**		-0.04	0.03
Spring ($\eta_{s4}-\eta_{s1}$)**		-0.09	0.03
6. Empirical correlation coefficients of ε_{kl}			
ρ_{l+k}		0.65	0.70
ρ_l		0.03	0.01
7. Standard deviation of ε_{kl}			
s_e		0.009	0.009
Number of observations	171	171	171
Number of estimated parameters	22	26	27
Weighted sum of squared residuals	477.75	170.44	171.20
P-value of the goodness-of-fit test	0	0.073	0.06
Jeffrey-Bayes posterior-probability statistics		304.12	310.02

** $\eta_{s1} = 0$ in the third column.

Table 2.2: Hazard model estimates - Men aged ≤ 28

Variables	TEST Ranking vs Sorting		GAMMA		GAMMA Constant Baseline R1		POINTS OF SUPPORT Constant Baseline R1	
		SD		SD		SD		SD
c	-0.64	0.02	-0.45	0.07	-0.49	0.06	-0.71	0.05
1. Duration (in quarters)								
2 (γ_2-c)	-0.26	0.02	0.00	0.04				
3 (γ_3-c)	-0.43	0.03	0.05	0.08				
4 (γ_4-c)	-0.63	0.03	0.04	0.12				
5 (γ_5-c)	-0.74	0.04	0.10	0.15				
6 (γ_6-c)	-0.86	0.05	0.14	0.18				
7 (γ_7-c)	-1.03	0.06	0.11	0.20				
8 (γ_8-c)	-1.19	0.07	0.09	0.22				
9 (γ_9-c)	-1.33	0.08	0.06	0.24				
10 ($\gamma_{10}-c$)	-1.43	0.10	0.08	0.26				
11 ($\gamma_{11}-c$)	-1.46	0.11	0.14	0.28				
12 ($\gamma_{12}-c$) [*]	-1.68	0.09	0.12	0.31				
2. Calendar time at outflow								
Cycle								
β_{c1}	-0.29	0.02	-0.34	0.04	-0.34	0.03	-0.40	0.03
β_{c2}	0.06	0.01	0.03	0.02	0.03	0.02	0.04	0.02
β_{c3}	0.01	0.01	0.03	0.02	0.03	0.02	0.02	0.02
β_{c4}	0.04	0.01	0.04	0.02	0.04	0.02	0.05	0.02
β_{c5}	0.07	0.01	0.07	0.02	0.06	0.02	0.05	0.02
Seasons								
Winter ($\beta_{s2}-c$)	-0.36	0.03	-0.33	0.04	-0.32	0.04	-0.31	0.04
Spring ($\beta_{s3}-c$)	0.00	0.02	0.01	0.03	0.02	0.03	0.02	0.03
Summer ($\beta_{s4}-c$)	-0.33	0.03	-0.26	0.04	-0.26	0.04	-0.26	0.04
3. Interaction terms								
ψ_c	-0.30	0.07						
ψ_s	-0.17	0.05						
ϕ			-0.55	1.61				
4. Variance of the Gamma at $t=0$								
η_{s1}			-0.45	0.20	-0.59	0.04		
$\sigma^2_{\theta}=\exp(\eta_{s1})$			0.64	0.128	0.55	0.022		
4'. Points of support								
π							0.67	0.02
ν_1							1.36	0.02
$\nu_2=(1-\pi\nu_1)/(1-\pi)$							0.29	0.03
$\text{var}[\nu]=\pi(\nu_1-1)^2/(1-\pi)$							0.26	0.05

* $\gamma_{18} = \dots = \gamma_{12}$

(Table continued on next page)

Table 2.2: (Continued)

5. Calendar time at inflow							
Cycle							
η_{cl}			-0.01	0.19	0.03	0.18	0.47
Seasons							
Autumn ($\eta_{k2}-\eta_{k1}$) ^{**}			-0.06	0.03	-0.08	0.03	-0.06
Winter ($\eta_{k3}-\eta_{k1}$) ^{**}			-0.08	0.03	-0.08	0.03	-0.08
Spring ($\eta_{k4}-\eta_{k1}$) ^{**}			-0.14	0.03	-0.13	0.03	-0.11
6. Empirical correlation coefficients of ε_{kl}							
ρ_{l+k}			0.75		0.74		0.59
ρ_l			0.04		0.05		0.14
7. Standard deviation of ε_{kl}							
S_{ε}			0.012		0.013		0.016
Number of observations		171	171	171	171	171	171
Number of estimated parameters		22	26	14	14	15	15
Weighted sum of squared residuals		677.55	174.18	174.27	174.27	158.72	158.72
P-value of the goodness-of-fit test		0	0.03	0.16	0.16	0.42	0.42
Jeffrey-Bayes posterior-probability statistics			307.82	246.25	246.25	235.84	235.84

^{**} $\eta_{s1} = 0$ in the fourth column.

Chapter 3

A New Light into Regional Unemployment Disparities in Belgium: Longitudinal Analysis of Grouped Duration Data

3.1 Introduction

The unemployment rate¹ increased steadily in Belgium after the first and the second oil price shocks: From 3% in 1973 to 19% in 1983. This evolution is illustrated in Figure 3.1. With the economic recovery of the mid eighties, the unemployment rate decreased to a level of 12%, which still lied far above the level reached in 1973. From 1990, the economic downturn pushed the unemployment rate up again. This evolution masks an important disparity between the two main regions of Belgium: Flanders and Wallonia. Up to 1983, the two regions had roughly the same performance in terms of unemployment, worse than in our bordering countries (Germany, France and the Netherlands). From

¹The unemployment rate is the ratio between the full-time registered unemployed people, entitled to unemployment benefits and actively looking for a job, and the population insured against unemployment.

1983, a diverging evolution seems to show up: The unemployment rate decreased markedly in Flanders, while unemployment remained at a high level in Wallonia. In 2000, the unemployment rate was 20% in Wallonia and 6% in Flanders. According to Binon *et al.* (1998), the diverging evolution in the unemployment rate across Belgian regions cannot be attributed to a different growth in the active population. The sources of these divergences must be found on the side of the unemployment stock.

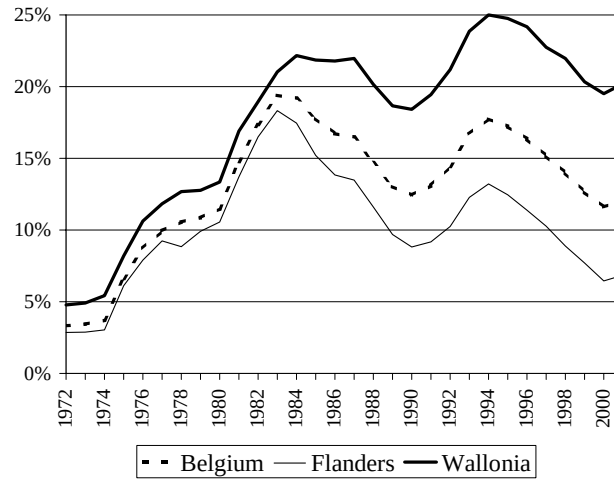


Figure 3.1: Unemployment rate in Belgium, Flanders and Wallonia

In this study, we investigate whether the diverging evolution in the unemployment stock in Flanders and Wallonia can be explained by different evolutions in their average unemployment duration and/or their unemployment incidence. To that purpose, we proceed in two stages (see Figure 3.2). In the first stage, the average unemployment duration is modelled through the specification of the hazard rate. We estimate a Mixed Proportional Hazard (MPH) model by region, and decompose variations in the aggregate outflow rate over calendar time between a general effect, i.e. changes in the exit rate of all currently unemployed, and a composition effect, i.e. fluctuations in the average quality of entrants into unemployment leaving the individual exit rates constant. The latter effect is made of variations in the observed and unobserved characteristics of those flowing into unemployment. We also specify a

non-proportional model to check whether the general effect is the same for unemployed workers with different schooling levels and sub-region of living, in each region. In the second stage, we decompose variations of the unemployment stock in Flanders and Wallonia into an incidence effect and the duration effect estimated in the first stage.

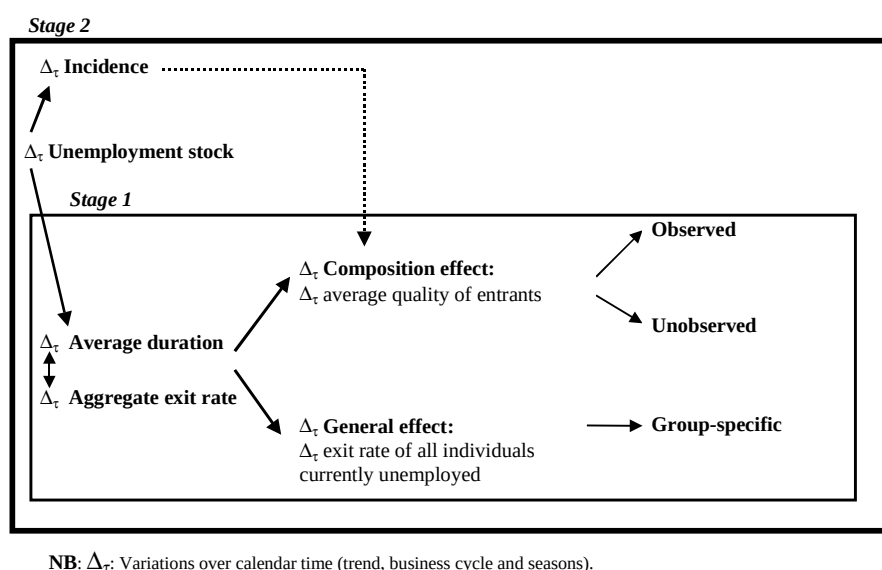


Figure 3.2: Full decomposition of the unemployment stock

We base our analysis on aggregate administrative data. We have Belgian census data relative to all unemployed male workers aged 25-44 and flowing into unemployment in the month of June, each year from 1972 to 1992. These data also contain a number of personal characteristics of the unemployed people. It is however impossible to track each individual spell through different years. We therefore group the data into homogeneous cohorts with respect to the year of inflow and a set of relevant characteristics. The latter include the age (measured in months), the education level, the province of living and the sector occupied before becoming unemployed. For each cohort, the outflows out of unemployment are counted on a yearly basis, from the time of inflow until the end of June 1993, date at which spells are right censored. Each observation in our data set therefore corresponds to a non-parametric estimation of

the annual outflow probability for a given cohort at a given duration (and by construction, calendar time).

In this study, we propose a formal decomposition of the variations in the aggregate hazard over time, allowing for observed and unobserved changes in the quality of the inflow. In our MPH model, the general effect is the estimated calendar time dependence of the hazard rate controlling for composition effects. With our micro data covering a long timespan (1972-1993), we capture part of the fluctuation in the composition of the inflow by conditioning the hazard on observed characteristics. The remaining variation, the unobserved composition effect, is accounted for by making the mean (and the variance) of the heterogeneity distribution dependent on a business cycle indicator at entry. The general effect is parametrised with a flexible polynomial function tracking cyclical and structural changes. We measure the observed composition effect by using the inflow distribution of the observed characteristics in our data set and their estimated effect on the hazard rate. The heterogeneity distribution is assumed to be Gamma. The estimated calendar time dependence of its mean is an indicator of the unobserved composition effect.

Our analysis breaks new ground in the empirical literature. Given the recent interest of European researchers in this question, there are few studies on the decomposition of the calendar time variations in unemployment duration for European countries (see, for France, Abbring *et al.* 2001a, Van den Berg and Van der Klaauw 2001; for the United Kingdom, Kalwij 2001; for Denmark, Rosholm 2001 and for Belgium, Chapter 2 of this thesis). This question has been investigated on US data since the mid 1980s already (see, e.g., Darby *et al.* 1985; Dynarski and Sheffrin 1990; Baker 1992; Imbens and Lynch 1993; Abbring *et al.* 2001b). Studies based on European data conclude that compositional effects are, if anything, of little importance, with the exception of Kalwij (2001). Among studies exploiting US data, results are rather mixed. Only Darby *et al.* (1985) conclude that the cyclical variability in average unemployment duration is predominantly explained by compositional effects. Using the same data, but covering a more recent period, Abbring *et al.* (1999) highlight that cyclical variability in the quality of entrants accounts for a significant share of the fluctuations in the US unemploy-

ment duration. On the other side, Imbens and Lynch (1993) conclude that the variation in the unemployment duration of young workers is general and cannot be explained by compositional effects. Below, we contrast our approach with the existing empirical studies by focusing on those which decompose variations in the outflow probability in a formal way.

The first contribution of our study results from the richness of the data. The use of aggregate data covering 21 years and stratified by a set of relevant characteristics allows us to control for changes in the inflow composition without relying (completely) on functional form assumptions. Most of the empirical studies exploit aggregate time-series data with a limited number of characteristics on the unemployed people such as sex, race and age group (see, e.g., Abbring *et al.* 2001a,b; Kalwij 2001; Chapter 2 of this thesis). Variations in the composition of inflow are then accounted for by specifying a MPH model where the heterogeneity distribution depends on calendar time at entry. Even if both the distribution of unobserved characteristics and its calendar time dependence are specified non-parametrically (see e.g. Abbring *et al.* 2001a), parametric restrictions are required for identification purposes. Studies based on macro data are forced to assume the absence of a trend in the composition of inflow. As a consequence, the structural part of the general effect is not necessarily rid of variations in the quality of entrants into unemployment. One exception is the study of Van den Berg and Van der Klaauw (2001) which combines aggregate time-series data with a micro data set covering a short time period. Their motivation is to identify the characteristics which are responsible for changes in the quality of inflow over time. They model jointly the distribution of the observed characteristics at entry into unemployment and the hazard rate. As in the previous studies, the macro data are used to identify the way the inflow distribution moves over time. But contrary to typical macro analysis, there is no need to impose restrictions on its time dependence: The use of another data set allows to relax the identification conditions². However, their estimated general effect can still reflect

²Since the duration dependence is identified from the micro dataset, the macro data identify the calendar time dependence of both the hazard rate and the inflow distribution without any functional form restrictions.

changes in the unobserved quality of entrants since the shape of the mixing distribution is not allowed to vary over time.

Some empirical studies also use longitudinal survey data on a long timespan to decompose calendar time variations in the aggregate outflow probability (see e.g. Imbens and Lynch 1993). Even if they do not cover all the population of unemployed workers, their sample size is sufficiently large to approximate the composition of inflow. Yet, none of them allow for an unobserved composition effect, so that their estimated general effect can still have two interpretations. One exception is Rosholm (2001) who exploits micro Danish data covering the period 1981-1991. Contrary to our model, his unobserved compositional effect is not built into the model though: The mean of the mixing distribution is not explicitly allowed to move with calendar time at the time of inflow. It is constructed in a somewhat ad-hoc way based on the parameter estimates of his model. The calendar time dependence of his hazard rate is therefore not necessarily free of variations in the unobserved characteristics of entrants.

The unobserved composition effect can be identified at the cost of some hypothesis. In this study, we choose to parametrise the time dependence of the distribution of unobserved characteristics by the number of entrants into unemployment (as in the Chapter 2). If this indicator does *not* vary *only* according to an exponential trend, identification is assured. As compared to the choice of Abbring *et al.* (1999) or Kalwij (2001) who use a traditional business cycle indicator³, the number of entrants is more directly related to the composition of inflow. Our indicator is therefore less likely to capture some part of the general effect as well. We could have specified the time dependence of the mixing distribution in a more flexible way with time dummies forced to be orthogonal to a linear trend (see Abbring *et al.* 2001a). If variations in the composition of inflow closely follow variations in the number of entrants into unemployment, our specification turns out to be a better alternative. For, it allows the unobserved composition effect to follow a trend (i.e. the trend in incidence), separately from the trend in the general effect. The plausibility of our parametric assumption is verified by analysing

³Abbring *et al.* (1999) use the help-wanted index while Kalwijn (2001) uses the detrended logarithm of the Gross Domestic Product.

the link between variations in the observed composition of entrants and variations in incidence.

The second contribution of our study comes from the estimation of a non-proportional hazard model in which the covariate effects may vary over time. This model allows us to check whether the general effect of the calendar time was the same for unemployed workers with different personal characteristics. Only Rosholm (2001) also interacts the covariate effects with the calendar time dependence of the hazard rate. However, only cyclical interactions are allowed for, ruling out the possibility that structural evolutions can affect differently the various groups of unemployed workers. Some authors (see e.g. Imbens and Lynch 1993, Van den Berg and Van der Klaauw 2001) argue that if variations in unemployment duration are mainly driven by a general effect, targeted policies are unlikely to be useful. Our findings suggest that even if composition effects are unimportant, there is a scope for labour market policies aimed at specific groups of unemployed workers as the least educated workers: For instance, the outflow rate of less educated unemployed workers in Wallonia deteriorated by 35% more than the exit rate of the highest educated workers on the whole period.

The plan of the chapter is as follows. The next section describes the data and gives some descriptive statistics on duration and incidence. The third section is devoted to the derivation of the MPH model, provides the formal decomposition of the aggregate hazard over calendar time and discusses the estimation results. In the fourth section, we extend our MPH model by allowing for non-proportional calendar time effects. The fifth section contains the decomposition of the unemployment stock into a duration and an incidence effect. The concluding part summarises our findings.

3.2 The data

3.2.1 Unemployment insurance scheme in Belgium and data collection

Each year since 1972, the Belgian Employment Agency (ONEm-RVA) takes a census of all unemployed workers on June 30. These data also

contain a number of individual characteristics of the unemployed people, such as sex, age, sub-region of living, education level, sector of previous employment, and the starting month of their unemployment spell. The unemployed workers are registered in different categories according to their administrative status. The largest group are full-time unemployed persons actively looking for a job and entitled to unemployment benefits. On average, 81% of entrants belongs to this category.

In Belgium, benefits entitlement is conditional on a sufficiently long employment record⁴. The period of entitlement to benefits is then in principle indefinite. One exception to this rule concerns the cohabitants, e.g. living with a working partner or with their parents. They can loose entitlements on grounds of ‘excessive’ unemployment duration (i.e. when elapsed duration becomes larger than 1.5 times the regional average duration). The level of the benefit is based on the level of previous labour earnings and the household type of the worker, but is bounded by a ceiling and a floor, depending on the household situation. Unemployment benefits for those who are not head of a family drop after 1 year and once more after 18 months if one is cohabitant. The data do not include any information about previous labour earnings or unemployment benefits paid to the unemployed worker. Finally, it should be noticed that the rules governing the unemployment benefit scheme and the functioning of the labour market are the same in all regions of Belgium.

The data at our disposal are the unemployment stock for the years 1972 up to 1993. They were made anonymous such that is impossible to track individual spells through different years. As explained below, this requires a grouping of the data.

3.2.2 Data selection

In order to avoid the initial condition problem, we construct an inflow data set of unemployment spells. We select all entrants in the month of June, each year from 1972 to 1992. As the yearly census of the unemployed workers occurs on June 30, the number of entrants excludes

⁴Graduated students who never worked can also be eligible after some waiting period.

those who left unemployment before the end of June. Since we aim to analyse the two main regions of Belgium (Flanders and Wallonia) separately, two data sets are created.

We only follow male workers aged between 25 and 44 years old at the begin of their unemployment spell. The main reason for this choice is that we cannot distinguish between unemployment spells ending in employment, participation in labour market programmes or withdrawal from the labour force. Outflows from unemployment are therefore treated globally. This is not likely to bias our results given that employment is the most frequent state of exit for the male unemployed workers: About 77% of them leave for employment, against 47% for the women (see FOREM 1995). In our sample, this fraction must be larger. For, the reported figure includes unemployed workers older than 44 years. These workers often enter a kind of early-retirement scheme, a policy heavily used after the mid eighties in Belgium for older workers.

Employment is also the most frequent destination for the young unemployed workers, aged less than 25 years old. However, the share of prime-aged men becoming employed in the outflow from unemployment is larger than the share of young people, since the latter participate more to education and training programs. Furthermore, the legislation concerning young people changed substantially more than for the prime-aged group during the 1972-1993 period (change in the age limit with respect to mandatory schooling, eligibility to benefits based on schooling etc.). These changes could have affected significantly both the composition and the number of young entrants into unemployment.

A second reason to focus on the prime-aged male unemployed is that most of them are head of household or live alone. They are therefore less likely to be sanctioned on ground of excessive unemployment duration⁵.

To reach more homogeneity in the data, only Belgian unemployed persons are retained in our analysis. Finally, we restrict ourselves to people officially registered as unemployed persons and who satisfy the OECD definition of unemployment, i.e. without employment, immediately available for employment and actively looking for a job. Our

⁵In 1992, less than 25% of the prime-aged men were cohabitants against more than 65% for the female unemployed workers (see ONEm 1992). These are estimates since the distribution of the household types by age is not available.

selection covers more than 94% of all entrants into unemployment.

3.2.3 Grouping of the data and induced biases

Since it is impossible to track individual spells of unemployment through time, we group the data into homogeneous cells with respect to some relevant characteristics. So we construct synthetic cohorts of unemployed workers, a cohort being defined by its year of inflow l and a set of individual characteristics x . For each cohort (l, x) , the outflows out of unemployment are counted on a yearly basis, from the time of inflow until the end of June 1993, date at which all spells are right censored. We have that $l \in \{0, 1, \dots, 20\}$. The variable k denotes unemployment duration, measured in yearly intervals from the month of inflow l . By construction of the data, $k \in \{1, 2, \dots, 21\}$.

The individual characteristics x are the level of education, as a proxy for the skill level, the sub-region where the unemployed person lives⁶, the sector of previous employment and the age at entry. Each characteristic is categorised into classes. We distinguish four levels of education: elementary school, junior high school, completed high school and higher education. The subregion of living is described by the province. The provinces are, for Flanders: Oost-Vlaanderen, West-Vlaanderen, Antwerpen, Limburg, Vlaams-Brabant and, for Wallonia: Hainaut, Liège, Luxembourg, Namur and Brabant wallon. It is more difficult to group the sectors of previous employment into meaningful categories. We group them into 13 broad classes. These 13 categories are (1) Agriculture, (2) Iron-steel industry and mining, (3) Chemical industry, (4) Metal manufacture, (5) Manufacture of non-metallic mineral products, glass and ceramics, (6) Manufacture of consumption and investment goods⁷, (7) Other manufacturing industries, (8) Energy and water production, (9) Building, (10) Private services like wholesale dealing, retail distribution, distribution trade, banking, insurance, transport, (11) Public services including education, (12) Others and (13) No previous

⁶The sub-region of living is not necessarily the sub-region where the unemployed worker will find a job.

⁷Including food, drink, tobacco, textile, leather, footwear and clothing, wooden furniture, paper and related industries, manufacture of motor vehicles and related activities.

employment. Age at entry is categorised in months. The grouping is thus very fine. As a result, 93% of the cohorts are made up of only one individual at the moment of inflow into unemployment.

Each observation in our data set corresponds to a non-parametric estimation of the annual outflow probability, $\hat{P}_{klx}$, for a given cohort (l, x) at a given duration k and, by construction, calendar time $l + k$. Let u_{klx} be the number of individuals in cohort (l, x) who are still unemployed at the start of the k^{th} duration interval and are therefore at risk of leaving unemployment within the $(l + k)^{th}$ quarter. Let f_{klx} be the number of these individuals who leave unemployment within the k^{th} duration interval. We can then estimate the probability of leaving unemployment, P_{klx} , by the Kaplan-Meier estimator of the hazard adapted to grouped data:

$$\hat{P}_{klx} = \frac{f_{klx}}{u_{klx}} \quad (3.1)$$

However, the non-parametric measure of the outflow probability $\hat{P}_{klx}$ is subject to biases. For, the non-observability of the individual spells of unemployment, and the consecutive grouping of the data, induces two sources of spurious outflows: (1) temporary exits out of unemployment (of less than three months) and (2) changes in the value of an individual characteristics x during the unemployment spell. Below, we give some light on these problems and the following correction of the data. In Appendix 1, we discuss in details the correction procedure applied to $\hat{P}_{klx}$.

The first source of spurious outflows is due to temporary exits. In Belgium, workers who exit unemployment for a period of less than three months keep the same starting date of their unemployment spell at their return. Given that the census of the unemployed workers occurs on June 30, it happens that some unemployed are not counted at a given year because they are in a training scheme or have a temporary job that day. They are still unemployed though and counted as such in a following census. Temporary exits introduce biases in our measure of the number of individuals in cohort (l, x) that leave unemployment during the k duration interval, f_{klx} . If an individual counted in u_{klx} exits unemployment temporarily around the start of the $k + 1$ duration

interval and returns within the next three months, then the number of outflows f_{klx} increases spuriously of one unit. Since the majority of cells in our data set counts at most one individual, the greater part of the temporary exits can be spotted and corrected for by setting the identified spurious risk sets to 1 (see the section ‘Temporary exits’ of Appendix 1 for details).

Change in the value of an individual characteristics x during the unemployment spell is the second source of spurious outflows. We illustrate the induced bias with the following example. Imagine that an unemployed worker i moves from province A to province B (A and B being in the same region), k years after his entry into unemployment, without flowing out of unemployment. This event is recorded as follows in our data set. On one hand, the number of outflows in the cohort of individual i increases spuriously of one unit at an elapsed duration of k years. On the other hand, the number of individuals at risk of leaving unemployment in the cohort which shares all the characteristics of the initial cohort but the province (province B), increases spuriously by one unit. Actually, these changes can result from administrative problems and do not necessarily reflect true modifications in the situation of the unemployed workers. In particular, we know that they cannot be attributed mostly to one variable, as for example moves between provinces or changes in education level during the unemployment spell.

Since a majority of cohorts are made of one individual, most of the individuals with a time-varying characteristic are identified by picking out cohorts where the risk-set is zero at the date of entry into unemployment and strictly positive in at least one of the following duration intervals. More formally, the number of spurious outflows in cohort l at duration interval k , $f_{kl}^S = \sum_x f_{klx}^S$, is approximately the number of observations with $u_{klx} < u_{k+1lx}$ (see Appendix 1 for details). Figure 3.3 gives the number of spurious outflows aggregated over duration and in proportion of the inflow over our observation period. The size of the problem is slightly higher in Wallonia - on average 10% of entrants - than in Flanders - on average 7%. This difference is due to the years 1985 and 1986 where this proportion reaches more than 30% in Wallonia⁸.

⁸The strong increase in the proportion of entrants with changing variables in 1985 and 1986 is partly explained by an important drop in the number of entrants these

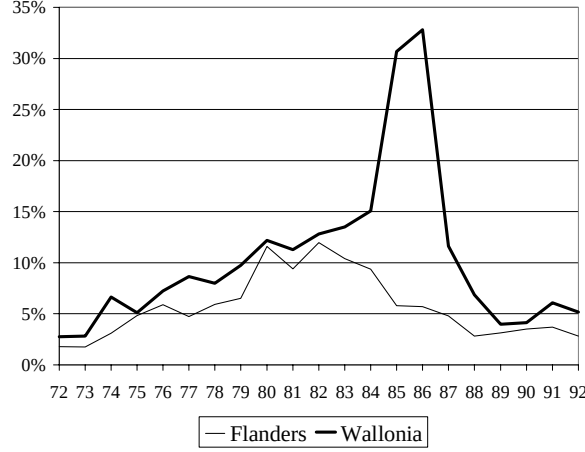


Figure 3.3: Proportion of entrants with changing value of their personal characteristics

It should be emphasised that the importance of the bias in $\hat{P}_{klx}$ due to time-varying characteristics is inversely related to the level of aggregation. In particular, if the cohorts were defined only in terms of duration and year of inflow, the Kaplan-Meier estimate of the aggregate outflow probability would be unbiased. On the other hand, the fine grouping of the data - mainly induced by measuring age on a monthly basis - allows us to spot individuals with time-varying characteristics.

In sum, the correction procedure applied to our data works as follows. We first correct the data for temporary exits. Second we calculate the number of spurious outflows in cohort l at duration interval k , f_{kl}^S . Third, we suppress all observations with $u_{klx} < u_{k+1lx}$ since they violate the condition: $0 \leq \hat{P}_{klx} \leq 1$. Finally, we apply the following correction to the non-parametric outflow probability (see Appendix 1):

$$\hat{P}_{klx}^* = \left(1 - \frac{f_{kl}^S}{f_{kl\cdot}}\right) \hat{P}_{klx} \quad (3.2)$$

where $f_{kl\cdot} = \sum_x f_{klx}$. This correction lies on the assumption that the (unobserved) number of spurious exits in cohort (l, x) during the k^{th} years (see Figure 3.5). We have no additional explanation of this finding at this point.

interval, f_{klx}^S , is proportional to f_{kl}^S with a factor of proportionality $(\frac{f_{klx}}{f_{kl}})$. In the sequel, we always use the data set with the corrected $\hat{P}_{klx}^*$. In order to lighten the notation, we note $\hat{P}_{klx}$. Notice that we apply this correction in each region separately, i.e. we made the implicit assumption that movements of unemployed people between regions are negligible with respect to movements within regions⁹. The low degree of labour mobility between Flanders and Wallonia is supported by the study of Candelon *et al.* (2000).

The obtained 63793 empirical probabilities ($\hat{P}_{klx}$) for Flanders and 45987 for Wallonia summarize the labour market histories of 40981 and 25334 unemployed persons¹⁰ respectively.

3.2.4 Descriptive statistics

In this sub-section, we present some descriptive statistics about unemployment, incidence and duration which are directly relevant to our formal analysis.

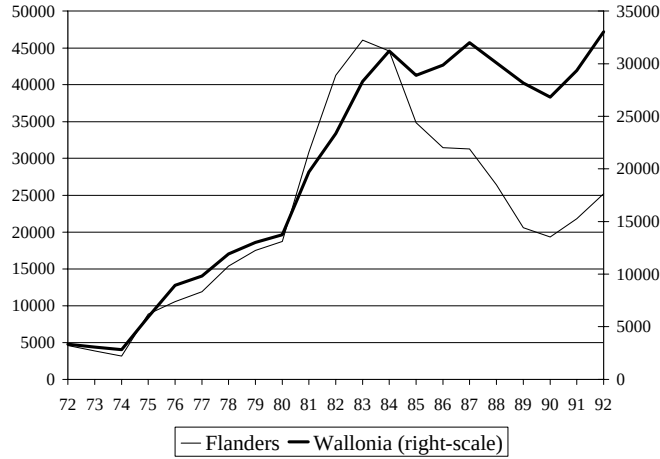


Figure 3.4: Total stock of unemployment in June (male aged 25-44)

Figure 3.4 shows the total stock of unemployment for men aged 25-44

⁹Applying other corrections (and assumptions) confirms that the chosen correction performs better.

¹⁰What corresponds to 37674 cohorts for Flanders and 23459 for Wallonia.

in our data set, in Flanders and Wallonia. As already stressed in the introduction, unemployment increased steadily in both region between 1973 and 1983. From 1983, a diverging evolution seems to show up: Unemployment decreased markedly in Flanders, while it remained at a high level in Wallonia. However, when we de-trend the two series, the picture is different: The divergence between the two regions seems to be driven by a diverging trend, while the cyclical variability in unemployment is similar across regions.

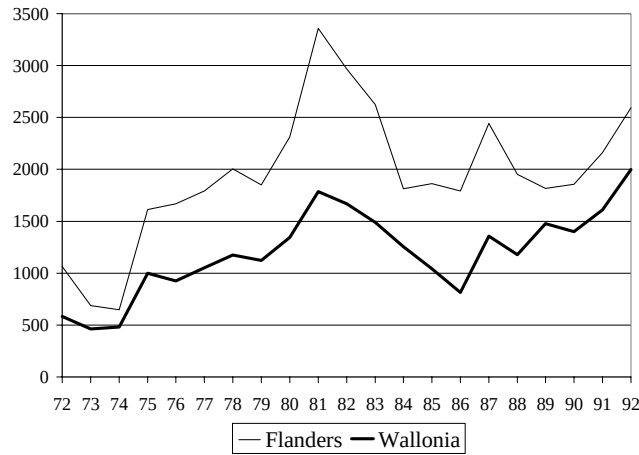


Figure 3.5: Inflow into unemployment in June

The number of people flowing into unemployment during the month of June l and still present at the end of the month, $u_{1l} = \sum_x u_{1lx}$, is our measure of the size of inflow into unemployment. Figure 3.5 shows the evolution of the inflow into unemployment in Flanders and Wallonia. The number of entrants is strongly increasing over time, slightly more markedly in Wallonia: at rates equal to 3.9% and 4.6% yearly in Flanders and Wallonia respectively¹¹. So, incidence cannot be the main cause of divergence in the evolution of unemployment between the two main regions of Belgium. Incidence also show a similar countercyclical behaviour in the two regions. In the second half of the 1970s there is

¹¹These rates are obtained by regressing the logarithm of the number of entrants in both regions on a constant term and a trend.

large increase in the inflow, particularly in Flanders, with a peak in 1981 (after the second oil shock). From 1982, the inflow into unemployment decreases in both regions, more importantly in Flanders, and rises again in the late eighties.

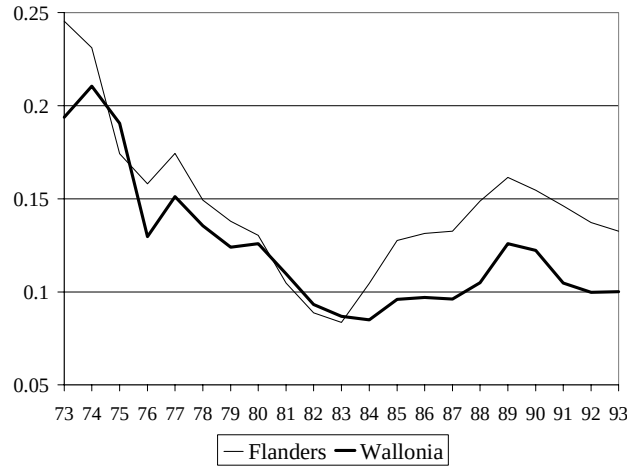


Figure 3.6: Empirical monthly hazard in the first duration interval

In order to see the evolution of unemployment duration in both regions, we calculate the Kaplan-Meier estimate of the aggregate outflow probability, in the first duration interval, $\hat{P}_{1l}$. Given that unemployment duration is measured in years, its evolution gives a fair view of the pattern of the exit probability for the population of interest. In the empirical analysis, we specify a MPH model. For purposes of comparison with the model estimates, we transform the empirical outflow probability into its continuous equivalent¹². Figure 3.6 shows the monthly empirical hazard¹³ in the first year of unemployment. Both regions exhibit a downward trend in the outflow rate over the period, at rates equal to -3.0% and -1.6% , in Flanders and Wallonia respectively¹⁴. So duration seems to drive the different structural evolutions in unemployment

¹²The transformation is: $\hat{h}_{1l} = -\ln(1 - \hat{P}_{1l})$.

¹³The monthly aggregate hazard is simply the yearly aggregate hazard divided by twelve.

¹⁴These rates are obtained by regressing the logarithm of the hazard rate in both regions on a constant term and a trend.

across regions. The cyclical variability in the exit rate is roughly similar in Flanders and Wallonia. In the next section, we try to determine the part of this structural and cyclical variation which is due to changes in the outflow rate of all currently unemployed workers and the part due to fluctuations in the average quality of entrants into unemployment.

The distribution in the June inflow of the personal characteristics x , i.e. $\frac{u_{11x}}{u_{11}}$, is used in our formal analysis to evaluate the impact of changes in the observed quality of entrants on the aggregate outflow rate. How does this distribution evolve during the observation period? The composition of the inflow is depicted in Appendix 3 for Flanders and Wallonia: Figures 3.15, 3.16 (level of education), Figures 3.17, 3.18 (province of residence) and Figures 3.19, 3.20 (sector of previous employment).

The distribution in the inflow of the *schooling level* changes significantly over the whole period. There is a decrease of entrants with at most an elementary degree, from 60% on average over the first half of the period (1972-1983) to 35% over the second half of the period in Flanders, and from 57% to 40% in Wallonia. All other schooling levels similarly increase their shares in the inflow. In both regions, the inflow distribution of the *province of residence* is in line with their shares in the active population. In Wallonia, the large majority of entrants live in Hainaut and Liège while in Flanders, the number of entrants by province of living is more evenly distributed. The distribution of the province of living remains fairly constant over the period in Wallonia. In Flanders, there is a rise of entrants living in Vlaams-Brabant and Limburg which is compensated by a decline in the number of entrants living in West-Vlaanderen. Finally, there is some changes in the distribution of entrants by *sector of previous employment* over the period. In both regions, the share of entrants working previously in the building industry is large and declines over the whole period, from 30% on average over the first half of the period to 15% over the second half¹⁵. The large share of entrants coming from the public service is partly a characteristic of the June inflow: At the end of this month, teachers who do not hold a fixed position have to register as unemployed workers. The proportion of workers previously employed in the public services rises slightly over

¹⁵This negative trend could be due to the increased severity of the entitlement rules which reduces the incentive to register for temporary laid-off workers.

the period in both regions. This can reflect the importance of subsidised jobs created by the government to fight unemployment. The share of entrants from the steel-iron industry is slightly higher in Wallonia than in Flanders (on average 16% and 14%), but remains stable over time. The proportion of workers previously employed in the private sector is similar in both regions (on average 18%) and increases weakly. Finally, the mean *age* of entrants is 33 years old in Flanders and Wallonia and does not change significantly over the period.

In sum, variations in the share of unemployed workers by schooling level, and to a less extent by sector of previous employment, could induce significant changes in the aggregate outflow rate in both regions. On the other hand, changes in the distribution of age and province of living are unimportant to account for fluctuations in the aggregate exit rate. As said *supra*, variations in the composition of inflow is only relevant in respect of personal characteristics that affect the exit probability. If the educational attainment is not a significant determinant of the hazard rate, the rising share of entrants with higher education cannot explain any trend in the aggregate outflow rate. Our duration analysis allows us to evaluate whether the schooling level and the sector of previous employment have a significative impact on the outflow rate.

3.3 The mixed proportional hazard model

3.3.1 Notations and assumptions

Let the variables l and t denote respectively the calendar time at the moment of inflow and unemployment duration. These variables are measured in years. The way the inflow is constructed in our data requires us to model calendar time at the moment of inflow, l , as a discrete time process. We have that $l \in \{0, 1, \dots, 20\}$ and by definition, that $t \equiv 0$ at the moment of inflow l . Although we analyse discrete data, we treat unemployment duration, t , as a continuous time process. So, $t \in R^+$. Otherwise, the specification would be sensitive to the time unit of the data (see Flinn and Heckman 1982). Misspecified duration intervals, i.e. not consistent with the unemployed behaviour, would then lead to

non-proportionality, violating the MPH specification imposed below¹⁶. Finally, when conditioning on the unemployment history such as required in mixture models, each individual is treated ‘as if’ s/he did not change characteristics.

We denote the hazard of an individual unemployed for t years and at risk of leaving unemployment at calendar time $l + t$, conditional on his set of observed characteristics x and on his unobserved characteristics v , by:

$$h(t | l + t, x, v) \quad (3.3)$$

and the survivor function at unemployment duration t by:

$$S(t | x, v) = \exp \left[- \int_0^t h(s | l + s, x, v) ds \right] \quad (3.4)$$

Here and in the sequel, the calendar time dependence is implicit in the notation of the survivor function.

We then specify a mixed proportional hazard (MPH) model in which we impose a continuous baseline hazard and constant calendar time effects within yearly intervals:

$$\forall t \in [k - 1, k) : h(t | l + t, x, v) = \exp [\varphi_1(k) + \varphi_2(l + k) + x\beta] v \equiv h_{klx} v \quad (3.5)$$

where $k \in \{1, \dots, 21\}$, $\varphi_1(k) = \int_{k-1}^k \varphi_1(t) dt$ and the functions $\varphi_1(\cdot)$ and $\varphi_2(\cdot)$ represent respectively the duration and calendar time dependence of the conditional hazard.

We assume that calendar time at the moment of inflow affects the shape of the mixing distribution (as in Abbring *et al.* 2001a or in Chapter 2).

¹⁶Note that the process is continuous except from conditioning on survival through the month of entry into unemployment. A ‘genuine’ continuous time process would require modeling spells that start and end within the same month. This would substantially complicate our specification.

By doing so, we allow for variations in the unobserved characteristics of entrants into unemployment. Using (3.4) and (3.5), the mixture survivor function at the end of year k can then be found to be:

$$S^m(k|l, x) = \int_0^\infty \exp \left[-v \sum_{j=1}^k h_{jlx} \right] dF_l(v) \quad (3.6)$$

where $F_l(\cdot)$ is the heterogeneity distribution. Below, we will specify this distribution as well as how it depends on calendar time at the inflow.

We parametrise $\varphi_1(k)$ as a piecewise-constant function:

$$\varphi_1(k) = c + \sum_{j=2}^{21} (\gamma_j - c) \delta_{jk}, \quad (3.7)$$

where δ_{jk} is the Kronecker delta and where we impose that $\forall j \geq 4 : \gamma_j = \gamma_4$. The latter restriction avoids erratic variation of the parameters induced by a too small number of observations at the tail of the duration distribution.

In the line of Abbring *et al.* (2001b), we represent the calendar time dependence of the hazard, $\varphi_2(l+k)$, by the following flexible parametric specification:

$$\varphi_2(l+k) = \sum_{i=1}^{12} \alpha_i p_i(l+k) \quad (3.8)$$

The effect of calendar time at exit on the hazard is modelled by a flexible twelfth degree polynomial in calendar time, $p_i(l+k)$, capturing both trend and business cycle effects¹⁷. To avoid multi-collinearity problems, we follow Abbring *et al.* (2001b) and use the orthogonal Chebyshev polynomial instead of an ordinary polynomial¹⁸.

¹⁷A twelfth degree polynomial should track the calendar time dependence of the hazard in a flexible way. Note that, in order to avoid the incidental parameter problem, the number of degrees should be constant or at least increase at a slower rate than the number of calendar time points. In the latter case, the ‘good’ asymptotic properties of the estimator cannot be guaranteed (see Gourieroux and Monfort 1995, p.189). However, this does not imply that the number of parameters should necessarily be fixed as the number of calendar time points grows, such as Merz (1999, p.333) claims in her critique on Van den Berg and Van der Klaauw (2001).

¹⁸The series of Chebyshev polynomials is obtained as follows (see Abramowitz and

3.3.2 The statistical model

We now turn to a description of the estimation procedure, which we choose to be Minimum Chi-Square (see Berkson 1944, Amemiya 1981, Cockx 1997). In a nutshell, this method consists in regressing for each cohort a transformation of the observed exit probability, i.e. the fraction of workers that leave unemployment within a particular duration interval given that they did not leave earlier, to its theoretical counterpart. The theoretical probability at the k^{th} duration interval for a worker of type x who is at risk of leaving unemployment within the $(l + k)^{th}$ year is:

$$P_{k|x} \equiv \Pr(k - 1 \leq T < k | T \geq k - 1, l + k, x) \quad (3.9)$$

Using (3.6), we then link this probability to the conditional hazard rate:

$$P_{k|x} = \frac{S^m(k - 1 | l, x) - S^m(k | l, x)}{S^m(k - 1 | l, x)} = 1 - \frac{\int_0^\infty \exp \left[-v \sum_{j=1}^k h_{j|x} \right] dF_l(v)}{\int_0^\infty \exp \left[-v \sum_{j=1}^{k-1} h_{j|x} \right] dF_l(v)} \quad (3.10)$$

We assume that V (random variable) is a Gamma variate¹⁹ of mean, $\mu_l = \frac{\lambda}{\delta_l}$, and variance, $\sigma_l^2 = \frac{\lambda}{\delta_l^2}$. As such, we allow the mean and the variance of V to vary proportionally over calendar time at the moment of inflow, l (as in Chapter 2). By normalisation, the mean is equal to one for $l = 0$. We therefore impose $\lambda = \delta_0$. Since the moment generating function of this Gamma variate is (see Lancaster 1990, p.328):

Stegun 1970, Table 22.3). First, linearly transform the domain of calendar time to the domain of orthogonality of the Chebyshev Polynomial, $[-1, 1]$, by means of $(x = l + k$ and $x_0 = 1)$:

$\hat{x}(x) = 2 \frac{x - x_0}{n - 1} - 1$, where n ($= 21$) is the number of calendar time intervals considered.

Then generate the series of orthogonal polynomials, $p_i(\hat{x})$, by means of:

$$p_i(\hat{x}) = \frac{i}{2} \sum_{j=0}^{\lfloor \frac{i}{2} \rfloor} (-1)^j \frac{(i-j-1)!}{j!(i-2j)!} (2\hat{x})^{i-2j} \text{ for } i = 1, 2, \dots, 12 \text{ and for } j \in R^+.$$

¹⁹The choice of a Gamma distribution for $F(v)$ can be justified by the result that, for a continuous v and under mild regularity conditions, the unobserved heterogeneity distribution among survivors at t converges to a Gamma distribution if $t \rightarrow \infty$ (see Abbring and Van den Berg 2001).

$$M_v \equiv E(e^{sV}) = \left(1 - \frac{s}{\delta_l}\right)^{-\lambda} \quad (3.11)$$

we are able to simplify greatly the last expression in (3.10).

Before presenting the implied model, we specify how the variables δ_l depends on calendar time at the inflow. We first introduce the following notation: $\delta_l = \exp(-\varphi_3(l))$. Unlike for the effect of calendar time on the hazard at the outflow, we do not specify a polynomial to capture the effect of calendar time at entry. We choose to characterise the effect of calendar time at the moment of inflow by a business cycle indicator:

$$\varphi_3(l) = \eta_0 + \eta_1 b(l) \quad (3.12)$$

The business cycle indicator, $b(l)$, is the logarithm of the number of flows into unemployment every month of June²⁰. We normalise $b(0) = 0$, so that $\lambda = \exp[-\eta_0]$. If this indicator does *not* vary *only* according to an exponential trend, identification is assured. We could have specified the time dependence of the mixing distribution in a more flexible way with a polynomial function forced to be orthogonal to a linear trend (see Abbring *et al.* 2001a). If variations in the unobserved composition of inflow closely follows variations in the number of entrants into unemployment, our specification turns out to be a better alternative. For, it allows the unobserved composition effect to follow a trend (i.e. the trend in incidence), separately from the trend in the general effect. The plausibility of our parametric assumption can be verified by checking whether variations in the observed composition of entrants coincide with variations in incidence.

Combining (3.10), (3.11) and (3.12), the outflow probability then becomes:

²⁰We also estimated a model with a second-order polynomial in $b(l)$. The coefficients of this polynomial are however very imprecisely estimated.

$$P_{klx} = 1 - \left[1 - \frac{\sigma_0^2 \mu_l \exp [\varphi_1 (k) + \varphi_2 (l + k) + x\beta]}{1 + \sigma_0^2 \mu_l \sum_{j=1}^k \exp [\varphi_1 (j) + \varphi_2 (l + j) + x\beta]} \right]^{\frac{1}{\sigma_0^2}} \quad (3.13)$$

where $\sigma_0^2 = \exp [\eta_0]$ and $\mu_l = \exp [\eta_1 b(l)]$. By construction, $\sigma_l^2 = \sigma_0^2 \exp [2\eta_1 b(l)]$.

Finally, we relate the theoretical outflow probability to the empirical probability. If we replace the probability of leaving unemployment, P_{klx} , by its estimate, $\hat{P}_{klx}$, given in (3.1), the equality of equation (3.13) does no longer holds exactly. For the observed aggregate exit probability is calculated on the basis of a finite sample. So we follow Cockx (1997) and obtain the following non-linear heteroskedastic regression model:

$$\begin{aligned} \hat{P}_{klx} = 1 - \left[1 - \frac{\sigma_0^2 \mu_l \exp [\varphi_1 (k) + \varphi_2 (l + k) + x\beta]}{1 + \sigma_0^2 \mu_l \sum_{j=1}^k \exp [\varphi_1 (j) + \varphi_2 (l + j) + x\beta]} \right]^{\frac{1}{\sigma_0^2}} \\ + \omega_{klx} + \varepsilon_{klx} \end{aligned} \quad (3.14)$$

where $\omega_{klx} = \hat{P}_{klx} - P_{klx} - \varepsilon_{klx}$ is the approximation error that reflects the stochastic nature of the empirical exit probability, $\hat{P}_{klx}$. The error ε_{klx} is a specification error which allows for random deviation from the true specification of the hazard rate. We assume that the latter has a distribution such that $E(\varepsilon_{klx}) = 0$ and $E(\varepsilon_{klx}^2) = s_\varepsilon^2$, and that they are not autocorrelated. Since conditional on the number of individuals at risk, u_{klx} , the number of outflows, F_{klx} , in the empirical estimator (3.1) has a binomial distribution with a probability of ‘success’ P_{klx} , Cockx (1997) shows that $E(\omega_{klx}) = 0$ and that a consistent estimate of the variance of ω_{klx} is:

$$\hat{s}_{klx}^2 = \left[\left(\hat{P}_{klx} \right) \left(1 - \hat{P}_{klx} \right) \right] \frac{1}{u_{klx}} \quad (3.15)$$

The estimation procedure consists in two-steps (see Amemiya and Nold 1975). In a first step we estimate the model (3.14) by Ordinary Least

Squares (OLS). On the basis of the OLS residuals ($\hat{v}_{klx}$) and of the estimated variance of the approximation error ($\hat{s}_{klx}^2$), we can calculate a consistent estimate of s_ε^2 :

$$\hat{s}_\varepsilon^2 = \frac{1}{N} \left\{ \sum_x \sum_{l=0}^{20} \sum_{k=1}^{21-l} \left[(\hat{v}_{klx})^2 - \hat{s}_{klx}^2 \right] \right\} \quad (3.16)$$

where N denotes the number of cells (i.e. observations) in our data set. In a second step, we estimate the statistical model (3.14) by Generalized Non-Linear Least Squares²¹. The obtained estimator is a modified version of the Minimum Chi-square estimator, first applied to duration data by Cockx (1997).

Because we have grouped data, we could use a χ^2 -goodness-of-fit test to evaluate the model specification. The size of our cells is however too small for applying large sample theory. Recall that 93% of the cells are made up of only one individual at entry. The normal approximation of the binomial distribution on which the χ^2 test relies is good as long as $u_{klx}P_{klx} \simeq f_{klx} > 5$ (see Hoel 1971, p.82). Testing therefore requires a re-grouping of the data²². However, whatever the considered grouping this condition remains violated for most cells with an unemployment duration larger than one year. This is because only very few long-term unemployed workers leave unemployment, implying $f_{klx} < 5$ for $k > 1$. We therefore choose to average $\hat{P}_{klx}$ over age and sector of previous employment and calculate a new weighted sum of squared residuals for observations with $k = 1$ only. The fraction of observations still violating $f_{klx} > 5$ is equal to 1% and 6% in Flanders and Wallonia respectively²³.

²¹Since the majority of cells counts only one individual in our data set, the empirical exit probability will mostly take two values: $\hat{P}_{klx} = 1$ or $\hat{P}_{klx} = 0$. As a consequence, the weight based on the variance of the approximation errors, $u_{klx} \left[\left(\hat{P}_{klx} \right) \left(1 - \hat{P}_{klx} \right) \right]^{-1}$, is no longer defined for these cases. We deal with this problem by replacing $\hat{P}_{klx}$ by $\hat{P}_{klx}(\hat{\theta})$ which is simply P_{klx} evaluated at the previous round estimated values of the set of unknown parameters ($\hat{\theta}$). The advantage of this method is that $\hat{P}_{klx}(\hat{\theta})$ will be never exactly equal to one or zero so that the weights are always defined (see Cockx 1997, p.395).

²²We are grateful to Bas van der Klaauw for pointing this out to us.

²³A grouping according to the variable ‘age’ only still leaves around 80% of cells with $f_{klx} < 5$ among observations with $k = 1$.

The adjusted weighted sum of squared residuals ($WSSR^*$) is distributed $\chi^2_{N^*-p^*}$ if the model is correctly specified, where N^* and p^* is the number of observations and parameters after re-grouping the data. The latter number is obtained by subtracting from the total number of parameters those concerning the variables used in the re-grouping and the duration parameters. Moreover, we can test the acceptability of restrictions on the parameters, for instance the absence of unobserved composition effects (i.e. $\eta_1 = 0$). If the constrained model is well specified, then the difference between the adjusted weighted sum of squared residuals of the constrained and the unconstrained model ($WRSS_0^* - WRSS^*$) is distributed $\chi^2_{(p^*-p_0^*)}$.

3.3.3 Decomposition of the aggregate hazard over calendar time

In this section, we show the theoretical decomposition of the aggregate hazard over calendar time. As stated in the introduction, the calendar time dependence of the aggregate hazard combines both a general effect, i.e. changes in the individual (or conditional) hazard, and a composition effect, i.e. fluctuations in the average quality of entrants leaving the individual hazard constant. The latter effect is made of variations in the observed and unobserved characteristics of those flowing into unemployment. In our modelling framework, the aggregate hazard is the conditional hazard of an individual with average observed and unobserved characteristics, both averages being allowed to vary over calendar time at the moment of inflow. Focusing on unemployed workers in their first duration class (i.e. $k = 1$)²⁴ and denoting by $\Pr(X = x | k = 1, l)$ the empirical density of X at $k = 1$ and l , the aggregate hazard at calendar time $l + 1$ is given by:

²⁴We do not calculate the aggregate hazard averaged over a larger number of duration intervals for the following reason. Since we have an inflow data set, not all duration classes are represented at the begin of the observation period. Therefore, considering more duration intervals decreases the timespan on which the aggregate hazard can be calculated. We have checked that the results of the decomposition are not affected by calculating the aggregate hazard on the basis of three duration intervals.

$$\bar{h}_{1l} = \sum_x \left[\int_0^1 h(t|l+t, x) E(v|l, T > t) dt \right] P(X = x | k = 1, l) \quad (3.17)$$

where the empirical density of X at l is estimated by:

$$\Pr(X = x | k = 1, l) = \frac{u_{1lx}}{u_{1l}} \quad (3.18)$$

Since the expression in square brackets is the mixture hazard evaluated at $k = 1$, we can write:

$$\bar{h}_{1l} = \sum_x [-\ln(S^m(1|l, x))] \frac{u_{1lx}}{u_{1l}} = \sum_x [-\ln(1 - P_{1lx})] \frac{u_{1lx}}{u_{1l}} \quad (3.19)$$

Substituting the expression of the outflow probability given in (3.13) into (3.19) and evaluating it at $k = 1$, the aggregate hazard at calendar time $l + 1$ is therefore:

$$\bar{h}_{1l} = \sum_x \left[\frac{1}{\sigma_0^2} \ln \left(1 + \sigma_0^2 \exp \left[c + \underbrace{\sum_{i=1}^{12} \alpha_i p_i(l+1)}_G + \underbrace{\eta_1 b(l)}_{UC} + \underbrace{x\beta}_{OC} \right] \right) \right] \underbrace{\frac{u_{1lx}}{u_{1l}}}_{OC} \quad (3.20)$$

The *general (G) effect* is the instantaneous effect of business conditions at exit on the hazard controlling for composition effects. In our model, we capture part of the variation in the composition of the inflow by conditioning the hazard on observed characteristics. The remaining variation, the unobserved composition effect, is accounted for by making the mixing distribution dependent on a business cycle indicator at entry. The polynomial function $\sum_{i=1}^{12} \alpha_i p_i(l+1)$ therefore measures the general effect of the calendar time on the aggregate hazard. The *observed composition (OC) effect* is the variation in the aggregate hazard due solely to changes in observed characteristics of those becoming

unemployed through time. Variations of the empirical density of X in the inflow, $\frac{u_{1lx}}{u_{1l}}$, captures the observed composition effect of the calendar time on the aggregate hazard. Note that changes in the inflow density affect the aggregate hazard *only if* these changes concern characteristics that have a significant impact on the conditional hazard. The *unobserved composition (UC) effect* is the variation in the aggregate hazard which is only explained by changes in unobserved characteristics of those entering unemployment through time. The linear function $\eta_1 b(l)$ measures the unobserved composition effect of the calendar time on the aggregate hazard, which simply reflects the calendar time dependence of the mean (and the variance) of the Gamma distribution.

We compute synthetic series of the aggregate hazard rate in order to determine the relative role of each of its time-varying component. Each series is obtained by fixing the other components to their value at the first calendar time interval, i.e. $l = 0$. This yields to the following time-series of the aggregate hazard (where superscript C refers to the sum of the observed and unobserved components):

$$\bar{h}_{1l}^G = \sum_x \left[\frac{1}{\sigma_0^2} \ln \left(1 + \sigma_0^2 \exp \left[c + \sum_{i=1}^{12} \alpha_i p_i (l+1) + x\beta \right] \right) \right] \frac{u_{10x}}{u_{10}} \quad (3.21)$$

$$\bar{h}_{1l}^{OC} = \sum_x \left[\frac{1}{\sigma_0^2} \ln \left(1 + \sigma_0^2 \exp \left[c + \sum_{i=1}^{12} \alpha_i p_i (1) + x\beta \right] \right) \right] \frac{u_{1lx}}{u_{1l}} \quad (3.22)$$

$$\bar{h}_{1l}^{UC} = \sum_x \left[\frac{1}{\sigma_0^2} \ln \left(1 + \sigma_0^2 \exp \left[c + \sum_{i=1}^{12} \alpha_i p_i (1) + \eta_1 b(l) + x\beta \right] \right) \right] \frac{u_{10x}}{u_{10}} \quad (3.23)$$

$$\bar{h}_{1l}^C = \sum_x \left[\frac{1}{\sigma_0^2} \ln \left(1 + \sigma_0^2 \exp \left[c + \sum_{i=1}^{12} \alpha_i p_i (1) + \eta_1 b(l) + x\beta \right] \right) \right] \frac{u_{1lx}}{u_{1l}} \quad (3.24)$$

We can then quantify the relative importance of the general and the composition effects in the total variation of the aggregate hazard over the whole period by an analysis of variance. Since our observation period

spans 20 years, structural and cyclical evolutions are separately investigated. We calculate the exponential trend in the three synthetic series ($\bar{h}_{1l}^G$, $\bar{h}_{1l}^{OC}$, $\bar{h}_{1l}^{UC}$) and we assume that the sum of these trends is equal to the trend in the aggregate hazard ($\bar{h}_{1l}$). This assumption is an approximation since the trend in the aggregate series does not sum up exactly the trend in the general and composition effects due to the non-linearity of each series. We then regress the de-trended logarithm of the aggregate hazard on the de-trended logarithm of the three synthetic series. On the basis of this model estimates, we calculate the part of the total variation in the aggregate hazard that is accounted for by a structural and a cyclical variation. Each type of variation is decomposed into the proportion explained by a general effect, an observed composition effect and an unobserved composition effect. The decomposition procedure is detailed in Appendix 2.

3.3.4 Empirical results

The estimation results for the mixture regression model specified in (3.14) are reported in Table 3.7 in Appendix 4, for Flanders and Wallonia. The constant term allows to calculate the hazard rate of a reference individual with an elementary school degree, living in Brabant wallon (resp. Vlaams-Brabant for Flanders), previously employed in the chemical industry and with the average unobserved characteristic (i.e. $v = 1$).

Consider first the performance of the models on the basis of the goodness-of-fit statistic. At a significance level of 5%, the model is rejected against the saturated model for both regions. This result was expected given the large number of observations used in the estimation. There is no evidence of specification errors as their estimated standard deviation is zero in both regions. Finally, we reject that the mean of the unobserved characteristics is constant over time ($\eta_1 = 0$) at a significance level of 5% in both regions. So changes in the unobserved quality of entrants can partly explain variations in the aggregate hazard in Flanders and in Wallonia.

Unobserved heterogeneity, duration dependence and covariate effects

Before we discuss the decomposition of the calendar time variation in the aggregate hazard, we first examine the shape of the baseline hazard and the estimated effect of the individual characteristics on the conditional hazard.

The result for the estimated variance of the heterogeneity distribution indicates a mild disparity between the unobserved characteristics of those flowing into unemployment. Since the variance of the Gamma distribution is allowed to fluctuate over time, we report its average estimated value over our observation period (its time dependence is discussed in the next section). In Flanders, the estimated variance is small but significantly positive: $\hat{\sigma}^2 = 0.20$ with a 95% confidence interval equals to $[0.15, 0.26]$. The variance is somewhat larger, but not significantly, in Wallonia: $\hat{\sigma}^2 = 0.29$ with a 95% confidence interval equals to $[0.21, 0.40]$.

The conditional hazard is significantly decreasing over unemployment duration. However, genuine negative duration dependence appears to be stronger in Flanders (see Figure 3.21 in Appendix 3). There is a 40% decrease in the individual hazard after two years of unemployment in Flanders while this decline is only equal to 25% in Wallonia. With respect to Wallonia and prime-aged men, we obtain a similar result in Chapter 2 on the basis of quarterly aggregate outflow probabilities for the 1989-1994 period. After four years of unemployment the conditional hazard has dropped by more than 60% in both regions with respect to its initial level. There is an important spurious negative duration dependence in the unconditional hazard: If we did not control for the observed and unobserved heterogeneity in the characteristics of the entrants into unemployment, there would be a 50% and 40% decrease after two years of unemployment in Flanders and Wallonia respectively, and 80% decrease after four years²⁵.

The estimates of the covariate effects indicate a more important disparity between the different groups of unemployed workers in Wallonia as compared to Flanders. In the MPH model, the covariate effects give the

²⁵The estimation is available upon request.

average effect of the observed characteristics on the exit rate over the 1972-1993 period. In the next stage, we aim to examine these disparities more carefully by analysing the way they have moved over time.

We first consider the effect of schooling on the conditional hazard within both regions. The hazard increases significantly with the level of educational attainment in both regions. However, the difference between the re-employment probabilities of workers by schooling level is much larger in Wallonia than in Flanders. For instance, having a higher education degree increases the re-employment probability by 25% in Wallonia while this increase amounts to 7% only in Flanders.

In Wallonia, the outflow rate is much lower for the workers who live in Hainaut, and in a less extent in Liège and Namur, than for those who live in Brabant wallon and Luxembourg. Living in Hainaut decreases the outflow rate by 25% as compared to living in the latter provinces. The difference between the exit rates according to the province of residence is less pronounced in Flanders, with the worst performance for Limburg.

The dispersion of the sectorial effects is also higher in Wallonia. For instance, there is a significant disparity in Wallonia between the outflow rates of those coming from the steel and mining industry and of those previously employed in the private services (the latter are 40% more likely to leave unemployment than the former), while this difference is not significative in Flanders. It should be stressed that the sector occupied before becoming unemployed is not necessarily the sector of re-employment. Therefore, differences between the re-employment probabilities in the sectorial dimension can be explained either by differential sectorial business conditions and/or by differential mobility of the unemployed workers between sectors.

Finally, the outflow rate decreases significantly with age, more importantly in Flanders. The exit rate of 40 years old workers is 33% and 26% lower than the one of the 25 years old workers in Flanders and Wallonia respectively²⁶. So even if we restrict our analysis to the 25-44 age group, age within this group still influences markedly the outflow probability.

²⁶We also estimated a model with a second-order polynomial in age. The coefficients of this polynomial are however very imprecisely estimated.

Decomposition of the aggregate hazard over calendar time

In this section, we look at the relative importance of macroeconomic conditions and compositional changes in the unemployment inflow to explain the variations in the aggregate hazard over calendar time. Figures 3.7 and 3.8 show the estimated monthly aggregate hazard²⁷ in the first year of unemployment without composition effects ($\bar{h}_{1l}^G$), with only composition effects ($\bar{h}_{1l}^C$) and with the combination of both ($\bar{h}_{1l}$), for Flanders and Wallonia respectively. The decomposition between the observed ($\bar{h}_{1l}^{OC}$) and unobserved composition effects ($\bar{h}_{1l}^{UC}$) is depicted in Figures 3.9 and 3.10.

Variations in the aggregate hazard seem to be dominated by a negative trend in Wallonia while cyclical changes appear to be relatively more important in Flanders. This observation is confirmed by the analysis of variance: 52% of the variation in the aggregate hazard ($\bar{h}_{1l}$) is accounted for by a structural variation while this share is only equal to 13% in Flanders.

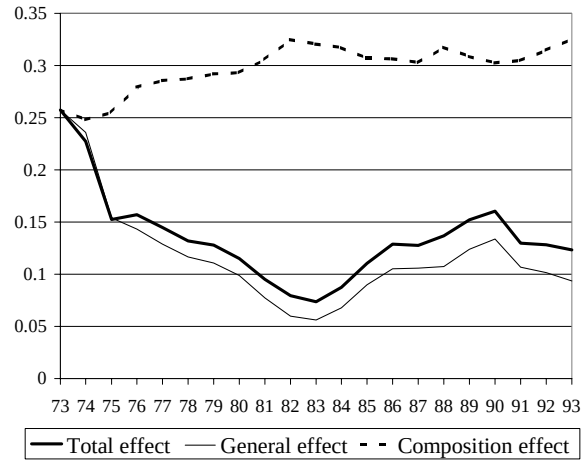


Figure 3.7: Decomposition of the monthly aggregate hazard (K=1) - Flanders

²⁷The monthly aggregate hazard is simply the estimated yearly aggregate hazard divided by twelve.

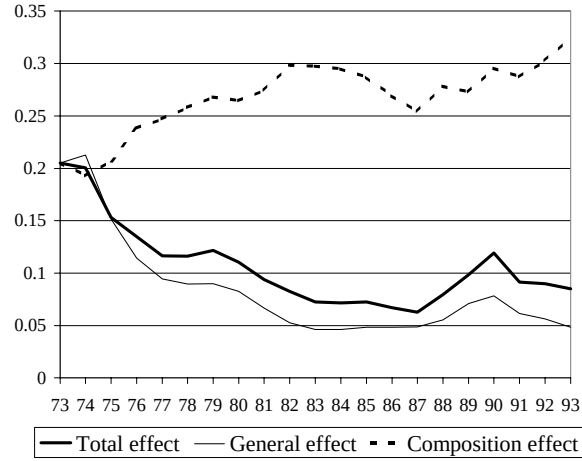


Figure 3.8: Decomposition of the monthly aggregate hazard ($K=1$) - Wallonia

The graphical decomposition also indicates that variations in the aggregate hazard are driven, in both regions, by fluctuations in the individual exit rate of all currently unemployed rather than by changes in the quality of entrants into unemployment. However, the composition effect accounts for a significant part of the structural variations in the aggregate hazard. According to the analysis of variance, changes in the composition of entrants explain 27% and 24% of the structural evolution in the aggregate hazard, in Flanders and Wallonia respectively, and only 13% and 14% of its cyclical variability²⁸.

As suggested by Figures 3.9 and 3.10, the unobserved component accounts for a larger share of the structural variation in the average quality of entrants than the observed one: 60% in Flanders and 70% in Wallonia. Changes in the unobserved quality also drive most of the cyclical variability in the composition effect: Only 5% and 30% of its variability comes from changes in the observed quality of entrants²⁹.

²⁸In the cyclical decomposition, there is a negative covariance between the general effect and both, the observed and unobserved composition effects. This negative covariance indicates that the cyclicalities of the general and the composition effects work in the opposite direction, thereby reducing the total variability in the aggregate hazard.

²⁹Since we parametrise the unobserved composition effect by the number of entrants

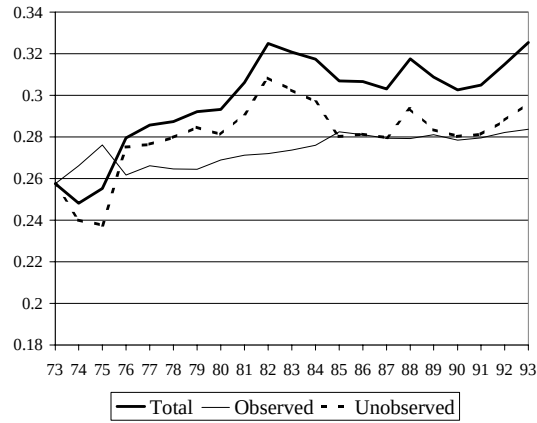


Figure 3.9: Composition effect - Flanders

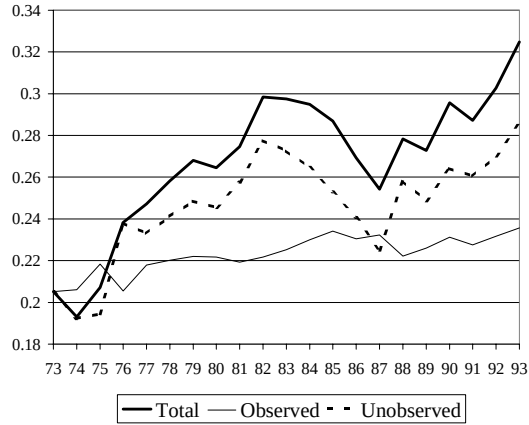


Figure 3.10: Composition effect - Wallonia

into unemployment, the cyclical variation in the unobserved quality of entrants follows the cycle of incidence. The amplitude of the cycle in the unobserved composition effect is given by the estimated value of the parameter η_1 .

It should be noticed that the results of the graphical decomposition and the variance analysis are hardly sensitive to the reference date chosen (i.e. $l = 0$)³⁰.

Below, we discuss the structural evolution in the components of the aggregate hazard by analysing their exponential trend, and their cyclicity by comparing their estimated cycle to a business cycle indicator.

Table 3.1: Structural evolution of the monthly aggregate hazard over 1973-1993

	Total effect		General effect		Composition effect	
	Wallonia	Flanders	Wallonia	Flanders	Wallonia	Flanders
Total variation	-53%	-28%	-69%	-43%	43%	22%
Yearly variation	-3.7%	-1.6%	-5.9%	-2.8%	1.8%	1.0%

Flanders and Wallonia exhibit both a decreasing trend in the aggregate outflow rate over 1973-1993 period at rates equal to -1.6% and -3.7% yearly, respectively³¹ (see Table 3.1). In 1993, the aggregate exit rate declined by 28% compared to its initial level in Flanders while this drop amounts to 53% in Wallonia. This downward trend only results from a structural decrease in the individual exit rate (i.e. in the *general effect*), at rates equal to -2.8% and -5.9% yearly in Flanders and Wallonia respectively³². The strong decline in the individual outflow rate over this period was mitigated at the aggregate level by an increase in the quality of those flowing into unemployment in both regions. The rising share of entrants with good re-employment prospects since 1972 has induced an annual increase in the aggregate outflow rate of 1% in Flanders and

³⁰By taking $l = 10$ (i.e. June 1982) as reference date in the decomposition analysis, the relative role of the composition effect in the structural variation of the aggregate hazard is 31% and 27% in Flanders and Wallonia respectively, and is unchanged in the cyclical decomposition.

³¹As compared to the Figure 3.6 reported in Section 3.2.4, there is a slight overestimation of the downward trend in the aggregate hazard in Wallonia as compared to the trend observed in the empirical aggregate hazard.

³²Notice that the stronger negative trend in the individual exit rate in Wallonia cannot be attributed to a migration (with a change in the place of residence) of the workers with good re-employment prospects to Flanders, which would have affected the composition of the unemployed population in the two regions. For, the mobility of workers between Flanders and Wallonia is very weak (see Candelon *et al.* 2000). Linguistic and cultural barriers play an important role in that respect. Some tracks of interpretation of the regional differences will be provided in Section 3.4.2.

1.8% in Wallonia. In the absence of this positive composition effect, the aggregate exit rate would have declined by 43% and 69% with respect to its initial level in Flanders and Wallonia respectively.

Table 3.2: Structural evolution of the composition effect over 1973-1993

	Total effect		Observed		Unobserved	
	Wallonia	Flanders	Wallonia	Flanders	Wallonia	Flanders
Total variation	43%	22%	12%	8%	28%	13%
Yearly variation	1.8%	1.0%	0.6%	0.4%	1.3%	0.6%

Table 3.2 shows that the upward trend in the composition of inflow is due to an improvement in both observed and unobserved quality of entrants, the trend in the latter component being much larger in Wallonia. The variance of the unobserved characteristics of entrants also increases over time, since it is simply twice the evolution of the mean. The structural rise in the observed quality of entrants is mainly attributed to an increase in the share of high educated workers in the unemployed population, who have on average a larger exit rate. The variance analysis indeed reveals that over the 1972-1993 period, changes in the distribution of schooling among entrants account for 80% and 90% of the increase in the observed quality of entrants in Flanders and Wallonia respectively.

In both regions, the cyclical variability in the aggregate hazard is driven by cyclical variations in the individual exit rate (i.e. in the *general effect*) rather than by composition effects. Given their respective role, we first examine the cyclical variability in the general effect. Figure 3.11 shows the detrended general effect in the two main regions of Belgium. In order to evaluate its cyclical pattern, we compare it to a Belgian business cycle indicator³³, the Kredietbank indicator (see Figure 3.12). This indicator starts in 1980, i.e. after the oil price shocks which coincide with an important rupture in the long-run growth of the Belgian economy³⁴.

³³There is no regional business cycle indicator in Belgium.

³⁴Over the 1960-1975 period, the long-run growth of the Belgian economy is 4.5% while it is only 1.9% in the 1976-1996 period (see Bodart 2000).

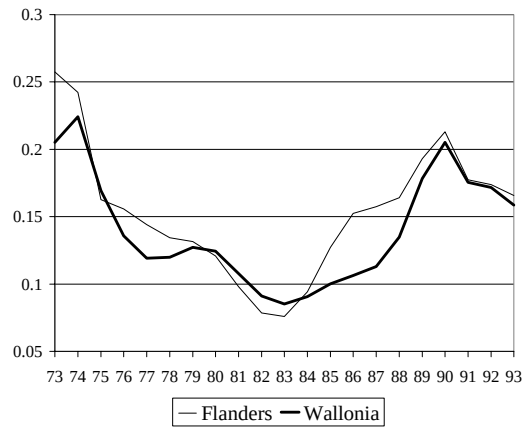


Figure 3.11: General effect over the cycle

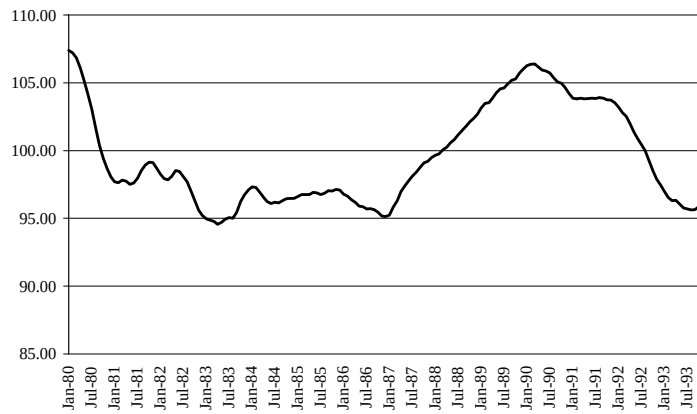


Figure 3.12: The Kredietbank indicator

The individual exit rate appears to be procyclical, its pattern being very similar in Flanders and in Wallonia over the whole period. The exit rate is sharply decreasing between 1974 and 1983: It declines by more than 60% in 1983 compared to its level in 1974. This strong decline of the outflow rate in Belgium coincides with the first and second oil price shocks in 1973 and in 1979. Over this period, employment decreases strongly in Belgium, the employment losses being concentrated in the industry. During the period of recovery, which starts with the devaluation of the Belgian Franc in 1982 and continues up to 1990, Wallonia lags Flanders continuously. Yet, the business revival on the outflow rate is observable in the two regions. From 1990, the economic downturn pushed the exit rate down again in both regions.

In Appendix 3, Figures 3.22 and 3.23 show the estimated cyclical variation in the observed quality of entrants for Flanders and Wallonia respectively. Even if its impact on the aggregate hazard is marginal, we can state that the observed composition of the inflow is countercyclical in both regions: The average quality of entrants into unemployment increases during recessions and falls in upturns. As suggested by the analysis of variance, the cyclical pattern in the observed composition of inflow is somewhat stronger in Wallonia. The positive sign of $\hat{\eta}_1$ (see Table 3.7 in Appendix 4) also indicates that the unobserved quality of entrants improves as labour market conditions deteriorate (i.e. when incidence increases). These results suggest that employers fire the most able workers only if they have no alternative, i.e. in a recession. Unable workers are made redundant all the time.

Our results concerning the unobserved composition effect could be sensitive to our parametric assumption: We assume that changes in the unobserved quality of entrants are proportional to changes in incidence. The pattern of the observed composition effect confirms the plausibility of this assumption. For, we observe that variations in the observed quality of entrants coincide with variations in incidence, in both the cyclical evolution and the structural evolution. As a result, our specification turns out to be a better alternative than a more flexible specification since it allows the unobserved composition effect to follow a trend (i.e. the trend in incidence), separately from the trend in the general effect.

We finish the discussion of our estimation results by comparing them

to those obtained in other studies. A more detailed interpretation of the results will be provided in the next section. Our results are in line with most of the studies based on European data. With the exception of Kalwij (2001) for the United Kingdom, they all conclude that composition effects are of minor importance to explain cyclical fluctuations in the aggregate hazard (see for France, Van den Berg and Van der Klaauw 2001, Abbring *et al.* 2001a; for Denmark, Rosholm 2001; for Belgium, Chapter 2 of this thesis). So the English-speaking countries seem to remain the exception, with variations in the quality of entrants driving a significant part of the variations in unemployment duration (see, for US, Darby *et al.* 1985 and Abbring *et al.* 1999). It should, however, be stressed that none of the reviewed studies decompose formally the structural variation in the aggregate outflow rate into a general and a composition effect. As is shown in this study, the role of the composition effect is, in this respect, relatively important.

Although they analyse a shorter timespan, Abbring *et al.* (2001a) also found that the individual exit rate trends downward significantly in France between 1982 and 1994, for the male unemployed workers. However, Abbring *et al.* estimate the composition effect non-parametrically, so that they were forced to assume the absence of a trend in the composition of inflow. As a result, the structural part of their general effect is not necessarily rid of variations in the quality of workers flowing into unemployment. If the quality of entrants had also improved over their observation period, the estimated trend of the individual exit rate in France would be upward biased. Using the same data, but combining them with a micro data set, Van den Berg and Van der Klaauw (2001) actually found a slightly increasing trend in the observed quality of entrants over the 1982-1994 period in France. Based on micro data covering the 1981-1990 period, Rosholm (2001) also estimated a downward trend in the individual exit rate from 1985 in Denmark. Again this estimated trend can be biased since he did not account for changes in the unobserved quality of entrants in a formal way.

The cyclical fluctuations in the individual hazard in Belgium seems similar to the one estimated in France (see Abbring *et al.* 2001a) and in the United Kingdom (see Kalwij 2001). In both countries, the individual exit rate is procyclical and drives the cyclical variation in the aggregate

hazard. However, the amplitude of the cycle is larger in Belgium and in the United Kingdom than in France. As regards to the cyclicity of the composition effect, our results are close to the one obtained in Chapter 2, but also in Van den Berg and Van der Klaauw (2001) and Kalwij (2001). They also found that the quality of entrants is countercyclical. It should be noted that Abbring *et al.* (2001a) found a slightly procyclical composition effect on the basis of the same data as in Van den Berg and Van der Klaauw (2001). However, the estimated composition effect in Abbring *et al.* (2001a) combines both an observed and unobserved component since they cannot condition the hazard rate on observed characteristics. Darby *et al.* (1985) and Rosholm (2001) also obtained a procyclical variation in the quality of those becoming unemployed. They attribute their findings to changing proportions of voluntary quitters and laid off workers over the cycle. Note that we do not capture voluntary quits in our data, since these workers are not eligible for unemployment benefits.

3.4 Decomposition of the general effect

In this section, we question whether the general effect of the calendar time on the aggregate hazard affects all unemployed in the same proportion in both regions of Belgium. For that purpose, we relax the proportionality assumption and allow the calendar time dependence of the conditional hazard to be specific to the personal characteristics x . This amounts to replace $\varphi_2(l+k)$ and $x\beta$ in the conditional hazard (3.5) by $\varphi_2(x, l+k)$:

$$\forall t \in [k-1, k) : h(t|l+t, x, v) = \exp[\varphi_1(k) + \varphi_2(x, l+k)] v \equiv h_{klx} v \quad (3.25)$$

where $\varphi_2(x, l+k)$ is specified as follows:

$$\varphi_2(x, l+k) = x\beta_0 + \sum_{i=1}^{12} x\beta_i p_i(l+k) \quad (3.26)$$

Using (3.25) and (3.26), the mixture model defined in (3.14) then becomes:

$$\hat{P}_{klx} = 1 - \left[1 - \frac{\sigma_0^2 \mu_l \exp [\varphi_1(k) + \varphi_2(x, l + k)]}{1 + \sigma_0^2 \mu_l \sum_{j=1}^k \exp [\varphi_1(j) + \varphi_2(x, l + j)]} \right]^{\frac{1}{\sigma_0^2}} + \omega_{klx} + \varepsilon_{klx} \quad (3.27)$$

Allowing for a separate polynomial in calendar time for each value of the personal characteristics would lead to imprecise and intractable parameter estimates. In a benchmark model, we therefore specify a separate twelfth degree polynomial by schooling level and allow for different trends only for the other explanatory variables³⁵. Moreover, we assume that the age effect is constant over our observation period.

3.4.1 Empirical results

The estimation results for the mixture regression model specified in (3.27) are reported in the first column of Table 3.8 and Table 3.9 in Appendix 4, respectively for Flanders and for Wallonia. The estimated trends by sub-region of living and sector of previous employment are expressed in deviation from the reference trend (one by schooling level).

Upon comparison with the estimates of Table 3.7, we conclude that the introduction of time-varying covariate effects does not influence the other parameter estimates. In particular, the estimated value of the parameter capturing unobserved composition effects, η_1 , is similar to the one estimated in the MPH model. Also notice that the performance of the model improves on the basis of the goodness-of-fit statistic. Nevertheless, the non-proportional model is still rejected against the saturated model at a significance level of 5%, for both regions. Before entering into a more detailed interpretation of the estimation results, we first question whether we can impose some restrictions on the time dependence of the covariate effects based on the χ^2 test³⁶.

³⁵We assume the same trend for the sectors ‘public employment’ and ‘energy’ since this latter concerns a too small number of observations.

³⁶In order to test for the significance level of the sectoral trends, we average $\hat{P}_{klx}$

With respect to the *schooling level*, results differ between regions. In Wallonia, the exit rate of the highest educated workers evolves differently from the three other schooling levels: At a significance level of 5%, we cannot reject that both the cyclical and structural patterns of the exit rate are the same for the three lowest education levels while they differ significantly for those who completed higher education. However, the difference between these two groups is mild as regards to the cyclical variability in their exit rates. In Flanders, we cannot reject that the structural evolution of the exit rate is the same for the two lowest schooling levels while it is significantly different for those who have at least an upper secondary degree. On the other hand, the cyclical evolution of the outflow rate is similar across schooling groups in Flanders. With respect to the *province of living*, only unemployed people living in Antwerp and Limburg in Flanders, Hainaut and Namur in Wallonia, have a different trend in their exit rate in comparison with the reference province. Finally, as regards to the *sector of previous employment*, we cannot reject that the effects of all sectors on the exit rate evolve similarly over our observation period at a significance level of 5% in Wallonia. In Flanders, we cannot reject that the exit rate of workers coming from the iron and steel industry has a different trend than the exit rate of those coming from the other sectors.

The second column of Table 3.8 and Table 3.9 in Appendix 4, respectively for Flanders and Wallonia, presents the estimation results of the mixture regression model (3.27) in which we set the restrictions which are not rejected according to the χ^2 test. For purposes of comparison between the two regions, we also impose the same cyclical evolution in the exit rates of all schooling groups in Wallonia and the absence of specific trends in the sectorial dimension in Flanders. The interpretation of the results is based on this restricted model.

The interest of the non-proportional hazard model is to decompose the structural evolution in the MPH general effect into group specific trends. To that purpose, we compute the general effect of the aggregate hazard rate, $\bar{h}_{1l}^G$ in (3.21), by group of workers with a diverging evolution in their outflow rate, for instance the low educated workers in the

over age, province of living and schooling level and calculate a new weighted sum of squared residuals on observations with $k = 1$.

province of Hainaut. We then calculate the exponential trend in each series. The trend estimated in the MPH general effect is then, approximately, a weighted sum of the trends in the group specific general effects, where the weights are the average share of each group in the inflow into unemployment.

Table 3.3: Structural evolution of the general effect over 1973-1993

		General effect	
		Wallonia	Flanders
MPH	Total variation	-69%	-33%
	Yearly variation	-5.8%	-1.9%
Low-educated*	Total variation	-70%	-36%
	Yearly variation	-6.1%	-2.1%
High-educated	Total variation	-56%	-27%
	Yearly variation	-4.1%	-1.5%

* Low-educated in Wallonia: Below higher education; Low-educated in Flanders: Below upper secondary.

Table 3.3 shows that the estimated trend of the MPH general effect masks a different trend for the low and high educated workers in both regions. In Wallonia, the outflow rate of less educated job seekers (below higher education) deteriorated more importantly than the exit rate of the highest educated workers on the whole period: at rates equal to -6.1% and -4.1% yearly, respectively. These rates are means over provinces. In 1993, the exit rate of the low-educated workers had declined to 70% of the initial rate while this drop amounts to 56% for the highest educated workers. Since the low educated workers represent, on average, 85% of entrants, the trend in the MPH general effect closely follows the pattern of their outflow rate. In Flanders, the outflow rate of less educated job seekers (below upper secondary) decreased at a rate equals to -3.1% yearly while it declined more mildly for the higher educated unemployed workers, at a rate of -1.9% yearly. In 1993, the exit rate of the low educated workers had decreased to 46% of the initial rate while this decline amounts to 32% for the high educated workers.

Table 3.4: Marginal effect of each schooling degree on the hazard

	Wallonia			Flanders		
	1973	1993	MPH	1973	1993	MPH
Higher education	-1%	42%	25%	25%	25%	25%
Upper secondary	18%	18%	18%	-5%	19%	9%
Lower secondary	31%	31%	31%	7%	7%	7%

Table 3.4 compares the marginal impact of each schooling degree on the exit rate in 1973 and in 1993, in both regions. We also report the average effect, such as estimated in the MPH model, in order to see the importance of allowing for time-varying covariate effects. In Wallonia, the disparity between exit rates by schooling level was already important in 1973, and reinforced markedly between the highest and the lower education levels over the whole period. For, having a higher education degree did not raise the re-employment rate in 1973, while it increased this rate by 42% in 1993. Table 3.4 also indicates that the disparity between the outflow rate by schooling level increased slightly in Flanders, between the lower and the upper secondary level. Having a upper secondary degree reduced the re-employment probability by 5% in 1973, while it increased the outflow rate by 19% in 1993. However, the disparity by educational attainment remained at a relatively low level in Flanders as compared to Wallonia.

Table 3.5: Effect of living in other provinces than Brabant wallon in Wallonia (resp. Vlaams-Brabant in Flanders) on the hazard

Wallonia	1973	1993	MPH	Flanders	1973	1993	MPH
Hainaut	-18%	-29%	-25%	Antwerpen	5%	-20%	-11%
Liège	-17%	-17%	-17%	Limburg	-37%	-1%	-17%
Namur	1%	-18%	-11%	Oost-Vlaanderen	-11%	-11%	-11%

The difference between the exit rates according to the province of residence also increased in Wallonia. Table 3.5 gives the effect on the outflow rate of living in other provinces than Brabant wallon (resp. Vlaams-Brabant in Flanders), in 1973 and 1993. Luxembourg (resp. West-Vlaanderen in Flanders) is not reported in these tables since both the level and the evolution of the outflow rate in this province is not significantly different than the one estimated in Brabant wallon (resp. Vlaams-Brabant). The re-employment prospects of those living in Hain-

aut were the worst among the provinces of Wallonia in 1973 and continued to deteriorate over the period. The outflow rate of workers living in Namur was similar to the one estimated in Brabant wallon in 1973, but got closer to the one estimated in Liège in 1993. On the contrary, the divergence between the re-employment prospects by province of residence reduced in Flanders. The re-employment prospects of those living in Antwerpen were the most favourable in 1973, but this ranking was reverse at the end of the period in favour of workers living in Limburg.

3.4.2 Tracks of interpretation for the regional divergences

As shown in the previous section, the larger decrease in the aggregate outflow rate in Wallonia over the 1973-1993 period is only due to a stronger trend in the individual re-employment prospects, which is twice as large the one estimated in Flanders. This section also reveals that the deterioration of the re-employment prospects reflects, in both regions, different evolutions across skill groups and provinces, mainly in Wallonia. In this sub-section, we review some possible causes of the regional disparities in Belgium and investigate whether our results can reinforce the existing evidence³⁷.

The stronger deterioration of the re-employment prospects in Wallonia is reflected in the employment growth across the regions of Belgium (see Sneessens *et al.* 1999). Table 3.6 shows the evolution of salaried employment, by sector and sub-periods, in Flanders and Wallonia. Over the 1973-1995 period, employment declined by 1.3% in Wallonia while it increased by 20% in Flanders. Table 3.6 also suggests that the poor employment performance in Wallonia over this period reflects both a more pronounced and persistent shock in the industry sector and an insufficient employment growth in the private services. The employment growth in the public services is similar in the two regions.

³⁷As emphasised in the data section, the rules governing the unemployment benefit scheme and the functioning of the labour market are the same in all regions of Belgium. These factors can therefore not be put forward to explain the regional divergences in Belgium. In footnote n°32, we also argue that the stronger negative trend in the individual exit rate in Wallonia cannot be attributed to a migration of the workers with good re-employment prospects to Flanders.

Table 3.6: Evolution of salaried employment, by sector and sub-periods, in % of the initial regional employment

	Industry		Private services		Public services		Total	
	Wallonia	Flanders	Wallonia	Flanders	Wallonia	Flanders	Wallonia	Flanders
1984/73	-19.1%	-12.5%	3.1%	7.3%	7.2%	5.8%	-8.8%	0.6%
1995/84	-6.6%	-1.0%	10.5%	17.0%	3.7%	3.4%	7.6%	19.4%
1995/73	-25.7%	-13.5%	13.5%	24.3%	10.9%	9.2%	-1.3%	20.0%

Source: Sneessens and Shadman-Mehta (2000, p.117)

Based on a shift-share analysis, some authors argue that the sectorial structure cannot account for the diverging employment growth in Flanders and Wallonia (see Binon *et al.* 1998, Mignolet and Vieslet 2000). This diverging evolution only results from a poor employment performance within the Walloon sectors³⁸. The effect of the sectorial structure appears to be weak or even favourable to Wallonia. This structure is against Wallonia for declining sectors in which the employment rate was high as compared to Flanders, like the iron-steel industry and mining. But at the same time, there are other declining sectors in which Flanders was more specialised. The shift-share analysis does not however provide the reasons of the poor employment performance in Wallonia.

According to Sneessens *et al.* (1999), structural imbalances between skill groups and sub-regions play a crucial role to explain the weakness of job creation in Wallonia³⁹. Their measure of mismatch is based on unemployment rates by level of education and province. The disparity between the demand and the supply of skills is, on average, lower in Flanders than in Wallonia, and increased more markedly in the latter region over the 1973-1993 period. With respect to the regional mismatch, the disparity between provinces became more pronounced in the two regions since the late seventies, but they disappeared progressively in Flanders since the mid eighties. As it is shown above, we obtain similar results based on re-employment probabilities by skill level and province.

³⁸The most detailed analysis distinguishes up to 58 sectors.

³⁹Other explanations are the lack of private investment in Wallonia in the eighties and the large share of public funds invested to declining sectors in this region (see Binon *et al.* 1998). There is no evidence that different evolutions in competitiveness (in terms of wage costs) can account for the diverging employment growth in Flanders and Wallonia.

The stronger rise of imbalances in the Walloon labour market is partly due to the nature of the shocks that hit this region in the seventies and early eighties (see Binon *et al.* 1998 and Sneessens *et al.* 1999). Unlike Flanders, employment losses were concentrated in some important sectors and provinces in Wallonia, particularly the steel and mining industry in the province of Hainaut. The extent of the de-industrialisation, and its concentration in large area, have certainly hampered the development of productive activities in Wallonia and the re-orientation of dismissed workers to growing sectors. Our results can give some lights on the latter fact. Both regions of Belgium lost employment in the steel and mining industry over the 1973-1993 period while they gained jobs in the private services (see Table 3.6). However, the re-employment prospects of workers previously employed in the former sector in Flanders are not significantly different from those of workers coming from the private services in Flanders, contrary to Wallonia (see Table 3.7 in Appendix 4 and Section 3.3.4). Although this result partly reflects larger job destructions in the Walloon industry, it can also indicate a better ability of Flanders to provide dismissed workers from declining sectors with skills suited to the new developing activities. An insufficient effort put into education and training in Wallonia must have played an important role in that respect (see Binon *et al.* 1998).

Concerning the schooling system, it appears that the vocational education in the upper secondary school in Wallonia attracts a larger share of students with poor learning ability as compared to Flanders. This composition effect can prevent the acquisition of skills that are directly valuable on the labour market. Wallonia is also characterised by a lower number of young people who achieve the upper secondary school, particularly with vocational and technical degrees. In a context of skill biased technological change, this feature of the educational system may discourage the emergence of new activities. These factors can explain why the re-employment prospects of workers with an upper secondary degree evolve similarly to those of the lowest educated ones in Wallonia while they evolve similarly to those of workers with higher education in Flanders. Another cause of the deficit of skilled labour in Wallonia is that the share of unemployed workers completing a training scheme

is much lower in this region than in Flanders⁴⁰. Given the particular nature of the de-industrialisation shock, the effort devoted to training should have been much higher in Wallonia.

Finally, we must make two remarks regarding the interpretation of skill and regional mismatches. First, one should be aware that the increasing disparity in the job finding rates by skill level is not solely compatible with a relative deficit of skilled labour. In Chapter 4, we show that these evolutions can partly reflect a more intense crowding out of lower educated workers by higher educated ones when jobs are scarce. Second, the strong disparity between the Walloon provinces also indicates that some of them perform relatively well. With a shift-share analysis, Toulemonde (2000) shows that over the 1973-1992 period, two Walloon provinces (Luxembourg and Brabant wallon) registered one of the best employment performance in Belgium while one Flemish province (Antwerp) was performing badly. According to our results, the aggregate exit rate estimated in Antwerp was actually similar to the one estimated in Luxembourg and Brabant wallon, in 1993. However, the relative size of these provinces in the Walloon labour market is relatively small.

3.5 Simulated stock of unemployment over calendar time

In this last section, we simulate the unemployment stock in June based on the previously estimated MPH model. The objective of this exercise is to determine the relative importance of incidence and duration in the dynamics of unemployment in Flanders and Wallonia. To that purpose, we decompose the variations in the simulated unemployment stock into an incidence and a duration effect by the analysis of variance. Structural and cyclical evolutions are separately investigated. Abbring *et al.* (2001b) follows a similar approach to decompose the cyclical variations in the U.S. unemployment rate into various incidence and duration components.

The unemployment stock is calculated from our inflow data set, i.e. it

⁴⁰Training policies are mostly within the competence of the regions in Belgium.

only accounts for entrants in the month of June. The simulated stock of unemployed workers at calendar time l , u_l , is the sum of the workers entered into unemployment at l and of those entered at $l - k$, $\forall k \in (1, 2, \dots, K)$, and surviving from $l - k$ up to l :

$$u_l = u_{1l} + \sum_{k=1}^K u_{1l-k} \cdot \sum_x \exp \left[- \sum_{i=1}^k \int_{i-1}^i h(t | l - k + t, x) E(v | l - k, T > t) dt \right] \frac{u_{1lx}}{u_{1l}} \quad (3.28)$$

where K is the number of durations accounted for in the simulated stock. The expression which comes after u_{1l-k} is simply the aggregate (mixture) survival function at the end of the duration interval k .

In order to determine the relative role of incidence and duration, we simulate two synthetic series of unemployment. Each series is obtained by fixing the other component to its value at the first calendar time interval, i.e. at $l = 0$. The simulated stock under the assumption that only incidence varies, u_l^{IN} , writes as follows:

$$u_l^{IN} = u_{1l} + \sum_{k=1}^K u_{1l-k} \sum_x \exp \left[- \sum_{i=1}^k \int_{i-1}^i h(t | 1, x) E(v | 0, T > t) dt \right] \frac{u_{10x}}{u_{10}} \quad (3.29)$$

where both the general and the composition effects of the calendar time on the aggregate hazard are fixed at their value at $l = 0$.

The simulated stock under the assumption that only duration varies, u_l^{DU} , is given by:

$$u_l^{DU} = u_{10} \cdot \left(1 + \sum_{k=1}^K \sum_x \exp \left[- \sum_{i=1}^k \int_{i-1}^i h(t | l - k + t, x) E(v | l - k, T > t) dt \right] \frac{u_{1lx}}{u_{1l}} \right) \quad (3.30)$$

where the expression between brackets can be interpreted as the average unemployment duration (over K duration intervals) at calendar time l . Its variation captures both the general and the composition effects of the calendar time.

Since we have an inflow data set, simulating the stock taking into account K duration intervals decreases our series by K simulated values. This could bias the relative share of structural and cyclical evolutions in the total variation of unemployment. For instance, the number of entrants is increasing at rates equal to 3.9% and 4.6% yearly over the 1972-1992 period, in Flanders and Wallonia respectively, while these rates are only equal to 0.8% and 2.3% over the 1975-1992 period⁴¹. This problem would justify to simulate the unemployment stock for short term unemployed workers only ($K = 1$), which allows for a decomposition over the 1973-1992 period. On the other hand, the role of duration will be underestimated by considering only one duration interval in the unemployment stock. For, variations in incidence lead to variations in the average unemployment duration when the conditional hazard exhibits true negative duration dependence. By focusing on the first duration interval only, we ignore this relationship and, as a result, we decrease the variability of duration. In order to limit the potential biases, we decide to examine the relative importance of structural and cyclical evolutions based on the stock of short term unemployment. The relative role of duration and incidence in the variability of unemployment is analysed for a more representative unemployed population. In the benchmark simulation, we choose $K = 3$, which allows for a simulation of unemployment over the 1975-1992 period, i.e. $\forall l \in \{3, 4, \dots, 20\}$. We then investigate the sensitivity of our results by including more duration intervals in the unemployment stock.

In order to quantify the relative importance of each component of the unemployment stock dynamics, we use the same analysis of variance than the one developed in Appendix 2. We calculate the exponential trend in the two synthetic series (u_l^{IN} , u_l^{DU}) and we assume that the sum of these trends is equal to the trend in the total stock (u_l). We then regress the de-trended logarithm of the total stock on the de-trended logarithm of the two synthetic series. On the basis of these model estimates, we calculate the part of the total variation in the unemployment stock that is accounted for by a structural and a cyclical variation. Each type of variation is decomposed into the proportion explained by an incidence and a duration effect.

⁴¹These rates are the same whether they are calculated on u_l^{IN} or u_{1l} .

Changes in unemployment are dominated by a positive trend in Wallonia while cyclical changes appear to be relatively more important in Flanders: 54% of the variation in unemployment is accounted for by a structural variation while this share is only equal to 27% in Flanders. This difference is explained by a stronger positive trend in duration and incidence in Wallonia. As regards to the relative role of duration and incidence, we simulate the unemployment stock up to $K = 7$ to obtain stable results. In Wallonia, 57% of changes in unemployment results from changes in duration⁴², while 43% results from variations in incidence. The decomposition is similar in Flanders: 55% of the total variability in unemployment is due to changes in duration⁴³ and 45% in incidence.

So our results indicate that *both* duration and incidence matter in the variation of unemployment in Belgium. The common belief is that changes in incidence is largely irrelevant in Europe (see, e.g., Layard *et al.* 1991; Mortensen and Pissarides 1999), such as claimed by Burgess and Thuron (2000, p.2) in their critique on the referred authors. Our estimated figures are actually close to those obtained by Abbring *et al.* (2001b) for U.S. Adopting a similar decomposition approach, they find that 57% of the cyclicalities in the U.S. unemployment rate is due to changes in duration and 43% to incidence.

The role of duration dependence on the simulated stock is illustrated in Figures 3.13 and 3.14, for Flanders and Wallonia respectively. These Figures compare the total stock of unemployment in June such as reported by the official statistics and the simulated stock of unemployment for $K = 1$, $K = 3$ and $K = 7$.

⁴²The relative contribution of duration is 60% and 56% in the structural and cyclical dimension respectively.

⁴³The relative contribution of duration is 51% and 69% in the structural and cyclical dimension respectively.

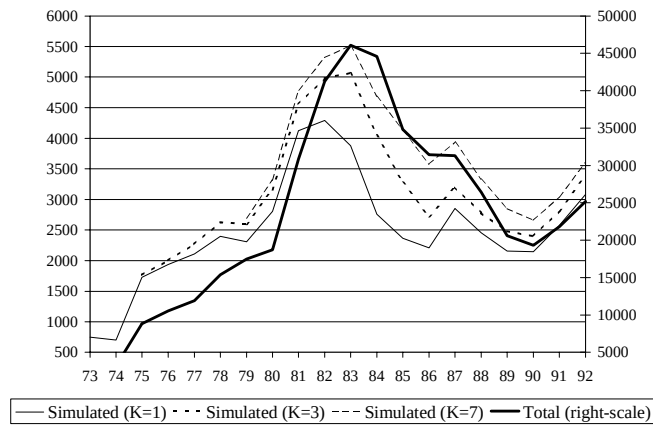


Figure 3.13: Stock of unemployment in June - Flanders

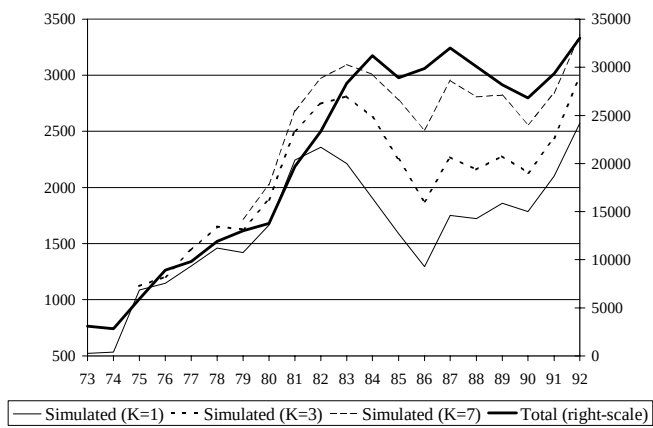


Figure 3.14: Stock of unemployment in June - Wallonia

When considering more duration intervals, the divergence between the simulated stock and the total stock decreases due to the smaller bias in the unemployment duration. Even if it only accounts for workers entered into unemployment in the month of June, the simulated stock fits the total stock of unemployment reasonably well. There is one exception, in 1986, where the simulated stock is decreasing while the total stock is mildly increasing. This divergence comes from a different evolution of the June inflow as compared to the evolution of the monthly average inflow, such as reported by the public employment agency. The inflow in June 1986 was substantially lower than the monthly average.

3.6 Conclusion

In this chapter, we investigated whether the diverging evolution in the unemployment stock in Flanders and Wallonia can be explained by different evolutions in their average unemployment duration and/or their unemployment incidence. To that purpose, we proceeded in two stages. In the first stage, we estimated a MPH model by region, and decompose variations in the aggregate outflow rate over calendar time between a general effect and a composition effect. We also specified a non-proportional model to check whether the general effect of the calendar time was the same for unemployed workers with different schooling levels and sub-region of living, in each region. In the second stage, we decomposed variations of the unemployment stock in Flanders and Wallonia into an incidence effect and the duration effect estimated in the first stage.

Over the 1973-1993 period, unemployment increased more markedly in Wallonia due to a stronger trend in average unemployment duration and, to a less extent, a more positive trend in incidence. As a consequence, changes in unemployment are dominated by an upward trend in Wallonia while cyclical changes are relatively more important in Flanders. Our results indicate that the composition of the unemployed population cannot explain the larger trend in the average unemployment duration in Wallonia. On the contrary, the structural rise in duration would have been higher in both regions if the average quality of entrants had not improved over the period. The larger increase in the average duration in

Wallonia is only due to a stronger trend in individual durations, which is twice as large as the one estimated in Flanders.

On the basis of our results, we also conclude that disemployability effects, even if they play a role, cannot explain a stronger trend in unemployment duration in Wallonia. For, genuine negative duration dependence is less important in this region than in Flanders. In the latter region, the relatively large degree of true negative duration dependence could partly account for the slight positive trend in its average unemployment duration: The existence of disemployability could have somewhat tempered the employment growth in Flanders over the eighties.

According to our results, the deterioration of the hiring probability in both regions reflects different evolutions across skill groups and provinces. In Wallonia, the disparity between exit rates by schooling level was already important in 1973, and reinforced markedly over the whole period. Having a higher education degree did not raise the re-employment rate in 1973, while it increased this rate by 42% in 1993. The disparity between the outflow rate by schooling level also widened in Flanders, but remained at a low level as compared to Wallonia. Moreover, the difference between the exit rates according to the province of residence rose in Wallonia while it reduced in Flanders. The hiring prospects of unemployed workers living in Hainaut were the worst among the provinces of Wallonia in 1973 and deteriorated steadily over the period. Our findings therefore suggest that even if composition effects cannot account for the structural drop in the outflow rate, there is a scope for labour market policies aimed at specific groups of unemployed workers.

Our results are therefore consistent with other Belgian studies (see Binon *et al.* 1998, Sneessens *et al.* 1999) which claim that structural imbalances between skill groups and sub-regions play an important role to explain the deterioration of the employment prospects in Wallonia. Two factors play a role here. First, unlike Flanders, employment losses were concentrated in some important sectors and provinces in Wallonia, particularly the steel and mining industry in the province of Hainaut. The extent of the de-industrialisation, and its concentration in large area, have certainly hampered the development of productive activities in Wallonia. An insufficient effort put into education and training in Wallonia also prevented to provide a large number of dismissed workers

with the appropriate skills required by the new developing activities.

The cyclical nature of unemployment is very similar in the two regions of Belgium and is characterised by a strong countercyclicality, in which variations in unemployment duration are slightly more important. In both regions, the cyclical variability in duration is driven by cyclical variations in the individual durations rather than by composition effects. Our results are thus in line with most of the studies based on European data, which conclude that composition effects are of minor importance to account for cyclical fluctuations in the aggregate hazard. Individual durations are countercyclical, their pattern being very similar in Flanders and in Wallonia over the whole period. Even if its impact on the aggregate hazard is marginal, we can state that the composition of the inflow is countercyclical in both regions: The average quality of entrants into unemployment increases during recessions and falls in upturns. This result suggests that employers fire the most able workers only if they have no alternative, i.e. in a recession. Less able workers are made redundant all the time.

One important conclusion of our results is also that *both* duration and incidence matter in the (cyclical and structural) variation of unemployment in Belgium while the common belief is that changes in incidence is largely irrelevant in Europe.

3.7 Appendix

3.7.1 Appendix 1: Data correction

In this appendix, we describe the correction procedure applied to the non-parametric outflow probabilities, $\hat{P}_{klx}$. The reason for correcting the data relates to their particular feature. The non-observability of the individual spells of unemployment, and the consecutive grouping of the data, induces two sources of spurious outflows: (1) Changes in time-varying characteristics during the unemployment spell and (2) temporary exits out of unemployment (of less than three months). In the sequel of this appendix, we first assume the absence of temporary exits and derive the appropriate correction to $\hat{P}_{klx}$. We then analyse the consequences of temporary exits. An identification problem leads us to consider two alternative corrections of the data.

No temporary exits

Denote u_{kl}^{yx} the number of individuals with entry date l and characteristics x at the beginning of duration interval k , who had characteristics y at the beginning of duration $k-1$, where x and y are two vectors of characteristics which can be identical. Also denote $u_{kl}^{\cdot x} = \sum_y u_{kl}^{yx}$, $u_{kl}^{y \cdot} = \sum_x u_{kl}^{yx}$, and $u_{kl}^{\cdot \cdot} = \sum_x \sum_y u_{kl}^{yx} = \sum_x \sum_y u_{kl}^{xy}$.

The true number of individuals with entry date l and characteristics x at the start of duration interval k that leave unemployment during this interval is given by:

$$\tilde{f}_{klx} = u_{kl}^{\cdot x} - u_{k+1l}^{x \cdot} \quad (\text{a})$$

In our data set, we can only condition on the characteristics of the current state since we cannot track individual spells through time. In other words we do not observe $u_{k+1l}^{x \cdot}$ but only u_{k+1l}^x . The number of individuals with entry date l and characteristics x at the start of duration interval k that leave unemployment during this interval is therefore approximated by:

$$f_{klx} = u_{kl}^{\cdot x} - u_{k+1l}^{\cdot x} \quad (\text{b})$$

This approximation is subject to two sources of bias which can possibly cancel out. First, an individual counted in $u_{kl}^{\cdot x}$ can move from x to y at the k^{th} duration interval without flowing out of unemployment. In that case, the number of outflows f_{klx} increases spuriously of one unit ($u_{k+1l}^{\cdot x}$ decreases of one unit). Second, an individual counted in $u_{kl}^{\cdot y}$ can move from y to x at the k^{th} duration interval without flowing out of unemployment. Then, the number of outflows f_{klx} decreases spuriously of one unit ($u_{k+1l}^{\cdot x}$ increases of one unit). The number of spurious outflows in the k^{th} duration interval conditional on entry date l and characteristics x at the start of duration interval k is given by:

$$\begin{aligned} f_{klx}^S &= f_{klx} - \tilde{f}_{klx} = -u_{k+1l}^{\cdot x} + u_{k+1l}^{\cdot x} \\ &= -u_{k+1l}^{xx} - \sum_{y \neq x} u_{k+1l}^{yx} + u_{k+1l}^{xx} + \sum_{y \neq x} u_{k+1l}^{xy} \\ &= \sum_{y \neq x} (-u_{k+1l}^{yx} + u_{k+1l}^{xy}) \end{aligned} \quad (\text{c})$$

where u_{k+1l}^{yx} (resp. u_{k+1l}^{xy}) are the number of individuals that become of type x (resp. y) in the k^{th} duration interval conditional on being of another type at the beginning of this interval. The term u_{k+1l}^{yx} (resp. u_{k+1l}^{xy}) leads to an underestimation (resp. overestimation) of the non-parametric outflow probability, $\hat{P}_{klx}$.

Notice that at the aggregate level, there is no spurious outflows (by use of (c)):

$$f_{kl}^S = \sum_x f_{klx}^S = \sum_x (-u_{k+1l}^{\cdot x} + u_{k+1l}^{\cdot x}) = -u_{k+1l}^{\cdot \cdot} + u_{k+1l}^{\cdot \cdot} = 0 \quad (\text{d})$$

This amounts to saying that over- and underestimations cancel out at the aggregate level:

$$\sum_{y \neq x} (-u_{k+1l}^{y \cdot} + u_{k+1l}^{\cdot y}) = 0 \Leftrightarrow \sum_{y \neq x} u_{k+1l}^{y \cdot} = \sum_{y \neq x} u_{k+1l}^{\cdot y} \quad (\text{e})$$

The aggregate non-parametric outflow probability, $\hat{P}_{kl\cdot}$, is therefore unbiased:

$$\hat{P}_{kl\cdot} \equiv \frac{\sum_x \tilde{f}_{klx}}{\sum_x u_{kl}^x} = \frac{\sum_x f_{klx}}{\sum_x u_{kl}^x} \quad (\text{f})$$

Finally note that we can only use observations with f_{klx} such that $0 \leq f_{klx} \leq u_{kl}^x$ to ensure that $0 \leq \hat{P}_{klx} \equiv \frac{f_{klx}}{u_{kl}^x} \leq 1$. This implies that before calculating $\hat{P}_{klx}$, we suppress all observations which do not satisfy the condition:

$$u_{k+1l}^x \leq u_{kl}^x \quad (\text{g})$$

Now suppose that cohorts are defined such that they are unique, i.e. $0 \leq u_{kl}^x \leq 1$. In that case, if $u_{k+1l}^x = u_{k+1l}^{yx} = 1$ ($y \neq x$), then $u_{kl}^x = 0$. Since the vector x is unique and the individual had characteristics y in interval k ($u_{kl}^y = 1$), there must be nobody with characteristics x in interval k . If we insert this in condition (g), we immediately see that this condition is always violated:

$$u_{k+1l}^x = 1 > u_{kl}^x = 0 \quad (\text{h})$$

The term u_{k+1l}^x should lead to an underestimation of the non-parametric outflow probability $\hat{P}_{klx}$ (see (c)). However, this type of observation will never be considered in the construction of $\hat{P}_{klx}$ since it violates condition (g).

On the other hand, if $u_{k+1l}^x = u_{k+1l}^{xy} = 1$ ($y \neq x$), then $u_{kl}^x = 1$ and condition (g) can never be violated:

$$u_{k+1l}^x = 0 \leq u_{kl}^x = 1 \quad (\text{i})$$

In that case, $u_{k+1l}^x = 0$ since the vector x is unique.

Consequently, when observations violating (g) are suppressed and cohorts are unique, spurious outflows always leads to an overestimation of the outflow (see (c)):

$$f_{klx}^S = \sum_{y \neq x} u_{k+1l}^{xy} \geq 0 \quad (\text{j})$$

Under the assumption of uniqueness, the number of spurious outflows in cohort l at duration interval k is therefore given by:

$$f_{kl.}^S = \sum_{y \neq x} u_{k+1l}^{y.} = \sum_{y \neq x} u_{k+1l}^{y.} \quad (\text{k})$$

where the last equality follows from (e). The number of spurious outflows is simply the number of transitions in cohort l at interval k from some y to x ($y \neq x$). This figure is known by our assumption: It is the number of individuals who violate condition (g):

$$f_{kl.}^S = \sum_x u_{k+1l}^{x.} \text{ for all observations s.t. } u_{kl}^{x.} < u_{k+1l}^{x.} \quad (\text{l})$$

We now assume that the number of spurious exits in cohort (l, x) during the k^{th} interval is proportional to this number with a factor of proportionality $(\frac{f_{klx}}{f_{kl.}})^{44}$:

$$\widehat{f}_{klx}^S = \left(\frac{f_{klx}}{f_{kl.}} \right) f_{kl.}^S \quad (\text{m})$$

This assumption of proportionality is arbitrary. Imagine for example that a majority of changes occur almost systematically between two levels of education. In that case, the proportional form (m) would clearly lead to large biases in the estimate of the true f_{klx}^S . We have however no reason to think that changes follow systematic patterns. In particular, we know that they cannot be attributed mostly to one variable. The proportionality assumption appears as the best alternative given the lack of better information.

⁴⁴The factor of proportionality depends on the fraction of observed transitions $\frac{f_{klx}}{f_{kl.}}$ rather than on $\frac{u_{klx}}{u_{kl.}}$ since we need only correct when there are effectively transitions in x .

The corrected non-parametric outflow probability, $\hat{P}_{klx}^*$, writes therefore as follows:

$$\hat{P}_{klx}^* = \frac{f_{klx} - \hat{f}_{klx}^S}{u_{kl}^x} = \left(1 - \frac{f_{kl\cdot}^S}{f_{kl\cdot}}\right) \frac{f_{klx}}{u_{kl}^x} = \left(1 - \frac{f_{kl\cdot}^S}{f_{kl\cdot}}\right) \hat{P}_{klx} \quad (\text{n})$$

If some cohorts are not unique, spurious outflows may lead to an underestimation of the outflows ($u_{k+1l}^{yx} > 0$ with condition (g) not violated) and $f_{kl\cdot}^S$ in (1) will not give (as a consequence) all the transitions in cohort l at interval k from some y to x ($y \neq x$). However, we will assume that if $u_{k+1l}^{yx} > 0$, condition (g) is always violated. We believe that this assumption is justified since a large majority of the cohorts are unique in our data set (93% at the entry into unemployment).

Departing from the uniqueness assumption requires however to adapt expression (1) in the following way:

$$f_{kl\cdot}^S = \sum_x (u_{k+1l}^x - u_{kl}^x) \text{ for all observations s.t. } u_{kl}^x < u_{k+1l}^x \quad (\text{o})$$

since if $u_{k+1l}^{yx} > 0$, u_{kl}^x is no more necessarily equals to 0 (although $u_{kl}^x < u_{k+1l}^{yx}$ by assumption).

Temporary exits

In Belgium, unemployed people who exit unemployment for a period of less than three months keep the same starting date of their unemployment spell at their return. The purpose of this rule is to maintain for the unemployed person the right to benefit from measures which are conditional to a given elapsed duration into unemployment⁴⁵. Given that the census of the unemployed workers occurs on June 30, it happens that some unemployed are not counted at a given year because they are in a training scheme or have a temporary job that day. However they are still unemployed and counted as such in a following census.

Temporary exits introduce an additional bias in our measure of the number of individuals in cohort (l, x) that leave unemployment during

⁴⁵Like the right to participate to active job-search workshop, vocational training and in-depth personal counseling.

the k duration interval, f_{klx} given in (b). If an individual counted in u_{kl}^x exits unemployment temporarily around the start of the $k + 1$ duration interval and returns within the next *three months*, then the number of outflows f_{klx} increases spuriously with one unit (since u_{k+1l}^x spuriously decreases of one unit). On the other hand, if an individual counted in u_{k+1l}^x was temporarily out of unemployment around the start of the k duration interval and returned within the next three months, the number of outflows f_{klx} increases spuriously with one unit (since u_{kl}^x spuriously increased with one unit).

Suppose again that cohorts are defined such that they are unique, i.e. $0 \leq u_{kl}^x \leq 1$. In that case, a temporary exit around the $k + 1$ duration interval always induces an overestimation of the outflows at the k^{th} interval: $u_{kl}^x = 1$ and $u_{k+1l}^x = 0$. In other respects, a temporary exit around the k duration interval followed by a *sufficiently long* unemployment spell always leads to a violation of condition (g): $u_{kl}^x = 0$ and $u_{k+1l}^x = 1$. We can therefore identify which $u_{kl}^x = 0$ corresponds to a temporary exit and correct appropriately for it. Of course, if an individual really flows out of unemployment during the year that follows his temporary exit, we will not be able to spot this temporary exit since condition (g) is not violated.

Formally, if condition (g) is violated at the k duration interval and the following condition holds simultaneously:

$$\exists j \in \{1, \dots, k - 1\} \mid u_{jl}^x = 1 \quad (p)$$

then $u_{kl}^x = 0$ is a temporary exit. If $j < k - 1$, the individual was temporary out of unemployment on June 30 several years consecutively, and all $u_{il}^x = 0$ with $i \in \{j + 1, \dots, k - 1\}$ are temporary exits. Notice that under the uniqueness assumption, the problem of temporary exits differs from the one of changing variables by condition (p). For, this condition is never satisfied when condition (g) is violated in the latter case. We simply correct the identified spurious risk sets by setting them to 1. This correction is done in the first place. We then calculate the number of spurious outflows due to changing characteristics (see (l)) and apply the correction (n) to the non-parametric outflow probability, $\hat{P}_{klx}$, by suppressing beforehand observations which violate (g).

When some cohorts are not unique, temporary exits are observationally equivalent to a problem of changing characteristics. Notice first then that departing from the uniqueness assumption requires to adapt condition (p) to the case of several individuals per cohort:

$$\exists j \in \{1, \dots, k-1\} \mid u_{jl}^x > u_{kl}^x \quad (q)$$

A violation of condition (g) at the k duration interval together with condition (q) satisfied are now necessary to have a case of temporary exit(s). If we neglect the problem of changing variables, the correction procedure is the following. First select the largest j such that condition (q) is satisfied. The number $u_{jl}^x - u_{kl}^x$ is then the number of individuals who exit temporarily. If $j = k-1$, we correct the risk sets u_{kl}^x as follows: $(u_{kl}^x)^* = u_{kl}^x + \text{Min}(u_{jl}^x - u_{kl}^x, u_{k+1l}^x - u_{kl}^x)$. If $j < k-1$, the individual(s) was (were) temporary out of unemployment on June 30 several years consecutively, and we correct all risk sets u_{il}^x with $i \in \{j+1, \dots, k\}$ as follows: $(u_{il}^x)^* = u_{il}^x + \text{Min}(u_{jl}^x - u_{il}^x, u_{k+1l}^x - u_{il}^x)$. This procedure has to be repeated until it is no more possible to find a j such that condition (q) is satisfied. All the temporary exits on June 30 from the consecutive unemployment censuses are then corrected.

However, a violation of condition (g) alongside with condition (q) fulfilled can now be interpreted as follows: An individual entered into unemployment at l moves from y to x in the k^{th} duration interval while there was another individual in cohort (l, x) at some duration $j < k$ who flows out of unemployment since then. However, we will assume that if condition (g) is violated and condition (q) satisfied, we have a case of temporary exit. We believe that this assumption is justified for the following reason. Since a large majority of the cohorts are unique in our data set (93% at entry), most of the spurious outflows due to changing characteristics will be picked out in cohorts where both conditions (g) and (p) are violated. In our data set, this concerns 7% of the total number of cohorts (and the same share of the total number of entrants). And from preliminary analysis on the data base, we approximate the number of individuals with changing variables to around 8% of the total number of entrants. In other respects, around 3% of the total number of cohorts satisfies the conditions required to pick out temporary exits. We

think that this number is too high to be, in a large majority, attributed to a problem of time-varying characteristics.

We therefore correct the spurious risk sets which can be attributed to temporary exits in the way explained *supra*. This correction is done in the first place. We then calculate the number of spurious outflows due to changing characteristics (see (o)) and apply the correction (n) to the non-parametric outflow probability, $\hat{P}_{klx}$, by suppressing beforehand observations which violate (g). As a sensitivity analysis, we construct another data set in which we assume the absence of temporary exits. This means that we consider the 3% of the total number of cohorts that violates conditions (g) and satisfies (q) as cases of time-varying characteristics. So we only follow the correction procedure of the first section of this appendix. We estimate the mixed proportional hazard model (3.14) based on these two alternative data sets. The 95%-confidence intervals of the estimated parameters in the two models overlap. For the reason outlined above, we choose to use the first data set.

3.7.2 Appendix 2: Variance decomposition

In this appendix, we derive the part of the total variation in the aggregate hazard, $\bar{h}_{1l}$ in (3.20), that is accounted for by a structural and a cyclical variation. Each type of variation is decomposed into the part explained by a general effect, an observed and unobserved composition effect. To that purpose, we first introduce the following notations: $y_l = \ln(\bar{h}_{1l})$, $x_{1l} = \ln(\bar{h}_{1l}^G)$, $x_{2l} = \ln(\bar{h}_{1l}^{OC})$ and $x_{3l} = \ln(\bar{h}_{1l}^{UC})$. We then regress the de-trended logarithm of the aggregate hazard on the de-trended logarithm of the three synthetic series:

$$y_l - \hat{b}(l - \bar{l}) = a + c_1 e_{1l} + c_2 e_{2l} + c_3 e_{3l} + \varepsilon_l$$

$$\text{with } e_{1l} = x_{1l} - \hat{\beta}_1 l; e_{2l} = x_{2l} - \hat{\beta}_2 l; e_{3l} = x_{3l} - \hat{\beta}_3 l; \hat{b} = \hat{\beta}_1 + \hat{\beta}_2 + \hat{\beta}_3$$

where $\bar{l}$ is the average value of l . In this regression, we assume that the sum of the exponential trends in the synthetic series is equal to the exponential trend in the aggregate hazard. The total variation in the aggregate hazard then decomposes as follows:

$$\sum_l (\hat{y}_l - \hat{a})^2 =$$

$$\left\{ \begin{array}{l} \underbrace{\hat{\beta}_1 \hat{b} \sum_l (l - \bar{l})^2}_G + \underbrace{\hat{\beta}_2 \hat{b} \sum_l (l - \bar{l})^2}_{OC} + \underbrace{\hat{\beta}_3 \hat{b} \sum_l (l - \bar{l})^2}_{UC} \\ + \hat{c}_1 \hat{b} \sum_l (l - \bar{l}) e_{1l} + \hat{c}_2 \hat{b} \sum_l (l - \bar{l}) e_{2l} + \hat{c}_3 \hat{b} \sum_l (l - \bar{l}) e_{3l} \end{array} \right\} \text{Trend}$$

$$\left\{ \begin{array}{l} + \hat{c}_1^2 \sum_l (e_{1l})^2 + \hat{c}_1 \hat{c}_2 \sum_l e_{1l} e_{2l} + \hat{c}_1 \hat{c}_3 \sum_l e_{1l} e_{3l} \\ + \hat{c}_2^2 \sum_l (e_{2l})^2 + \hat{c}_1 \hat{c}_2 \sum_l e_{1l} e_{2l} + \hat{c}_2 \hat{c}_3 \sum_l e_{2l} e_{3l} \\ + \hat{c}_3^2 \sum_l (e_{3l})^2 + \hat{c}_1 \hat{c}_3 \sum_l e_{1l} e_{3l} + \hat{c}_2 \hat{c}_3 \sum_l e_{2l} e_{3l} \\ + \hat{c}_1 \hat{b} \sum_l (l - \bar{l}) e_{1l} + \hat{c}_2 \hat{b} \sum_l (l - \bar{l}) e_{2l} + \hat{c}_3 \hat{b} \sum_l (l - \bar{l}) e_{3l} \end{array} \right\} \text{Cycle}$$

where *Trend* and *Cycle* refer to the part of the total variation in y_l that is accounted for a structural and a cyclical evolution respectively, and where G , OC and UC refer to the part explained by the general, observed composition and unobserved composition effects in each type of evolution. The total variation of y_l in the structural and cyclical dimensions is simply the sum of G , OC and UC in each of these dimensions. The ratio between each component and its corresponding total variation measures the proportion of the variance in the aggregate hazard accounted for each component.

Some components of the variance of y_l could, however, be negative, reflecting either a negative estimated parameter ($\hat{\beta}_i$) in the trend decomposition or a negative covariance between two effects in the trend or cyclical decomposition. Intuitively, a negative (resp. positive) covariance between two components reduces (resp. amplifies) the variability in the aggregate hazard since both components moves in the opposite (resp. same) direction. If one part of the variance of y_l is negative, we assume that the total variability in y_l is a weighted sum of each of its components, in which the weights sum to one. These weights measure the proportion of the variance of y_l accounted for by each component.

3.7.3 Appendix 3: Figures

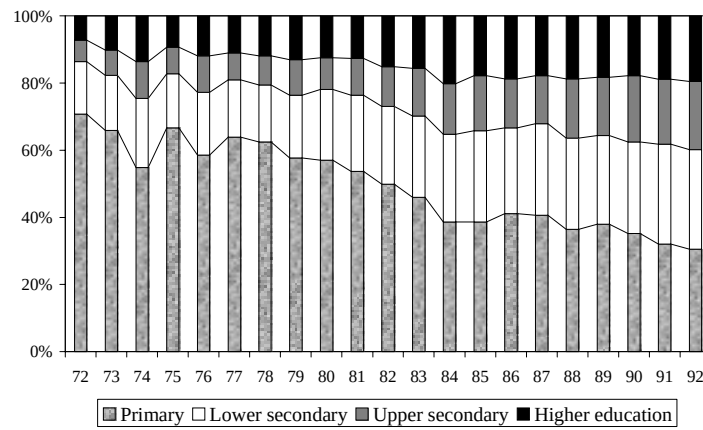


Figure 3.15: Distribution of the level of education at entry - Flanders



Figure 3.16: Distribution of the level of education at entry - Wallonia

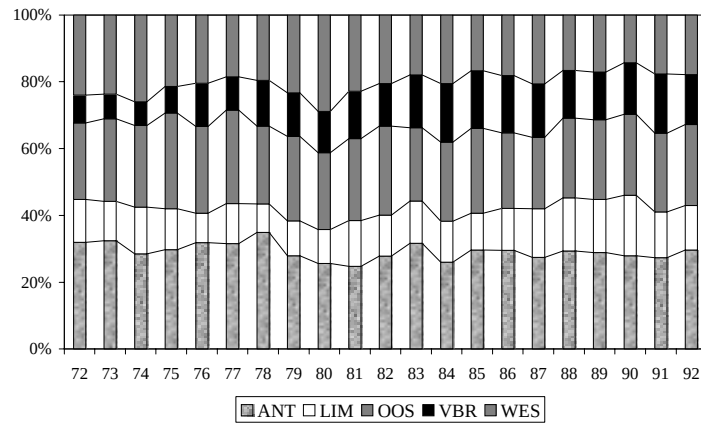


Figure 3.17: Distribution of the province of residence at entry - Flanders

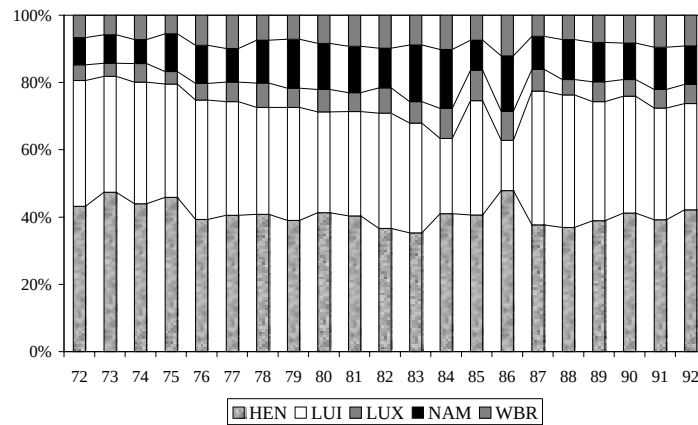


Figure 3.18: Distribution of the province of residence at entry - Wallonia



Figure 3.19: Distribution of the sector at entry - Flanders

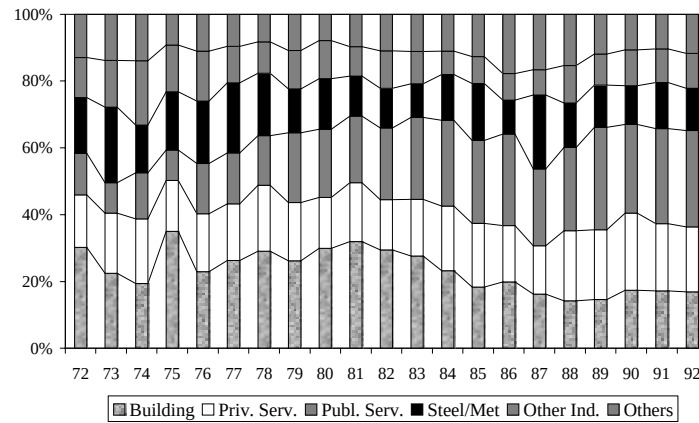


Figure 3.20: Distribution of the sector at entry - Wallonia

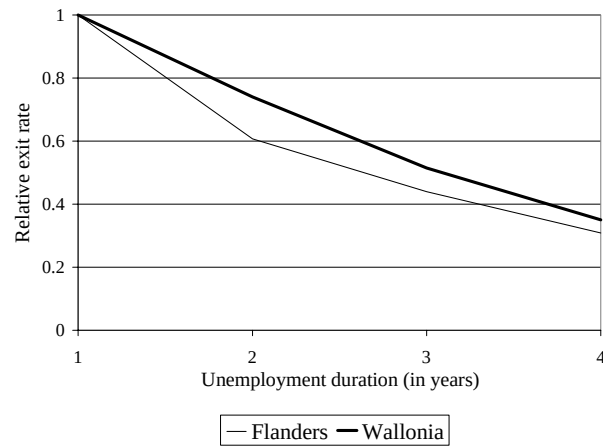


Figure 3.21: Baseline hazard

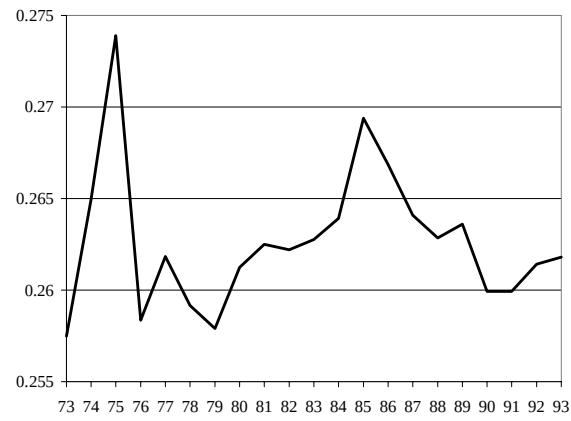


Figure 3.22: Observed composition effect over the cycle - Flanders



Figure 3.23: Observed composition effect over the cycle - Wallonia

3.7.4 Appendix 4: Estimation results

Table 3.7: Hazard model estimates - Mixed Proportional Hazard Model

Variables	Flanders	SD	Wallonia	SD
Constant term*	3.42	0.16	2.25	0.18
1. Covariate effects				
Age (in months - log)	-0.87	0.04	-0.64	0.05
Education				
Junior high school	0.22	0.02	0.27	0.02
Completed high school	0.31	0.02	0.43	0.03
Higher education	0.37	0.02	0.65	0.03
Sub-region of living				
Antwerpen	-0.08	0.02		
Limburg	-0.19	0.02		
Oost-Vlaanderen	-0.12	0.02		
West-Vlaanderen	0.04	0.02		
Liège			-0.19	0.03
Luxembourg			0.02	0.04
Namur			-0.11	0.03
Hainaut			-0.29	0.03
Sector of previous employment				
Agriculture	0.41	0.06	0.18	0.08
Iron-steel industry and mining	0.13	0.06	-0.14	0.06
Metal manufacture	0.08	0.04	0.07	0.05
Manufacture of non-metallic products	0.01	0.07	-0.16	0.08
Manufacture of consumption and investment goods	0.07	0.04	0.01	0.06
Other industries	0.18	0.06	0.06	0.09
Energy and water production	-0.12	0.12	-0.11	0.13
Building	0.12	0.04	0.14	0.05
Private services	0.19	0.04	0.24	0.05
Public services	0.02	0.04	0.04	0.05
Others	0.20	0.06	0.52	0.07
No previous employment	0.14	0.05	0.05	0.07

Note: In **bold**, estimates not significantly different from zero at 5%.

* Reference individual in Flanders (resp. Wallonia): Elementary school, Vlaams-Brabant (resp. Brabant wallon), Chemical industry, $v = 1$.

(Table continued on next page)

Table 3.7: (Continued)

2. Calendar time at outflow			
	α_1	-0.42 0.02	-0.70 0.03
	α_2	0.49 0.02	0.46 0.02
	α_3	-0.23 0.01	-0.12 0.02
	α_4	-0.08 0.01	-0.10 0.02
	α_5	-0.01 0.01	-0.07 0.01
	α_6	0.12 0.01	0.00 0.01
	α_7	0.03 0.01	0.11 0.01
	α_8	-0.11 0.01	-0.05 0.01
	α_9	0.06 0.01	0.02 0.01
	α_{10}	-0.04 0.02	-0.03 0.02
	α_{11}	-0.02 0.01	-0.06 0.01
	α_{12}	-0.13 0.01	-0.08 0.01
3. Duration (in years)			
	2 $(\gamma_2 - c)$	-0.50 0.03	-0.30 0.03
	3 $(\gamma_3 - c)$	-0.82 0.04	-0.67 0.05
	4 $(\gamma_4 - c)^{**}$	-1.18 0.05	-1.05 0.06
4. Variance of the Gamma at $l=0$			
	η_c	-1.84 0.14	-1.73 0.16
	$\sigma_0^2 = \exp(\eta_c)$	0.16 0.02	0.18 0.03
5. Calendar time at inflow			
	η_1	0.20 0.04	0.35 0.05
Number of estimated parameters		38	38
Number of observations		63793	45987
Weighted sum of squared residuals		52089.6	35944.5
Adjusted number of parameters (after regrouping)		22	22
Adjusted number of observations (after regrouping)		420	420
Adjusted weighted sum of squared residuals (after regrouping)		541.66	544.76
P-value of the goodness-of-fit test		0.00	0.00

** $\gamma_{21} = \dots = \gamma_4$

Table 3.8: Hazard model estimates - Mixed Non-Proportional Hazard Model - Flanders

Variables	Benchmark	SD	Restrictions	SD
Constant term [*]	3.46	0.16	3.46	0.16
1. Covariate effects (time dependent)				
Age (in months - log)	-0.88	0.04	-0.88	0.04
Education				
Elementary school				
β1	-0.36	0.08	-0.44	0.03
β2	0.52	0.03	0.49	0.02
β3	-0.23	0.02	-0.23	0.01
β4	-0.08	0.02	-0.08	0.01
β5	-0.02	0.01	-0.01	0.01
β6	0.13	0.01	0.12	0.01
β7	0.05	0.01	0.03	0.01
β8	-0.10	0.02	-0.11	0.01
β9	0.08	0.02	0.06	0.01
β10	-0.05	0.02	-0.04	0.02
β11	-0.02	0.02	-0.02	0.01
β12	-0.15	0.02	-0.13	0.01
Junior high school				
β0	0.19	0.03	0.23	0.02
β1	-0.30	0.09	-0.44	0.03
β2	0.45	0.05	0.49	0.02
β3	-0.19	0.03	-0.23	0.01
β4	-0.08	0.03	-0.08	0.01
β5	0.00	0.03	-0.01	0.01
β6	0.10	0.03	0.12	0.01
β7	0.02	0.03	0.03	0.01
β8	-0.12	0.03	-0.11	0.01
β9	0.02	0.03	0.06	0.01
β10	-0.02	0.04	-0.04	0.02
β11	-0.05	0.03	-0.02	0.01
β12	-0.10	0.03	-0.13	0.01

Note: In **bold**, estimates not significantly different from zero at 5%.
In grey, restricted parameters.

* Reference individual: Elementary school, Vlaams-Brabant, Chemical industry, $v = 1$.

(Table continued on next page)

Table 3.8: (Continued)

Completed high school			
β_0	0.27 0.05	0.29 0.02	
β_1	-0.29 0.11	-0.33 0.03	
β_2	0.45 0.07	0.49 0.02	
β_3	-0.24 0.05	-0.23 0.01	
β_4	-0.07 0.05	-0.08 0.01	
β_5	0.01 0.04	-0.01 0.01	
β_6	0.03 0.04	0.12 0.01	
β_7	0.10 0.04	0.03 0.01	
β_8	-0.20 0.05	-0.11 0.01	
β_9	0.10 0.05	0.06 0.01	
β_{10}	-0.03 0.05	-0.04 0.02	
β_{11}	-0.01 0.04	-0.02 0.01	
β_{12}	-0.09 0.04	-0.13 0.01	
Higher education			
β_0	0.30 0.04	0.35 0.02	
β_1	-0.18 0.10	-0.33 0.03	
β_2	0.44 0.06	0.49 0.02	
β_3	-0.24 0.05	-0.23 0.01	
β_4	-0.08 0.05	-0.08 0.01	
β_5	-0.01 0.04	-0.01 0.01	
β_6	0.14 0.04	0.12 0.01	
β_7	-0.02 0.04	0.03 0.01	
β_8	-0.04 0.04	-0.11 0.01	
β_9	0.03 0.04	0.06 0.01	
β_{10}	-0.02 0.04	-0.04 0.02	
β_{11}	-0.01 0.03	-0.02 0.01	
β_{12}	-0.11 0.04	-0.13 0.01	
Sub-region of living			
Antwerpen (β_0)	-0.05 0.02	-0.06 0.02	
($\beta^*_1 - \beta_1$)	-0.15 0.04	-0.12 0.03	
Limburg (β_0)	-0.22 0.02	-0.23 0.02	
($\beta^*_1 - \beta_1$)	0.15 0.04	0.23 0.03	
Oost-Vlaanderen (β_0)	-0.11 0.02	-0.12 0.02	
($\beta^*_1 - \beta_1$)	-0.07 0.04	0.00	
West-Vlaanderen (β_0)	0.05 0.02	0.04 0.02	
($\beta^*_1 - \beta_1$)	-0.04 0.04	0.00	

(Table continued on next page)

Table 3.8: (Continued)

Sector of previous employment				
Agriculture (β_0)	0.42	0.06	0.41	0.06
($\beta^*1-\beta_1$)	-0.05	0.10	0.00	
Iron-steel industry and mining (β_0)	0.01	0.06	0.10	0.06
($\beta^*1-\beta_1$)	0.29	0.11	0.00	
Metal manufacture (β_0)	0.09	0.04	0.08	0.04
($\beta^*1-\beta_1$)	-0.04	0.07	0.00	
Manufacture of non-metallic products (β_0)	0.01	0.07	0.00	0.07
($\beta^*1-\beta_1$)	-0.20	0.13	0.00	
Manufacture of consumption and investment goods (β_0)	0.08	0.04	0.07	0.04
($\beta^*1-\beta_1$)	-0.05	0.07	0.00	
Other industries (β_0)	0.15	0.06	0.15	0.06
($\beta^*1-\beta_1$)	-0.32	0.11	0.00	
Energy and water production (β_0)	-0.12	0.12	-0.13	0.12
($\beta^*1-\beta_1$)	-0.04	0.07	0.00	
Building (β_0)	0.13	0.04	0.12	0.04
($\beta^*1-\beta_1$)	-0.07	0.07	0.00	
Private services (β_0)	0.20	0.04	0.19	0.04
($\beta^*1-\beta_1$)	-0.06	0.07	0.00	
Public services (β_0)	0.02	0.04	0.02	0.04
($\beta^*1-\beta_1$)	-0.04	0.07	0.00	
Others (β_0)	0.20	0.06	0.21	0.06
($\beta^*1-\beta_1$)	0.01	0.11	0.00	
No previous employment (β_0)	0.14	0.06	0.13	0.05
($\beta^*1-\beta_1$)	-0.06	0.10	0.00	
2. Duration (in years)				
2 (γ_2-c)	-0.49	0.03	-0.49	0.03
3 (γ_3-c)	-0.81	0.04	-0.81	0.04
4 (γ_4-c)**	-1.15	0.06	-1.16	0.05
3. Variance of the Gamma at $l=0$				
η_c	-1.81	0.14	-1.83	0.14
$\sigma^2_{0=\exp(\eta_c)}$	0.16	0.02	0.16	0.02
4. Calendar time at inflow				
η_l	0.20	0.04	0.20	0.04
Number of estimated parameters	89		41	
Number of observations	63793		45987	
Weighted sum of squared residuals	51821.0		51988.8	
Adjusted number of parameters (after regrouping)	62		25	
Adjusted number of observations (after regrouping)	420		420	
Adjusted weighted sum of squared residuals (after regrouping)	425.67		472.39	
P-value of the goodness-of-fit test	0.008		0.004	
P-value of the restrictions test			0.13	

** $\gamma_{21} = \dots = \gamma_4$

Table 3.9: Hazard model estimates - Mixed Non-Proportional Hazard Model - Wallonia

Variables	Benchmark	SD	Restrictions	SD
Constant term*	2.25	0.18	2.27	0.18
1. Covariate effects (time dependent)				
Age (in months - log)	-0.64	0.05	-0.65	0.05
Education				
Elementary school				
β1	-0.57	0.10	-0.68	0.04
β2	0.47	0.03	0.45	0.02
β3	-0.11	0.02	-0.12	0.02
β4	-0.07	0.02	-0.10	0.02
β5	-0.07	0.02	-0.07	0.01
β6	0.03	0.02	0.00	0.01
β7	0.11	0.02	0.11	0.01
β8	-0.08	0.02	-0.05	0.01
β9	0.01	0.02	0.02	0.01
β10	-0.02	0.02	-0.03	0.02
β11	-0.07	0.02	-0.06	0.01
β12	-0.08	0.02	-0.07	0.01
Junior high school				
β0	0.26	0.04	0.27	0.02
β1	-0.57	0.11	-0.68	0.04
β2	0.42	0.05	0.45	0.02
β3	-0.10	0.04	-0.12	0.02
β4	-0.12	0.04	-0.10	0.02
β5	-0.05	0.03	-0.07	0.01
β6	-0.02	0.03	0.00	0.01
β7	0.13	0.03	0.11	0.01
β8	-0.06	0.03	-0.05	0.01
β9	-0.01	0.03	0.02	0.01
β10	-0.04	0.04	-0.03	0.02
β11	-0.09	0.03	-0.06	0.01
β12	-0.07	0.03	-0.07	0.01

Note: In **bold**, estimates not significantly different from zero at 5%.
In grey, restricted parameters.

* Reference individual: Elementary school, Brabant wallon, Chemical industry, $v = 1$.

(Table continued on next page)

Table 3.9: (Continued)

Completed high school			
β_0	0.41 0.05	0.44 0.03	
β_1	-0.60 0.12	-0.68 0.04	
β_2	0.41 0.07	0.45 0.02	
β_3	-0.15 0.06	-0.12 0.02	
β_4	-0.09 0.05	-0.10 0.02	
β_5	-0.08 0.04	-0.07 0.01	
β_6	-0.05 0.04	0.00 0.01	
β_7	0.12 0.04	0.11 0.01	
β_8	0.00 0.05	-0.05 0.01	
β_9	0.02 0.05	0.02 0.01	
β_{10}	0.00 0.06	-0.03 0.02	
β_{11}	-0.03 0.04	-0.06 0.01	
β_{12}	-0.05 0.04	-0.07 0.01	
Higher education			
β_0	0.62 0.05	0.61 0.03	
β_1	-0.42 0.13	-0.50 0.04	
β_2	0.46 0.08	0.45 0.02	
β_3	-0.08 0.06	-0.12 0.02	
β_4	-0.19 0.05	-0.10 0.02	
β_5	-0.01 0.04	-0.07 0.01	
β_6	-0.05 0.04	0.00 0.01	
β_7	0.11 0.04	0.11 0.01	
β_8	0.01 0.05	-0.05 0.01	
β_9	0.09 0.05	0.02 0.01	
β_{10}	-0.08 0.06	-0.03 0.02	
β_{11}	-0.04 0.04	-0.06 0.01	
β_{12}	-0.12 0.04	-0.07 0.01	
Sub-region of living			
Liège (β_0)	-0.17 0.03	-0.19 0.03	
($\beta^*_1 - \beta_1$)	-0.06 0.05	0.00	
Luxembourg (β_0)	0.00 0.04	0.02 0.04	
($\beta^*_1 - \beta_1$)	0.08 0.08	0.00	
Namur (β_0)	-0.09 0.04	-0.09 0.03	
($\beta^*_1 - \beta_1$)	-0.13 0.06	-0.10 0.04	
Hainaut (β_0)	-0.26 0.03	-0.27 0.03	
($\beta^*_1 - \beta_1$)	-0.11 0.05	-0.07 0.03	

(Table continued on next page)

Table 3.9: (Continued)

Sector of previous employment				
Agriculture (β_0)		0.21	0.09	0.18 0.08
($\beta^*_1 - \beta_1$)		-0.13	0.14	0.00
Iron-steel industry and mining (β_0)		-0.12	0.06	-0.14 0.06
($\beta^*_1 - \beta_1$)		-0.09	0.11	0.00
Metal manufacture (β_0)		0.10	0.06	0.07 0.05
($\beta^*_1 - \beta_1$)		-0.13	0.09	0.00
Manufacture of non-metallic products (β_0)		-0.15	0.08	-0.16 0.08
($\beta^*_1 - \beta_1$)		0.01	0.13	0.00
Manufacture of consumption and investment goods (β_0)		0.03	0.06	0.01 0.06
($\beta^*_1 - \beta_1$)		-0.08	0.10	0.00
Other industries (β_0)		0.09	0.09	0.06 0.09
($\beta^*_1 - \beta_1$)		-0.18	0.15	0.00
Energy and water production (β_0)		-0.11	0.13	-0.12 0.13
($\beta^*_1 - \beta_1$)		-0.02	0.09	0.00
Building (β_0)		0.15	0.05	0.14 0.05
($\beta^*_1 - \beta_1$)		-0.06	0.09	0.00
Private services (β_0)		0.24	0.05	0.24 0.05
($\beta^*_1 - \beta_1$)		-0.02	0.09	0.00
Public services (β_0)		0.04	0.05	0.04 0.05
($\beta^*_1 - \beta_1$)		-0.02	0.09	0.00
Others (β_0)		0.47	0.07	0.52 0.07
($\beta^*_1 - \beta_1$)		0.17	0.12	0.00
No previous employment (β_0)		0.17	0.08	0.03 0.07
($\beta^*_1 - \beta_1$)		-0.31	0.12	0.00
2. Duration (in years)				
2 ($\gamma_2 - c$)		-0.30	0.03	-0.30 0.03
3 ($\gamma_3 - c$)		-0.66	0.05	-0.66 0.05
4 ($\gamma_4 - c$)**		-1.04	0.06	-1.04 0.06
3. Variance of the Gamma at $l=0$				
η_c		-1.74	0.16	-1.73 0.16
$\sigma^2_{\eta} = \exp(\eta_c)$		0.18	0.03	0.18 0.03
4. Calendar time at inflow				
η_l		0.34	0.05	0.34 0.05
Number of estimated parameters		89		41
Number of observations		45987		45987
Weighted sum of squared residuals		35808.1		35875.2
Adjusted number of parameters (after regrouping)		62		25
Adjusted number of observations (after regrouping)		420		420
Adjusted weighted sum of squared residuals (after regrouping)		446.55		502.62
P-value of the goodness-of-fit test		0.001		0.000
P-value of the restrictions test				0.02

** $\gamma_{21} = \dots = \gamma_4$

Chapter 4

Is there Job Competition and Skill Mismatch among Unemployed Workers in Belgium?

4.1 Introduction

Low educated workers are the most vulnerable to unemployment in Belgium. Figure 4.1 depicts the unemployment rate by schooling level in 1977, 1981 and over the period 1989-1998¹. Unemployment increased during this period for all schooling groups, but at quite different rates. In 1998, the unemployment rate of the less educated workers (with at most a lower secondary degree²) increased by a factor of 2.5 as compared to its level in 1977 while this factor only amounts to 1.25 for workers who completed higher education. The Belgian ratio between the unemployment rate of these two schooling groups was also, in 1995, one of

¹In Belgium, there is not time-series on the working population by level of educational attainment. This information is available on an annual basis in the labour force surveys since 1989 only. In Figure 4.1, unemployment rates by schooling level are calculated on the basis of a socio-economic survey in 1977 and the population census in 1981.

²A lower (resp. upper) secondary degree corresponds to 9 (resp. 12) years of education.

the largest among 15 OECD countries³ (see OECD 1997a). It should however be noted that the rising disparities in the unemployment rate by level of education is more a feature of Wallonia, the French speaking region in the South of Belgium⁴ (see Figures 1.4 and 1.5 in Chapter 1).

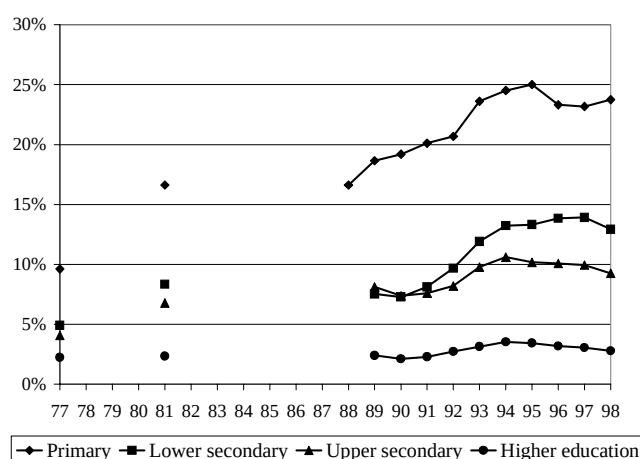


Figure 4.1: Unemployment rate by level of education in Belgium

The relative rise in the unemployment rate of the lower educated workers took place despite a growing share of high educated workers in the labour force. In Chapter 3, we also show that the more rapid increase in the unemployment rate of the low educated workers from the late seventies is partly driven by a stronger positive trend in their unemployment duration. The outflow rate of low educated unemployed workers in Belgium deteriorated by 30% more than the exit rate of the highest educated workers over the period 1973-1993.

Two explanations are consistent with these observed facts. The increasing disparity between unemployment rates by schooling level can be driven by a structural skill mismatch. According to this view, the economic growth came with a change in the composition of labour demand biased against the low skilled workers (by the introduction of new technologies, de-industrialisation and/or international competition), without an equivalent adjustment in the composition of labour supply (see,

³Belgium comes in fourth, after the United States, Ireland and Luxemburg.

⁴Belgium is divided into three regions: Wallonia, Flanders and Brussels.

for example, Drèze and Sneessens 1997; Autor *et al.* 1998; Berman *et al.* 1998; Machin and Van Reenen 1998). These structural evolutions, together with a downward rigid wage structure, led to a growing skill mismatch between the demand and the supply of labour: An excess demand of high skilled workers coexists with an excess supply of low skilled workers.

The second explanation attributes the observed evolutions to the crowding out of lower educated workers by workers with a higher education. In the literature, this phenomenon is also called job competition, bumping down or ladder effect (see, for example, Green *et al.* 1999; Dolado *et al.* 2000; Gautier 2001). Contrary to the skill mismatch story, a general slowdown of the economic growth reduced the demand for both skilled and unskilled workers⁵. In such a context, more educated workers tried to compensate the decreased demand by extending job search on the skill segment below their own. Adopting this search behaviour, they crowded out lower educated unemployed in their segment. At the bottom of the skill ladder, the lowest educated were condemned to unemployment or inactivity. This process was reinforced by a simultaneous rise in the supply of highly educated workers.

Notice that skill mismatch and job competition are not mutually exclusive. The first explanation emphasises the role of the *composition* of employment growth and labour supply on the observed evolutions while the second stresses the importance of the *level* of employment growth.

This chapter aims to determine the relative importance of job competition and skill mismatch for a population of unemployed job searchers in Belgium. Our analysis breaks new ground in the empirical literature. First, no other empirical studies tried to disentangle the two explanations even though this question is highly relevant from a policy perspective. We should however stress from the outset that the available data allow us to evaluate the extent of job competition and skill mismatch *only* for a selective population of unemployed workers, which excludes young school leavers and on-the-job searchers. This means that one must be *extremely cautious* with the interpretation of our results as well

⁵The slowdown of economic growth could reflect a depressed capital accumulation due to excessively high labour costs (see Daveri and Tabellini 1997) or coordination failures (see Drèze 1997; Shadman-Mehta and Sneessens 1998).

as with their policy implications. Besides, we should also keep in mind that our study is restricted to Wallonia, and to the early nineties, period characterised by a strong deterioration of the economic prospects in all European countries.

Second, empirical research on skill mismatch and job competition needs the researcher to assign the ‘true’ skill requirements to vacancies and filled jobs to the skill attainment of workers. Researchers often rely on reports of employers or workers to assign these skill requirements, and use the educational degree as measure of the skill level. However, there are reasons to believe that these reports are biased. For instance, employers can increase their educational requirements in order to attract the best candidates for the job or simply because they know that there is a large number of highly educated job seekers (see Green *et al.* 1999). If the schooling profile of the job is evaluated through external experts, the information must be frequently updated since the job content may change with the introduction of new technologies. We avoid these biases by estimating the distribution of jobs according to the required level of education.

A number of studies evaluated the extent of skill mismatch by computing mismatch indicators (see for Belgium, Sneessens *et al.* 1999, and for other countries, Jackman and Roper 1987; Jackman *et al.* 1990; Manacorda and Petrongolo 1999). However, all measures of mismatch are built on models which ignore the mobility of workers between segments of the labour market, so that they exclude the crowding out process. If such a process takes place, the mismatch indicators are biased. As an example, the mismatch indicator in Sneessens *et al.* (1999) is the ratio of skilled to total employment rates. Skilled employment is measured by the share of highly educated⁶ people in the working population. According to this ratio, there has been a growing imbalance between the demand and the supply of skills in Belgium from the late seventies and up to the mid eighties. But this increase could partly reflect a more intense crowding out of lower educated workers by higher educated ones. Other indicators suffer from the same type of measurement problem.

Up to now, most of the empirical evidence on job competition relies

⁶Highly educated workers are those who at least completed an upper secondary degree.

on measures of overeducation, which give the share of workers with a higher schooling level than the one required to perform the job. There is a growing interest in the overeducation literature, witness the special issue of the *Economics of Education Review* (19, April 2000) on this question. Up to days, a limited number of studies tried to evaluate the incidence of overeducation for Belgium (see Van Hoof 1996 and Denolf *et al.* 1999). However, there is an important methodological issue in this literature (cf. *supra*).

A few studies use a different empirical approach to evaluate the extent of job competition. Van Ours and Ridder (1995) estimate a matching function by schooling level, allowing for job competition between job seekers with different levels of education. Their parameter of interest is the share of more educated job seekers that compete with less educated ones. Their results could, however, be sensitive to the classification of vacancies according to the level of educational attainment, which is registered by the employers⁷. They do not find evidence for job competition, except at the top segment of the labour market. In a search model, Gurgand (1999) shows that the number of more educated unemployed workers should be a determinant of the hiring probability of the less educated workers in the presence of job competition. This prediction is tested empirically in a reduced form model with data on the flows from unemployment by level of education. His preliminary findings confirm significant job competition between workers with higher education and those with secondary education. Finally, Gautier *et al.* (2001) test whether more highly educated workers occupy simple jobs in cyclical downturns on the basis of a firm-worker data set. To that purpose, they measure, for each job complexity level, the difference between average schooling of the inflow and the outflow (at the firm level), and test whether this variable is larger in downturns. They found evidence of countercyclical job competition at only one of the lower job complexity levels. Only cyclical crowding out is investigated though.

In our study, we estimate the extent of job competition and skill mismatch among the unemployed population in Wallonia. As in Gurgand (1999), we use data on the flows from unemployment by level of educa-

⁷The data used by Van Ours and Ridder (1995) are collected from vacancy surveys to employers.

tion and the total number of job vacancies registered at the public employment agency. We focus on male unemployed workers for the period June 1989 - February 1994. The probability of leaving unemployment is modelled in a matching function framework. As in Van Ours and Ridder (1995), we assume that the job market is segmented by schooling level and that each segment is characterised by the same job matching technology. In the presence of job competition, all unemployed workers search for jobs in their own segment and some fraction search simultaneously in the segment just below their own. The hiring probability is then made of two components: the probability of finding a job corresponding to his schooling profile and the probability of finding a downgrading job.

Contrary to Gurgand (1999), we estimate the structural form of the outflow rate by schooling level without relying on a reduced form specification. The extent of job competition at each schooling level is estimated alongside with the distribution of job offers by level of education. Estimating the distribution of job offers by schooling level allows us to calculate unbiased mismatch indicators. However, we only observe unemployed workers who separated from their employers in our data set. As a consequence, our estimation of vacancies by schooling level concerns only those intended to this selective population. So, as emphasised above, we can just evaluate the extent of skill mismatch *within this selective population*.

The plan of the chapter is as follows. In the next section, we derive the theoretical expression of the job finding rate in the presence of job competition. Section 4.3 describes the data. In Section 4.4, we derive the regression model. Section 4.5 is devoted to the discussion of our estimation results. To increase the reliability of our findings, we investigate the sensitivity of our model estimates to changes in the specification in Section 4.6. The concluding part summarises our findings.

4.2 Model specification

4.2.1 Definitions, notations and assumptions

We consider a segmented labour market where labour demand is differentiated by the education level required to perform a job and labour

supply by the level of educational attainment of the individuals. The education level is indexed by $i \in (1, 2, \dots, I)$, the type of segment and the type of individual being characterised by a subscript and a superscript respectively. I is the highest schooling level. Labour demand corresponds to firms posting vacancies while labour supply is restricted to unemployed workers effectively looking for a job.

In this context, job competition occurs when the education level of a job searcher is greater than the level required to perform the job. By assumption, the unemployed workers with at most an elementary school degree are not able to crowd out any other workers, while those who completed the highest education level are protected from any competition. We are aware that education is an imperfect indicator of skills. The schooling level alone is available in our data set though. In this framework, we also define skill mismatch as the imbalance between the labour demand and supply by educational level: Some schooling levels are characterised by an excess number of job offers, other levels by an excess number of job seekers. Notice that mismatch is used with a different sense in the search and matching literature: Mismatch exists whenever jobs and workers do not meet instantaneously due to the search and application process (see Pissarides 2000, p.22). Our definition is also more general than the one found in the literature on structural unemployment, in which ‘skill mismatch’ often relates to a particular type of imbalance in the labour market: An excess number of high skilled job offers coexist with an excess number of low skilled job seekers (see, e.g., Drèze and Sneessens 1997).

We describe the meeting process between the job offers and the unemployed workers by the matching function and we treat the matching process as a continuous-time process. In our framework, the matching function relates, at calendar time τ , the number of hirings in segment i , $F_{i\tau}$, to the number of vacancies and the number of effective job seekers in segment i , respectively $V_{i\tau}$ and $S_{i\tau}$. The latter number is measured in effective units to account for heterogeneity within each segment. In the empirical analysis, observed personal characteristics, such as unemployment duration, are used to approximate the heterogeneity within segments. Assuming a Cobb-Douglas specification without any restriction on its returns to scale, the matching function in segment i is given

by:

$$F_{i\tau} = (S_{i\tau})^\alpha (V_{i\tau})^\beta \quad (4.1)$$

where $\alpha > 0$ and $\beta > 0$ are assumed to be independent of i .

If the labour market is perfectly segmented, (i) the unemployed workers of education level i , U_τ^i , look for jobs only in their own segment: $S_{i\tau} = \bar{e}^i U_\tau^i$ where $\bar{e}^i$ represents the average matching effectiveness of the unemployed workers with schooling level i (see Jackman *et al.* 1989), and (ii) the vacancies requiring education level i , $V_{i\tau}$, can only be filled by workers who have the corresponding level: $F_{i\tau} = F_\tau^i$ where F_τ^i is the number of vacancies filled by unemployed workers with education level i . We assume that the average matching effectiveness, $\bar{e}^i$, may vary between levels of educational attainment only because the composition of effective units differs between these groups and that $\bar{e}^i$ is time-invariant. The matching function in segment i then becomes:

$$F_\tau^i = (\bar{e}^i U_\tau^i)^\alpha (V_{i\tau})^\beta \quad (4.2)$$

Let $\theta_{i\tau}$ denote tightness (i.e. the vacancy-unemployment ratio) in segment i and $\tilde{\theta}_{i\tau}$ its equivalent measure in efficiency units:

$$\tilde{\theta}_{i\tau} = \frac{V_{i\tau}}{\bar{e}^i U_\tau^i} \quad (4.3)$$

The absence of skill mismatch is defined formally as: $\forall i : \tilde{\theta}_{i\tau} = \tilde{\theta}_\tau$. So mismatch implies different V-U ratios across schooling groups. Jackman and Roper (1987) come to this definition of mismatch by maximising the total number of hirings in a segmented job market characterised by the same job matching technology⁸. In Appendix 1, we develop an equilibrium search model *à la* Pissarides (2000) with two types of jobs and workers (high skilled and low skilled) and perfect segmentation of the labour market. This simple model shows that skill biased technological change, i.e. an increase in the relative productivity of high skilled jobs,

⁸Except from their educational attainment, workers are assumed to be homogeneous, so that $\bar{e}^i = 1$.

is not the only possible determinant of skill mismatch in a steady-state equilibrium. Tightness may also vary across skill segments due to differences in bargaining power, separation rate, unemployment benefit and hiring costs between segments.

Notice that the most common measures of skill mismatch are based on unemployment rates by skill level: One is based on unemployment rate ratios (see Jackman *et al.* 1990), the other on unemployment rate differences (see, e.g., Sneessens and Shadman-Mehta 1995)⁹. The first indicator is derived from a Nairu model with a segmented labour market. The second index is built on a model with explicit skilled labour constraints and aggregation over micromarkets. Under both settings, the case of no mismatch is defined as the absence of differences between unemployment rates by skill group. The model derived in Appendix 1 also indicates that the definition of no mismatch based on tightness indicators implies the absence of differences between unemployment rates if the separation rate does not depend on the skill level.

Using (4.2) and (4.3), the rate at which a job seeker of education level i finds a job is then given by:

$$h_{\tau}^i \equiv \frac{F_{\tau}^i}{U_{\tau}^i} = \bar{e}^i (\bar{e}^i U_{\tau}^i)^{\alpha-1} (V_{i\tau})^{\beta} = \bar{e}^i (\bar{e}^i U_{\tau}^i)^{\alpha+\beta-1} (\tilde{\theta}_{i\tau})^{\beta} \quad (4.4)$$

Under the assumption of constant returns to scale (CRS), i.e. $\alpha + \beta = 1$, there is a one-to-one relationship between the hiring rate of a job-seeker with schooling level i and tightness in his segment. If $\bar{e}^i$ is the same in each segment, disparity of the job finding rates between schooling levels can only be explained by skill mismatch. With increasing returns to scale (IRS), i.e. $\alpha + \beta > 1$, the hiring rates by education level may differ even in the absence of skill mismatch. If there is no skill mismatch, segments with a greater number of effective job seekers will be characterised by a higher matching rate. This positive relationship stems from the fact that under IRS, the number of potential contacts between job seekers and firms increases when the size of the market is larger (see e.g. Teulings and Gautier 2000).

⁹If we distinguish high skilled (H) and low skilled (L) labour, the two indicators are defined as follows: $M1 = \exp\left(\frac{1}{2} \text{var}\left(\frac{UR_i}{UR}\right)\right)$, $i = H, L$ and $M2 = \frac{1-UR_H}{1-UR}$.

In the next section, we allow for job competition between workers of different schooling levels and show that this competition can also explain the divergence in job finding rates by education level.

4.2.2 The effect of job competition

With job competition, the labour market is not perfectly segmented: (i) The unemployed workers of schooling i , U_τ^i , can search for a job in their own segment and in a segment requiring an educational attainment below their own level, and (ii) the job offers designed for education i , $V_{i\tau}$, can be filled by unemployed workers with the required level or by overeducated workers. We only allow job competition at one level downward and exclude upward competition. These two assumptions are realistic given that we classify education into relatively broad categories in the empirical analysis.

We assume simultaneous job search: All unemployed workers of type i search for a job in their own segment and some fraction, λ_τ^i with $0 \leq \lambda_\tau^i \leq 1$, search simultaneously in the segment just below their own. By assumption, λ_τ^i is only defined for $i \in \{2, 3, \dots, I\}$. Therefore, the number of workers searching for a job in segment i , $S_{i\tau}$, comprises both the unemployed workers of schooling i , U_τ^i , and the unemployed workers of schooling $i+1$ who decide to compete with those former for jobs in segment i , $\lambda_\tau^{i+1} U_\tau^{i+1}$. Not all unemployed workers will necessarily adopt this search behaviour. For, the probability of receiving an adequate job offer may decrease when taking a downgrading position, making some unemployed workers reluctant to job competition even on a temporary basis. Overeducation may signal to future employers the lack of other skill attributes and thus reduce the opportunity of getting a more adequate job (see McCormick 1990). Moreover, a period of overeducation is likely to deteriorate the skills acquired at school and therefore, impede the access to higher paid jobs. Finally, accepting a downgrading position may also decrease the time devoted to search a more favourable position as compared to the time available when remaining unemployed.

An alternative assumption to simultaneous search is segmented job search (as in Van Ours and Ridder 1995). Under this assumption, the unemployed workers decide to search for a job *either* in their own seg-

ment *or* in the segment just below their own. In that case, the number of workers searching for a job in segment *i*, $S_{i\tau}$, would include both the unemployed workers of schooling *i* who decide to search for jobs in their own segment, $(1 - \lambda_\tau^i) U_\tau^i$, and the unemployed workers of schooling *i* + 1 who choose to compete with those former for jobs in segment *i*, $\lambda_\tau^{i+1} U_\tau^{i+1}$. We do not assume segmented job search for the following reason. The motivation behind this assumption is that the market of job offers is segmented and that job offers are costly to locate. Unemployed workers must therefore decide to devote their search effort to one segment only. Even if some search channels are targeted to specific types of jobs (e.g. internet), most of them cover a large range of job opportunities (e.g. public employment agency, newspaper advertisements), so that it does not seem very difficult for a worker to see (and to apply for) different types of job offers simultaneously. This argument is reinforced by the fact that we only allow for job competition at one level downward.

However, $S_{i\tau}$ is not simply the sum of the overeducated job seekers and those with the required schooling. Contrary to Van Ours and Ridder (1995), we allow each type of job seekers to have a specific effectiveness in the matching process. We normalise the matching effectiveness of the adequately educated workers to one and attribute to the overeducated job seekers an effectiveness parameter z_τ^i , only defined for $i \in \{2, 3, \dots, I\}$. So the number of unemployed workers who are willing to downgrade becomes in effective units: $z_\tau^{i+1} (\lambda_\tau^{i+1} e^{i+1} U_\tau^{i+1})$. We do not restrict the value of z_τ^i to be larger or smaller than one. Recently, Gautier (2001) shows that the employers may have a preference for one type of job seekers, but the direction of this preference is ambiguous. *Ceteris paribus*, an employer prefers to hire an overeducated worker if he is more productive than a lower educated one (the match surplus is larger)¹⁰. However, the employer must account for the fact that the overeducated worker will quit the firm as soon as he finds a better job, what implies higher turnover costs and reduces the expected match surplus.

The efficiency parameter z_τ^i is however not identified separately from the job competition parameter since both vary in the same dimensions.

¹⁰This statement holds whether the wages are posted, i.e. the wage is the same for a particular job irrespective of the worker type, or bargained over by each worker type.

Only their product, $\kappa_\tau^i = z_\tau^i \lambda_\tau^i$, is identified. But we can still make some inference on the value of both parameters. If $\kappa_\tau^i > 0$ then there is job competition, i.e. $\lambda_\tau^i > 0$. If $\kappa_\tau^i > 1$, the overeducated job seekers are more likely to be hired than those who have just the required schooling level, i.e. $z_\tau^i > 1$. If $0 < \kappa_\tau^i \leq 1$, the matching effectiveness of the overeducated workers can be higher, equal or lower than the adequately educated workers. In any case, the exact value taken by z_τ^i and λ_τ^i is a matter of interpretation. The cyclical evolution of these parameters should be similar. For instance, a rise in the demand for high skilled workers should reduce both the extent (λ^i) and the effectiveness (z^i) of job competition. Since this shock increases the probability of finding a high skilled job, employers will be more reluctant to hire overeducated workers on low skilled jobs (see Gautier 2001, Dolado *et al.* 2000).

In the presence of crowding out, $S_{i\tau} = \bar{e}^i U_\tau^i + \kappa_\tau^{i+1} \bar{e}^{i+1} U_\tau^{i+1}$, and thus the matching function given in (4.1) takes the form:

$$F_{i\tau} = (\bar{e}^i U_\tau^i + \kappa_\tau^{i+1} \bar{e}^{i+1} U_\tau^{i+1})^\alpha (V_{i\tau})^\beta \quad (4.5)$$

The total number of hirings for unemployed workers of education level i , F_τ^i , is now made of two components: $F_{i\tau}^i$ and $F_{i-1\tau}^i$ which denote the number of vacancies filled by unemployed workers of schooling i in segment i and $i - 1$ respectively. Since the rate at which an effective unemployed worker of type i finds a job is the same for all types of effective job seekers:

$$\frac{F_{i\tau}^i}{\bar{e}^i U_\tau^i} = \frac{F_{i\tau}}{S_{i\tau}} = \frac{F_{i\tau}^{i+1}}{\kappa_\tau^{i+1} \bar{e}^{i+1} U_\tau^{i+1}} \quad (4.6)$$

the total number of hirings for unemployed workers of education level i is, by combining (4.5) and (4.6):

$$\begin{aligned} F_\tau^i &= F_{i\tau}^i + F_{i-1\tau}^i \\ &= \bar{e}^i U_\tau^i \left[(\bar{e}^i U_\tau^i + \kappa_\tau^{i+1} \bar{e}^{i+1} U_\tau^{i+1})^{\alpha-1} (V_{i\tau})^\beta \right. \\ &\quad \left. + \kappa_\tau^i (\bar{e}^{i-1} U_\tau^{i-1} + \kappa_\tau^i \bar{e}^i U_\tau^i)^{\alpha-1} (V_{i-1\tau})^\beta \right] \end{aligned} \quad (4.7)$$

and the rate at which an unemployed worker of education i finds a job is given by:

$$\begin{aligned} h_{\tau}^i &\equiv \frac{F_{\tau}^i}{U_{\tau}^i} \\ &= \bar{e}^i \left[(\bar{e}^i U_{\tau}^i + \kappa_{\tau}^{i+1} \bar{e}^{i+1} U_{\tau}^{i+1})^{\alpha-1} (V_{i\tau})^{\beta} \right. \\ &\quad \left. + \kappa_{\tau}^i (\bar{e}^{i-1} U_{\tau}^{i-1} + \kappa_{\tau}^i \bar{e}^i U_{\tau}^i)^{\alpha-1} (V_{i-1\tau})^{\beta} \right] \end{aligned} \quad (4.8)$$

Using the definition of tightness given in (4.3), the job finding rate can be rewritten as:

$$\begin{aligned} h_{\tau}^i &= \bar{e}^i \left[(S_{i\tau})^{\alpha+\beta-1} (\tilde{\theta}_{i\tau})^{\beta} \left(\frac{\bar{e}^i U_{\tau}^i}{S_{i\tau}} \right)^{\beta} \right. \\ &\quad \left. + \kappa_{\tau}^i (S_{i-1\tau})^{\alpha+\beta-1} (\tilde{\theta}_{i-1\tau})^{\beta} \left(\frac{\bar{e}^{i-1} U_{\tau}^{i-1}}{S_{i-1\tau}} \right)^{\beta} \right] \end{aligned} \quad (4.9)$$

In this setting, the presence of job competition can also explain some disparity between job finding rates by schooling levels. In order to analyse the role of job competition on the hiring rate, we impose the absence of skill mismatch ($\forall i : \tilde{\theta}_{i\tau} = \tilde{\theta}_{\tau}$), equal average matching effectiveness across segments ($\forall i : \bar{e}^i = \bar{e}$) and CRS ($\alpha + \beta = 1$). Under these assumptions, equation (4.9) can be rearranged and becomes:

$$h_{\tau}^i = \bar{e} (\tilde{\theta}_{\tau})^{\beta} \left[\left(\frac{U_{\tau}^i}{\underbrace{U_{\tau}^i + \kappa_{\tau}^{i+1} U_{\tau}^{i+1}}_{\leq 1}} \right)^{\beta} + \kappa_{\tau}^i \left(\frac{U_{\tau}^{i-1}}{\underbrace{U_{\tau}^{i-1} + \kappa_{\tau}^i U_{\tau}^i}_{\leq 1}} \right)^{\beta} \right] \quad (4.10)$$

In equation (4.10), the disparity of the job finding rates between schooling levels can only be explained by job competition. The first and the second term between brackets represents, respectively, the negative effect of competition from the higher schooling level on the hiring rate and the positive effect of searching for downgrading jobs. Undoubtedly, the hiring rate of the lowest educated workers is negatively affected by

job competition since they are not able to crowd out any other workers. Likewise, the hiring rate of workers who complete the highest schooling level can only be positively affected by job competition since they are protected from any competition. For the intermediate schooling levels, the effect of crowding out on their outflow rate depends on the competition they face from the higher education level as compared to the competition they exert on the lower level. Notice that with increasing returns to scale, low skilled unemployed workers could actually benefit from the competition of higher skilled workers since a greater number of effective job seekers implies a higher matching rate, other things being equal.

4.3 The data

Our analysis exploits quarterly census data relative to male workers entering insured unemployment in Wallonia. All these people were previously employed and are full-time registered. Besides the quarter of inflow, these data are stratified according to a limited number of characteristics: the unemployment duration, the age group (less than 29 years old, and between 29 and 44 years old) and the educational level. Education is grouped into four classes: (1) no education or elementary school, (2) lower secondary, (3) upper secondary and (4) higher education. The variables $i \in \{1, 2, 3, 4\}$ and $a \in \{1, 2\}$ denote the schooling and age group respectively.

In our data set, the inflow in a given quarter is equal to the number of workers entering unemployment in this quarter and who are still unemployed at the end of the quarter in which they enter¹¹. The observation period consists of 19 quarterly intervals¹², the first interval starting on the 1th of June 1989, the last one ending on the 28th of February 1994. So there are 18 cohorts of unemployed¹³ (a cohort being defined by its quarter of inflow), stratified by age group and schooling level. For each

¹¹This restriction allows to neglect temporary exits (for administrative reasons for example).

¹²Four quarters are defined: (Jun,Jul,Aug); (Sep,Oct,Nov); (Dec,Jan,Feb); (Mar,Apr,May).

¹³There are 18 cohorts instead of 19 as there is, by definition, no exit defined for those entering the unemployment pool in the 19th quarter.

cohort, the outflows from unemployment are counted on a quarterly basis, from the time of inflow up to four quarters of unemployment or up to the end of February 1994, date at which all spells are right censored. Let the variables c and k denote respectively calendar time at the moment of outflow and unemployment duration. These variables are measured in quarters. We have that $c \in \{1, 2, \dots, 18\}$ and $k \in \{1, 2, 3, 4\}$. By construction, calendar time at the moment of inflow, l , is equal to $c - k$. In the sequel, the subscript x replaces at times subscripts a and k .

So our data provide information on U_{akc}^i , the number of individuals of schooling i and age a who have been unemployed for $k - 1$ quarters and who are at risk of leaving unemployment within the c^{th} quarter, and on F_{akc}^i , the number of these individuals who leaves unemployment within the c^{th} calendar time interval. We therefore assume that filling a vacant job (in segment i or $i - 1$) is the only reason of flowing out of unemployment. There are two potential sources of bias when the number of filled vacancies is approximated by the number of workers flowing out unemployment.

First, our data do not allow us to identify unemployment spells ending in employment. Workers may flow out of unemployment to participate in a labour market scheme or to withdraw from the labour force. Since the size of these movements may vary over the cycle (see Petrongolo and Pissarides 2001), they can lead to biased estimates of the matching elasticities. Our results should be marginally affected though, given that employment is the most frequent state of exit for male unemployed workers: About 77% of them leave for employment (see FOREM 1995). In our sample, this fraction must be larger. For, the reported figure includes unemployed workers older than 44 years. These workers often enter a kind of early-retirement scheme, a policy heavily used after the mid eighties in Belgium for older workers. Moreover, our vacancy data also include jobs in public employment schemes, also called ‘relief jobs’¹⁴, excluded from the fraction of 77%. A second potential source of bias is the non-observability of the flow from job to job. Ignoring this flow may also bias the matching elasticities since the fraction of employed job seekers filling vacancies varies over the business cycle (see e.g. Broersma

¹⁴Direct job creation for the unemployed generates vacancies that are registered by the public employment agency.

and Van Ours 1998). However, we expect this bias to be small, since job offers are assumed to be proportional to the vacancies registered at the public employment agency. These offers are primarily aimed at unemployed job seekers.

The fraction of workers with schooling i and type x who fill a vacancy during the time interval c is therefore equal to the empirical exit probability, $\hat{P}_{xc}^i$, which expresses as follows:

$$\hat{P}_{xc}^i = \frac{F_{xc}^i}{U_{xc}^i} \quad (4.11)$$

Table 4.1 gives the empirical outflow probability in the first duration quarter by schooling level, averaged over the observation period and age. The hiring probability rises with the education level, the marginal increase being the largest for the highest educated workers.

Table 4.1: Average empirical outflow probability in the first duration interval by level of education

	P^i
Higher education ($i = 4$)	0.64
Upper secondary ($i = 3$)	0.39
Lower secondary ($i = 2$)	0.30
No education or elementary school ($i = 1$)	0.28

Figure 4.2 shows the de-seasonalised evolution of these probabilities over time. In order to focus on the time evolution, we normalise the probability to one at the first calendar time interval (autumn 1989). The deterioration of the economic conditions from the early nineties is associated with a marked decline of the hiring probabilities. However, the outflow probability of the less educated workers (below higher education) is more heavily hit by the recession in 1993 than the one of the highest educated workers: The exit probability of the less educated drops by about 35% in August 1993 compared to its level in November 1989 while this drop is only by 15% for those who completed higher education.

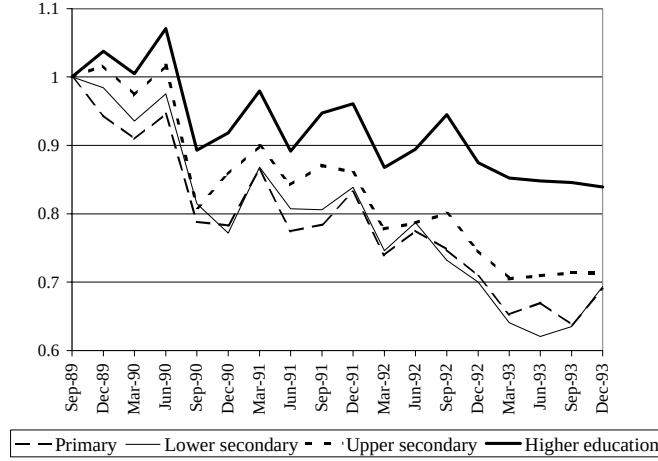


Figure 4.2: Cyclical dependence of the empirical outflow probability by level of education

There is also some seasonal variation in the outflow probability. As expected, the summer and the winter time impede a lot the exit from unemployment, while the labour market conditions are more favourable in the autumn and in the spring.

Our analysis also exploits the number of job vacancies registered at the public employment agency, including relief jobs. Except for these jobs where registration is systematic, the decision to register is actually taken by the employers. During the period 89-94, job offers are not classified according to the required education level¹⁵. So we do not observe V_{ic} , but only V_c .

The vacancy data provide information on the stock of vacancies at the begin of the calendar time interval c , VS_c , and the flow of new vacancies between $c - 1$ and c , VF_c . Following preliminary estimations on the matching function, we only retain the number of new job offers though. For, only the inflow of new vacancies significantly affects the number of matches¹⁶. Since the stock of vacancies does not influence significantly

¹⁵This information is available since October 1995.

¹⁶This finding is compatible with the stock-flow matching model of Coles and Smith (1998). In their setting, unemployed workers have complete information about the available job offers and apply simultaneously to all the ones that they find acceptable. This assumption implies that the stock of unemployed workers only match with the

the number of matches, we impose the following assumption:

$$V_c = VF_c^O + \pi VF_c^R \quad (4.12)$$

where superscripts O and R stand for ‘ordinary’ and ‘relief’ vacancies respectively. The parameter π allows to examine the relative importance of direct job creation for the unemployed in the outflow process as compared to ordinary vacancies (as in Haskel and Jackman 1988).



Figure 4.3: Flow of job offers at the Public Employment Agency

Figure 4.3 shows the flow of both types of job offers during our observation period. The share of direct job creation in the total number of vacancies registered by the employment agency is relatively high (on average 30%) in comparison with their share in total employment. Registration of relief jobs is indeed systematic while vacancies registered by the employers at the employment agency represent only a proportion of the total number of vacant jobs in the economy (40% in 1995, see OECD 1997b). The flow of ordinary vacancies presents a declining trend which coincides with the economic downturn characterising the early nineties.

flow of new job offers while new entrants into unemployment only prospect the existing stock of vacancies. Coles and Smith’s assumption captures a realistic feature of some search markets, such as the public employment agency, where information on job offers is highly centralised and directly available.

The decrease in the flow of relief jobs is more surprising since we would expect higher outlays for direct job creation in recessions. It is rather budget restrictions and increased expenditures on training schemes in the early nineties that would explain the declining importance of relief jobs in Wallonia. There are also some seasonal variations in the number of vacant jobs. As expected, the summer time impedes a lot the number of job offers while these are the largest in the spring.

The number of unemployed workers at the start of the time interval c , U_c^i , is computed from our data on U_{xc}^i such as defined above. Since we have an inflow data set, not all duration classes are represented at the begin of the observation period. For the first three calendar time intervals, there are some durations missing. We estimate the number of unemployed in the missing duration classes by exploiting the information on the number of unemployed workers in the observed duration classes. The way we estimate these numbers can be found in Appendix 2. Without filling the missing data, there would be an artificial increase in the number of unemployed workers as time proceeds, affecting the estimation of the matching elasticities. In order to evaluate the sensitivity of our results to our correction, we compare them to the results obtained by making the observation period start at the fourth calendar time intervals. Estimation results are similar.

The number of unemployed workers in each schooling level is depicted in Figure 4.4. Given that duration is censored at four quarters in our data set, these are only short-term unemployed workers¹⁷. Unemployment rises for all levels of education, the increasing trend being much less pronounced for the highest educated workers. All series present some seasonality which is similar to the one observed in the flow of job offers: peak in the spring and off-peak in the summer.

¹⁷In the analysis, it is assumed that the long-term unemployed workers (with a duration larger than one year) are not effective candidates for the job offers (their efficiency parameter is close to zero).

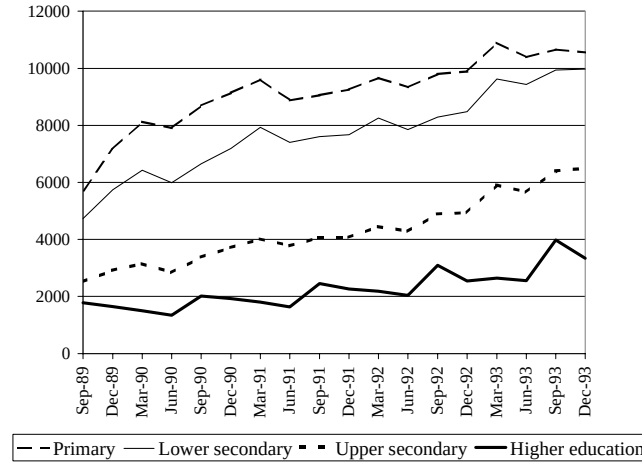


Figure 4.4: Short-term unemployment by level of education

4.4 The regression model

In the theoretical model, we assumed that the job market is segmented by schooling level i and that each segment is characterised by the same job matching technology. Within each segment, workers are heterogeneous and meet vacancies with different rates of effectiveness. In the empirical analysis, we assume that the matching effectiveness of an individual only varies according to the two observed dimensions: the age class a and the elapsed unemployment duration t . As in Van Ours and Ridder (1995), we assume that the matching effectiveness does not depend on the educational level¹⁸. As such, we can denote the hazard rate of any worker by $h_{at\tau}^i$ and the individual matching effectiveness by e_{at} .

To relate $h_{at\tau}^i$ to $h_{at\tau}^i$, note that the rate at which an effective unemployed worker with schooling level i and observed characteristics a and t finds a job is the same for all types of effective job seekers:

¹⁸Since unemployment duration and age are partially correlated with the educational attainment, the latter variables may capture some heterogeneity in the search effectiveness according to the schooling level.

$$\frac{F_{at\tau}^i}{e_{at}U_{at\tau}^i} = \frac{F_{at\tau}^i}{\bar{e}^i U_{\tau}^i} \quad (4.13)$$

Therefore,

$$h_{at\tau}^i \equiv \frac{F_{at\tau}^i}{U_{at\tau}^i} = \frac{e_{at}}{\bar{e}^i} h_{\tau}^i \quad (4.14)$$

where h_{τ}^i is given in (4.8).

The theoretical model was formulated in continuous time. The advantage of such a formulation is that the model specification does not depend on the time unit chosen (see Flinn and Heckman 1982). The data used for the empirical analysis are, however, only available at quarterly intervals. The flow of new vacancies, V_c , is the sum of those vacancies opened between $c - 1$ and c , F_{xc}^i is the sum of individuals flowing from unemployment between $c - 1$ and c , and U_c^i is the stock of unemployed workers present at the beginning of quarter c . The assumption that these variables and e_{at} are constant within each quarterly interval allows an exact relation between the continuous time model and the discrete time data:

$$\forall t \in [k - 1, k), \tau \in [c - 1, c) : h_{at\tau}^i = h_{akc}^i \quad (4.15)$$

Combining (4.8), (4.14) and (4.15), the model then becomes:

$$\begin{aligned} h_{xc}^i = & e_x \left[(\bar{e}^i U_c^i + \kappa_c^{i+1} \bar{e}^{i+1} U_c^{i+1})^{\alpha-1} (V_{ic})^{\beta} \right. \\ & \left. + \kappa_c^i (\bar{e}^{i-1} U_c^{i-1} + \kappa_c^i \bar{e}^i U_c^i)^{\alpha-1} (V_{i-1c})^{\beta} \right] \end{aligned} \quad (4.16)$$

where the average matching effectiveness of the unemployed workers of schooling i , $\bar{e}^i$, is simply given by:

$$\bar{e}^i = \frac{\sum_x e_x U_{xc}^i}{U_c^i} \quad (4.17)$$

Its dependence on the schooling level i only reflects that the composition of effective job seekers differs between segments.

Since job offers are not classified according to the required education level in our data set, the distribution of the total number of job offers requiring education level i is unknown alongside with the job competition parameters. It would be too restrictive to impose that the total number of job offers by schooling level is only a share of the job offers notified at the public employment agency. For, the latter represent a (varying) proportion of the total number of vacant jobs in the economy. For instance, this proportion was estimated at around 40% in 1995 (see OECD 1997b). For the highest education levels, this proportion must be smaller since the probability that an employer notifies a job at the employment agency is likely to decrease with the schooling level of the worker in demand. We therefore assume that the share of job offers by schooling level, v_{ic} , is proportional to the observed number of job offers, V_c , *without* requiring that the sum of these shares is equal to one:

$$\forall i : V_{ic} = v_{ic} V_c \quad (4.18)$$

Estimating the distribution of job offers by schooling level¹⁹ can turn out to be a better strategy than exploiting data on the number of job vacancies by level of education. For, the schooling level registered in the employment agency is the level required by the employer in the hiring process and not necessarily the one required to perform the job. For instance, employers could increase their educational requirements in order to attract the best candidates for the job or simply because they know that there is a large number of highly educated job seekers (see Green *et al.* 1999). On the other hand, employers could formally ask for a lower education level than actually required for the job while hiring only candidates with the required schooling. This strategy would allow to lower wages of new entrants in occupation where the educational attainment plays an important role in wage determination (see Hartog 2000).

¹⁹Notice that we could not interpret the parameter v_{ic} as vacancy parameter by education level if the matching efficiency, e_x , was dependent on i . For, v_{ic} would then be the product of a vacancy and an efficiency parameter.

For purposes of identification (see Appendix 3), we cannot allow for interactions between calendar time and schooling level for both vacancy and job competition parameters. We impose a common evolution to the job competition parameters and let the vacancy parameters evolve differently according to the education level. It seems realistic to assume that the distribution of job offers by schooling level varies through the business cycle. Besides, imposing a common time dependence to the job competition parameters does not imply that the *number* of overeducated job seekers in each segment, $\kappa_c^{i+1}U_c^{i+1}$, evolves similarly through time. We represent the time dependence of v_{ic} and κ_c^i by the following parametric specification, in which we decompose both functions into a cyclical part and a seasonal part:

$$v_{ic} = \exp \left(v_{i0} + \sum_{n=1}^2 v_{in} p_n(c) + \sum_{s=2}^4 (v_{is} - v_{i0}) s(c) \right), \quad i = 1, 2, 3, 4 \quad (4.19)$$

and

$$\kappa_c^i = \exp \left(\kappa_0^i + \sum_{n=1}^2 \kappa_n p_n(c) + \sum_{s=2}^4 (\kappa_s - \kappa_0^i) s(c) \right), \quad i = 2, 3, 4 \quad (4.20)$$

The time dependence of the vacancy and job competition parameters is specified with a second degree polynomial in calendar time, $p_n(c)$, capturing business cycle effects, and with dummy variables, $s(c)$, capturing seasonal effects²⁰. To avoid multi-collinearity problems, we follow Abbring *et al.* (2001b) and use the orthogonal Chebyshev polynomial instead of an ordinary polynomial²¹.

²⁰In the estimation, we take the seasonal dummies in deviation from their mean.

²¹The series of Chebyshev polynomials is obtained as follows (see Abramowitz and Stegun 1970, Table 22.3). First, linearly transform the domain of calendar time to the domain of orthogonality of the Chebyshev Polynomial, $[-1, 1]$, by means of ($x = c$ and $x_0 = 1$):

$\hat{x}(x) = 2 \frac{x - x_0}{n - 1} - 1$, where n ($= 18$) is the number of calendar time intervals considered.

Then generate the series of orthogonal polynomials, $p_i(\hat{x})$, by means of:

$$p_i(\hat{x}) = \frac{i}{2} \sum_{j=0}^{\lfloor \frac{i}{2} \rfloor} (-1)^j \frac{(i-j-1)!}{j!(i-2j)!} (2\hat{x})^{i-2j} \text{ for } i = 1, 2 \text{ and for } j \in R^+.$$

Since we estimate and do not condition on the observed number of vacancies by level of education, the reader might be worried that the number of unemployed workers by level of educational attainment is correlated with the residuals of the regression model. This is because employers are likely to adjust the number of vacancies at a particular skill level to the number of available workers at that skill level (see e.g. Gautier 2001). If the actual number of opened vacancies deviates from the estimated one, this induces the above-mentioned correlation. We claim that our specification of V_{ic} is sufficiently flexible to capture the structural behaviour of employers, so that random deviations are unlikely to be correlated with the number of unemployed workers of a particular educational level.

Finally, we parametrise e_x according to a proportional specification:

$$e_x = e_{ak} = \exp \left[\sum_{j=2}^4 \gamma_k \delta_{jk} + \eta_2 \delta_{2a} \right] \quad (4.21)$$

where δ_{jk} is the Kronecker delta, γ_k is the duration effect and η_2 is the age effect (i.e. being aged 29-44). We normalise $e_{11} = 1$.

We now turn to a description of the estimation procedure. Since we rely on grouped data, Minimum Chi-Squares is a natural estimation method (Berkson 1944, Amemiya 1981; for an application on transition data, see Cockx 1997 and Cockx and Ridder 2001). In a nutshell, this method consists in regressing a transformation of the empirical exit probability, $\hat{P}_{xc}^i$, to its theoretical counterpart. The theoretical probability at the k^{th} duration interval for a worker of schooling i and age group a who is at risk of leaving unemployment within the c^{th} quarter is:

$$P_{xc}^i \equiv \Pr(k-1 \leq T < k | T \geq k-1, c, i, a) \quad (4.22)$$

We then link this probability to the hazard rate defined in (4.16):

$$P_{xc}^i = \frac{S(k-1) - S(k)}{S(k-1)} = 1 - \exp[-h_{xc}^i] \quad (4.23)$$

where $S(k)$ is the survivor function at unemployment duration k and is given by:

$$S(k) = \exp \left[- \sum_{s=1}^k h_{asc}^i \right] \quad (4.24)$$

where $c = l + s$. Inverting the relationship (4.23) yields:

$$z_{xc}^i = \log [-\log (1 - P_{xc}^i)] = \log (h_{xc}^i) \quad (4.25)$$

If we replace the probability of leaving unemployment by its estimate, $\hat{P}_{xc}^i$, in (4.25), the equality of this equation does no longer hold exactly. For the empirical outflow probability is calculated on the basis of a finite sample. We follow Cockx (1997) and expand $\log [-\log (1 - \hat{P}_{xc}^i)]$ in a Taylor series around P_{xc}^i . We then obtain a non-linear heteroskedastic regression model:

$$\hat{z}_{xc}^i = \log (h_{xc}^i) + \omega_{xc}^i + \varepsilon_{xc}^i, \quad i = 1, 2, 3, 4 \quad (4.26)$$

where ω_{xc}^i is the approximation error that reflects the stochastic nature of the empirical outflow probability $\hat{P}_{xc}^i$ and where ε_{xc}^i is a specification error which allows for random deviation from the true specification of the outflow rate. We estimate the statistical model (4.26) by Generalized Non-Linear Least Squares. The details of the estimation procedure can be found in Appendix 4.

Because we have grouped data, we can use a χ^2 -goodness-of-fit test to evaluate the model specification (see Amemiya 1981). The weighted sum of squared residuals ($WSSR$) is distributed $\chi_{N-N_\theta}^2$ if the model is correctly specified, where N denotes the number of cells and N_θ is the number of parameters. Moreover, we can test the acceptability of restrictions on the parameters, for instance the absence of job competition (i.e. $\forall i, c : \kappa_c^i = 0$). The difference between the weighted sum of squared residuals of the constrained and the unconstrained model ($WRSS_0 - WRSS$) is distributed $\chi_{(N_\theta - N_{\theta_0})}^2$ ²².

²²For the purpose of this test statistic, the constrained model is estimated with the estimated variance and covariance of the specification errors in the unconstrained model.

4.5 Empirical results

For purpose of presentation, the estimation results are provided in Appendix 5. In the first column of Table 4.7, we report the estimation results of the regression model (4.26). Notice that the value of the v_i parameters is meaningless since they contain a common scale parameter. They can only be interpreted in relative terms. Before entering into a more detailed interpretation of the estimation results, we first question whether we can impose some restrictions on this regression model according to the χ^2 test.

We first impose that v_{1c} , v_{2c} and v_{3c} are constant over the business cycle, i.e. $\forall i \in \{1, 2, 3\} : v_{in} = 0$ in (4.19). The estimation results are presented in the second column of Table 4.7. This restriction implies that the evolution of the job offers at the lower segments follows the dynamic pattern of V_c , while there is a specific time variation for the high skilled vacancies. Such a specification is not rejected at a significance level of 61%. We choose to impose these restrictions in our regression model since the parameters are otherwise too imprecisely estimated to warrant a sensible discussion.

We then look at the elasticities of the matching function (see the second column of Table 4.7). The estimated elasticity of matches with respect to unemployment (α) and vacancies (β) is respectively 0.52 (0.14) and 0.81 (0.12). So there is evidence of mild increasing returns to scale of the order of 1.33 (0.24), although the sum of the elasticities is not statistically different from one. This result is confirmed by the χ^2 -test which does not reject constant returns to scale at a significance level of 15% (see the third column of Table 4.7)²³. Moreover, even if the flow of jobs opened as public employment schemes for the unemployed increases the number of matches ($\pi = 0.10$), it does not affect it significantly (see the fourth column of Table 4.7)²⁴.

Since we cannot reject these restrictions, we choose to discuss the parameter estimates on the basis of the regression model (4.26) on which we impose, besides $\forall i \in \{1, 2, 3\} : v_{in} = 0$, constant returns to scale

²³The unconstrained model of this test is the regression model (4.26) with $\forall i \in \{1, 2, 3\} : v_{in} = 0$, in the second column of Table 4.7.

²⁴idem.

($\alpha + \beta = 1$) and $\pi = 0$. Imposing CRS will also allow a better comparison with other empirical studies which directly impose this restriction (as in Van Ours and Ridder 1995). This model will be our benchmark model. The results are reported in the first column of Table 4.8. The standard errors of the estimated parameters are smaller with this specification. The estimated elasticity of matches with respect to unemployment and vacancies is respectively 0.37 and 0.63. Using the flow of hirings as dependent variable, Van Ours and Ridder (1995) estimate similar matching elasticities with a matching function allowing for job competition. The elasticity on unemployment is generally higher (of the order of 0.7) in studies estimating traditional matching function at the aggregate level with the total outflow from unemployment as dependent variable (see Petrongolo and Pissarides 2001). Note that the probability of being matched decreases markedly with unemployment duration. Besides, workers aged between 29 and 44 years old are significantly less likely of being hired than younger workers: The exit rate of prime-aged men is 22% lower than the one of young men.

Finally, consider the performance of our benchmark model on the basis of the goodness-of-fit statistic. The model is not rejected against the saturated model (P-value=47%). Note also that the standard deviation of the specification errors, ε_{xc}^i , is of the order of .10 for the different schooling groups. For the highest education level ($i = 4$), the specification error accounts for only 3% of the variation in the dependent variable while it contributes to a more important variation for the lower schooling levels (about 10%). Since the determinants of the exit rate by schooling level are inter-related in case of job competition, specification errors are correlated. As expected, the correlation is particularly large between adjacent education levels.

4.5.1 Job competition and vacancy parameters

Let us now look at which schooling levels there is job competition in our benchmark model. The first column of Table 4.2 indicates that there is significant job competition at each schooling level. However, its extent increases markedly with the educational attainment of the worker. On average over our observation period, $\kappa^4 = 6$ while $\kappa^3 = 1.5$ and $\kappa^2 =$

0.4. Since $\kappa^i > 1$ for $i = 3, 4$, the overeducated job seekers with these schooling levels are more likely to be hired than those of have just the required level, i.e. $z^i > 1$ for $i = 3, 4$. The job competition parameter for the workers at the top of the education ladder is so high that we cannot exclude that all unemployed workers with higher education search for jobs normally filled by workers with an upper secondary degree (i.e. $\lambda^4 = 1$). Adopting this search behaviour they are about 6 times more likely to be hired than the workers who just completed upper secondary. Since $\kappa^2 < 1$, we cannot state whether the search effectiveness of the overeducated job searchers with a lower secondary degree is higher, equal or lower than the adequately educated workers.

Table 4.2: Average estimated value of the job competition and vacancy parameters

	κ^i	V_i/V_1
Higher education ($i = 4$)	6.04 [3.19,11.43]	0.01 [0.00,0.05]
Upper secondary ($i = 3$)	1.55 [1.10,2.18]	0.27 [0.14,0.49]
Lower secondary ($i = 2$)	0.43 [0.28,0.64]	0.76 [0.53,1.10]
No education or elementary school ($i = 1$)	-	1

Note: Benchmark model; Between [.], 95% confidence interval.

As expected, we reject a specification without job competition, i.e. $\forall i, c : \kappa_c^i = 0$, according to the χ^2 -test (see the second column of Table 4.8 in Appendix 5). Even if the job competition parameter is relatively small at the lower secondary level, we also clearly reject the absence of job competition between workers with a lower secondary degree and those with at most an elementary degree according to the χ^2 -test (see the third column of Table 4.8). These results differ markedly from Van Ours and Ridder (1995). They found evidence of significant job competition only at the top segment of the labour market, between workers with a higher vocational degree and academically educated workers. These workers share the same schooling group in our analysis.

Finally, job competition appears to be countercyclical in Wallonia, as observed in comparing a Belgian business cycle indicator²⁵ (the Kredietbank indicator) and the estimated second degree polynomial function

²⁵There is no regional business cycle indicator in Belgium.

in Figure 4.5. The extent of job competition increases significantly with the strong deterioration of the economic conditions from 1991. Gautier *et al.* (2001) found evidence of countercyclical job competition at only one of the lower job complexity levels: At this level, the difference between average schooling of the inflow and the outflow (at the firm level) increases in downturn.

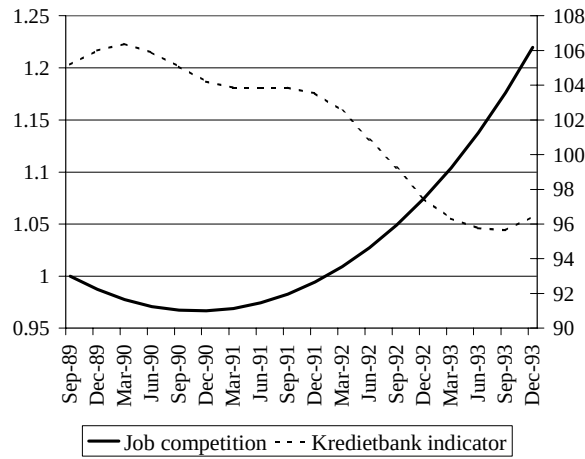


Figure 4.5: Cyclical dependence of job competition and the Kredietbank indicator (right scale)

As regards to the distribution of job offers by level of education, the estimated v_4 parameter indicates that there is almost no job offers for the unemployed workers with higher education. For the other segments of the labour market, the number of job offers decreases with the required schooling level. The second column of Table 4.2 gives the average estimated value V_{ic} with respect to its value in the segment requiring at most an elementary degree ($i = 1$). While 100 are opened for workers with almost no education, only 1 is posted for workers who completed higher education with a 95% confidence interval equal to $[0, 5]$ ²⁶.

²⁶The scarcity of jobs offered at the top segment of the education ladder would actually be reinforced if v_i was the product of a vacancy and efficiency parameter (see footnote n°19). For, the highly educated unemployed workers are likely to search more intensively than lower educated workers given that the level of unemployment benefits is upward bounded.

The χ^2 -test shows that the v_2 parameter does not differ significantly from the v_1 parameter on average and over seasons (see the second column of Table 4.9 in Appendix 5). Besides, we cannot reject that the seasonal variation in v_3 and v_4 is the same (see the third column of Table 4.9). The seasonal coefficients of the v_i parameters must be interpreted as the specific variation of the job offers by schooling level through seasons beyond the common seasonality observed in V_τ . For instance, the number of job offers for the two lowest schooling levels ($i = 1, 2$) is smaller in the winter time than what the aggregate statistics on job offers suggest.

The estimated series of job offers at the highest schooling level also presents some significant time variation. At the beginning of the period, there is merely no jobs proposed to the highest educated unemployed workers. When the economic conditions deteriorate in 1992, they receive some job offers. This result would partly explain why the exit probability of the highest educated workers was less affected by the recession in 1993 than the one of the other schooling groups (see Figure 4.2). With the recovery of the early 1994, the number of jobs offered to the highest educated unemployed people falls back again around zero.

4.5.2 Interpretation of the results

We now turn to the interpretation of our parameter estimates. How could we first explain the importance of job competition among the unemployed workers in Wallonia? As stressed in chapter 4, this region is characterised by a *structural* weakness of job creation since the mid eighties. Over the 1984-1995 period, employment increased by 7.6% in Wallonia while it rose by almost 20% in Flanders (see Table 4.3). In comparison with the employment performances of our bordering countries during this period, those registered in the Walloon region are very bad (see Sneessens *et al.* 1999). For the period that we consider, the employment growth in Wallonia was further hampered by the strong deterioration of the economic prospects observed in all European countries. The relative scarcity of jobs in Wallonia certainly induced more educated unemployed to extend job search on the skill segment below their own, thereby crowding out lower educated unemployed in their

own segments. This process was at its height in the economic trough of 1993 (see Figure 4.5).

Table 4.3: Evolution of salaried employment, by sector and sub-periods, in % of the initial regional employment

	Industry		Private services		Public services		Total	
	Wallonia	Flanders	Wallonia	Flanders	Wallonia	Flanders	Wallonia	Flanders
1984/73	-19.1%	-12.5%	3.1%	7.3%	7.2%	5.8%	-8.8%	0.6%
1995/84	-6.6%	-1.0%	10.5%	17.0%	3.7%	3.4%	7.6%	19.4%
1995/73	-25.7%	-13.5%	13.5%	24.3%	10.9%	9.2%	-1.3%	20.0%

Source: Sneessens and Shadman-Mehta (2000, p.117)

How could we then explain the relative scarcity of jobs offered to the unemployed workers with a high level of education, particularly those who completed higher education, who, as a result, exert an intense job competition on the lower segments? In our data set, we only observe unemployed workers who separated from their employers and who did not directly find a new job. Therefore, our estimation of vacancies by schooling level concerns *only those intended to this selective population*, which excludes young school leavers and employed job seekers²⁷.

Employed job seekers can represent a large fraction of the total number of job seekers in the upper segments of the labour market where labour mobility is important. Moreover, the share of students who leave school with higher education is nowadays relatively large: In the early nineties, 33.4% of a cohort of young children achieved this level in the French-speaking education, against 29.6% and 37% who attained at most an upper and a lower secondary degree respectively (see Dal and Dupierreux 1996). Given the depressive economic context, employers might then not need to propose job offers requiring high skills to the unemployed workers. For the other levels of education, the unemployed population that we consider is less likely to be an avoidable pool of recruitment.

When the labour market is characterised by search frictions, there must be objective factors to justify such recruitment practices. One can for instance argue that dismissed workers who completed higher education

²⁷Voluntary quitters are eligible for unemployment benefits after a waiting period of 26 to 52 weeks (see OECD 1997b).

are likely to be a selective population of the total group of higher educated workers with lower skill attributes (others than the skills acquired at school). However, in a context of low employment growth and abundant supply of high school graduates, such recruitment practices can be observed even if the skill attributes of the unemployed workers does not differ markedly to those of other job seekers²⁸.

Finally, how could we explain that for the jobs requiring an upper secondary degree, the unemployed workers with higher education are much more likely to be hired than those who have just the required schooling level? In comparison with our bordering countries and with Flanders, the distribution of young people by level of educational attainment has a particular feature in Wallonia: This region is characterised by a relatively high share of high school graduates, but also by a relatively low number of young people who achieve an upper secondary degree (see Binon *et al.* 1998). The scarcity of graduates at this level of education mainly concerns the vocational and technical degrees²⁹. In a context of skill biased technological change, employers may then be inclined to hire more educated workers on jobs normally filled by workers with a technical degree of the upper secondary school. Note that a large majority of unemployed workers with higher education have a vocational or technical degree of three years at the latest: 60%, against 30% with an university degree³⁰.

4.5.3 Decomposition of the exit rate by schooling level

In order to better understand the scope of our results, we decompose the determinants of the estimated exit rate by schooling level in the benchmark model. For the easiness of interpretation, we use the expression of the hazard rate given in (4.10), with tightness indicators measured

²⁸Note that the average quality of entrants into unemployment improves during recessions and falls in upturns according to the findings of Chapter 3. This cyclical pattern in the composition of entrants could explain why employers propose some jobs to the high skilled unemployed workers when the economic conditions deteriorate (see the above results on the vacancy parameters).

²⁹Students who completed a general degree are more likely to enrol to higher education (see Dal and Dupierreux 1996), whose access is relatively easy in Belgium in comparison with other European countries.

³⁰These figures are obtained from the monthly reports of the public employment agency (ONEm) and are averages over our observation period.

in effective units ($\tilde{\theta}_i$). We take the average value of our estimates and regressors and set $e_x = 1$. This yields the following decomposition of $\hat{h}_x^i$ by schooling level, where $\hat{\beta} = 0.63$, $\hat{S}_i = \bar{e}^i U^i + \hat{\kappa}^{i+1} \bar{e}^{i+1} U^{i+1}$ and the figure in **bold** refers to the value of $\hat{h}_x^i$ when setting $\forall i : \hat{\kappa}^i = 0$:

Higher education ($i = 4$):

$$\underbrace{\hat{h}_x^4}_{\substack{0.72 \\ \mathbf{0.04}}} = \underbrace{\left(\tilde{\theta}_4 \right)_{0.01}^{\hat{\beta}}}_{0.04} + \underbrace{\hat{\kappa}_6^4}_{\substack{6}} \underbrace{\left(\tilde{\theta}_3 \right)_{0.13}^{\hat{\beta}} \left(\frac{\bar{e}^3 U^3}{\hat{S}_3} \right)_{0.24}^{\hat{\beta}}}_{0.11} \quad (4.27)$$

Upper secondary ($i = 3$):

$$\underbrace{\hat{h}_x^3}_{\substack{0.53 \\ \mathbf{0.28}}} = \underbrace{\left(\tilde{\theta}_3 \right)_{0.13}^{\hat{\beta}} \left(\frac{\bar{e}^3 U^3}{\hat{S}_3} \right)_{0.24}^{\hat{\beta}}}_{0.11} + \underbrace{\hat{\kappa}_{1.5}^3}_{1.5} \underbrace{\left(\tilde{\theta}_2 \right)_{0.22}^{\hat{\beta}} \left(\frac{\bar{e}^2 U^2}{\hat{S}_2} \right)_{0.53}^{\hat{\beta}}}_{0.26} \quad (4.28)$$

Lower secondary ($i = 2$):

$$\underbrace{\hat{h}_x^2}_{\substack{0.40 \\ \mathbf{0.39}}} = \underbrace{\left(\tilde{\theta}_2 \right)_{0.22}^{\hat{\beta}} \left(\frac{\bar{e}^2 U^2}{\hat{S}_2} \right)_{0.53}^{\hat{\beta}}}_{0.26} + \underbrace{\hat{\kappa}_{0.4}^2}_{0.4} \underbrace{\left(\tilde{\theta}_1 \right)_{0.26}^{\hat{\beta}} \left(\frac{\bar{e}^1 U^1}{\hat{S}_1} \right)_{0.74}^{\hat{\beta}}}_{0.35} \quad (4.29)$$

Primary or no education ($i = 1$):

$$\underbrace{\hat{h}_x^1}_{\substack{0.35 \\ \mathbf{0.43}}} = \underbrace{\left(\tilde{\theta}_1 \right)_{0.26}^{\hat{\beta}} \left(\frac{\bar{e}^1 U^1}{\hat{S}_1} \right)_{0.74}^{\hat{\beta}}}_{0.35} \quad (4.30)$$

Unemployed workers who completed higher education have a large outflow rate (on average, 0.72) due to the strong competition they exert on the jobs normally filled by those with an upper secondary degree. They compensate the lack of job offers for their services by searching for jobs in the lower segment. In this competition for jobs, there are by far preferred to those who have just the required schooling level. If they had no access to jobs requiring an upper secondary degree, the exit rate of workers with higher education would be 0.04. As a result, unemployed workers with an upper secondary degree search for jobs at the lower secondary segment to mitigate the effects on their exit rate of both the competition from the higher schooling group and the relative scarcity of jobs in their segment. This search strategy induces a significant rise in their outflow rate, from 0.11 to 0.53. Moreover, the net effect of job competition on their exit rate is positive since it would be equal to 0.28 in the absence of job competition.

For the same reasons than their more educated counterparts, some unemployed workers with a lower secondary degree offer their work at the bottom of the ladder. Even if their competition is not very strong as compared to the competition they face from the higher educated workers, the outflow rate of workers with a lower secondary degree is relatively high, on average 0.40, due to a relative large number of job offers in their own segment. The net effect of job competition on their exit rate is close to zero since it would be set to 0.39 otherwise. The outflow rate of the workers with at most an elementary degree is negatively affected by the search behaviour of the unemployed workers with a lower secondary degree: Their exit rate equals to 0.35 and 0.43 with and without job competition respectively.

This decomposition analysis indicates that job competition is the *only* cause of the increase in the transition rate out of unemployment with the educational attainment of the worker. Notice that the ranking of the exit rates by schooling level would be reversed in the absence of job competition since the number of job offers strongly decreases with the level of education.

4.6 Sensitivity analysis

To increase the reliability of our findings, we investigate the sensitivity of our model estimates to changes in the specification. First, we estimate our benchmark model for young people only (aged ≤ 28). One may indeed question whether the extent of job competition is influenced by the age of the unemployed worker. The empirical literature indeed suggests that young people with little work experience and on-the-job training are more incline to search for jobs below their educational attainment (see e.g. Forgeot and Gautier 1997). The estimation results are presented in the second column of Table 4.10 (in Appendix 5) while the first column reports the estimates of our benchmark model. We conclude that only the matching elasticities differ between these two models ($\hat{\beta} = 0.75$ for those aged ≤ 28). In particular, the job competition and vacancy parameters are similar to those obtained for the whole population.

Second, we specify a model in which we impose that the share of job offers by schooling level, v_{ic} , is only a fraction of the observed number of job offers, V_c , i.e. we require that the sum of these shares equals to one:

$$V_{ic} = v_{ic}V_c, \quad \text{with } \forall c : \sum_{i=1}^4 v_{ic} = 1 \quad (4.31)$$

This restriction would be sensible if the unemployed workers looked only for jobs registered at the employment agency and if employers were reluctant to hire them through other search channels. Since the vacancies published by the Belgian employment agency represent a small and selective fraction of the actual number of job offers (see above), we believe that restriction (4.31) is too strong. Indeed, this restriction is rejected at a significance level of 1%³¹. If reliable data on vacancies were available, imposing this restriction would allow to confront estimated distribution of job offers by schooling level with official statistics.

Finally, we specify a model in which we estimate directly tightness indicators rather than vacancy parameters. The advantage of such a specification is that it allows to test formally whether there is skill mismatch among the unemployed population that we consider. Recall that

³¹Estimation results are available upon request.

in our framework, skill mismatch implies different V-U ratios ($\tilde{\theta}_i$) across schooling groups. As compared to the mismatch index calculated by Jackman and Roper (1987), we do not need to rely on vacancies data by schooling level since these are estimated. We must however make two observations on our measure of skill mismatch and on its interpretation.

One may first question whether the use of V-U ratios is still relevant in the presence of job competition. With job competition, the unemployed workers of schooling i can also be candidates for vacancies in segment $i-1$. From the firm's perspective, they should therefore be accounted for when measuring tightness in segment $i-1$. From a policy point of view, the relevant measure of tightness by schooling level remains, however, the ratio of job offers to the number of job seekers whose schooling profile is appropriate to the one required to perform the job, i.e. $\tilde{\theta}_i$.

Second, the measure of skill mismatch depends the quality of the data. A number of empirical studies use registered job offers and unemployed workers. These are just a part of the actual number of vacancies and job seekers in the economy. As stressed in the previous section, our estimation of vacancies by schooling level concerns only those intended to dismissed unemployed workers, what excludes school leavers and employed job searchers. So we can just evaluate the extent of skill mismatch *within this selective population* in our analysis. To obtain a reliable measure of skill mismatch on the labour market, one should need data on all types of job seekers.

We define tightness in a slightly different way than the definition given in (4.3). We normalise the V-U ratio in segment i by the aggregate V-U ratio (expressed in effective units), which we denote $\tilde{\theta}_{ic}^*$:

$$\tilde{\theta}_{ic}^* = \frac{\frac{V_{ic}}{\bar{e}^i U_c^i}}{\frac{V_c}{U_c}} \quad \text{with } V_c = \sum_i V_{ic} \text{ and } U_c = \sum_i \bar{e}^i U_c^i \quad (4.32)$$

This specification allows the number of job offer by education, V_{ic} , to be still proportional to the observed number of job offers V_c :

$$V_{ic} = (\bar{e}^i U_c^i) \theta_{ic}^* \frac{V_c}{U_c} \quad (4.33)$$

Substituting (4.33) into (4.16) and assuming CRS, the hazard model

for the schooling level i is therefore given by the following non-linear expression:

$$h_{xc}^i = e_x \left[\left(1 + \kappa_c^{i+1} \frac{\bar{e}^{i+1} U_c^{i+1}}{\bar{e}^i U_c^i} \right)^{-\beta} \left(\tilde{\theta}_{ic}^* \right)^\beta + \kappa_c^i \left(1 + \kappa_c^i \frac{\bar{e}^i U_c^i}{\bar{e}^{i-1} U_c^{i-1}} \right)^{-\beta} \left(\tilde{\theta}_{i-1c}^* \right)^\beta \right] \left(\frac{V_c}{U_c} \right)^\beta \quad (4.34)$$

where we represent the time dependence of $\tilde{\theta}_i^*$ by a similar parametric specification as v_i :

$$\tilde{\theta}_{ic}^* = \exp \left(\theta_{i0} + \sum_{n=1}^2 \theta_{in} p_n(c) + \sum_{s=2}^4 (\theta_{is} - \theta_{i0}) s(c) \right), \quad i = 1, 2, 3, 4 \quad (4.35)$$

In the second column of Table 4.11 (see Appendix 5), we report the estimation results of our benchmark model in which we replace h_{xc}^i by its expression in (4.34). In this model we cannot impose that $\forall i \in \{1, 2, 3\} : \theta_{in} = 0$. For, this restriction is rejected at a significance level of 5% according to the χ^2 -test. The absence of time variation in $\tilde{\theta}_{ic}^*$ would mean that the V-U ratio in segment i follows the evolution of the aggregate V-U ratio. From our benchmark model, we know that the evolution of the job offers at the lower segments follows the dynamic pattern of V_τ . Therefore, this rejection should come from a slight diverging time variation in the number of unemployed workers across schooling groups (see Figure 4.4). The performance of the model with tightness parameters is similar to our benchmark model on the basis of the goodness-of-fit statistic. Upon comparison between these two models, we conclude that only the time dependence of the job competition parameters differs. However, the second degree polynomial function is far from being precisely estimated in the second model. More generally, standard errors are larger in the model with tightness parameters than in our benchmark model.

Table 4.4 reports the average estimated value of the job competition and tightness parameters in this new model. The latter are normalised by the V-U ratio estimated in the lowest segment ($i = 1$)³². Although

³²These estimated V-U ratios are very close to the ratios that we can calculate in

their confidence interval is relatively large, we conclude that the V-U ratios decrease from the lowest to the highest segments of the labour market. According to the χ^2 -test, we cannot reject *both* the absence of cyclical variation in $\theta_{ic}^* \forall i \in \{1, 2, 3\}$ and a similar V-U ratio in the two lowest segments of the labour market ($i = 1, 2$) at a significance level of 6.8% (see the second column of Table 4.12 in Appendix 5). The last column of Table 4.12 also indicates that the V-U ratios in the upper segments of the labour market ($i = 3, 4$) are significantly lower from the one estimated in the bottom segments, on average (P-value= 0.6%).

Table 4.4: Average estimated value of the job competition and tightness parameters

	κ^j	θ_i / θ_1
Higher education ($i = 4$)	5.90 [2.93,11.93]	0.03 [0.01,0.42]
Upper secondary ($i = 3$)	1.65 [1.08,2.54]	0.51 [0.21,1.23]
Lower secondary ($i = 2$)	0.46 [0.32,0.68]	0.78 [0.56,1.13]
No education or elementary school ($i = 1$)	-	1

Note: Benchmark model with tightness parameters; Between [.], 95% confidence interval.

These results indicate that the smaller amount of vacancies at the upper secondary level is partially compensated by a lower number of unemployed workers with this schooling level. However, there is still a shortage of vacancies in the upper secondary level as regards to the two lower segments of the labour market. On the other hand, even if the number of unemployed workers with higher education is relatively low, the job offers intended for this type of labour is really too scarce. According to our estimates, there would be not enough job offers requiring a diploma of higher education, and in a less extent, an upper secondary degree, for the unemployed workers.

In the previous section, we argued that the relative scarcity of jobs proposed to the unemployed workers with higher education reflects a recruitment behaviour of employers in a context of low job creation. Given the abundant supply of high educated graduates on the labour market, employers will be less inclined to propose job offers requiring high skills

our benchmark model.

to the unemployed workers. For the other levels of education, the unemployed workers are less likely to be an avoidable pool of recruitment. Since we analyse the demand of skills for a particular population of job seekers, our results are *not inconsistent with* a story of skill biased technological change. In our empirical framework, we need data on all types of job seekers by level of education to obtain a *reliable measure* of the demand of skills in the economy, and so mismatch.

Even if this model is rejected at a significance level of 5%, one can be interested in the estimated value of the tightness parameters in the absence of job competition. Table 4.5 reports the average estimated value of the V-U ratio in a model with $\forall i, c : \kappa_c^i = 0$ (see also the second column of Table 4.13 in Appendix 5). Contrary to our preferred model, the V-U ratio *increases* significantly from the lowest to the highest segment of the labour market. Since we impose the absence of job competition, this *must* be the case for the estimated hazard to fit the data, i.e. the increase in the outflow rate with the educational attainment of the worker. In this model, skill mismatch in the unemployed population is important but is now characterised by a relatively large amount of job offers and a small number of unemployed workers in the top segments of the labour market and the opposite in the bottom segments.

Table 4.5: Average estimated value of the tightness parameters in a model without job competition

	κ^i	θ_i / θ_1
Higher education ($i = 4$)	0	3.52 [2.40,5.21]
Upper secondary ($i = 3$)	0	1.98 [1.57,2.49]
Lower secondary ($i = 2$)	0	1.31 [1.18,1.46]
No education or elementary school ($i = 1$)	-	1

Note: Benchmark model with tightness parameters and $\forall i, c : \kappa_c^i = 0$; Between [.], 95% confidence interval.

We also report in Table 4.6 the estimated job competition parameters in the absence of skill mismatch in the unemployed population (on average), i.e. $\forall i : \theta_{i0} = \theta_{10}$ and $\theta_{in} = 0$ in (4.35) (see the last column of Table 4.12 in Appendix 5). The latter restriction is needed for identification

purposes: We cannot allow for two common time dependence (in κ^i and $\tilde{\theta}_i^*$). As said supra, this model is rejected at a significance level of 0.6%. Here, the job competition parameter also increases with the educational attainment of the worker. However, its estimated value is lower than in our benchmark model in which the shortage of job offers in the upper segments of the labour market strengthens the extent of job competition at the highest level of education.

Table 4.6: Average estimated value of the job competition parameters in a model without skill mismatch

	κ^i	θ_i / θ_1
Higher education ($i = 4$)	1.09 [1.02,1.17]	1
Upper secondary ($i = 3$)	0.65 [0.60,0.71]	1
Lower secondary ($i = 2$)	0.24 [0.22,0.26]	1
No education or elementary school ($i = 1$)	-	1

Note: Benchmark model with tightness parameters and $\forall i : \theta_{i0} = \theta_{10}$ and $\theta_{in} = 0$; Between [.], 95% confidence interval.

4.7 Conclusion

The aim of this chapter was to determine the relative importance of job competition and skill mismatch for a population of unemployed job searchers in Belgium. To that purpose, we used administrative data on the exit rates from unemployment by level of education and on the total number of job vacancies registered at the public employment agency. Our observation period ranged from June 1989 to February 1994. The outflow rate was modelled in a matching function framework. We assumed that the job market is segmented by schooling level and that each segment is characterised by the same job matching technology.

With job competition, all unemployed workers search for jobs in their own segment and some fraction search simultaneously in the segment just below their own. Under this assumption, the transition rate out of unemployment by level of education is made of two components: The probability of finding a job corresponding to his schooling profile and the probability of finding a downgrading job. We estimated, by Minimum

Chi-Squares, the structural form of the exit rate out of unemployment by level of educational attainment. The parameters of interest are the extent of job competition at each schooling level and the distribution of job offers according to the required level of education.

We found that there is significant job competition among the unemployed workers in Wallonia. Moreover, its extent increases markedly with the educational attainment of the worker. The job competition parameter for the workers at the top of the education ladder is so high that we cannot reject the hypothesis that all unemployed workers with higher education search for jobs normally filled by workers with an upper secondary degree. Adopting this search behaviour they are about 6 times more likely to be hired than are the workers who just completed upper secondary school. The extent of job competition also went up with the economic downturn of the early nineties.

Our results also indicated that there is almost no jobs offered to the unemployed workers who completed higher education. For the other types of unemployed people, the number of vacancies requiring an upper secondary degree is significantly smaller than the job offers at the lower levels of education. If we take into account the supply of skills, we concluded that there is a relative shortage of job offers requiring a diploma of higher education, and in a less extent an upper secondary degree, for the unemployed workers in Wallonia.

We claimed that the scarcity of jobs in Wallonia must account for the intense job competition among unemployed workers. Since the mid eighties, this region is characterised by a *structural* weakness of job creation in comparison with Flanders and our bordering countries. For the period that we consider, the employment growth in Wallonia was further hampered by the strong deterioration of the economic prospects. The weakness of job creation in Wallonia certainly induced more educated unemployed to extend job search on the skill segment below their own, thereby crowding out lower educated unemployed in their segment.

We also argued that the few number of jobs proposed to the unemployed workers with higher education reflects a recruitment behaviour of employers when jobs are scarce. In our data set, we only observe dismissed unemployed workers. Therefore, our estimation of vacancies by schooling level concerns *only those intended to this selective population*,

which excludes young school leavers and employed job seekers. Given the large supply of highly educated school leavers and the scarcity of jobs, employers will not be inclined to propose job offers requiring high skills to the unemployed workers. As a result, the most educated unemployed exert an intense job competition on the lower segments. For the lower levels of education, the unemployed population that we consider is less likely to be an avoidable pool of recruitment, so that we estimated relatively more job offers for the low educated unemployed.

Since we estimate the demand of skills for a particular population of job seekers, our results are of course *not inconsistent with* a story of skill biased technological change. In our empirical framework, we would need data on all types of job seekers by level of educational attainment to obtain a *reliable measure* of the demand of skills in the economy, and so mismatch. The very good employment prospects of unemployed workers with higher education on jobs normally requiring an upper secondary degree can actually be consistent with a *relative* increase in the demand of high skills. Compared with our bordering countries and Flanders, there is a low number of young people who achieve the upper secondary school in Wallonia, particularly with vocational and technical degrees. In a context of skill biased technological change, employers may then be inclined to hire overeducated workers on jobs normally filled by workers with a technical diploma of the upper secondary school. Our argument is reinforced by the observation that a large majority of unemployed workers with higher education have a vocational or technical degree of three years at the latest.

4.8 Appendix

4.8.1 Appendix 1: Equilibrium search model

In this appendix³³, we develop an equilibrium search model *à la* Pissarides (2000) with two types of jobs and workers (high educated and low educated) and perfect segmentation of the labour market. The objective of this simple model is to show that skill biased technological change, i.e. an increase in the relative productivity of high skilled jobs, is not the only possible determinant of skill mismatch in a steady-state equilibrium. Tightness may also vary across skill segments due to differences in bargaining power, separation rate, unemployment benefit and hiring costs between segments.

We assume that the job market is perfectly segmented by education level i : (i) The unemployed workers of education level i , U^i , look for jobs only in their own segment, and (ii) the vacancies requiring the education level i , V_i , can only be filled by workers who have the corresponding level. Apart from their educational attainment, workers are assumed to be homogeneous. Each segment is characterised by the same job matching technology: $F_i = f(U^i, V_i)$ ³⁴. The matching efficiency does not depend on the educational level and is normalised to one in all segments. Let $\theta_i = \frac{V_i}{U_i}$ denote tightness in segment i . Under constant returns to scale, the rate at which vacant jobs become filled is: $q(\theta_i) \equiv \frac{F_i}{V_i}$ and the rate at which a worker finds a job is: $\theta_i q(\theta_i) \equiv \frac{F_i}{U_i}$. We assume that workers are risk-neutral workers and that each firm has only one type of job.

³³This appendix is attributable to Bruno Van der Linden.

³⁴To obtain a unique equilibrium for the unemployment rate, the matching function must exhibit constant returns to scale (see Pissarides 2000). This requirement is *a priori* not compatible with the stock-flow matching model of Coles and Smith (1998) which exhibits increasing returns to scale (IRS). In this model, the stock of unemployed workers only match with the flow of new job offers, as it is assumed in our empirical analysis, while new entrants into unemployment only prospect the existing stock of vacancies. Since we only observe time intervals of discrete length (one quarter), new entrants are also assumed to match only with the flow of new job offers. Gregg and Petrongolo (1997) show that IRS are actually precluded if we consider time periods of discrete length (for the data process), which create extra congestion externalities as compared to the continuous-time model of Coles and Smith. This result is confirmed in our empirical analysis which does not reject constant returns to scale at a significance level of 15%.

For a worker with education level i , V_i^e and V_i^u denote the expected utility of employment and unemployment respectively. Let r be the discount rate, w_i the labour cost, ϕ_i the job separation rate and z_i the unemployment benefit. In a steady-state equilibrium, V_i^e and V_i^u satisfy the following conditions:

$$rV_i^e = w_i + \phi_i (V_i^u - V_i^e) \quad (\text{a1})$$

$$rV_i^u = z_i + \theta_i q(\theta_i) (V_i^e - V_i^u) \quad (\text{b1})$$

Combining (a1) and (b1), the net expected utility of finding a job is then given by:

$$V_i^e - V_i^u = \frac{w_i - z_i}{r + \phi_i + \theta_i q(\theta_i)}$$

For a firm in segment i , the expected value from a vacant and an occupied job is denoted Π_i^v and Π_i^e respectively. Let y_i be the constant marginal product of a filled vacancy and c_i the fixed cost of a vacant job per unit of time. Assuming steady-state, Π_i^v and Π_i^e satisfy the following conditions:

$$r\Pi_i^v = -c_i + q(\theta_i) (\Pi_i^e - \Pi_i^v) \quad (\text{c1})$$

$$r\Pi_i^e = y_i - w_i + \phi_i (\text{Max}(\Pi_i^v; \Pi_j^v) - \Pi_i^e) \quad (\text{d1})$$

where Π_j^v is the expected value from a vacant job in the other skill segment.

In equilibrium, vacancies are opened as long as they yield a positive expected returns. Therefore, the equilibrium condition for the supply of vacancies is $\Pi_i^v = 0$. Using (c1) and (d1), this equilibrium condition can be rewritten as follows:

$$\frac{y_i - w_i}{(r + \phi_i)} = \frac{c_i}{q(\theta_i)} \quad (\text{e1})$$

This relationship is the vacancy-supply curve which equates the recruitment cost to the expected discounted income stream.

The wage rate is derived from the maximisation of the following Nash product in each segment:

$$Max_{w_i} (V_i^e - V_i^u)^{\gamma_i} (\Pi_i^e - \Pi_i^v)^{1-\gamma_i} \quad (\text{f1})$$

where γ_i is the bargaining power ($0 < \gamma_i < 1$). Assuming that the recruitment cost is proportional to y_i : $c_i = x_i y_i$, the first-order condition can be written as:

$$w_i = (1 - \gamma_i) z_i + \gamma_i y_i (1 + x_i \theta_i) \quad (\text{g1})$$

which is the wage-setting curve. Substituting (g1) into (e1), we obtain:

$$(1 - \gamma_i) (y_i - z_i) - \frac{r + \phi_i + \theta_i q(\theta_i)}{q(\theta_i)} x_i y_i = 0 \quad (\text{h1})$$

This equation defines an implicit relationship for equilibrium tightness in segment i :

$$\theta_i = \Theta(y_i, \gamma_i, \phi_i, z_i, x_i; r) \quad (\text{i1})$$

In a steady-state equilibrium, tightness varies across skill segments due to differences in productivity (y_i), bargaining power (γ_i), separation rate (ϕ_i), unemployment benefit (z_i) and hiring costs (x_i).

We can then derive the equilibrium unemployment rate in skill segment i , $u_i = \frac{U_i}{L_i}$, where L_i is the labour force of education i . In the steady-state, the flow into unemployment is equal to the flow out of unemployment:

$$\phi_i (1 - u_i) = \theta_i q(\theta_i) u_i \quad (\text{j1})$$

Hence, the steady-state unemployment rate in skill segment i is:

$$u_i = \frac{\phi_i}{\phi_i + \theta_i q(\theta_i)} \quad (\text{k1})$$

Combining (i1) and (k1), this equation defines an implicit relationship for the equilibrium unemployment rate in segment i :

$$u_i = v(\gamma_i, y_i, \phi_i, z_i, x_i; r) \quad (\text{11})$$

which has the same determinants than equilibrium tightness.

From (k1), the unemployment rates by skill level are the same under two conditions: (1) $\forall i : \theta_i = \theta$ and (2) $\forall i : \phi_i = \phi$. Therefore, the definition of no mismatch based on tightness indicators ($\forall i : \theta_i = \theta$) implies the absence of differences between unemployment rates if the separation rate is the same across skill segments.

4.8.2 Appendix 2: Data correction

Since we have an inflow data set, not all duration classes are represented at the begin of the observation period. For the first three calendar time intervals, there are some durations missing. We estimate the number of unemployed in the missing duration classes by exploiting the information on the number of unemployed workers in the observed duration classes. We approximate the missing observations in the following way:

For $c = 1$ and $k \in (2, 3, 4)$:

$$\tilde{U}_{akc}^i = U_{a1c}^i \exp \left(- \sum_{i=1}^{k-1} \tilde{h}_{akc}^i \right) \quad (\text{a2})$$

For $c = 2$ and $k \in (3, 4)$:

$$\tilde{U}_{akc}^i = U_{ak-1c-1}^i \exp \left(- \tilde{h}_{ak-1c}^i \right) \quad (\text{b2})$$

For $c = 3$ and $k = 4$:

$$\tilde{U}_{akc}^i = U_{ak-1c-1}^i \exp \left(- \tilde{h}_{ak-1c}^i \right) \quad (\text{c2})$$

where $\tilde{h}_{akc}^i$ is the hazard rate of an individual of type i and a at duration k and calendar time c . This is estimated by regressing a transformation of $\hat{P}_{akc}^i$ on duration and calendar time dummies for each combination of education level (i) and age group (a). This correction relies on two assumptions which only concern equation (a2): (i) The number of entrants into unemployment at $c \in (-2, -1, 0)$ is the same as the number of entrants at $c = 1$ and (ii) the calendar time dependence of the hazard rate at $c \in (-2, -1, 0)$ is the same as the one at $c = 1$. These assumptions can be justified since the state of the business cycle at the begin of our observation period was close to the one observed three quarters earlier (economic peak at the end of the eighties).

4.8.3 Appendix 3: Identification issues

In this appendix, we give the linear approximation of the expression (4.16) around $\kappa_c^i = 0$ in order to understand the conditions under which our parameters are identified. A Taylor series expansion of $\log(h_{xc}^i)$ around $\kappa_c^i = 0$ in equation (4.16) yields:

$$\begin{aligned} \log(h_{xc}^4) &\cong \log(e_x) + (\alpha - 1) \log(U_c^4) + \beta \log(V_c) + \beta \log(v_{4c}) \\ &\quad + \kappa_c^4 \left(\frac{U_c^4}{U_c^3} \right)^{1-\alpha} \left(\frac{v_{3c}}{v_{4c}} \right)^\beta \end{aligned}$$

$$\begin{aligned} \log(h_{xc}^3) &\cong \log(e_x) + (\alpha - 1) \log(U_c^3) + \beta \log(V_c) + \beta \log(v_{3c}) \\ &\quad + \kappa_c^3 \left(\frac{U_c^3}{U_c^2} \right)^{1-\alpha} \left(\frac{v_{2c}}{v_{3c}} \right)^\beta + \kappa_c^4 (\alpha - 1) \left(\frac{U_c^4}{U_c^3} \right) \end{aligned}$$

$$\begin{aligned} \log(h_{xc}^2) &\cong \log(e_x) + (\alpha - 1) \log(U_c^2) + \beta \log(V_c) + \beta \log(v_{2c}) \\ &\quad + \kappa_c^2 \left(\frac{U_c^2}{U_c^1} \right)^{1-\alpha} \left(\frac{v_{1c}}{v_{2c}} \right)^\beta + \kappa_c^3 (\alpha - 1) \left(\frac{U_c^3}{U_c^2} \right) \end{aligned}$$

$$\begin{aligned} \log(h_{xc}^1) &\cong \log(e_x) + (\alpha - 1) \log(U_c^1) + \beta \log(V_c) + \beta \log(v_{1c}) \\ &\quad + \kappa_c^2 (\alpha - 1) \left(\frac{U_c^2}{U_c^1} \right) \end{aligned}$$

The matching elasticities, α and β , are identified from, respectively, the variations of U^i and V in each equation. The individual search effectiveness, e_x , is identified by the variation of h^i in the duration and age dimensions. Then consider the identification of the constant term in the job competition and vacancy functions, respectively κ_0^i in (4.20) and v_{i0} in (4.19). Identification of κ_0^i comes from variations of the $U^i - U^{i-1}$ ratio in the equations of h_{xc}^i and h_{xc}^{i-1} . If the evolution of U^i does not exactly follows the evolution of U^{i-1} , identification of κ_0^i is ensured. The parameter v_{i0} is then simply a constant term by schooling level, identified by the remaining variation between exit rates by schooling levels. As a consequence, we must assume that the individual search effectiveness, e_x , does not depend on the level of education. If we allow v_i to vary over calendar time, we cannot allow another parameter to vary

simultaneously with calendar time and education. This is because only one set of parameters, v_{in} and v_{is} in (4.19), can capture the remaining interaction between the calendar time and the schooling level in the model. We can allow at most for a common calendar time effect in κ^i , i.e. κ_n and κ_s in (4.20).

4.8.4 Appendix 4: Two-step estimation procedure

In this appendix, we give the estimation procedure of the model (4.26):

$$\hat{z}_{xc}^i = \log(h_{xc}^i) + \omega_{xc}^i + \varepsilon_{xc}^i, \quad i = 1, 2, 3, 4 \quad (\text{a3})$$

$$\text{with the approximation error } \omega_{xc}^i = \frac{\hat{P}_{xc}^i - P_{xc}^i}{(1 - P_{xc}^i) \log(1 - P_{xc}^i)}$$

Since the number of outflows, F_{xc}^i , in the empirical estimator $\hat{P}_{xc}^i$ has a binomial distribution with a probability of ‘success’ P_{xc}^i conditional on the number of individuals at risk, U_{xc}^i , Cockx (1997) shows that $E(\omega_{xc}^i) = 0$ and that a consistent estimate of the variance of ω_{xc}^i is³⁵:

$$(\hat{s}_{xc}^i)^2 = \hat{P}_{xc}^i \left[\left(1 - \hat{P}_{xc}^i\right) \left[\log\left(1 - \hat{P}_{xc}^i\right)\right]^2 \right]^{-1} \frac{1}{U_{xc}^i} \quad (\text{b3})$$

The estimated variance matrix of the approximation error, say $\hat{\Omega}_{xc}$, has therefore the following form:

$$\hat{\Omega}_{xc} = \begin{bmatrix} (\hat{s}_{xc}^1)^2 & 0 & 0 & 0 \\ 0 & (\hat{s}_{xc}^2)^2 & 0 & 0 \\ 0 & 0 & (\hat{s}_{xc}^3)^2 & 0 \\ 0 & 0 & 0 & (\hat{s}_{xc}^4)^2 \end{bmatrix} \quad (\text{c3})$$

The specification errors, ε_{xc}^i , have a distribution such that $E(\varepsilon_{xc}^i) = 0$ and that $E(\varepsilon_{xc}^i \varepsilon_{xc'}^j) = \sigma_{ij}$ for $c' = c$ for all i and j , and $E(\varepsilon_{xc}^i \varepsilon_{xc'}^j) = 0$ for $c' \neq c$ for all i and j . Their variance-covariance matrix is denoted Σ . With these distributional assumptions, the specification errors can differ across education level and can be correlated. The latter assumption is needed for given the determinants of the outflow rate by schooling level are inter-related in case of job competition. The approximation errors ω_{xc}^i are assumed to be independent of the specification errors ε_{xc}^i for all

³⁵The covariance is zero.

i and c . The variance-covariance matrix for the errors in model (a3) has therefore the block diagonal form (the subscripts xc have been replaced by one subscript denoting a particular x and c combination):

$$\Lambda = \begin{bmatrix} \Omega_1 + \Sigma & & & \\ & \Omega_2 + \Sigma & & \\ & & \dots & \\ & & & \Omega_N + \Sigma \end{bmatrix} = \Omega + (I \otimes \Sigma) \quad (\text{d3})$$

where Σ is the variance-covariance matrix of the specification errors, Ω is the block diagonal matrix $[\Omega_{xc}]$, I is an identity matrix of order $N = 132$ (the number of x and c combinations), and $\otimes$ is the Kronecker product.

The estimation procedure consists then in two-steps. In a first step we estimate the model (a3) by Ordinary Least Squares (OLS). On the basis of the OLS residuals $(\hat{v}_{xc}^i)$ and of the estimated variance of the approximation error $(\hat{s}_{xc}^i)^2$, we can calculate a consistent estimate of the covariance matrix Σ , say $\hat{\Sigma}$:

$$\hat{\Sigma} = S - \frac{1}{N} \sum_{s=1}^N \hat{\Omega}_s \quad (\text{e3})$$

$$\text{with } S = \left[\left\{ \frac{1}{N} \sum_{s=1}^N \hat{v}_s^i \hat{v}_s^j \right\} \right]$$

where the variance-covariance matrix S is the unadjusted residual covariance matrix. In a second step, we estimate the variance-covariance matrix Λ by combining $\hat{\Omega}$ and $\hat{\Sigma}$ in the form of (d1) and apply GLS to the model (a3).

4.8.5 Appendix 5: Estimation results

Table 4.7: Hazard model (4.26) estimates and specification tests

Variables		SD		$v_{in}=0$ ($i=1,2,3$)		SD		$\alpha+\beta=1$		SD		$\pi=0$		SD	
1. Matching elasticities															
	β	0.73	0.13	0.81	0.12	0.66	0.05	0.63	0.04						
	α	0.62	0.25	0.52	0.14	0.34		0.37							
	π	0.18	0.40	0.10	0.27	-0.19	0.20	0.00							
2. Matching efficiency															
Duration (in quarters)															
	γ_2	-0.24	0.02	-0.24	0.02	-0.24	0.02	-0.24	0.02						
	γ_3	-0.40	0.02	-0.41	0.02	-0.40	0.02	-0.40	0.02						
	γ_4	-0.57	0.02	-0.57	0.02	-0.57	0.02	-0.57	0.02						
Age (aged 29-44 years old)															
	η_2	-0.26	0.02	-0.26	0.02	-0.25	0.02	-0.26	0.02						
3. Vacancy parameters															
Primary (v_{1c})															
	constant	-5.60	3.23	-4.82	2.08	-1.30	0.21	-1.46	0.12						
	winter	-0.25	0.10	-0.22	0.07	-0.33	0.06	-0.31	0.06						
	spring	0.14	0.10	0.11	0.06	0.09	0.08	0.15	0.05						
	summer	-0.04	0.08	-0.03	0.07	-0.12	0.05	-0.12	0.06						
	p1	-0.08	0.08	0.00		0.00		0.00							
	p2	0.08	0.05	0.00		0.00		0.00							
Lower secondary (v_{2c})															
	constant	-6.03	3.27	-5.11	2.09	-1.57	0.26	-1.73	0.19						
	winter	-0.22	0.10	-0.20	0.08	-0.32	0.06	-0.30	0.06						
	spring	0.12	0.10	0.08	0.07	0.05	0.08	0.11	0.06						
	summer	0.01	0.08	0.01	0.07	-0.08	0.06	-0.08	0.06						
	p1	0.10	0.14	0.00		0.00		0.00							
	p2	-0.15	0.11	0.00		0.00		0.00							
Upper secondary (v_{3c})															
	constant	-7.00	3.31	-6.01	2.05	-2.57	0.39	-2.78	0.34						
	winter	-0.40	0.12	-0.38	0.11	-0.55	0.06	-0.54	0.06						
	spring	-0.47	0.15	-0.48	0.13	-0.68	0.07	-0.65	0.06						
	summer	-0.74	0.24	-0.70	0.20	-1.03	0.09	-1.05	0.09						
	p1	0.13	0.16	0.00		0.00		0.00							
	p2	-0.21	0.16	0.00		0.00		0.00							
Higher education (v_{4c})															
	constant	-22.40	12.38	-20.71	7.75	-18.58	7.18	-17.74	6.53						
	winter	-1.09	0.86	-1.12	0.78	-2.03	0.85	-1.96	0.88						
	spring	-0.40	0.87	-0.54	0.67	-1.06	0.63	-0.98	0.63						
	summer	-1.36	1.26	-1.05	0.98	-1.64	0.91	-1.83	1.00						
	p1	19.25	14.71	18.47	10.34	19.15	9.90	17.56	8.91						
	p2	-9.46	7.73	-0.79	4.84	-8.82	4.43	-8.13	4.03						

Note: In grey, restricted parameters.

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Table 4.7: (Continued)

4. Job competition parameters								
Lower secondary (κ^2_{L})								
constant	-0.72	0.12	-0.79	0.31	-0.82	0.20	-0.84	0.21
Upper secondary (κ^3_{U})								
constant	0.57	0.16	0.50	0.23	0.46	0.18	0.45	0.17
Upper secondary (κ^4_{U})								
constant	1.90	0.32	1.89	0.40	1.81	0.33	1.81	0.32
Common time dependence								
p1	-0.16	0.15	0.05	0.05	0.10	0.04	0.10	0.04
p2	0.27	0.14	0.03	0.03	0.05	0.03	0.06	0.03
5. Standard deviation of the specification errors (ϵ^i_{xc})								
σ_{11}	0.11							
σ_{22}	0.11							
σ_{33}	0.11							
σ_{44}	0.07							
6. Correlation of the specification errors (ϵ^i_{xc})								
σ_{12}	0.87							
σ_{13}	0.50							
σ_{14}	0.25							
σ_{23}	0.46							
σ_{24}	0.10							
σ_{34}	0.93							
Number of observations	528		528		528		528	
Number of estimated parameters	36		30		29		28	
Weighted sum of squared residuals	504.43		508.94		503.60		504.25	
P-value of the goodness-of-fit test	0.339							
P-value of the restrictions test			0.608		0.152		0.259	

Table 4.8: Benchmark model estimates (Model (4.26) with $\forall i \in \{1, 2, 3\} : v_{in} = 0; \alpha + \beta = 1; \pi = 0$) and specification tests on the job competition parameters

Variables	SD		$\kappa_c^j=0$	SD		$\kappa_0^2=0$	SD	
1. Matching elasticities								
β	0.63	0.04	0.51	0.03	0.54	0.04		
$\alpha=1-\beta$	0.37		0.49		0.46			
2. Matching efficiency								
Duration (in quarters)								
γ_2	-0.24	0.02	-0.24	0.02	-0.24	0.02		
γ_3	-0.40	0.02	-0.41	0.02	-0.41	0.02		
γ_4	-0.57	0.02	-0.58	0.02	-0.58	0.02		
Age (aged 29-44 years old)								
η_2	-0.26	0.02	-0.25	0.02	-0.26	0.02		
3. Vacancy parameters								
Primary (v_{1c})								
constant	-1.46	0.12	-2.19	0.14	-2.07	0.13		
winter	-0.31	0.06	-0.42	0.07	-0.37	0.07		
spring	0.15	0.05	0.20	0.07	0.20	0.06		
summer	-0.12	0.06	-0.19	0.07	-0.15	0.07		
Lower secondary (v_{2c})								
constant	-1.73	0.19	-2.00	0.12	-1.45	0.12		
winter	-0.30	0.06	-0.46	0.07	-0.38	0.06		
spring	0.11	0.06	0.13	0.06	0.13	0.06		
summer	-0.08	0.06	-0.18	0.07	-0.15	0.06		
Upper secondary (v_{3c})								
constant	-2.78	0.34	-2.08	0.09	-3.30	0.42		
winter	-0.54	0.06	-0.33	0.07	-0.60	0.08		
spring	-0.65	0.06	0.02	0.07	-0.70	0.08		
summer	-1.05	0.09	-0.34	0.08	-1.19	0.11		
Higher education (v_{4c})								
constant	-18.11	6.79	-2.07	0.05	-16.49	4.98		
winter	-1.99	0.88	-0.73	0.07	-2.11	0.94		
spring	-1.00	0.64	-0.80	0.06	-1.12	0.63		
summer	-1.82	1.00	-1.39	0.10	-2.48	1.15		
p1	18.08	9.27	0.07	0.03	15.07	6.74		
p2	-8.37	4.19	0.01	0.03	-6.85	2.95		

Note: In grey, restricted parameters.

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Table 4.8: (Continued)

4. Job competition parameters					
Lower secondary (κ^2_c)					
constant	-0.84	0.21			
Upper secondary (κ^3_c)					
constant	0.45	0.17		-0.03	0.10
Upper secondary (κ^4_c)					
constant	1.81	0.32		1.73	0.30
Common time dependence					
p1	0.10	0.04		-0.02	0.03
p2	0.06	0.03		0.04	0.03
5. Standard deviation of the specification errors (ϵ_{xc}^i)					
σ_{11}	0.11				
σ_{22}	0.11				
σ_{33}	0.11				
σ_{44}	0.07				
6. Correlation of the specification errors (ϵ_{xc}^i)					
σ_{12}	0.86				
σ_{13}	0.46				
σ_{14}	0.24				
σ_{23}	0.47				
σ_{24}	0.14				
σ_{34}	0.93				
Number of observations	528		528		528
Number of estimated parameters	28		23		27
Weighted sum of squared residuals	501.777		546.24		522.69
P-value of the goodness-of-fit test	0.469				
P-value of the restrictions test			0.000		0.000

Table 4.9: Benchmark model estimates (Model (4.26) with $\forall i \in \{1, 2, 3\} : v_{in} = 0; \alpha + \beta = 1; \pi = 0$) and specification tests on the vacancy parameters

Variables	SD		$v_{1c}=v_{2c}$		$v_{3s}=v_{4s}$	
1. Matching elasticities						
β	0.63	0.04	0.63	0.04	0.63	0.04
$\alpha=1-\beta$	0.37		0.37		0.37	
2. Matching efficiency						
Duration (in quarters)						
γ_2	-0.24	0.02	-0.24	0.02	-0.24	0.02
γ_3	-0.40	0.02	-0.40	0.02	-0.40	0.02
γ_4	-0.57	0.02	-0.57	0.02	-0.57	0.02
Age (aged 29-44 years old)						
η_2	-0.26	0.02	-0.26	0.02	-0.26	0.02
3. Vacancy parameters						
Primary (v_{1c})						
constant	-1.46	0.12	-1.55	0.11	-1.45	0.12
winter	-0.31	0.06	-0.31	0.05	-0.31	0.06
spring	0.15	0.05	0.13	0.05	0.15	0.05
summer	-0.12	0.06	-0.10	0.05	-0.12	0.06
Lower secondary (v_{2c})						
constant	-1.73	0.19	-1.55		-1.74	0.19
winter	-0.30	0.06	-0.31		-0.29	0.06
spring	0.11	0.06	0.13		0.11	0.06
summer	-0.08	0.06	-0.10		-0.08	0.06
Upper secondary (v_{3c})						
constant	-2.78	0.34	-2.80	0.32	-2.85	0.36
winter	-0.54	0.06	-0.54	0.06	-0.60	0.05
spring	-0.65	0.06	-0.65	0.06	-0.67	0.05
summer	-1.05	0.09	-1.05	0.09	-1.09	0.08
Higher education (v_{4c})						
constant	-18.11	6.79	-17.38	6.10	-14.88	4.98
winter	-1.99	0.88	-1.98	0.87	-0.60	
spring	-1.00	0.64	-0.94	0.61	-0.67	
summer	-1.82	1.00	-1.99	1.07	-1.09	
p1	18.08	9.27	17.01	8.28	13.73	6.55
p2	-8.37	4.19	-7.91	3.77	-6.48	3.17

Note: In grey, restricted parameters.

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Table 4.9: (Continued)

4. Job competition parameters						
Lower secondary (κ^2)						
constant	-0.84	0.21	-1.21	0.07	-0.82	0.20
Upper secondary (κ^3)						
constant	0.45	0.17	0.29	0.11	0.48	0.17
Upper secondary (κ^4)						
constant	1.81	0.32	1.81	0.28	1.88	0.35
Common time dependence						
p1	0.10	0.04	0.10	0.05	0.09	0.04
p2	0.06	0.03	0.07	0.03	0.06	0.03
Number of observations	528		528		528	
Number of estimated parameters	28		24		25	
Weighted sum of squared residuals	501.78		506.72		505.80	
P-value of the goodness-of-fit test	0.469					
P-value of the restrictions test			0.293		0.259	

Table 4.10: Benchmark model estimates and estimates for young people only

Variables	Benchmark	SD	Age <=28	SD
1. Matching elasticities				
β	0.63	0.04	0.76	0.04
$\alpha=1-\beta$	0.37		0.24	
2. Matching efficiency				
Duration (in quarters)				
γ_2	-0.24	0.02	-0.20	0.02
γ_3	-0.40	0.02	-0.35	0.03
γ_4	-0.57	0.02	-0.50	0.03
Age (aged 29-44 years old)				
η_2	-0.26	0.02		
3. Vacancy parameters				
Primary (v_{1c})				
constant	-1.46	0.12	-1.85	0.11
winter	-0.31	0.06	-0.25	0.06
spring	0.15	0.05	0.13	0.05
summer	-0.12	0.06	-0.08	0.06
Lower secondary (v_{2c})				
constant	-1.73	0.19	-1.72	0.13
winter	-0.30	0.06	-0.25	0.05
spring	0.11	0.06	0.09	0.05
summer	-0.08	0.06	-0.02	0.06
Upper secondary (v_{3c})				
constant	-2.78	0.34	-2.53	0.27
winter	-0.54	0.06	-0.43	0.06
spring	-0.65	0.06	-0.53	0.06
summer	-1.05	0.09	-0.82	0.08
Higher education (v_{4c})				
constant	-18.11	6.79	-17.48	8.09
winter	-1.99	0.88	-2.05	0.85
spring	-1.00	0.64	-1.24	0.65
summer	-1.82	1.00	-1.74	0.85
p1	18.08	9.27	18.12	11.27
p2	-8.37	4.19	-7.94	4.71

Note: In grey, restricted parameters.

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Table 4.10: (Continued)

4. Job competition parameters			
Lower secondary ($\kappa^2_{\mathcal{D}}$)			
constant	-0.84	0.21	-0.95 0.19
Upper secondary ($\kappa^3_{\mathcal{D}}$)			
constant	0.45	0.17	0.47 0.18
Upper secondary ($\kappa^4_{\mathcal{D}}$)			
constant	1.81	0.32	1.80 0.36
Common time dependence			
p1	0.10	0.04	0.16 0.06
p2	0.06	0.03	0.04 0.04
5. Standard deviation of the specification errors ($\varepsilon^i_{\mathcal{X}\mathcal{C}}$)			
σ_{11}	0.11		0.09
σ_{22}	0.11		0.09
σ_{33}	0.11		0.09
σ_{44}	0.07		0.04
6. Correlation of the specification errors ($\varepsilon^i_{\mathcal{X}\mathcal{C}}$)			
σ_{12}	0.86		0.89
σ_{13}	0.46		0.54
σ_{14}	0.24		0.31
σ_{23}	0.47		0.50
σ_{24}	0.14		0.51
σ_{34}	0.93		0.86
Number of observations	528		264
Number of estimated parameters	28		27
Weighted sum of squared residuals	501.78		258.84
P-value of the goodness-of-fit test	0.469		0.158

Table 4.11: Benchmark model estimates with vacancy parameters and with tightness parameters

Variables	Benchmark	SD	θ^*_{ic}	SD
1. Matching elasticities				
β	0.63	0.04	0.62	0.11
$\alpha=1-\beta$	0.37		0.37	
2. Matching efficiency				
Duration (in quarters)				
γ_2	-0.24	0.02	-0.24	0.02
γ_3	-0.40	0.02	-0.40	0.02
γ_4	-0.57	0.02	-0.57	0.02
Age (aged 29-44 years old)				
η_2	-0.26	0.02	-0.25	0.02
3. Vacancy or tightness parameters				
Primary (v_{1c} or θ^*_{1c})				
constant	-1.46	0.12	-0.45	0.29
winter	-0.31	0.06	-0.36	0.09
spring	0.15	0.05	0.12	0.06
summer	-0.12	0.06	-0.18	0.08
p1			0.01	0.09
p2			0.14	0.06
Lower secondary (v_{2c} or θ^*_{2c})				
constant	-1.73	0.19	-0.77	0.40
winter	-0.30	0.06	-0.33	0.09
spring	0.11	0.06	0.08	0.07
summer	-0.08	0.06	-0.12	0.08
p1			0.18	0.12
p2			-0.10	0.11
Upper secondary (v_{3c} or θ^*_{3c})				
constant	-2.78	0.34	-1.22	0.65
winter	-0.54	0.06	-0.54	0.10
spring	-0.65	0.06	-0.64	0.09
summer	-1.05	0.09	-1.00	0.17
p1			0.04	0.15
p2			-0.17	0.15
Higher education (v_{4c} or θ^*_{4c})				
constant	-18.11	6.79	-9.41	4.12
winter	-1.99	0.88	-1.19	0.68
spring	-1.00	0.64	-0.82	0.59
summer	-1.82	1.00	-2.00	1.22
p1	18.08	9.27	8.96	4.72
p2	-8.37	4.19	-4.61	2.58

Note: In grey, restricted parameters.

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Table 4.11: (Continued)

4. Job competition parameters				
Lower secondary ($\kappa^2_{\mathcal{L}}$)				
constant	-0.84	0.21	-0.72	0.13
Upper secondary ($\kappa^3_{\mathcal{U}}$)				
constant	0.45	0.17	0.55	0.17
Upper secondary ($\kappa^4_{\mathcal{U}}$)				
constant	1.81	0.32	1.82	0.33
Common time dependence				
p1	0.10	0.04	-0.15	0.16
p2	0.06	0.03	0.26	0.15
5. Standard deviation of the specification errors (ε^i_{xc})				
σ_{11}	0.11		0.11	
σ_{22}	0.11		0.11	
σ_{33}	0.11		0.11	
σ_{44}	0.07		0.07	
6. Correlation of the specification errors (ε^i_{xc})				
σ_{12}	0.86		0.87	
σ_{13}	0.46		0.50	
σ_{14}	0.24		0.25	
σ_{23}	0.47		0.47	
σ_{24}	0.14		0.11	
σ_{34}	0.93		0.92	
Number of observations	528		528	
Number of estimated parameters	28		34	
Weighted sum of squared residuals	501.78		502.34	
P-value of the goodness-of-fit test	0.469		0.388	

Table 4.12: Benchmark model estimates with tightness parameters and specification tests on the tightness parameters

Variables			$\theta_{1c}^* = \theta_{2c}^*$ and $\theta_{in=0}^*$ (i=1,2,3)		$\theta_{i0}^* = \theta_{10}^*$ (i=2,3) and $\theta_{in=0}^*$ (i=1,2,3)		$\theta_{i0}^* = \theta_{10}^*$ (i=2,3,4) and $\theta_{in=0}^*$ (i=1,2,3,4)	
	SD		SD		SD		SD	
1. Matching elasticities								
β	0.62	0.11	0.55	0.04	0.56	0.04	0.55	0.04
α	0.38		0.38		0.38		0.38	
2. Matching efficiency								
Duration (in quarters)								
γ_2	-0.24	0.02	-0.24	0.02	-0.24	0.02	-0.24	0.02
γ_3	-0.40	0.02	-0.41	0.02	-0.41	0.02	-0.40	0.02
γ_4	-0.57	0.02	-0.58	0.02	-0.58	0.02	-0.58	0.02
Age (aged 29-44 years old)								
η_2	-0.25	0.02	-0.25	0.02	-0.25	0.02	-0.25	0.02
3. Tightness parameters								
Primary (θ_{1c}^*)								
constant	-0.45	0.29	-0.79	0.14	-0.81	0.14	-0.87	0.13
winter	-0.36	0.09	-0.39	0.06	-0.40	0.06	-0.41	0.06
spring	0.12	0.06	0.11	0.05	0.12	0.06	0.13	0.06
summer	-0.18	0.08	-0.20	0.06	-0.23	0.06	-0.24	0.06
p1	0.01	0.09	0.00		0.00		0.00	
p2	0.14	0.06	0.00		0.00		0.00	
Lower secondary (θ_{2c}^*)								
constant	-0.77	0.40	-0.79		-0.81		-0.87	
winter	-0.33	0.09	-0.39		-0.41	0.07	-0.46	0.07
spring	0.08	0.07	0.11		0.09	0.06	0.04	0.07
summer	-0.12	0.08	-0.20		-0.15	0.07	-0.22	0.07
p1	0.18	0.12	0.00		0.00		0.00	
p2	-0.10	0.11	0.00		0.00		0.00	
Upper secondary (θ_{3c}^*)								
constant	-1.22	0.65	-1.43	0.36	-0.81		-0.87	
winter	-0.54	0.10	-0.63	0.07	-0.52	0.08	-0.29	0.10
spring	-0.64	0.09	-0.70	0.08	-0.53	0.08	-0.15	0.11
summer	-1.00	0.17	-1.15	0.10	-0.91	0.10	-0.48	0.11
p1	0.04	0.15	0.00		0.00		0.00	
p2	-0.17	0.15	0.00		0.00		0.00	
Higher education (θ_{4c}^*)								
constant	-9.41	4.12	-30.48	33.09	-9.50	21.11	-0.87	
winter	-1.19	0.68	-1.99	1.44	-1.61	0.67	-0.69	0.09
spring	-0.82	0.59	-0.37	2.77	-2.00	0.87	-0.75	0.10
summer	-2.00	1.22	-2.95	3.69	-10.45	91.29	-1.43	0.16
p1	8.96	4.72	35.09	42.54	5.50	2.26	0.00	
p2	-4.61	2.58	-18.33	24.49	-3.45	1.34	0.00	

Note: In grey, restricted parameters.

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Table 4.12: (Continued)

4. Job competition parameters							
Lower secondary (κ^2)							
constant	-0.72	0.13	-1.13	0.06	-1.28	0.05	-1.45 0.04
Upper secondary (κ^3)							
constant	0.55	0.17	0.26	0.10	-0.09	0.05	-0.42 0.04
Upper secondary (κ^4)							
constant	1.82	0.33	1.65	0.23	1.09	0.05	0.09 0.04
Common time dependence							
p1	-0.15	0.16	-0.05	0.04	-0.10	0.05	-0.02 0.05
p2	0.26	0.15	0.03	0.03	0.07	0.04	0.00 0.04
Number of observations	528		528		528		528
Number of estimated parameters	34		24		26		23
Weighted sum of squared residuals	502.34		519.62		520.21		528.55
P-value of the goodness-of-fit test	0.388						
P-value of the restrictions test			0.068		0.022		0.006

Table 4.13: Benchmark model estimates with tightness parameters and specification tests on the job competition parameters

Variables	SD		$\kappa_c^j=0$	SD
1. Matching elasticities				
β	0.62	0.11	0.57	0.09
$\alpha=1-\beta$	0.38		0.43	
2. Matching efficiency				
Duration (in quarters)				
γ_2	-0.24	0.02	-0.24	0.02
γ_3	-0.40	0.02	-0.40	0.02
γ_4	-0.57	0.02	-0.57	0.02
Age (aged 29-44 years old)				
η_2	-0.25	0.02	-0.25	0.02
3. Tightness parameters				
Primary (θ_{1c}^*)				
constant	-0.45	0.29	-0.94	0.29
winter	-0.36	0.09	-0.39	0.09
spring	0.12	0.06	0.13	0.06
summer	-0.18	0.08	-0.20	0.08
p1	0.01	0.09	0.01	0.07
p2	0.14	0.06	0.07	0.04
Lower secondary (θ_{2c}^*)				
constant	-0.77	0.40	-0.67	0.25
winter	-0.33	0.09	-0.43	0.10
spring	0.08	0.07	0.07	0.06
summer	-0.12	0.08	-0.18	0.08
p1	0.18	0.12	-0.03	0.08
p2	-0.10	0.11	0.06	0.04
Upper secondary (θ_{3c}^*)				
constant	-1.22	0.65	-0.27	0.18
winter	-0.54	0.10	-0.30	0.08
spring	-0.64	0.09	0.01	0.06
summer	-1.00	0.17	-0.26	0.09
p1	0.04	0.15	-0.05	0.08
p2	-0.17	0.15	0.05	0.04
Higher education (θ_{4c}^*)				
constant	-9.41	4.12	0.30	0.09
winter	-1.19	0.68	-0.47	0.10
spring	-0.82	0.59	-0.41	0.08
summer	-2.00	1.22	-0.88	0.18
p1	8.96	4.72	0.02	0.07
p2	-4.61	2.58	0.00	0.03

Note: In grey, restricted parameters.

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Table 4.13: (Continued)

4. Job competition parameters		
Lower secondary (κ^2)		
constant	-0.72	0.13
Upper secondary (κ^3)		
constant	0.55	0.17
Upper secondary (κ^4)		
constant	1.82	0.33
Common time dependence		
p1	-0.15	0.16
p2	0.26	0.15
Number of observations	528	528
Number of estimated parameters	34	29
Weighted sum of squared residuals	502.34	517.51
P-value of the goodness-of-fit test	0.388	
P-value of the restrictions test		0.010

Chapter 5

General Conclusion

The objective of our doctoral thesis is to question the causes of unemployment persistence in Belgium and by this way, to contribute to the design of more effective labour market policies. To that purpose, we conduct an in-depth econometric analysis of the flows out of unemployment in this country. We summarise here the main results of the three chapters of our doctoral thesis. For each chapter, we then show how their findings improve both the diagnosis of unemployment persistence and the design of active labour market policies in Belgium. Finally, we give the main methodological contributions of the three chapters and provide some tracks for future research.

5.1 Summary of the results

In **Chapter 2**, we investigate what causes the aggregate exit rate out of unemployment to decline strongly over duration and to vary over calendar time in Wallonia. To that purpose, we specify a mixed proportional hazard (MPH) model where the distribution of heterogeneity depends on seasons and the business cycle at the time of entry. We also allow the true duration dependence of the exit rate to vary non-proportionally between a boom and a recession in order to test the ranking hypothesis, a recruitment rule which consists in hiring the candidate with the shortest unemployment duration. We estimate our model by Minimum Chi-Squares on quarterly exit rates of male workers flowing into un-

employment between June 1989 and February 1994. We distinguish between two age groups, workers aged less than 29 and between 29 and 44 years old.

For both age groups, we find that heterogeneity induces significant spurious negative duration dependence of the aggregate exit rate out of unemployment. During a recession, the individual outflow rate of prime-aged men is, if anything, slightly decreasing over the first 1.5 years of unemployment, and exhibits significant negative duration dependence onwards. After two years and a half of unemployment the exit rate has dropped by 20%. When the labour market conditions ameliorate, duration dependence is slightly positive. It has been shown that this provides evidence of ranking for the adult unemployed. For the young men, the individual exit rate cannot be rejected to be constant over all durations, whatever the state of the business cycle. Ranking is therefore not important for the young unemployed.

For the men aged 29-44, the procyclical variation of the aggregate exit rate in Wallonia is driven by a cyclical fluctuation in the individual exit rate of all currently unemployed (i.e. general effect) rather than by a change in the average quality of the new entrants within the economic cycle (i.e. composition effect). This finding is in line with the results obtained with French data. On the other hand, the strong decline in the individual outflow rate of the young workers in recession seems to be mitigated at the aggregate level by a significant increase in the quality of those flowing into unemployment. Seasonal fluctuations in the aggregate exit rate are the result of large seasonal variations both in the individual outflow rate and in the average characteristics of the inflow.

In **Chapter 3**, we investigate whether the diverging evolution in the unemployment stock in Flanders and Wallonia can be explained by different evolutions in their average unemployment duration and/or their unemployment incidence. To that purpose, we proceed in two stages. In the first stage, we estimate a MPH model by region, and decompose variations in the aggregate outflow rate over calendar time between a general effect and a composition effect. We also specify a non-proportional model to check whether the general effect of the calendar time was the same for unemployed workers with different schooling levels and province of living, in each region. In the second stage, we decompose variations

of the unemployment stock in Flanders and Wallonia into an incidence effect and the duration effect estimated in the first stage. We estimate our model by Minimum Chi-Squares on yearly exit rates of male workers aged 25-44 and flowing into unemployment in the month of June, each year from 1972 to 1992.

Over the 1973-1993 period, unemployment increased more markedly in Wallonia due to a stronger trend in average unemployment duration and, to a less extent, a more positive trend in incidence. As a consequence, changes in unemployment are dominated by an upward trend in Wallonia while cyclical changes are relatively more important in Flanders. Our results indicate that the composition of the unemployed population cannot explain the larger trend in the average unemployment duration in Wallonia. On the contrary, the structural rise in duration would have been higher *in both regions* if the average quality of entrants had not improved over the period. The larger increase in the average duration in Wallonia is only accounted for by a stronger trend in individual durations, which is twice as large the one estimated in Flanders.

According to our results, the deterioration of the re-employment probability in both regions reflects different evolutions across skill groups and provinces. In Wallonia, the disparity between exit rates by schooling level was already large in 1973, particularly at the lower levels of education, and reinforced markedly over the whole period. Having a higher education degree did not raise the re-employment rate in 1973, while it increased this rate by 42% in 1993. The disparity between the outflow rate by schooling level also widened in Flanders, but remained at a low level as compared to Wallonia. Moreover, the difference between the exit rates according to the province of residence rose in Wallonia while it reduced in Flanders. The hiring prospects of unemployed workers living in Hainaut were already the worst among the provinces of Wallonia in 1973 and deteriorated steadily over the period.

The cyclical nature of unemployment is very similar in the two regions of Belgium and is characterised by a strong countercyclicality, in which variations in unemployment duration are slightly more important than variations in incidence. In both regions, the cyclical variability in duration is driven by cyclical variations in the individual durations rather than by changes in the quality of entrants. Our results are thus in line

with most of the studies based on European data, which conclude that composition effects are of minor importance to account for cyclical fluctuations in the aggregate exit rate out of unemployment. Individual durations are countercyclical, their pattern being very similar in Flanders and in Wallonia over the whole period. Even if its impact on the aggregate exit rate is marginal, we can state that the composition of the inflow is countercyclical in both regions: The average quality of entrants into unemployment increases during recessions and falls in upturns.

An important finding of our study is also that *both* duration and incidence matter in the (cyclical and structural) variation of unemployment in Belgium while the common belief is that changes in incidence is largely irrelevant in Europe.

True negative duration dependence of the outflow rate appears to be stronger in Flanders. There is a 40% decrease in the individual exit rate after two years of unemployment in Flanders while this decline is only equal to 25% in Wallonia. We also find that the remaining disparity in the quality of the unemployed workers is weak when one accounts for observed differences in their characteristics. Finally, the outflow rate decreases significantly with age, more markedly in Flanders. So even if we restrict our analysis to the 25-44 age group, age within this group still influences markedly the outflow probability.

The aim of **Chapter 4** is to determine the relative importance of job competition and skill mismatch for a population of unemployed job searchers in Belgium. To that purpose, we use administrative data on the exit rates from unemployment by level of education and on the total number of job vacancies registered at the public employment agency. Our observation period ranges from June 1989 to February 1994. The outflow rate was modelled in a matching function framework. We assume that the job market is segmented by schooling level and that each segment is characterised by the same job matching technology.

With job competition, all unemployed workers search for jobs in their own segment and some fraction search simultaneously in the segment just below their own. Under this assumption, the transition rate out of unemployment by level of education is made of two components: The probability of finding a job corresponding to his schooling profile and the probability of finding a downgrading job. We estimate, by Minimum

Chi-Squares, the structural form of the exit rate out of unemployment by level of educational attainment. The parameters of interest are the extent of job competition at each schooling level and the distribution of job offers according to the required level of education.

We find that there is significant job competition among the unemployed workers in Wallonia. Moreover, its extent increases markedly with the educational attainment of the worker. The job competition parameter for the workers at the top of the education ladder is so high that we cannot reject the hypothesis that all unemployed workers with higher education search for jobs normally filled by workers with an upper secondary degree. Adopting this search behaviour they are about 6 times more likely to be hired than are the workers who just completed upper secondary school. The extent of job competition also went up with the economic downturn of the early nineties.

Our results also indicate that there is almost no jobs offered to the unemployed workers who completed higher education. For the other types of unemployed people, the number of vacancies requiring an upper secondary degree is significantly smaller than the job offers at the lower levels of education. If we take into account the supply of skills, we conclude that there is a relative shortage of job offers requiring a diploma of higher education, and in a less extent an upper secondary degree, for the unemployed workers in Wallonia. How do we explain these findings?

We claim that the scarcity of jobs in Wallonia must account for the intense job competition among unemployed workers. Since the mid eighties, this region is characterised by a *structural* weakness of job creation in comparison with Flanders and our bordering countries. For the period that we consider, the employment growth in Wallonia was further hampered by the strong deterioration of the economic prospects. The weakness of job creation in Wallonia certainly induced more educated unemployed to extend job search on the skill segment below their own, thereby crowding out lower educated unemployed in their segment.

We also argue that the few number of jobs proposed to the unemployed workers with higher education reflects a recruitment behaviour of employers when jobs are scarce. In our data set, we only observe unemployed workers who separated from their employers and who did not directly find a new job (i.e. dismissed workers). Therefore, our es-

timation of vacancies by schooling level concerns *only those intended to this selective population*, which *excludes* young school leavers and employed job seekers. Given the large supply of highly educated school leavers and the scarcity of jobs, employers will not be inclined to propose job offers requiring high skills to the unemployed workers. As a result, the most educated unemployed exert an intense job competition on the lower segments. For the lower levels of education, the unemployed population that we consider is less likely to be an avoidable pool of recruitment, so that we estimate relatively more job offers for the low educated unemployed.

Since we estimate the demand of skills for a particular population of job seekers, our results are of course *not inconsistent with* a story of skill biased technological change. In our empirical framework, we would need data on all types of job seekers by level of educational attainment to obtain a *reliable measure* of the demand of skills in the economy, and so mismatch. The very good employment prospects of unemployed workers with higher education on jobs normally requiring an upper secondary degree could actually be consistent with a *relative* increase in the demand of high skills. Compared with our bordering countries and Flanders, there is a low number of young people who achieve the upper secondary school in Wallonia, particularly with vocational and technical degrees. In a context of skill biased technological change, employers may then be inclined to hire overeducated workers on jobs normally filled by workers with a technical diploma of the upper secondary school. Our argument is reinforced by the observation that a large majority of unemployed workers with higher education have a vocational or technical degree of three years at the latest (60%, against 30% with an university degree).

5.2 What are the implications of these results on the diagnosis of unemployment persistence in Belgium?

The analysis of **Chapter 2** reveals that there is no marked evidence of true negative duration dependence of the exit rates out of unemployment in Wallonia, once controlling for heterogeneity in the unemployed

population. On the basis of these results, we conclude that deterioration of skills and demotivation during unemployment, even if they play a role, *cannot be the main channels* of unemployment persistence in Wallonia. The hysteresis diagnosis of unemployment persistence originates from the United Kingdom where individual exit rates exhibit strong negative duration dependence. Empirical studies on unemployment duration and heterogeneity in Europe have proven that the United Kingdom remains the exception in a large pool of countries where there is no marked evidence of true negative duration dependence. Among this group, the duration dependence of the individual outflow rate in Wallonia resembles much to the one that is found in the Netherlands and in France.

In **Chapter 3**, we find that a structural change in the composition of the unemployed population *cannot explain* the larger increase in the average unemployment duration in Wallonia. In *both* regions of Belgium, the quality of entrants improved over the 1973-1993 period due to a rise in the share of high educated workers in the inflow, who have on average a larger transition rate out of unemployment. The larger increase in the average duration in Wallonia is only accounted for by a stronger trend in individual unemployment durations, which is twice as large as the one estimated in Flanders.

On the basis of our findings, we conclude that disemployability effects, even if they play a role, cannot explain this diverging evolution. For, true negative duration dependence is less important in Wallonia than in Flanders. Besides, the relative role of duration and incidence in the unemployment dynamics is similar in the two regions. In Flanders, the relatively large degree of true negative duration dependence could partly account for the slight positive trend in its average unemployment duration: The existence of disemployability effects could have somewhat tempered the employment growth in Flanders over the eighties.

Our results are also consistent with other Belgian studies (see Binon *et al.* 1998, Sneessens *et al.* 1999) which claim that structural imbalances between skill groups and sub-regions play a crucial role to explain the deterioration of the employment prospects in Wallonia. We find that disparities in the exit rate from unemployment between workers with different skills and province of living increased markedly in Wallonia, while they remain at a relatively low level in Flanders. According to the

above authors, one important explanation of the rising disparities between skill groups in Wallonia is the lack of investment in education and training policies. By preventing to provide a large number of dismissed workers with the appropriate skills required by the labour market, this contributed to hamper the development of new economic activities in Wallonia.

Beyond the different trend in their average unemployment duration and incidence over the 1973-1993 period, we show that the cyclical pattern of unemployment is *very similar* in Flanders and Wallonia. Even if its impact on average unemployment duration is marginal, the average quality of the inflow increases during recessions and falls in upturns in both regions. This result suggests that employers fire the most able workers only if they have no alternative, i.e. in a recession. Less able workers are made redundant all the time.

Notice that the findings of **Chapter 2** and **Chapter 3** cast serious doubt on the reliability of the studies which attempted to disentangle true from spurious duration dependence in Belgium (see Spinnewyn 1982, Plasman 1993 and Mahy 1994). Using strong parametric assumptions (Weibull) regarding the pattern of the true duration dependence, they estimate a significant *positive* duration dependence in the individual exit rate out of unemployment for Belgium. These results confirm the importance of specifying, as it is done in our analysis, the shape of the true duration dependence with sufficient flexibility. Finally, note that the positive duration dependence found by Plasman (1993) is not inconsistent with the findings of Chapter 2. For, he restricts his analysis to young school leavers, excluded from our study.

The results of **Chapter 4** indicate significant job competition between *dismissed* unemployed workers in Wallonia, particularly between workers with higher education and those who just completed the upper secondary school. As it is shown in our study, job competition is the only cause of the increase in the transition rate out of unemployment with the educational attainment of these workers. Since the analysis of Chapters 2 and 4 are based on the *same definition of unemployment*, we can therefore conclude that the high degree of heterogeneity in the exit rates found in Chapter 2 is partly driven by a crowding out process.

Can we, however, infer from these results that job competition is a ma-

jor cause of the increasing disparity in the exit rates by level of education identified in Chapter 3? Besides the fact that they cover a different time period, the data used in Chapter 3 *include* young school leavers who were excluded from the analysis of Chapters 2 and 4. As suggested in Chapter 4, the relative role of job competition and skill mismatch will be sensitive to the addition of more types of job seekers in the analysis. The inclusion of young graduates is likely to boost the estimate number of job offers requiring a high level of education, and to lower the extent of job competition at the top segment of the labour market.

Since we estimate the extent of job competition and the demand of skills for a particular population of job seekers in Chapter 4, our results are *not inconsistent with* a change in the composition of labour demand biased against the low skilled workers. Our results only indicate that the weakness of job creation in Wallonia induced a strong job competition process among the dismissed unemployed workers in this region. It does not rule out that employment growth in Wallonia has skill biased features and/or that a deficit of skilled labour have contributed to hamper the development of new economic activities in this region.

5.3 What are the implications of these results on the design of active labour market policies in Belgium?

The findings of **Chapter 2** suggest that public outlays to active labour market policies (ALMPs) should not primarily focus on temporary work experience schemes with little training content. These schemes are often aimed at preventing or countering the process of demotivation and skill deterioration likely to arise after a prolonged unemployment spell. Our results show that even if it plays a role, this process is of little importance to explain the low employability of the long-term unemployed in comparison with the importance of their intrinsic skills (interpreted in a very broad sense). Given this diagnosis, it is unlikely that temporary work programs are *by themselves* sufficient to upgrade durably the employability of the long duration unemployed workers in Wallonia.

The Walloon authorities devote an important part of their ALMPs

resources to *temporary* recruitment subsidies in the private or public sector, targeted at the long-term unemployed workers (see Dejemeppe and Cockx 1998). So our findings call for a policy reform in Wallonia. It can however be argued that the mild true negative duration dependence of the exit rates in Wallonia is the consequence of the current ALMPs in this region. For instance, subsidies provided to employers hiring long-term unemployed can alter their position in the ranking process, and make them again active in the competition for jobs. Even if this were so, our analysis suggests that there is no reason to spend further resources to temporary recruitment subsidies in Wallonia.

In **Chapter 3**, we find that Flanders is characterised by a larger degree of true negative duration dependence than in Wallonia. This result suggests that there is more scope for temporary recruitment subsidies in the Flemish region. Given the strong negative trend in the re-employment prospects in Wallonia, structural policies are called for to stimulate the long-term employment growth in this region. These are discussed with the policy recommendations of Chapter 4.

Some authors argue that targeted policies are unlikely to be useful if changes in the composition of entrants play a minor role to explain variations in the aggregate outflow probability. In Chapter 3, we challenge this view by specifying a model which allows the exit rate out of unemployment to evolve *differently* across skill groups and provinces. Even if the structural decline of the re-employment rate in Wallonia cannot be related to a change in the composition of entrants into unemployment, there is a scope for ALMPs aimed at specific groups of unemployed workers. For, the hiring prospects of the low educated unemployed deteriorated more markedly than those of the highest educated ones over the 1973-1993 period in this region.

In **Chapter 4**, we find that there is significant job competition among the *dismissed* unemployed workers in Wallonia. From our results, one could expect that the vitality of employment growth in the recent years lowers the extent of job competition among the unemployed population in Wallonia. This evolution remains to be confirmed. However, given the structural weakness of job creation in the Walloon region, it is unlikely that the recent economic growth will be sufficient to significantly reduce the incentives to job competition. Structural policies are therefore called

for to stimulate the long-term employment growth.

Among these policies, one *should not exclude* education and training programmes. This statement challenges the typical view on the policy implications of job competition. It is often argued that such policies are inefficient when job competition exists, since they would only reinforce the job competition process and waste further productive resources. However, this view is based on a *static* line of arguments. According to some authors, an *insufficient* effort put into education and training in Wallonia contributed to hamper the development of new activities after the de-industrialisation shock of the late seventies. In such a context, training schemes and improvements in the regular educational system can help to reduce the extent of job competition in Wallonia, and thereby unemployment. By providing a large number of dismissed workers with the appropriate skills required by the labour market, they can encourage the development of productive activities in this region.

In comparison with our bordering countries, the effort devoted to training is small in Belgium. In 2000, only 3.7% of the unemployed workers participated to a training scheme in Belgium against 5.8% in our bordering countries (see CESRW 2001, pp.118-119). These figures mask an important disparity between the two main regions of Belgium: In 2000, the share of unemployed workers participating to a training scheme in Flanders was almost twice as large than in Wallonia. Since Wallonia is characterised by a relatively low number of graduates from the upper secondary school, improvements in the regular educational system must also be encouraged, particularly in what concerns the vocational and technical education.

In the recent years, the Belgian authorities increased the resources devoted to reductions of labour costs: In 2001, the total amount of reductions was almost 4 times higher than its level in 1995. These are across-the-board reductions, but they also focus the lower segment of the labour market since low paid workers benefit from larger reductions of labour costs. The Walloon region could complement these policies by recruitment subsidies which combine work experience and on-the-job training. However, there is also a need of supply-side policy instruments, specific to the Walloon region.

5.4 What are the methodological contributions and the tracks for future research?

In **Chapter 2**, we significantly improve the fit of our statistical model in departing from the ‘pure’ proportionality assumption. We show that the extent of spurious negative duration dependence can be underestimated in a model ignoring the non-proportionality of the outflow rate in duration and the business cycle, i.e. the ranking hypothesis (for the prime-aged men only). However, we are aware that the time-duration interaction implied by ranking is specified in an imperfect way. For identification purposes, we cannot allow for non-proportionality within the two sub-periods, but only between two sub-periods. Moreover the timespan covered by our data is too short for conducting a proper sensitivity analysis by considering different sub-periods.

Further research is therefore called for. Both a longer observation period and additional continuous regressors could help better identifying the interaction generated by ranking. However, one should also be aware that assuming proportionality in other continuous regressors could be as imperfect as assuming the absence of time-duration interaction within sub-periods. For instance, our study suggests that the duration dependence, and so ranking, may not be similar across age groups. The common assumption that age affects the exit rate out of unemployment proportionally may accordingly lead to incorrect conclusions. Another route to test the ranking hypothesis is the use of multiple spells data which allow to identify the distribution of unobserved heterogeneity *without* imposing the proportional assumption.

In **Chapter 3**, we propose a complete and formal decomposition of the variations in the aggregate outflow rate over time, focusing on both cyclical and structural variations. In particular, none of the existing studies decompose formally the structural variation in the aggregate outflow rate into a general and a composition effect. Besides, we choose to parametrise the time dependence of the distribution of unobserved characteristics by the number of entrants into unemployment (as in Chapter 2). If variations in the composition of inflow closely follow variations in the number of entrants into unemployment, our specification turns out to be a better alternative than a non-parametric one. For, our para-

metric assumption allows the unobserved composition effect to follow a trend (i.e. the trend in incidence), separately from the trend in the general effect. The pattern of the observed composition effect confirms the plausibility of our assumption since we observe that variations in the observed quality of entrants coincide with variations in incidence, in both the cyclical and the structural dimension.

Further work is called for to study the behaviour of the probability of flowing *into* unemployment over the last decennia in the two main regions of Belgium, and to investigate whether this behaviour differs according to the level of education and the province of living. This analysis would also enable us to decompose variations in the *unemployment rate* rather than in the stock.

In **Chapter 4**, we estimate the structural form of the outflow rate by level of education without relying on a reduced form specification. This estimation approach conducts to a better interpretation of our parameter estimates. In addition, our empirical framework does not need to rely on the reports of employers or workers concerning the skill requirements of a job, contrary to most of the empirical research on skill mismatch and job competition. For, we estimate directly both the extent of job competition and the distribution of job offers according to the required level of education.

However, the available data allow us to evaluate the extent of job competition and skill mismatch *only* for dismissed unemployed workers, which excludes young school leavers and on-the-job searchers. In particular, our estimation of job offers by the required level of education concerns only those intended to this selective population. To evaluate the extent of skill mismatch in the economy as a whole, we should need data on all types of job seekers. This is material for future research.

Another track of future research is related to the policy recommendations of job competition. As emphasised above, it is often argued that education and training policies are inefficient when job competition exists. In our thesis, we challenge this view: Training schemes and improvements in the regular educational system can help to reduce the extent of job competition in Wallonia, and thereby unemployment, by encouraging the development of new productive activities in this region. In a recent literature, we can also find arguments against such a view.

Even if education and training policies can lead to temporary situations of overeducation, employers will progressively adjust the tasks of the jobs (and the wages) according to the skill profile of the workers. A number of recent works have indeed shown that the composition of jobs adjust to the composition of workers in the long run (see Acemoglu 1998, 1999, Beaudry and Green 1998, Gautier 2001). Further research is therefore called for. A promising track is to develop a theoretical framework in a *dynamic* setting, allowing explicitly for two types of workers (skilled and unskilled) and two types of jobs (complex and simple). A particular issue would be then to set the conditions under which ‘overeducation’ may persist in the long run.

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