UNEMPLOYMENT AND CHANGES IN THE AGE COMPOSITION OF THE WORKFORCE IN BRITAIN

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ABSTRACT

This thesis considers the linkages between the age composition of the population and the incidence of unemployment. The first two chapters investigate the macro implications of demographic change, the second two focus on the age-variation in experience of unemployment at the micro level.

It is well known both that the probability of being unemployed varies with age and that, thanks to large fluctuations in the birth rate over the last half century, the age composition of the labour force has undergone profound change. We employ a shift-share analysis to identify the role played by shifts in the composition of the labour force in determining the behaviour of the unemployment rate. If workers acquire human capital as they age, demographic change implies a shift in the distribution of skills across the workforce. Drawing on an established theoretical model, we re-examine the evolving mismatch between the demand for, and the supply of, different skills in the labour market, and the role it played in determining the aggregate unemployment rate over the recent past.

If we want to understand the extent to which it is the same individuals who are unemployed through time, we have to look beyond the aggregate unemployment rate. We therefore focus on the distribution of unemployment across individuals – and in particular across age groups – when we aggregate across their separate spells, and the implications a concentration of unemployment on a small number of individuals might have for wage setting behaviour. If past experiences of unemployment scar individuals – increasing their probability of being unemployed in the future – this might explain the persistence in experiences of unemployment we observe. Drawing upon the survival analysis literature, we investigate a particular variant of the scarring hypothesis – that past experiences of unemployment significantly reduce the conditional probability of escaping current spells.

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CHAPTER 1

INTRODUCTION

This research was motivated by two observations. First, that experiences of unemployment vary significantly by age, and in particular, that youths suffer higher unemployment rates than older members of the working age population. Second, that large fluctuations in the birth rate in the first few decades of the post-war era ensured that the age composition of the working age population of the United Kingdom has undergone profound change in recent decades. Taken together our facts suggest that demographic change might have the potential to offer new insights into the behaviour of the UK labour market – and in particular the unemployment rate – over the recent past. This thesis explores the links between the age composition of the working age population and various features of the labour market.

Youths always suffer higher unemployment rates than adults. It is argued that this unemployment differential reflects the fact that youths have a higher probability of flowing into unemployment than adults – either because they are more likely to be employed in unstable, low quality job matches, or because firms are more likely to lay off younger members of their workforce in the face of a negative demand shock. From the mid 1980s onwards the youth share of the labour force fell almost monotonically as the baby bust generation entered the labour market while the larger cohorts of baby boomers entered adulthood. Chapter 2 of this thesis investigates what part of the behaviour of the aggregate unemployment rate between 1984 and 1998 can be explained by this shift in the age composition of the working age population towards those groups who always suffer lower unemployment rates. Following Shimer (1998) we employ a shift–share analysis which decomposes the change in the aggregate unemployment rate over the period into that part which can be explained by changes in the age-specific unemployment rates at a given age-composition of the labour force, and that part which can be explained by a shift in the age composition of the labour force for a given set of age-specific unemployment rates. We find that between 1984 and 1998 demographic change can explain just over half a percentage point of the five and a half percentage point fall in the aggregate unemployment rate over that period.

However, there is another channel through which demographic change can have an impact upon the aggregate unemployment rate, over and above changing the age composition of the workforce. That is, the age specific unemployment rates themselves may not be entirely independent of the these shifts in the relative supply of different age groups in the labour force. In particular, we might expect that the unemployment rate of a given group will increase in response to a rise in that groups relative share of the labour force – an effect commonly referred to as 'generational crowding'. In order to identify these effects precisely you need to observe the counterfactual – i.e., other things equal what would have happened to the age-specific unemployment rates in the absence of demographic change – but of course the counterfactual is unobservable. In fact, the raw correlations in the data do not suggest that were any significant generational crowding effects over the period in question (or at least not in the direction theory would suggest). Nevertheless, in order to quantify the potential impact of any generational crowding effects, we draw on existing estimates of the elasticity of the age-specific unemployment rates with respect to their population shares to produce a quantitative estimate of the indirect impact of demographic change on the aggregate unemployment rate.

Of course, demographic factors are not the only forces which can shift the age composition of the labour force. For example, rising participation in post-compulsory education over the period will have almost certainly led to a decline in the fraction of the youth population who are either employed or seeking work. In order to control for these non-demographic shifts in participation we apply two alternative modifications of our approach as follows. First, we correct the time series profiles of the labour force shares of each group by applying a constant activity rate to the populations of each age group. Given the observed unemployment rates of each group, our decomposition proceeds as before, to give the hypothetical impact of the shift in the age composition of the *population* on the aggregate unemployment rate. Second, we integrate the inactive into our analysis directly by performing a shift-share decomposition of the change in the fraction of the *working-age population* who are unemployed into changes in the age-composition of the population and changes in the fraction of each cohort who are unemployed.

One atypical feature of demographic shocks to the working age population is that they are eminently predictable – huge migratory flows and catastrophic surges in the death rate aside – future shifts in the age composition of the working age population can be observed in data on birth rates available today. In the final section of Chapter 2 we use current projections of the future age composition of the population to construct a forecast of the future impact of demographic change on the aggregate unemployment rate. In fact, on that basis, demographic change can be expected to have a negligible impact on the unemployment rate until 2011.

As they age workers typically add to their stock of human capital through formal training programmes and more generally, informal exposure to the workplace. The age composition of the working age population is therefore one factor which can help explain the distribution of skills across the workforce. The mismatch literature has established that under certain conditions (when the wage setting function is convex or when wages are set throughout the labour market according to conditions in the market for the most skilled members of the workforce) the evolution of the demand for, and the supply of, different skills in the labour market can help explain the behaviour of the aggregate unemployment rate. The consensus in the literature is that any net shift in the relative demand for different skills over recent decades can explain little of the movement in aggregate unemployment. However, previous research has typically focused on only a narrow definition of an individual's skill based on their highest level of educational attainment. Chapter 3 of this thesis draws upon this mismatch literature to investigate whether an appreciation of the relationship between an individual's age and the stock of human capital they hold can offer any new perspective on the role that shifts in the net demand for different skills have played in shaping the performance of the UK labour market. It is well understood that the rise in participation in post compulsory education in the UK may have partially offset the impact of the infamous skill biased shift in labour demand which permeated through the labour markets of the developed world in recent decades. It is our contention that population ageing provided a second potentially benign supply shock – over the period, the share of the experienced, highly trained (older) workers rose , while the share of inexperienced, untrained (young) workers fell.

Throughout this chapter we follow standard practice in the literature and divide the workforce into a small number of discrete groups, within which all individuals are assumed to be identically skilled, although here we classify individuals according to their age as well as their highest level of educational attainment. Using data from the Labour Force survey on individual's labour market status, and data from the General Household Survey on individual's wages we are able to calculate the unemployment rate and average wage for the members of each of our constructed skill groups. This data reveals the stark variation by age in the average wages and unemployment rates of those who share a common level of educational attainment which must reflect in part our stylised fact – that an individual's age is an important determinant of his, or her, level of skill.

In some sense a natural place to look for the impact of skill biased supply and demand shocks in the labour market is in the outcomes of each of these groups. Using standard dispersion measures from the literature we illustrate the divergence in outcomes in the labour market since 1979; it does indeed appear that there has been increased dispersion of wages across skill groups, although the evidence is less clear cut in terms of the skill specific unemployment rates. However, in order to quantify the impact of any net shift in the demand for different skills on the unemployment rate we require a measure of skill measure and a model which articulates the link between the behaviour of that measure and the unemployment rate. Manacorda and Petrongolo (1999) consider a model in which heterogeneous labour is the only input in production and the technology is Cobb Douglas. Equilibrium for each group is then determined by the intersection of the implied labour demand curves (under perfect competition) and double logarithmic (or convex) wage setting functions. A natural measure of skill mismatch in this framework is the ratio of the wage bill shares of a given pair of groups divided by the ratio of their labour force shares, so that a skill neutral demand shock leaves the relative wages and employment rates of the two groups unchanged. Algebraic manipulation then allows us to identify the role played by the evolution of these mismatch measures in determining the behaviour of the aggregate unemployment rate.

Aside from our more inclusive definition of skill, we generalise this model in two ways. First, we relax the restrictive assumption on the elasticity of substitution between different skill inputs in the production function by assuming a C.E.S. technology. Second, we allow for the possibility that wages may be set by a 'leading' (i.e. the highest) skill sector of the labour market. Our model therefore has two unknowns – the elasticities of the production and wage setting functions – and given parameter values for each, we can identify the impact of rising skill mismatch on the aggregate unemployment rate.

Our results are as follows. Mismatch between the demand for and supply of different skills in the labour market did increase over the 1980s but remained broadly unchanged over the early 1990s. Contrary to previous research in the literature, we find that for reasonable parameter values our model implies that this increase in skill mismatch can explain a significant proportion of the behaviour of the aggregate unemployment rate over the period.

Between 1983 and 1996 an average of 45,000 men flowed into claimant unemployment each week. However, the experiences of those men differed sharply – some left the claimant count within days, while others remained for months, even years. This observation has led academics and policy makers alike to focus on the duration of unemployment spells – and in particular long term spells – as a key indicator of distress in the labour market. However, it is also true that many of those who leave the claimant count will flow back within a relatively short space of time. Therefore in the long run it is not necessarily the case that unemployment is concentrated solely upon those trapped in long term spells. Only by aggregating across spells can we get a true perspective of which individuals are chronically unemployed, and how much unemployment they suffer in the long run, and this is the observation that motivates Chapter 4 of this thesis.

One of the key research agendas in the macro-labour literature has been to find a convincing explanation for the woeful performance of the European labour market over the 1980s and much of the 1990s – in particular the extremely high rates of unemployment suffered by most European countries throughout that period. Blanchard (2000) argues that the favoured explanation for this '*Eurosclerosis*' – that the incidence of long term unemployment failed to restrain wage pressure – is insufficient both on empirical and perhaps more decisively on theoretical grounds. He argues that insiders (or wage setters) know there is always a chance that they may become unemployed and given the low outflow rate from unemployment they may ultimately become long term unemployed; therefore the plight of the long term unemployed should moderate their behaviour. Blanchard argues that it is the heterogeneity in individual's probability of becoming and remaining unemployed that is crucial – insiders should be concerned with their own risk of being unemployed, which may not be reflected by the aggregate unemployment rate. If the distribution of unemployment is heavily concentrated on a few unfortunate individuals, then even if the aggregate unemployment rate is high, insiders probability of being unemployed for any length of time may be low and wages will not respond. Blanchard proposes a particular demographic variant of this hypothesis – if increases in unemployment are heavily concentrated on the youngest members of the workforce then increases in aggregate unemployment will not restrain wage setting by adults whose probability of being unemployed will not have changed.

Chapter 4 has two core elements. First, we establish the stylised facts of the distribution of the total number of days of unemployment experienced by working age men across all the spells they suffer in a given period using the JUVOS cohort dataset, which contains entire spell histories of a random 5% sample of the claimant unemployed. We evaluate the extent to which unemployment is heavily concentrated on a relatively small number of men, and in particular the evidence to support Blanchard's hypothesis these unfortunate few are overwhelmingly youths. Second, we illustrate how this distribution varies across and between the economic cycles to give an insight into the pressure exerted on wages by the claimant unemployed.

We define the distribution of unemployment in terms of the fraction of a given period each male in our panel is claimant unemployed, which we compare against the natural benchmark of the distribution of spell lengths in that period. We identify the following stylised facts. Between two to four million men have some experience of claimant unemployment each year over the course of three to five million spells; over a four year period, about five million men claim unemployment benefits over the course of ten million spells. In any given year recurrent unemployment is quite rare – about three quarters of a million men will make more than one claim for benefit each year – but over a longer period of time it becomes a more pervasive phenomenon. Experiences of unemployment are quite polarised – one in ten of all claimant spend less than four weeks of a given year unemployed, while about one in five are permanently unemployed throughout the year. Per head of population youths are indeed more likely to suffer an experience of unemployment, but on an individual basis they suffer less days of unemployment than older members of the workforce. Finally, while the change in the claimant count each week is relatively small, the gross flows into and out of claimant count are relatively large – so the distribution of unemployment across individuals is far from static. If we define the chronically unemployed as those who spend the majority of a given period unemployed, then over a year they typically explain about three quarters of all days lost to unemployment. Per head of population, youths are also over represented among the chronically unemployed, however they are under represented compared to the number of youths who make any claim for unemployment benefit. We therefore argue that while there is considerable evidence to suggest unemployment is concentrated on relatively few individuals which may well have implications for wage setting, it is not the case that those individuals are overwhelmingly youths as Blanchard contends.

There is good reason to believe that for a given aggregate unemployment rate, a more concentrated distribution of unemployment might impose less restraint on wage setting than we would otherwise expect. However, given our ignorance of the actual features of the distribution of unemployment which wage setters respond to, if we want to make qualitative statements about the pressure exerted on wages by unemployment at different points in time, we require a conceptual framework which ranks different distributions in a plausible manner. In the latter half of Chapter 4 we use two such approaches: the first focuses on the degree of inequality in the distribution, the second on the degree of polarisation, drawing on the work of Esteban and Ray (1992). These two approaches rank distributions in different ways – it is quite conceivable for a distribution to be unequal yet unpolarised (for example, a uniform distribution) or equal yet polarised (for example, a discrete distribution with only two point masses) – and we therefore look for points of consensus between these two approaches when drawing conclusions about the pressure exerted on wages by the distribution of unemployment. Our key results are as follows. Over the cycle the distribution is most polarised during a slump and yet most unequal in a boom reflecting the fact that in a boom the gap between those suffering the most and the least unemployment narrows in *absolute terms*, but widens in *proportionate terms*. However, both conceptual approaches deliver a consistent interpretation of the concentration of unemployment over time - the degree of both inequality and polarisation in the distribution of unemployment has fallen and so other things equal, we might expect greater restraint on the part of wage setters who can now expect to suffer a greater (if not equal) share of the burden of unemployment.

That in the aggregate data the instantaneous exit rate, or *hazard*, from unemployment declines with the duration of the spell is well known. Some argue that this observation reflects the a sorting effect at the individual level – those who have the highest probability of escaping unemployment do so first, and therefore the average probability of escape of those who remain will decline. Others suspect that the declining hazard is more than just a mirage in the aggregate data – the experience of unemployment has a corrosive effect on the individual, slowing reducing their probability of escape. The damage to an individual may be either direct – eroding their stock of human capital or psychological well being making them less attractive to potential employers, or indirect – where there is a stigma attached to being unemployed as firms who lack information on job applicants use the duration of an individual's spell as a signal of their potential productivity.

A recent body of research has focused on a potential implication of this hypothesis – upon exiting the spell the slate might not be wiped clean: the erosion of human capital, psychological damage or stigma may not be undone. The experience of unemployment then leaves a scar – those who have an experience of unemployment may suffer a wage penalty on re-employment, and/or they may be more likely to become or remain unemployed in the future.

Chapter 5 of this thesis contributes to this nascent literature by testing for the presence of a particular variant of the scarring hypothesis – *lagged duration dependence effects* – where controlling for differences between individuals and the labour markets in which they search, the duration of past experiences of unemployment significantly depress the hazard. Moreover, given the results found elsewhere in the literature, and the potential implications for policy, we also test whether these scarring effects differ significantly by age.

Our econometric approach to identification draws on the established survival analysis methodology. In order to plausibly identify any lagged duration dependence effects we require a comprehensive set of controls for all other factors which might affect the conditional probability of escape from unemployment, and an econometric model of how the hazard is affected by these variables. Our set of controls includes both local labour market data specific to the individual, information on their wage and other employment conditions when they were last employed taken from the NES dataset and an individual specific random effect to control for other unobservable differences between individuals. Given our uncertainty over the form of the hazard function, we adopt a non-parametric functional forms to minimise any potential mis-specification bias in our results.

Finally, our results are as follows. There is indeed evidence that, controlling for differences between individuals and the labour markets in which they search, the longer the spells of unemployment an individual has suffered in the past then the lower their conditional probability of escaping a current spell of unemployment. These lagged duration dependence effects are clearly significant in the JUVOS panel. However, we can find no robust evidence to suggest that these lagged duration dependence effects intensify with age. Indeed, we find the opposite to be the case – that the young are more seriously affected by an experience of unemployment in the past.

CHAPTER 2

THE AGGREGATE IMPACT OF DEMOGRAPHIC CHANGE ON THE UK UNEMPLOYMENT RATE

1. INTRODUCTION

Most models of the labour market take it as given that inflationary pressures develop when unemployment falls below its natural or equilibrium rate—this assumption is at the heart of the Phillips curve relationship, and the expectations-augmented models that followed it. So recent developments in the labour market have puzzled economists: in August 1999, for example, the number of people out of work and claiming benefit fell to a 19-year low and yet the RPIX inflation rate was at its lowest level for more than five years.

One explanation of this puzzle is that the natural or equilibrium unemployment rate may have fallen, enabling the actual unemployment rate to fall substantially without generating a pick-up in inflation. Mainstream explanations for such a fall in the natural rate have tended to focus on the decline in union bargaining power, reduced generosity of unemployment benefits and increased deregulation in the labour market. This chapter examines another supply-side explanation, which has received less attention in the United Kingdom: that the natural rate has fallen because of changes in the age composition of the labour force. Youths always have higher unemployment rates than adults, and presumably have higher natural rates as well. The proportion of youths in the labour force almost halved over the past decade, so we would expect the aggregate unemployment rate and the natural rate to have fallen as a result.

Most of the existing literature investigating the impact of demographic change on the unemployment rate has focused on the US labour market. In a recent paper, Shimer

(1998) claims that demographic factors can explain the bulk of 'low-frequency fluctuations' in US unemployment since World War II, raising the aggregate unemployment rate by about 2 percentage points over the 1960s and 1970s, and then reducing it by about 1½ percentage points thereafter. This chapter provides a comparable quantitative estimate of the fall in the UK unemployment rate that can be accounted for by the decline in the youth share of the labour force.

Section 2 of this Chapter presents two key stylised facts, which together suggest that demographic change could indeed have played a significant role in explaining recent developments in the UK labour market. First, that the proportion of youths in the UK labour force has fallen dramatically over the past decade. Second, that youths always have higher unemployment rates than adults, and that this can be attributed to the fact that they have higher inflow rates into unemployment. In Section 3 we briefly review the literature to explain why youths suffer higher unemployment rates than adults, irrespective of their relative shares of the labour force. We argue that the youth unemployment problem is caused either by high quit rates among younger workers, or by firms discriminating against their younger employees when they lay off workers. This is consistent with youths having high unemployment rates because they have high inflow rates into unemployment.

In Section 4 we survey the 'shift-share' methodology developed in the literature, and use it to provide a range of estimates of the impact on the unemployment rate of demographic change in the labour force. We conclude that the decline in the youth share of the UK labour force can explain approximately 55 basis points of the fall in the aggregate unemployment rate between 1984 and 1998.

Demographic change can have a further indirect impact on the aggregate unemployment rate if the group-specific unemployment rates depend on the composition of the labour force – through so called generational crowding effects. In Section 5 we assess whether shifts in the composition of the labour force over the period did indeed have a material impact on the youth and adult unemployment rates. We find little robust evidence for these generational crowding effects; however, we illustrate how demographic change could explain a far greater proportion of the change in the aggregate unemployment rate under fairly reasonable assumptions on the size of these generational crowding effects.

The proportion of the population in each age group that is economically active (either employed or actively searching for work) can and does vary over time, and this will lead to further changes in the composition of the labour force. Section 6 discusses two alternative approaches that seek to control for these changes in the labour force participation rates of each age group, in order to isolate the impact of demographic change. Qualitatively, the results are the same as before. Demographic change explains only a relatively small fraction of the overall change in the unemployment rate between 1984 and 1998, but appears to be the principal determinant of the changes in the composition of the labour force.

Finally, in Section 7, we use current projections of the future size and composition of the labour force (based on data on fertility rates, and forecasts of future patterns of migration, mortality and activity rates) to project the implications for the unemployment rate in the near future. We conclude that shifts in the composition of the labour force are unlikely to have a significant impact on the unemployment rate over the next decade.

2. STYLISED FACTS

2.1 DEMOGRAPHIC CHANGE

The United Kingdom, like most of the developed world, has experienced a sustained period of significant demographic change in the postwar period. The crude birth rate[1] increased rapidly through the late 1950s and early 1960s, from 15 in 1955 to 18.5 in 1964, then collapsed to a low of 11.5 in 1977. It has since stabilised (see Figure 2.1). These changes were echoed 16 years later in the size of the youth cohort entering the

[1]The total number of births each year, multiplied by a thousand and divided by the population.

labour market (see Figure 2.2): the proportion of 16–19 year olds in the labour force peaked at 9.9% in 1981, but by 1994 had fallen back to 5.8%.

Figure 2.2 illustrates the dramatic fall in the youth share of the labour force between the late 1970s and the mid-1990s. Although the huge fall in the birth rate that occurred once the baby boom had ended will certainly have reduced the number of youths in the working-age population, there are a number of other factors that might have affected the *youth share of the labour force*. Principal among these is the proportion of each youth cohort that remains within the education system. Over the past two decades the United Kingdom has experienced a period of sustained expansion in the post-compulsory education system, with the number of youths attending further and higher education colleges more than doubling between 1980 and 1995 (see Figure 2.3). Of course, although some fraction of these students will also seek part-time employment to supplement their income, increased participation in the education system is almost certain to have reduced the rate of economic activity among youths.

FIGURE 2.1 : THE CRUDE BIRTH RATE : BIRTHS PER THOUSAND PEOPLE

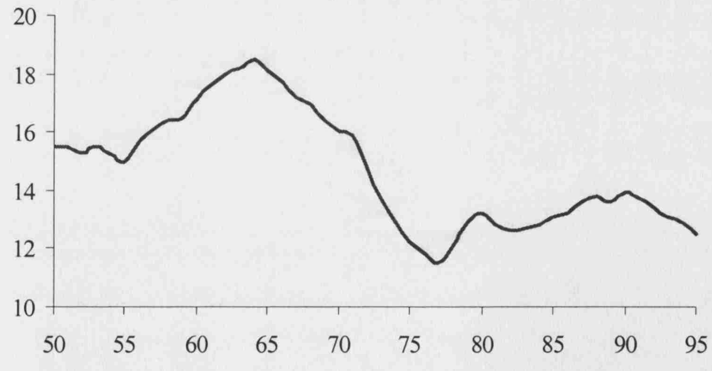
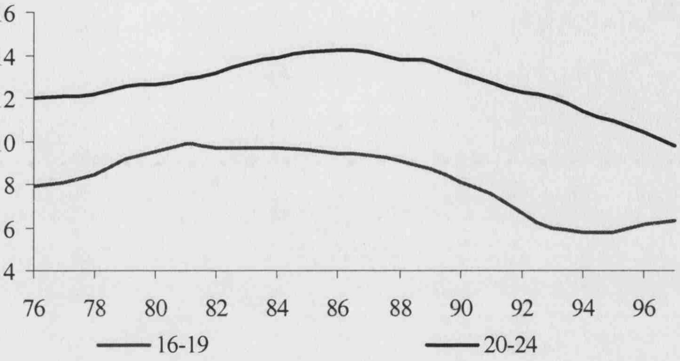
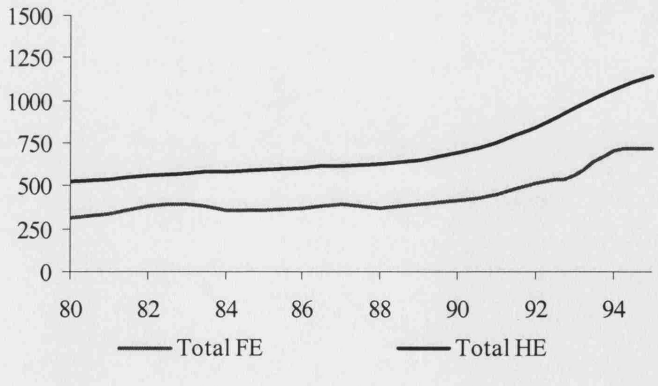


FIGURE 2.2 : THE YOUTH SHARE OF THE LABOUR FORCE (%)



For those aged 16 to 17 the activity rate fell by more than 4 percentage points, and for those aged between 18 and 24 it fell by 7 percentage points. This had a significant impact on the number of youths in the labour force—if activity rates had remained at their 1984 levels there would have been approximately 400,000 more youths in the labour force (approximately half the increase in the number of youths entering further and higher education, reflecting the fact that a number of students are also classified as economically active).

FIGURE 2.3 : NUMBERS OF STUDENTS IN FURTHER AND HIGHER EDUCATION (THOUSANDS)



To put this in context, in 1984 there were 6¼ million youths aged between 16 and 24 in the labour force, but by 1998 there were less than 4½ million. In other words, approximately a quarter of the total fall in the number of youths in the labour force over the period was a result purely of changes in the proportion of the youth population either employed or actively searching for work. However, changes in youth activity rates will not necessarily have affected the composition of the labour force over the period to the same extent as they have the number of youths in the labour force. We know that there have been large changes in the rates of economic activity across all age groups in the working age population – although not all in the same direction (see Figure 6.1 later and Gregg and Wadsworth (1999)). To a first approximation, only differential changes in the participation rate of a specific age group will have an impact on the aggregate unemployment rate.

2.2 THE YOUTH UNEMPLOYMENT GAP

Youths always have a higher unemployment rate than adults (see Figure 2.4). This differential is persistent, but varies across the cycle. The unemployment rate is identically equal to the product of the *inflow rate* into unemployment and the average *duration* of unemployment. So if U is the stock of unemployment, S is the inflow into unemployment, and N is the size of the labour force, then in steady state:

$$\frac{U}{N}=\frac{S}{N}\times\frac{U}{S} \qquad [2.1]$$

In steady state, the number of people entering unemployment must equal the number leaving it. Letting H denote the total outflow from unemployment, we get:

$$\frac{U}{N}=\frac{S}{N}\times\frac{U}{H} \qquad [2.2]$$

The final term of this expression is the reciprocal of the outflow rate, so the unemployment rate in steady state can be expressed as the inflow rate into unemployment rate divided by the outflow rate from it:

$$\frac{U}{N} = \frac{S/N}{H/U} \qquad [2.3]$$

The UK data show that youths have higher unemployment rates because they have a higher propensity to become unemployed. Once unemployed, however, their outflow rates from unemployment appear, if anything, to be marginally higher than those of adults; as a result, at any given point in time, a far smaller proportion of unemployed youths have been unemployed for an extended period (see Figure 2.5)[2]. Put another way, although large numbers of young people flow into unemployment each period, very few end up becoming long-term unemployed.

FIGURE 2.4 : UNEMPLOYMENT BY AGE GROUP

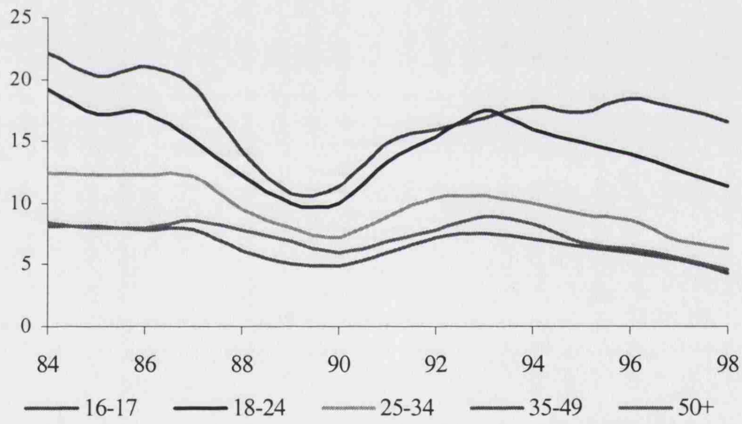
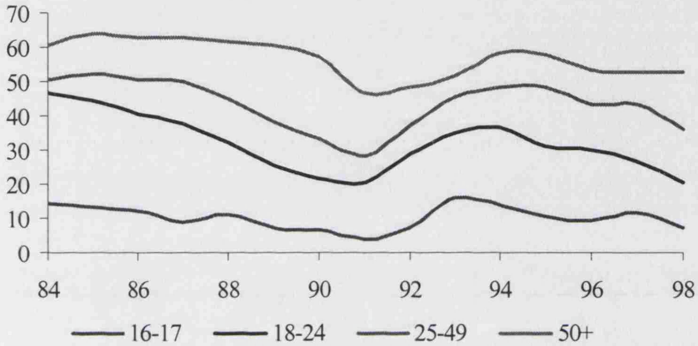


Figure 2.4 also reveals that, relative to all other age groups in the labour force, youths have had increasingly higher unemployment rates over the period. When the labour market began to recover in the mid-1990s, the unemployment rate of the youngest members of the labour force was the most sluggish to react—between 1993 and 1996 the unemployment rate of 16–17 year olds actually increased, while the rates of all other groups fell. By 1998, while the unemployment rate of most other age groups had fallen by about a third, the unemployment rate of 16–17 year olds was still at its 1993 level.

[2] For further details see Appendix Table A.2.2, and Chapter 4 of this thesis.

This may well be a consequence of increased participation in post-compulsory education—if, as seems likely, those members of each cohort with the best employment prospects enter further and higher education, then over time the average employability of those youths who enter the labour force aged 16 will fall.

FIGURE 2.5 : PERCENTAGE OF THE UNEMPLOYED WITH DURATIONS GREATER THAN A YEAR BY AGE GROUP



So our two stylised facts are that the proportion of youths in the labour force has fallen substantially over the past 15 years; and that youths always have higher rates of unemployment than adults because they have higher inflow rates into unemployment. Given the orders of magnitude of the relevant variables, demographic change in the labour force could have been large enough to have had a significant effect on aggregate unemployment.

3. THE AGE UNEMPLOYMENT RATE DIFFERENTIAL

In the following section we shall give a brief overview of the reasons why youths suffer higher unemployment rates than adults. It should be noted that it is not our intention to use the available data to distinguish between these competing (or indeed complementary hypotheses). Instead, we simply aim to underline why it is that we believe that the age unemployment differential is a persistent feature of the labour market. outline the existing explanations of why youths suffer higher unemployment rates than adults. Of course, it is plausible that as the composition of the labour force changes the differential between the youth and adult unemployment rates may vary. However, irrespective of the shifts in the composition of the labour force we have discussed, theory and evidence suggest that our stylised fact – that youths have higher unemployment rates than adults – will always be true (Topel (1998)). Our discussion begins with the simple observation that turnover in the labour market appears to be greatest for younger workers. Indeed, Gregg and Wadsworth (1995) estimate that more than half of all the job changes during the course of a working lifetime occur before the age of 30, and a quarter before the age of 20. It appears that these higher job separation rates (and thus the age unemployment differential itself) can be explained either by discrimination against youths when firms are forced to lay-off staff, or by the greater propensity of young workers to quit their jobs.

3.1 FIRMS' LAY-OFF POLICIES

Firms are periodically forced to lay-off some of their employees, both in response to transitory and permanent shifts in demand, and as a result of periodic restructuring of the workplace to increase efficiency or profitability. If firms disproportionately concentrate lay-offs among their youngest employees, this might help to explain the higher youth inflows into unemployment. There are two main reasons why lay-offs may be concentrated among younger workers. First, that firms are constrained in who will be laid off – by prior agreement to 'last in, first out' (LIFO) rules, which disproportionately target younger workers; and second, that firms choose to lay off their youngest employees.

3.1.1 NEGOTIATED LIFO RULES

In their survey of 'Pay and Employment Determination in Britain', Oswald and Turnbull (1985) find that LIFO is the most widely used method for choosing who will be made compulsorily redundant in a slump. The LIFO rule, which will typically be introduced at the behest of unions[3], discriminates against those most recent entrants to the workforce, when the firm is forced to lay off staff. Youths are, almost by definition, recent entrants to any firm. Of the 350 establishments surveyed by Oswald and Turnbull, 64% used LIFO as their criterion to decide enforced redundancies. Although the recent decline in the coverage of trade union bargaining may well have reduced the use of LIFO rules in deciding who is laid off, it is likely to remain important wherever unions have retained significant bargaining strength.

3.1.2 FIRMS CHOOSING TO LAY OFF YOUNGER WORKERS

Firms may choose to lay off their younger employees in the face of a negative demand shock. Older workers will have acquired a considerable amount of valuable workplace-relevant human capital during their time in the labour market. These skills will be costly for the firm to replace, both in terms of the financial cost of hiring and training replacements, but also because it will take a new entrant a certain amount of time to acquire familiarity with the workplace. If the firm chooses to lay off skilled incumbents it may be difficult to replace them when demand recovers. Conversely, young new entrants have little general or firm-specific workplace human capital and will still be in plentiful supply when demand recovers. For this reason, the firm may decide to preserve the skilled core members of its workforce and to concentrate lay-offs where possible amongst the least-skilled new entrants.

The incentive to lay off younger less-skilled workers may be counterbalanced by the fact that they will almost certainly be paid substantially less than older members of the workforce, so the simplest way to cut labour costs significantly would be to lay off the more expensive older workers. However, there are sunk costs in hiring and/or training staff to replace skilled employees, and firms may not be able to continue to operate effectively without their skilled core workers. So lay-offs might still be concentrated amongst the least skilled, despite the fact that they are cheaper to employ. In the Oswald-

[3] Public choice arguments suggest that LIFO rules, which give increased job security to the majority of employees, are likely to be adopted by union representatives and will continue to be so.

Turnbull survey, 47% of firms reported deciding enforced redundancies according to the criterion of those who were 'least skilled or competent'. In addition, if firms believe that youths are more likely to quit than adults they may delay training younger employees, which will prolong the period for which young entrants to the firm will be viewed as low-skill workers (Farber (1994)).

3.2 YOUTHS' HIGHER PROPENSITY TO QUIT

Young people quit their jobs more frequently. There are two main reasons why they may do so: they may be employed in types of jobs that encourage them to quit more often, or they may behave differently from adults in the labour market.

3.2.1 LOW-WAGE/SECONDARY SECTOR JOBS

The probability that an individual will quit a job is generally taken to be inversely proportional to the wage offered, so low-wage industries are generally high-turnover industries. The labour market is often characterised as comprising two sectors: a primary sector of high-wage jobs, for which there are job queues and for which voluntary quits (into unemployment) are rare; and a secondary sector of low-skill jobs, characterised by low pay, poor working conditions and limited prospects for training or future wage growth.

Low pay is in fact remarkably concentrated in a very small number of industries—half of all the low paid work in just six occupations (see Metcalf (1999a)). As younger workers are concentrated in the secondary sector (two fifths of those aged 18–20, and more than half of those aged 16–17 work in the retailing and hospitality industries, both of which are classic low-pay employers (see Metcalf (1999b)), they will be more likely to quit their jobs than older workers. This might also explain their higher inflow rates into unemployment. So, on this explanation, it is not that young people necessarily have an intrinsically higher probability of quitting their jobs than adults, but simply that they happen to work in the high-turnover secondary sector in disproportionate numbers.

But why are youths more likely to be employed in the secondary sector? If youths have lower reservation wages, they will be willing to accept low-wage jobs that adults will reject; and their reservation wages may be lower either because they have only limited access to government benefit when unemployed[4], or because their wages may be supplemented by contributions from their parents.

Adult workers may also be at a distinct advantage when applying for vacancies in the primary sector—they will be more productive (having acquired work-related human capital through 'on the job' training programmes), and can provide references from previous employers that signal their ability and work ethic (i.e. that they don't shirk). With insufficient experience in the labour market to have obtained such workplace training or to have developed a reputation for good working attitudes, youths will be at a distinct disadvantage to an adult with otherwise identical observable productivity characteristics. So young workers are likely to be forced initially to accept vacancies in the secondary sector.

3.2.2 'JOB SHOPPING'

An individual may be unable to assess how productive, and hence how well paid, he will be in a particular job until he accepts it[5]. Consequently Jovanvic (1979) argues that individuals may sample a number of jobs, many of which they will quit when the match is revealed as unproductive—a process known as 'job shopping'.

In effect, high job mobility is the mechanism by which the young progress towards a 'lifetime' job. Youths do not have higher inflows because they have less work experience *per se*, but the fact that they have been searching in the labour market for such a short time makes it more likely that they are still employed in a relatively low-quality, low-

[4] Those aged 18 to 24 received £40.70 Jobseeker's Allowance per week while those aged 25 and above received £51.40, under both the contribution-based and income-based schemes (Benefits Agency (1999)).

wage job, and are therefore more likely to quit. It may also be that, because of their inexperience in the labour market, youths are more reliant on sampling jobs in order to discover their productivity; adults, on the other hand, may be better able to assess a vacancy's worth on inspection. So youths may accept, and then rapidly quit, jobs that adults would not have accepted in the first place.

Manning (1998) argues that the earnings-experience profile of both men and women can largely be explained by this model of job search. In particular, he argues that the fact that displaced workers suffer a loss in earnings when they re-enter employment, even after controlling for tenure (and hence acquired firm-specific capital in their former jobs) is indicative of the fact that search capital has been destroyed, and the individual will have to resume shopping for a lifetime job. The employment hazard (the conditional probability that a job match will end, given that it has survived to that date) actually appears to increase in the first few months of a job's life — a finding that is consistent with workers disregarding any initial information about the quality of the match, instead waiting for sufficient information to make an informed decision about the prospects of the current job (Farber (1994)). However, after about three months, the employment hazard begins to decline—the job has been revealed as either of high or low quality and the majority of unproductive matches will be destroyed.

This theory of 'job shopping' implies that new entrants to the labour market suffer a temporary unemployment penalty since they have to search for a productive job match—and so a fall in the number of youths in the labour market may reduce the unemployment rate because there are less of these new entrants to the labour market. However, in Section 2.1 we discussed how part of the fall in the youth share of the labour force over the period can be explained by increased participation in post-compulsory education, which involves no real fall in the number of new entrants to the labour market, only an increase in their average age upon arrival. If graduate entrants into the labour force also suffer an unemployment penalty due to job shopping, then a fall in the youth share of the

[5] Following Nelson (1970), jobs are then said to be 'experience goods'; conversely, if an individuals productivity in a vacancy can be observed on inspection, without actually accepting and sampling the

labour force caused by increased participation in the education system might be expected to have no effect on the aggregate unemployment rate.

However, there could be a number of reasons why, when graduates enter the labour market, they may be at less of a disadvantage than non-graduates. They may, for example, have a clearer idea of the sort of industry and firm in which they want to work, based on the specialisation of their education and the availability of free college careers advisory services. So they will require a shorter period of job shopping. They may be inherently more attractive to employers, either because they will have acquired more human capital (or at least are able to more effectively signal their innate productivity) or because employers believe that they are more mature and less likely to shirk; so they may be better able to apply directly for primary sector jobs. Finally, older entrants to the labour market may have higher reservation wages, either because they enjoy less parental financial support or because they have increased access to adult levels of government benefit. If any of these factors applies, then although all individuals must temporarily suffer high inflow rates into unemployment when they enter the labour market, the size and duration of this 'unemployment penalty' will fall with the age (or amount of human capital) of the entrant.

Over time the unemployment rate of those aged 18 to 24, an increasing proportion of whom will have recently entered the labour market, has fallen relative to other age groups in the labour force (see Figure 2.4). So it appears that any 'inflow penalty' incurred by graduates entering the labour force is more than offset by the increase in human capital that they acquired by staying longer in the education system. So changes in the composition of the labour force caused by increased participation in further and higher education can still affect the aggregate unemployment rate—since by increasing the duration of education and the age at which they arrive in the labour market, new entrants can reduce the unemployment penalty that they suffer on entry.

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match then jobs are said to be 'pure search goods'.

3.3 GENERATIONAL CROWDING AND THE YOUTH UNEMPLOYMENT RATE

The youth unemployment rate cannot necessarily be taken as being independent of demography, as it is possible that the youth unemployment rate itself might be sensitive to the proportion of youths in the labour force. The empirical evidence (Freeman and Bloom (1986)) suggests that the unemployment rate of a group, and in particular of youths, may be increasing in its share of the labour force. A number of factors will affect the size of these 'generational crowding' effects: the existence, level and coverage of any youth minimum wage legislation; the degree of substitutability and/or complementarity with other groups in the labour force; and the elasticity of demand for youth labour (Freeman and Bloom (1986)).

So the shift in the composition of the labour force away from the young may have led to a fall in the youth unemployment rate, irrespective of any cyclical effects. However, as long as youth unemployment rates remain above those of adults (which they always do) then shifts in the labour force away from youths will still reduce the aggregate unemployment rate.

4. THE QUANTITATIVE IMPORTANCE OF DEMOGRAPHIC CHANGE

So youths have (significantly) higher unemployment rates than prime-age adults, and since the early 1980s the demographic composition of the labour force has undergone significant change. In order to quantify the importance of these facts for measured unemployment, we can decompose changes in the aggregate unemployment over time into two parts: the part accounted for by changes in the unemployment rates of the separate age groups in the labour force; and that accounted for by changes in the composition of the labour force itself. This so called 'shift-share' approach has its origins in the work of Perry (1970), but can also be found in Summers (1986), Shimer (1998), Katz and Krueger (1999) and Horn and Heap (1999), among others.

4.1. SHIFT – SHARE ANALYSIS : A TECHNICAL INTRODUCTION.

In order to explain how some of the measures used in this analysis are derived we provide a brief overview of shift share analysis. Consider a variable z defined as the product of two component variables x and y. We wish to decompose the change in z between time [0] and time [T] into that explained by the change in x over the period, and that explained by the change in y:

$$\Delta z = z_T - z_0 = x_T y_T - x_0 y_0 = x_T y_T - x_0 y_T + x_0 y_T - x_0 y_0$$

$$= y_T (x_T - x_0) + x_0 (y_T - y_0)$$

$$= y_T \times \Delta x \quad + \quad x_0 \times \Delta y \qquad [4.1]$$

We can interpret the products : $y_T \times \Delta x$, $x_0 \times \Delta y$ as the change in z due to the change in x and y respectively. However, our decomposition is completely arbitrary – we could equally have added and subtracted the product $x_T y_0$ which yields:

$$\Delta z = y_0 \times \Delta x \quad + \quad x_T \times \Delta y \qquad [4.2]$$

Alternatively, we could use the product : $x_t \times \Delta y$, where [t] is some time period in the interval (0,T), and decompose the change in z accordingly :

$$\Delta z = x_t \times \Delta y \quad + \quad (\Delta z - (x_t \times \Delta y)) \qquad [4.3]$$

Of course, to the extent that x and y vary over the period, the proportion of the change in z we attribute to the change in x and y will differ according to the arbitrary choice of base year [t] we use for our decomposition.

We can of course perform the exact same form of decomposition as that shown in [4.1] – [4.3] on a summation. Consider the sum Z of N separate terms: z_i, where each term is defined as the product: $x_i \times y_i$. The change in Z between time [0] and time [T] can be decomposed into that explained by the change in the x_i's and that explained by the change in the y_i's over that interval as follows:

$$\Delta Z = \sum_i^N z_{iT} - \sum_i^N z_{i0} = \sum_i^N x_{iT} \cdot y_{iT} - \sum_i^N x_{i0} \cdot y_{i0}$$

$$\therefore \Delta Z = \sum_i^N y_{iT} \times \Delta x_i + \sum_i^N x_{i0} \times \Delta y_i \qquad [4.4]$$

or alternatively:

$$\Delta Z = \sum_i^N y_{i0} \times \Delta x_i + \sum_i^N x_{iT} \times \Delta y_i \qquad [4.5]$$

and finally, for some period [t] in the interval (0,T) :

$$\Delta Z = \sum_i^N y_{it} \times \Delta x_i + \left(\Delta Z - \left(\sum_i^N y_{it} \times \Delta x_i \right) \right) \qquad [4.6]$$

Again, if the x_i and y_i's vary over the period, then the separate decompositions we have described will not give equivalent explanations of the proportion of the change in Z 'caused' by changes in the x_i's, and that 'caused' by changes in the y_i's.

Finally, returning to the initial example, let us assume that x and the y are not exogenous, so that a change in one of the variables might cause a change in the other. Specifically, let us assume a uni-directional causality in that x is assumed to affect y but not the reverse. Now the decomposition :

$$\Delta z = y_0 \times \Delta x \quad + \quad x_T \times \Delta y \qquad [4.7]$$

will underestimate the importance of changes in x in explaining the observed change in z , since some fraction of the change in y is also caused by the change in x. Therefore if we decompose the change in y as follows:

$$\Delta y = \Delta y(x) \quad + \quad \Delta y(\varepsilon) \qquad [4.8]$$

where $\Delta y(x)$ reflects changes in y caused by the change in x, and $\Delta y(\varepsilon)$ reflects that residual part of the change in y not caused by the change in x. Then we have that:

$$\Delta z = y_0 \times \Delta x + x_T \times \Delta y(x) + x_T \times \Delta y(\varepsilon) \qquad [4.9]$$

where the sum of the first two terms should now be interpreted as the change in z explained by the change in x .

4.2 ACCOUNTING FOR CHANGES IN THE AGGREGATE UNEMPLOYMENT RATE

We can directly apply the shift – share methodology outlined above to decompose the change in the aggregate unemployment rate into changes in the group specific labour force shares and unemployment rates. The aggregate unemployment rate at time *t* can be defined as the weighted average of the unemployment rates of all the separate age groups in the labour force, where the weights are simply the respective group's share of the labour force:

$$U_t = \sum_i \omega_t(i) \times u_t(i) \qquad [4.10]$$

where $\omega_t(i)$ defines the share of the labour force who are members of group (i) and $u_t(i)$ captures the group-specific unemployment rate at time *t*. So a fall in aggregate unemployment must by definition originate from either a change in the composition of the labour force towards groups with lower unemployment rates, a fall in the unemployment rates of some or all groups, or some combination of the two.

Following the terminology used by Katz and Krueger (1999), we define the *age-constant unemployment rate*[6] as the weighted average of the age-specific unemployment rates, where the weights are now the shares of the labour force of each group in a certain base year t_0:

$$U^{AC}_{t1,t0} = \sum_i \omega_{t0}(i) \times u_{t1}(i) \qquad [4.11]$$

where $\omega_{t0}(i)$ is the benchmark share of group (i) in the labour force at time t_0. It captures what would have happened to aggregate unemployment, given the observed changes in group unemployment rates, if there had been no age-related demographic change (i.e. if the labour force shares had remained at their levels in t_0).

[6] In Shimer's terminology this is the genuine unemployment rate.

Katz and Krueger suggest the use of the *difference* between the aggregate unemployment rate and this age-constant unemployment rate at time *t*—or the age adjustment to the unemployment rate (AAU)—as a measure of the impact of demographic change, which will take the form:

$$U_{t1} - U^{AC}_{t1,t0} = \sum_i \left(\omega_{t1}(i) - \omega_{t0}(i) \right) \times u_{t1}(i) \qquad [4.12]$$

This residual captures the part of the evolution of aggregate unemployment that cannot be explained by shifts in the age-specific unemployment rates alone, and which must therefore be caused by shifts in the composition of the labour force. However, given the shifts in participation across different age groups in the population, it may well be the case that some part of the change in the aggregate rate which appears to be explained by changes in the age-specific rates is actually a result of shifts in the composition of the labour force; in other words, the age specific rates are not exogenous to the composition of the labour force. We shall go on to discuss this issue in greater depth in Section 6.

The other extreme is to measure what would have happened to the unemployment rate had all the age-specific unemployment rates remained constant (i.e. abstracting from all the economic factors determining unemployment), and instead only the composition of the labour force had changed. The unemployment rate as it would have been if driven purely by demographic change, or as Katz and Krueger term it the *age-driven unemployment rate*[7], is thus:

$$U^{AD}_{t1,t0} = \sum_i \omega_{t1}(i) \times u_{t0}(i) \qquad [4.13]$$

where: $u_{t0}(i)$ is the benchmark unemployment rate of group (i) at time t_0. The numerical level of this rate is (by construction) dependent on the levels of unemployment in the

base year, and so it does not in any sense measure the unemployment 'caused' by demographic factors. But we can interpret the difference between the age-driven rate at time t_1 and unemployment in the base year t_0 as the implied change in the aggregate unemployment rate due to demographic pressures—which we call the
age-driven change in the unemployment rate (ADCU):

$$U^{AD}_{t1,t0} - U_{t0} = \sum_i \left(\omega_{t1}(i) - \omega_{t0}(i) \right) \times u_{t0}(i) \qquad [4.14]$$

Shimer also suggests using a chain-weighted measure (CWM) to identify the change in unemployment attributable to demographics (Shimer (1998)), defined as:

$$\Delta_{t1,t0} = \sum_{t=t0}^{t1-1} \left\{ \sum_i \left(\omega_{t+1}(i) - \omega_t(i) \right) \times \left(\frac{u_{t+1}(i) + u_t(i)}{2} \right) \right\} \qquad [4.15]$$

Since by definition, $\Delta_{t0,t0} = 0$, we can decompose our chain-weighted measure as follows:

$$\begin{aligned} \Delta_{t1,t0} &= \Delta_{t1,t0} - \Delta_{t0,t0} \\ &= \Delta_{t1,t0} - \Delta_{t1-1,t0} + \Delta_{t1-1,t0} - \Delta_{t1-2,t0} + \text{etc.} \\ &= \left(\Delta_{t1,t0} - \Delta_{t1-1,t0} \right) + .. + \left(\Delta_{t0+1,t0} - \Delta_{t0,t0} \right) \qquad [4.16] \end{aligned}$$

So if each individual term—the change in his chain-weighted measure between years t and $t+1$—is thought of as capturing the demographic change between these two years, then the overall measure describes the cumulative effect of demographic change over the period, which is not as sensitive to the choice of base year, because of the implicit

[7] In Shimer's terminology this is the demographic unemployment rate.

averaging involved in the calculation of the chain-weighted measure. However, this measure of demographic change is itself still sensitive to economic factors—if youth activity rates vary more than those of adults over the cycle, for example, any demographic shift towards the young will be exaggerated during a boom as more youths are drawn into the labour force (Shimer (1998)).

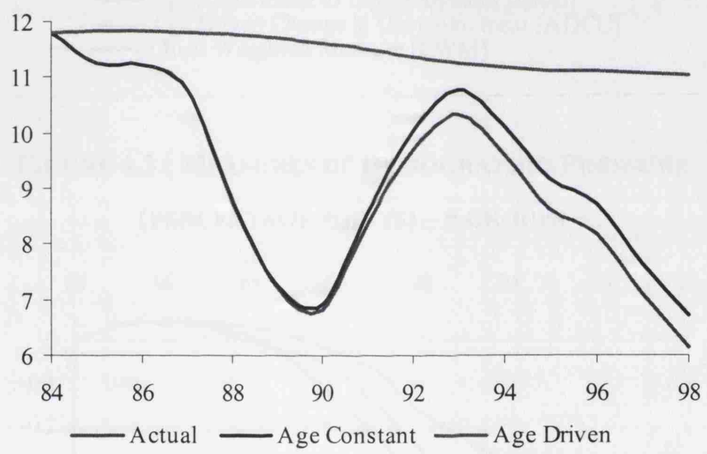
4.3 EMPIRICAL EVIDENCE

Consistent data on unemployment rates by age group are available only from 1984, so we cannot examine the direct effect of the entry of the baby boomers into the labour market (the majority of those born at the peak of the baby boom, in 1964, would have entered the labour market some four years before the data start). We can, however, explore the impact of the large fall in the birth rate between 1964 and 1977. Using data from the Labour Force Survey, we initially divide the labour force into two groups—youths (aged less than 25) and adults—but for comparison we also repeat the calculations for a finer disaggregation of the labour force into five different age groups. An examination of how sensitive our results are to changing the base year of our calculations is deferred to Section 4.4.

Using a simple two-part decomposition into youths and adults, the age-constant unemployment rate (shown in Figure 4.1) tracks the actual unemployment rate quite closely for most of the period, and the two series are virtually indistinguishable up until 1989. However, the shift in the youth composition of the labour force is not captured by the age-constant rate and for this reason the actual unemployment rate declines further than the age-constant rate. The path of the age-driven unemployment rate captures this shift away from the young in the labour force and therefore also falls over the period. However, because it is benchmarked on 1984 unemployment rates, it is unaffected by the large fall in all the age-specific unemployment rates as the economy recovered from the severe slump in the early 1980s.

The relevant factor for present purposes is the changes in these series. In quantitative terms, the age-driven unemployment rate fell by almost 77 basis points over the period, while the aggregate unemployment rate declined by 566 basis points; so demographic change explains approximately 14% of the fall in the unemployment rate on this measure. On the other hand, the age-constant unemployment rate fell by some 511 basis points, and so explains 90% of the fall in the aggregate rate; so the age adjustment to the unemployment rate implies that demographic change explains about 10% of the fall in the aggregate rate.

FIGURE 4.1 : TIME PATH OF ACTUAL, AGE DRIVEN AND AGE CONSTANT UNEMPLOYMENT RATES (%) – 2GROUPS.



The chain-weighted measure (not shown in Figure 4.1) fell by about 50 basis points, and so accounts for about 9% of the fall in aggregate unemployment over the period. It would appear, then, that demographic change in the labour force explains about 50 to 75 basis points, or 9% to 14%, of the fall in the aggregate unemployment rate between 1984 and 1998 (see Figure 4.2).

FIGURE 4.2 : MEASURES OF DEMOGRAPHIC PRESSURE

(PERCENTAGE POINTS) – 2 GROUPS

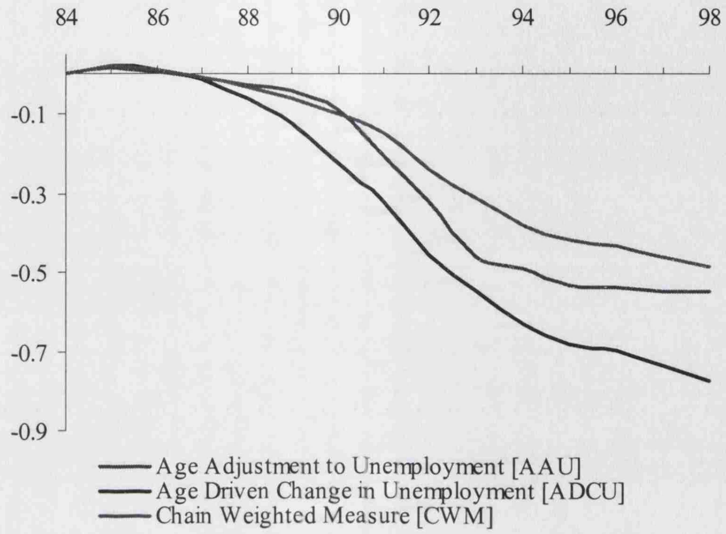
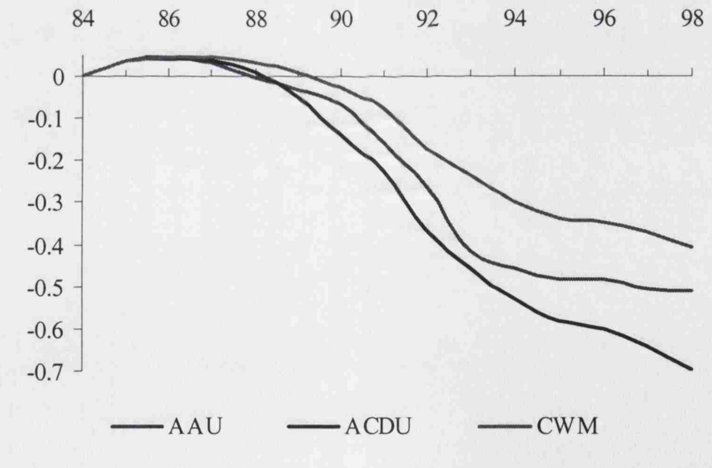


FIGURE 4.3 : MEASURES OF DEMOGRAPHIC PRESSURE

(PERCENTAGE POINTS) – 5 GROUPS



These results may of course be sensitive to the way in which we have divided the labour force. So we repeat the analysis, sub-dividing the labour force further into five separate age groups: 16–17, 18–24, 25–34, 35–49, and 50 and over. The pattern that emerges is qualitatively very similar to that obtained by dividing the labour force into just youths and adults. In quantitative terms, the age-driven unemployment rate now falls by some 69 basis points between 1984 and 1998, explaining almost an eighth of the fall in aggregate unemployment over that period. The age-constant unemployment rate falls by some 514 basis points, explaining 91% of the fall in the aggregate unemployment rate (therefore the age adjustment to unemployment explains the remaining 9% of the fall in the aggregate rate). Finally, the chain-weighted measure falls by about 40 basis points, explaining about 7% of the decline in the aggregate rate. So on this disaggregated basis, the percentage of the fall in aggregate unemployment that can be explained by demographic change lies between 7% and 12%, or about 40 to 70 basis points (see Figure 4.3). The role of demographic change is in fact marginally reduced compared with the simple youths/adults decomposition.

4.4 CHANGING THE BASE YEAR

These results take unemployment rates and labour force composition in 1984 as the base for calculating the age-constant and age-driven unemployment rates over the period. But this is arbitrary and we can test whether the results are qualitatively or quantitatively sensitive to this choice, repeating the analysis using each year in the sample in turn as the anchor. Of course, our calculations of the age-constant and age-driven unemployment rates are now in part retrospective, and we must amend our definitions of the age adjustment to the unemployment rate and the age-driven change in the unemployment rate accordingly. The age adjustment to unemployment, given age-constant unemployment calculated using base year (x), is now defined as the difference between the change in the unemployment rate and the change in the age-constant unemployment rate over the period:

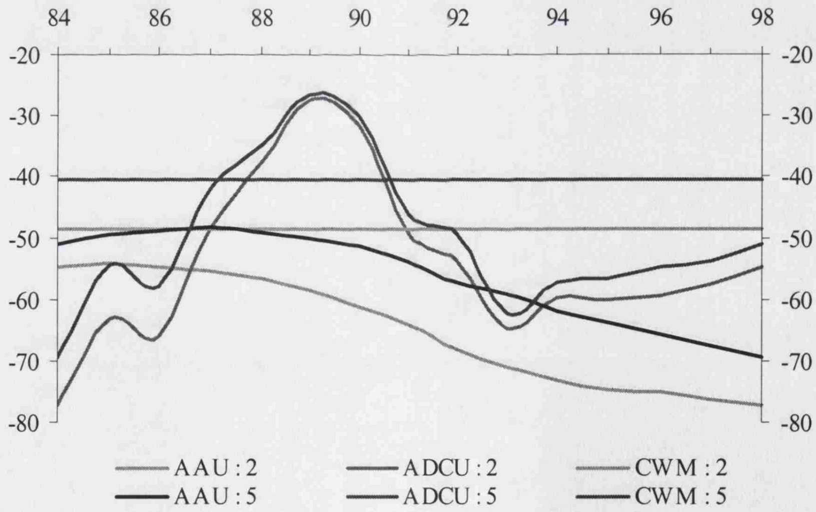
$$\left(U_{98} - U_{84}\right) - \sum_{i} \omega_x(i)\left(u_{98}(i) - u_{84}(i)\right) \qquad [4.17]$$

The age-driven change in the unemployment rate is now defined as the difference between what the unemployment rate would have been in 1998 and 1984, had group-specific unemployment rates remained at their values in the base year (x):

$$\sum_{i} u_x(i)\left(\omega_{98}(i) - \omega_{84}(i)\right) \qquad [4.18]$$

The chain-weighted measure of demographic unemployment is of course unaffected, as it is based on the actual composition of the labour force and group unemployment rates in each year (see Figures 4.4 and 4.5). It turns out that the choice of base year has a significant effect on our other measures of the impact of demographics on the unemployment rate – in the figure below we graph the estimated impact of demographic change for each of our three measures using each year of the period as a base year (see Figures 4.4 and 4.5). The mean estimates of the change in actual unemployment explained by each of our measures across all available base years (1984 to 1998) are shown in Table 4.A.

FIGURE 4.4 : VARIATION IN MEASURES OF THE IMPACT OF DEMOGRAPHIC CHANGE BY BASE YEAR (BASIS POINTS)



The fact that our results are sensitive to the base year is no surprise, as each base represents a different set of values for the composition of the labour force and group unemployment rates on which our calculations are based. The variation in our estimates of the impact of demographic change by base year can therefore be explained in terms of the variation across years in the dispersion of the age specific unemployment rates and the composition of the labour force.

While the actual composition of the labour force in each period used to calculate the age-driven unemployment rate is common to all base years, the group-specific unemployment rates that they modify are not. If all the group-specific unemployment rates were higher in 1984 than 1998, then the age-driven unemployment rate will be higher across the period if we use 1984 as a base year rather than 1998. The age-driven *change* in the unemployment rate over the period will be unaffected by such differences, but will still be sensitive to differences in the *dispersion* of the unemployment rates between base years: the greater the difference between the unemployment rates, the more that changes in the composition of the labour force will matter. The variation in the change in the age-driven unemployment rate [ADCU] by base year can (see the pink and red lines in Figures 4.4 and 4.5) thus be explained by base year variations in the age-related unemployment rate differentials (see Figure 4.6).

FIGURE 4.5 : VARIATION IN MEASURES OF THE IMPACT OF DEMOGRAPHIC CHANGE BY BASE YEAR (PERCENTAGE OF CHANGE IN UNEMPLOYMENT EXPLAINED)

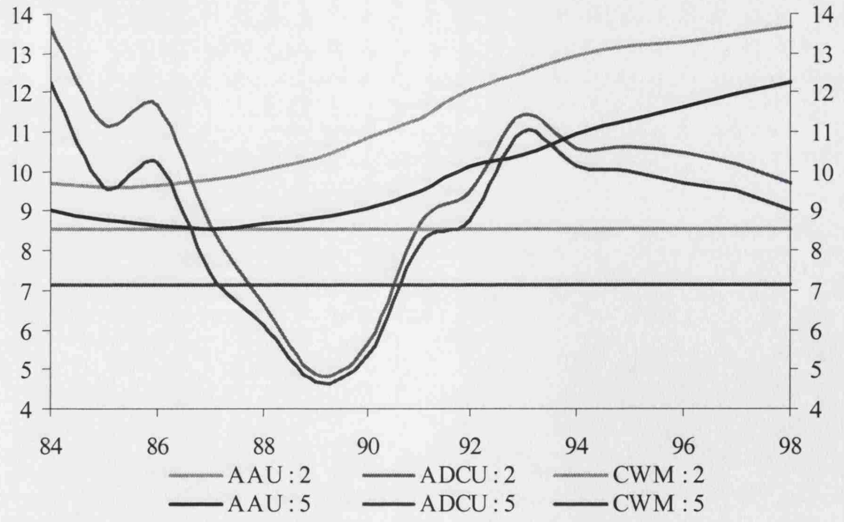
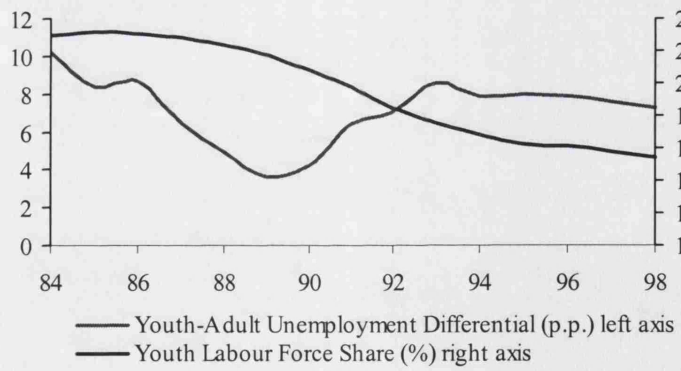


TABLE 4.1 : SUMMARY OF ESTIMATES OF THE IMPACT OF DEMOGRAPHIC CHANGE ON THE UNEMPLOYMENT RATE

	Basis points		Percentage explained	
Index of demographic pressure :	2 groups	5 groups	2 groups	5 groups
Average age adjustment to unemployment	-65	-56.5	11.5	10
Average age-driven change in unemployment	-54.1	-49.8	9.6	8.8
Average chain-weighted measure	-48.5	-40.5	8.6	7.2

The age adjustment to the unemployment rate, on the other hand, holds the labour force composition constant at its base year level. Between 1984 and 1998, the youth unemployment rate fell further than the adult rate in absolute terms (see Figure 2.4) and the youth share of the labour force was almost monotone decreasing over the period, only increasing (marginally) between 1984 and 1985. So the later our base year, the lower the weight we will place on the group unemployment rate which changes the most, and the smaller our estimate of the change in the age-constant unemployment rate will be.

FIGURE 4.6 : YOUTH SHARE OF THE LABOUR FORCE AND THE YOUTH-ADULT UNEMPLOYMENT DIFFERENTIAL



As a result, demographic change as measured by the age adjustment to the unemployment rate will explain more of the change in unemployment, the later our choice of base year. The increase in the age adjustment to the unemployment rate [AAU] over this period (see the blue lines in Figures 4.4 and 4.5) can therefore be explained by the near-monotone fall in the youth share of the labour force (see Figure 4.6).

5. 'GENERATIONAL CROWDING': COHORT SIZE AND UNEMPLOYMENT RATE INTERACTIONS

The above analysis implicitly assumes that age-specific unemployment rates are unaffected by the size of each age-group as a proportion of the labour force. Any interactions between the size of a group and its unemployment rate will not be attributed to demographic change on the measures we have used, since they capture only the direct compositional effect. If, for example, the increase in the youth unemployment rate in the late 1970s and early 1980s (as the baby boomers entered the labour force) was partly caused by the rapid expansion of that cohort through so-called 'generational crowding' effects, then the reverse effect might be observed as the proportion of young people in the labour force declined. Both the youth share of the labour force and the youth unemployment rate would have declined as a result of demographic change. Shimer (1998) finds that these generational crowding effects have a significant role in explaining changes in the aggregate unemployment rate. By themselves, the changes in the age-specific unemployment rates caused by shifts in the composition of the labour force implied about a 1 percentage point increase in the US aggregate unemployment rate between 1954 and 1980 (almost exactly a half of the total impact that he estimates demographic change had over the period). However, other factors might also lead to a relative improvement in youth unemployment rates, coincidental with the fall in the youth share of the labour force. For example, there could be a change in firms' preferences towards youth labour, or a shift in demand by consumers towards companies that disproportionately employ youths (Freeman and Bloom (1986)).

Shimer offers a useful illustrative measure of these generational crowding effects, which he defines as follows:

$$\rho = \frac{\left(\tilde{\omega}_{t1} - \tilde{\omega}_{t0}\right) \cdot \left(\tilde{u}_{t1} - \tilde{u}_{t0}\right)}{\left|\tilde{\omega}_{t1} - \tilde{\omega}_{t0}\right| \cdot \left|\tilde{u}_{t1} - \tilde{u}_{t0}\right|} \in [-1,1] \qquad [5.1]$$

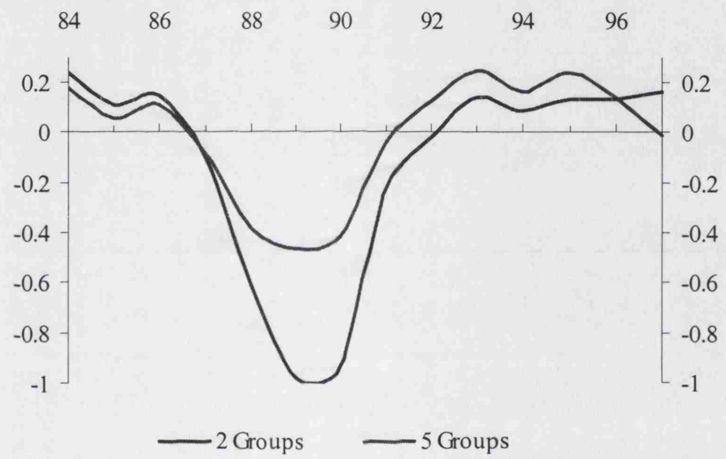
where $\tilde{\omega}_{ti}, \tilde{u}_{ti}$ are the vectors of labour market shares and unemployment rates respectively in each time period. The numerator of Shimer's measure is the scalar product of the change in the vector of labour market shares, and the change in the vector of the unemployment rates—which effectively captures the degree of correlation between them. This correlation coefficient is then normalised by the absolute size of the change in the two vectors captured by the denominator. If this measure – 'analogous to a correlation' – is positive then in a period of demographic change, those groups whose share of the labour force changes will experience relative changes in their unemployment rates in the same direction, which would support the notion of generational crowding. Conversely, if the measure is negative, then those groups whose share of the labour force increases would enjoy a relative fall in their unemployment rates.

Taking the whole sample, if we divide the labour force into youths and adults, ρ takes the value 0.24; if we divide it into five separate groups, the measure falls to 0.17. The underlying message remains the same: there appears to be clear evidence of generational crowding of the kind that, when the youth share of the labour force declined, the youth unemployment rate also fell relative to other groups in the labour force.

But this result is not robust. Choosing any year between 1987 and 1991 as the starting point, the evidence is of *perverse* generational crowding effects (i.e. a negative correlation coefficient), with youths experiencing relatively higher unemployment rates as their share of the labour force fell (see Figure 5.1).

Given that the youth share of the labour force was steadily decreasing across the entire period, the sign of the correlation coefficient will depend crucially on the direction of change of the youth/adult unemployment differential. We know that this gap increased after 1989, despite the falling youth share of the labour force, which is why the Shimer statistic suggests perverse generational crowding effects. A neutral assumption, on the available evidence, might be that the UK group-specific unemployment rates have been independent of the composition of the labour force, and that the statistics computed earlier are indeed appropriate measures of the effect of demographic change on unemployment[8].

FIGURE 5.1 : VARIATION IN SHIMER'S CORRELATION COEFFICIENT BY BASE YEAR



Of course, if this assumption is incorrect, then we will only capture the direct effect of demographic change on the aggregate unemployment rate; the indirect effect, through changes in the group specific unemployment rates caused by changes in the composition of the labour force, will be lost. To illustrate the sensitivity of our results to this assumption of no generational crowding effects we carry out the following back of the envelope calculation. Using the results of Korenman and Neumark (2000), who find that across a sample of 15 OECD countries over the period 1970-1994, the elasticity of youth unemployment rates (relative to adults) with respect to relative cohort size (defined as the ratio of the youth to adult population) is of the order of 0.5, we can estimate the impact of

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[8] It could be the case that generational crowding effects depend on the cyclical position of the economy. The correlation coefficient appears to be positive in the mid 1980s and early 1990s when the economy was in recession, and negative in the late 1980s when the economy entered recovery. We do not investigate this hypothesis in this paper.

changes in the age specific unemployment rates caused by demographic change $\Delta u_i(\omega)$ on the unemployment rate. The following decomposition illustrates our approach:

$$\Delta u = \sum_i \Delta \omega_i \times u_{i,84} + \sum_i \Delta u_i(\omega) \times \omega_{i,98} + \sum_i [\Delta u_i - \Delta u_i(\omega)] \times \omega_{i,98} \qquad [5.2]$$

where the first term captures the direct effect of demographic change on the aggregate unemployment rate, the second the indirect effect due to generational crowding, and the final term is the residual. Now in order for this decomposition to be operational we need to know the precise impact of demographic change on the age specific unemployment rates. Korenman and Neumark find that a 2 % increase in the relative youth cohort size (the population aged 16-24 divided by the population aged 25-54) leads to an increase in the relative youth unemployment rate (the youth rate divided by the adult rate) of 1 %. Therefore, if we ignore any other factors which might have affected the youth adult unemployment differential over the period, we can calculate the relative youth unemployment rate in 1998 as follows:

$$\left(\left(\frac{u_{y,98}(\omega) / u_{a,98}(\omega)}{u_{y,84} / u_{a,84}} \right) - 1 \right) = \frac{1}{2} \times \left(\left(\frac{P_{y,98} / P_{a,98}}{P_{y,84} / P_{a,84}} \right) - 1 \right) \qquad [5.3]$$

where P_{it} is the number of people in the population in age group (i) in year (t). If we assume that generational crowding effects work solely through the youth unemployment rate, i.e. : $u_{a,98}(\omega) = u_{a,98}$, then we can estimate what the youth unemployment rate would have been under these circumstances :

$$u_{y,98}(\omega) = u_{a,98} \times \frac{u_{y,84}}{u_{a,84}} \times \frac{1}{2} \times \left(\left(\frac{P_{y,98} / P_{a,98}}{P_{y,84} / P_{a,84}} \right) + 1 \right) \qquad [5.4]$$

On the basis of these calculations we estimate that, *ceteris paribus*, given the adult unemployment rate in 1998, the shift in the composition of the labour force should have reduced the youth unemployment rate to approximately 8.6%; whereas the actual youth rate 12.3% in 1998. The youth unemployment rate in 1998 is thus several percentage points higher than we would have otherwise expected given the adult unemployment rate at that time, and the shift in the composition of the population away from youths that occurred.

If we assume that this deterioration in the youth labour market would have been even more extreme in the absence of demographic change (i.e. the generational crowding effects will have partially offset the increase in the youth unemployment rate) then we will have underestimated the impact of demographic change on the aggregate rate. Using our standard decomposition above, we find that the indirect effect of demographic change through the age specific unemployment rates is over twice as large as the direct effect we have concentrated on up to now. On the basis of Korenman and Neumark's estimate of the elasticity of the relative youth unemployment rate, we find that demographic change can explain almost a half of the total fall in the aggregate unemployment rate.

TABLE 5.1 : SUMMARY OF ESTIMATES OF THE IMPACT OF DEMOGRAPHIC CHANGE ON THE UNEMPLOYMENT RATE, CONTROLLING FOR GENERATIONAL CROWDING

	Basis points	Percentage explained
Direct Effect of Demographic Change	-77	13.66
Indirect Effect of Demographic Change	-170	29.98
Age Driven Change in Unemployment	-247	43.64
Residual	-319	56.36

However, we need to be cautious in interpreting these results. As Korenman and Neumark note, when the baby bust cohort entered the labour market, the relative fall in the youth unemployment rate implied by their results failed to materialise – in fact, their position continued to deteriorate, rather than improve. Their explanation for this apparently contradictory result is that changes in the demand for youths caused by other factors (downturns in the business cycle, technological change, international trade) swamped the beneficial effects of the fall in the relative supply of youths in the labour market (Korenman and Neumark (2000) p.2). If however, the deterioration in the youth labour market was in some way caused by the decline in the youth share of the labour force then our estimates above will seriously exaggerate the role of demographic change in explaining the fall in the aggregate unemployment rate.

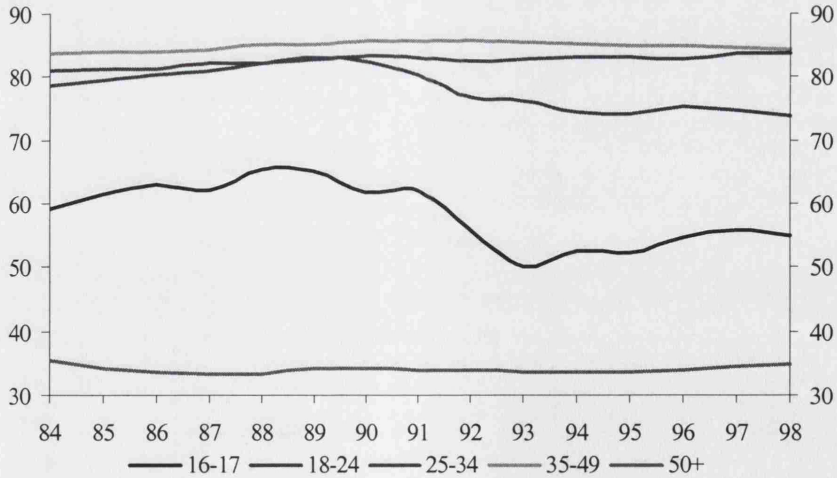
One plausible explanation for just such a link lies in the fact that over time the average level of human capital of youths in the labour force may be falling, since year-on-year an increasing fraction of each cohort stays on in further and higher education. Shimer (2000) offers an another alternative explanation, based on the efficiency of job search. He argues that across the states and regions of the United States an increase in the youth share of the labour market causes the youth unemployment rate *to fall* (with an elasticity of about – 1.5) and the adult unemployment to fall even further (with an elasticity in excess of -2). He then goes on to present a theoretical model which explains these results, incorporating on-the-job search into the standard Mortensen-Pissarides search model. The presence of a trading externality – that it is easier for agents to match, when few are currently in good matches – ensures that the efficiency of the matching process increases with the number of agents actively searching for work. Young workers are assumed to be more mobile (more likely to partake of on-the-job search) than adults, and therefore there is a greater incentive for firms to post vacancies for a younger workforce, raising job creation – which will reduce the unemployment rates of both youths and adults. When Shimer turns to apply his methodology to the Korenman and Neumark dataset he finds: "no significant correlation between unemployment rates and the youth share of the population, which supports neither the cohort crowding hypothesis nor mine (Shimer (2000) p.4)"

It appears then that if we are willing to accept that through generational crowding effects a decline in the youth share of the labour force will lead to a fall in the relative youth unemployment rate, then demographic change can explain a far greater proportion of the change in the aggregate unemployment rate over the period. However, there remains little convincing evidence that a decline in the youth share of the labour force does in fact deliver significant reductions in the relative youth unemployment rate. We therefore retain those estimates based on the neutral assumption of no generational crowding effects as our central, if also conservative, estimates of the effect of demographic change.

6. CONTROLLING FOR CHANGES IN ACTIVITY BY AGE GROUP

In the previous section we estimated how much of the change in the aggregate unemployment rate can be accounted for by changes in the composition of the labour force. However, as we discussed in Section 2.1, changes in the composition of the labour force are not driven exclusively by demographic forces, but also by changes in the proportion of the population actively engaged in the labour force, and so our results should not be interpreted as capturing only the impact of the change in the composition of the population on the unemployment rate, which is the motivation of this chapter.

FIGURE 6.1 : ACTIVITY RATES BY AGE (%)



As Figure 6.1 illustrates, the most striking change in the rate of activity in the population over the period occurred among the young—between 1984 and 1998 the activity rate of 16 to 24 year olds fell by more than 6½ percentage points—which was almost certainly due to the growth in participation in post-compulsory education. However, changes in activity have not been confined to youths—in 1998, approximately 5% more of the 25 to 34 year olds in the population were either employed or actively searching for work than in 1984. Clearly, changes of this magnitude have the capacity to affect the size and composition of the labour force, and so they also have the potential to affect the unemployment rate. If we wish to measure accurately the proportion of the total change in the unemployment rate that can be explained purely by demographic change in the population then we need to control for these changes in labour force participation by age group.

In order to isolate the effect of demographic change on the aggregate labour market we pursue two separate modifications of the shift-share methodology outlined in the previous section. The first essentially holds activity rates constant and calculates the hypothetical impact on the unemployment rate of changes in the composition of the labour force consistent with changes in the composition of the underlying population, given the observed behaviour of the group-specific unemployment rates. The second focuses instead on the impact of changes in the composition of the working-age population on the fraction of the *population* that is unemployed.

6.1 THE IMPACT OF CHANGES IN THE POPULATION SHARES ON THE UNEMPLOYMENT RATE

We have argued that the shift-share decomposition employed in the previous section will not measure precisely the impact of demographic change on the unemployment rate, because our estimates will also incorporate the effect of changes in the group-specific activity rates on the composition of the labour force. Given information on the proportion of each age group in the population that is economically active in a given year, $\eta_t(i)$, and the aggregate activity rate in that year, $\overline{\eta}_t$, it is straightforward to calculate what the composition of the labour force would have been in that year given the changes in the composition of the population, had activity rates remained at their levels in year t_0

throughout the period. If for each year t we define $\bar{\eta}_t^{t0}$ as the (hypothetical) aggregate activity rate, given the actual composition of the population in that year, but assuming that the age-specific activity rates remained at their levels in year (t_0), then the labour force share of group (i) of whom there were $P_t(i)$ individuals out of a total population $\bar{P}_t$ in year t, would have been:

$$\omega_t^{t0}(i) = \frac{\eta_{t0}(i) \times P_t(i)}{\bar{\eta}_t^{t0} \times \bar{P}_t} = \frac{\eta_{t0}(i)}{\eta_t(i)} \times \frac{\bar{\eta}_t}{\bar{\eta}_t^{t0}} \times \frac{\eta_t(i) \times P_t(i)}{\bar{\eta}_t \times \bar{P}_t}$$

$$= \frac{\eta_{t0}(i)}{\eta_t(i)} \times \frac{\bar{\eta}_t}{\bar{\eta}_t^{t0}} \times \omega_t(i) \qquad [6.1]$$

where $\omega_t(i)$ is group (i)'s actual share of the labour force in year t. However, our modification is not trivial. In Section 3.3 we discussed the possibility that the unemployment rate of a specific group may depend upon the relative size of that group in the labour force—generational crowding effects. So whenever the hypothetical labour force shares diverge from those we observe, there is the possibility that the group unemployment rates will also differ from those we observe, which will affect the accuracy of our shift-share decomposition. However, given the lack of any robust evidence to support the existence of significant generational crowding effects (see Section 4.5), we assume that the group-specific unemployment rates are entirely independent of the composition of the labour force, and so use the observed pattern of unemployment for our alternative shift-share decomposition. There is one further complication with this approach. Had the composition of the labour force and the group unemployment rates followed the hypothetical path we have assumed, then the time path of aggregate unemployment would also have differed from what we observe. So, when calculating the importance of demographic change in explaining changes in the aggregate unemployment rate, we need to modify our estimate of the change in the unemployment rate accordingly:

$$\Delta U^{t0} = \sum_{i}\left(\omega_{98}^{t0}(i) \times u_{98}(i) - \omega_{84}^{t0}(i) \times u_{84}(i)\right) \qquad [6.2]$$

We can repeat this approach for each year in the sample, in each case holding activity rates constant and using the observed composition of the labour force and pattern of unemployment rates in that year to calculate our standard estimates of the impact of demographic change on the unemployment rate. Our results are shown in Table 6.1.

TABLE 6.1 : SUMMARY[9] OF THE IMPACT OF DEMOGRAPHIC CHANGE ON THE UNEMPLOYMENT RATE, CONTROLLING FOR CHANGES IN ACTIVITY RATES BY AGE GROUP

	Basis points		Percentage explained	
Index of demographic pressure:	2 groups	5 groups	2 groups	5 groups
Average age adjustment to unemployment	-51.9	-46.7	9.4	8.5
Average age-driven change in unemployment	-42.8	-41.2	7.8	7.5
Average chain-weighted measure	-39.8	-36.9	7.2	6.7

It appears that once we control for changes in the activity rates of each group over the period, demographic change caused a smaller fall in the aggregate unemployment rate than that estimated in the previous section. This result is not that surprising since we are now controlling for the shift in the composition of the labour force towards low unemployment groups that followed increased participation in post-compulsory

[9] A comprehensive set of our results can be found in Appendix Tables A.6.1.1 and A.6.1.2.

education. Similarly, falling inactivity among those aged between 25 and 34, *ceteris paribus*, increased the size of the labour force, which further exacerbated the observed fall in the youth share of the labour force, and so further exaggerated previous estimates of the impact of demographic change on the unemployment rate. However, shifts in the composition of the labour force driven purely by demographic change in the population still explain about a 45 basis point fall in the unemployment rate over the period.

6.2 THE IMPACT OF DEMOGRAPHIC CHANGE ON THE FRACTION OF THE POPULATION THAT IS UNEMPLOYED

An alternative estimate of the impact of demographic change on the proportion of individuals of working age who are unemployed can be obtained by repeating our shift-share analysis using working-age population shares and the ratio of each age group who are unemployed. The advantage of this approach is of course that we can abstract from all changes in labour force participation by focusing on changes in the composition of the working-age population—which is affected solely by demographic forces. However, the drawback is that we will not be estimating the impact of demographic change on the unemployment rate itself.

We can repeat the analysis, as before using each year in turn as a base for our calculations, and the results from this alternative shift-share decomposition are given in Table 6.2. Overall, our results indicate the smallest role for demographic change in explaining the absolute and proportional fall in the fraction of individuals who are unemployed. However, this is largely due to the fact that the gap between the proportion of the youth and adult populations who are unemployed is significantly smaller than the differential between the youth and adult unemployment rates[10]. So shifts in the composition of the working-age population can be expected to have a more marginal role in explaining changes in the fraction of the whole population that is unemployed.

We have outlined two alternative approaches here to that presented in the previous section, each of which seeks to isolate the effect of demographic change on the

[9] See Appendix Table A.5.3.

unemployment rate. Unsurprisingly, both show that once we control for changes in labour force participation rates by age, shifts in the composition of the labour force explain less of the change in the aggregate unemployment rate over the period. However, it still appears that demographic change in the population was the predominant cause of the change in the composition of the labour force, and hence of the estimated change in the unemployment rate that it produced.

TABLE 6.2. : SUMMARY[11] OF THE IMPACT OF DEMOGRAPHIC CHANGE ON THE FRACTION OF THE WORKING-AGE POPULATION WHO ARE UNEMPLOYED

	Basis points		Percentage explained	
Index of demographic pressure:	2 groups	5 groups	2 groups	5 groups
Average age adjustment to unemployment	-37.6	-32.2	8.5	7.4
Average age-driven change in unemployment	-31	-28.9	7	6.6
Average chain-weighted measure	-27.8	-24.6	6.3	5.6

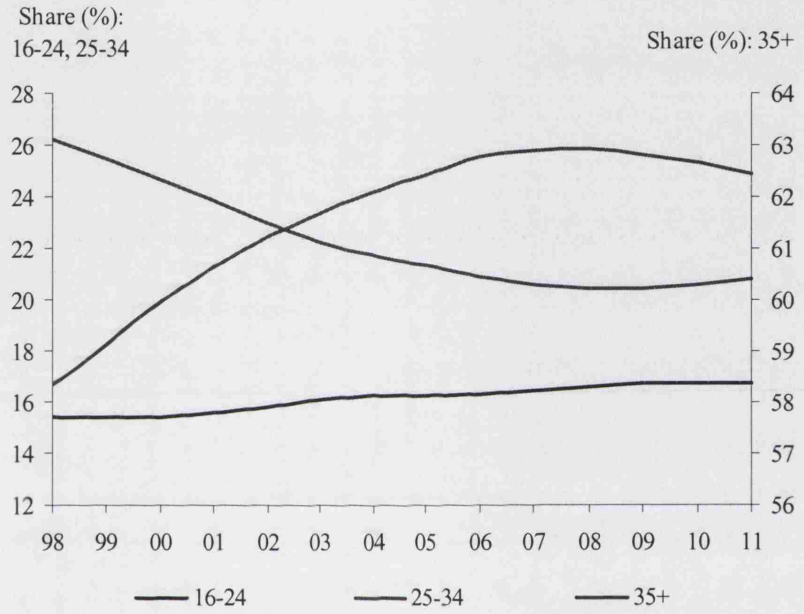
7. THE EFFECT OF DEMOGRAPHY ON FUTURE UNEMPLOYMENT

The focus of this chapter has so far been retrospective, investigating how much of the change in the aggregate unemployment rate can be explained by demographic pressures. However, shifts in the composition of the population will doubtless continue, and we now attempt to predict the likely implications of demographic change on the unemployment rate in the near future. Given reasonable assumptions on the pattern of fertility and mortality rates, and the size and direction of cross-border migration, we can project the resident population into the future. In order to estimate the composition and size of the labour force, we also need to forecast the percentage of each of the separate groups in the

[11] A comprehensive set of our results can be found in Appendix Tables A.6.2.1 and A.6.2.2.

labour force that will be either employed or actively searching for work[12]. The following analysis is based on projections of the composition of the labour force given in the June 1998 edition of *Labour Market Trends.*

FIGURE 7.1 : PROJECTION OF THE COMPOSITION OF THE LABOUR FORCE : 1998-2011



We can identify three broad trends in the projections of the labour force illustrated in Figure 7.1 above: first, that the youth share of the labour force begins to recover from the baby bust and slightly increases over the period; second, that the number of people aged between 25 and 34 declines quite sharply (quite unsurprisingly—this is the generation of youngsters in the baby bust, ten years into the future when they reach maturity); and third, that the relative share of the older section of the labour force—aged 35 years and over—increases (as the bulge in fertility rates in the early 1960s passes through the age distribution).

[11] These projections of the group-specific activity rates typically rely on four separate sets of explanatory variables: the level or change in the level of the unemployment rate, the number of dependent children aged under 5 per woman, lagged activity rates, and time trends to capture other structural factors (see Armitage and Scott (1998), page 291).

Since youths have higher unemployment rates than adults, the slight shift towards the young is likely marginally to drive up the unemployment rate (an effect which might be amplified by any generational crowding effects), as will a decrease in the numbers of 25–34 year olds with lower unemployment rates than younger workers. However those above 35 years of age have unemployment rates lower still than those in early adulthood (in 1998 the unemployment rate for those aged 25–34 was 6.3%, while for those 35 years and older it was 4.4%), and therefore an increase in the proportion of those aged 35 and over in the labour force should drive the unemployment rate down.

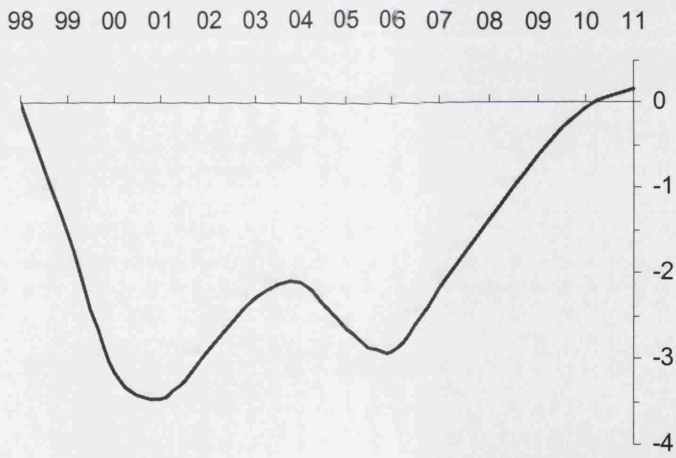
Given these projections of the composition of the labour force, we can make a tentative forecast of the implied change in the aggregate unemployment rate due to demographic pressures. Taking 1998 as the base year, we divide the labour force into the three broad groups described above and calculate the age-driven change in the unemployment rate based on the observed unemployment rates of each of these groups in our base year (see equation [4.14]):

$$\sum_i \left(\omega_t(i) - \omega_{1998}(i)\right) \times u_{1998}(i) \qquad [7.1]$$

Given the projected increases in the labour force shares of both the high and low-unemployment groups, the impact of demographic change is relatively weak throughout the period (see Figure 7.2 below) — at most, demographic pressures will be responsible for a fall of about 3½ basis points in the aggregate unemployment rate. However, the potential for these benign demographic forces to reduce the unemployment rate has already been almost exhausted. The age-driven unemployment rate is projected to fall until 2001, and thereafter, following a short period of turbulence, to be at its level in 1998. Of course, in the interim, any generational crowding effects from changes in the composition of the labour force might amplify these results. But, on the basis of these results, it is difficult to draw any conclusion other than that, however important demographic change might have been in the evolution of the unemployment rate in the past 20 years, there is little evidence that it will have much effect for the foreseeable future.

However, as we have emphasised previously, shifts in the composition of the labour force can arise not only through demographic change in the population, but also through changes in the proportion of each age group that is economically active[13]. Nevertheless, controlling for any projected changes in the age-specific activity rates over the period has a negligible effect on our estimates of the reduction in the unemployment rate implied by future shifts in the composition of labour force. Finally, when we turn to the impact of demographic change on the proportion of the working-age population that is unemployed we find results that are quantitatively similar to our original projections.

FIGURE 7.2 : PROJECTED AGE DRIVEN CHANGE IN THE UNEMPLOYMENT RATE (BASIS POINTS)



Therefore, it appears that irrespective of the particular method used, demographic change in the population is likely to have a negligible effect on the aggregate unemployment rate over the next decade.

[12] For example, it is estimated that irrespective of any increase in the number of youths in the population, approximately 150,000 more youths will be economically active in 2011 than in 1998.

8. CONCLUSIONS

The proportion of youths in the UK labour force has almost halved over the past 15 years. Since youths have a higher unemployment rate than adults (although this differential varies across the cycle), and the aggregate unemployment rate is simply the weighted average of the age-specific unemployment rates, a shift of this kind in the composition of the labour force should have been reflected in a fall in the aggregate unemployment rate.

Quantitatively, demographic pressures do indeed appear to explain part of the change in actual unemployment. Although we have shown that this is sensitive to the precise measure we use and particularly the assumption made about the base year, our best estimate is that approximately 55 basis points[14] of the fall in the unemployment rate between 1984 and 1998 (or about 10% of the total change) can be explained by changes in the composition of the labour force. We also find no robust evidence that youths have become relatively more likely to become unemployed, through generational crowding effects, as their share of the labour force declined. However, if the decline in the youth share did reduce youth unemployment rates below the level they would otherwise have been, then our previous estimates seriously under-estimate the true impact of demographic change on the unemployment rate. Taking a reasonable estimate of the elasticity of the relative youth unemployment rate to their relative share of the population from the literature, we find that changes in the age composition of the labour force alone between 1984 and 1998 can explain almost a half of the total fall in the aggregate unemployment rate over the period.

However, demographic pressures were not the only forces that affected the composition of the labour force over the period. Changes in the fraction of each age group either employed or actively searching for work clearly affect the composition of the labour force and therefore will also affect the unemployment rate. Once we control for these shifts in labour force participation rates by age group we find that, unsurprisingly, demographic change explains less of the change in the unemployment rate over the period. However, it appears that the shift in the composition of the population caused by the baby boom and bust still explains about 45 basis points[15] of the fall in the unemployment rate over the period.

Finally, on the basis of current projections, it appears that future shifts in the composition of the labour force will have little effect on the unemployment rate over the next decade. However, to some extent, this masks the fact that the benign impact of demographic change is likely to be offset by increases in youth activity rates.

[14] This is approximately equal to the average (over all base years) of the age-driven change in the unemployment rate, the age adjustment to the unemployment rate and the chain-weighted index, when the labour force is divided into only youths and adults (actual figure = 55.67 basis points).

[15] As before, this is equal to the average (over all base years) of the age-driven change in the unemployment rate, the age adjustment to the unemployment rate and the chain-weighted index, when the labour force is divided into only youths and adults.

APPENDIX 1: TABLES

TABLE A.2.2 THE DURATION STRUCTURE OF UNEMPLOYMENT BY AGE

	16 - 17				18 - 24			
	Unemployment Rate	Percentage unemployed			Unemployment Rate	Percentage unemployed		
		< 6 months	6–12 months	> 1 year		< 6 months	6–12 months	> 1 year
1984	22	62.9	22.5	14.6	19.2	33.5	19.9	46.5
1985	20.3	62.6	24.1	13.3	17.1	36.4	18.9	44.7
1986	20.9	66.2	21.4	12.4	17.3	37	22.4	40.6
1987	19.4	64	26.9	9.1	15	40.3	21.8	37.9
1988	14.2	69	20	11	12.3	44.8	23	32.2
1989	10.8	82	10.8	7.2	9.9	54.6	19.7	25.7
1990	11.3	80	13.3	6.7	9.9	62.8	15.6	21.6
1991	14.9	80.9	15.3	3.8	13.3	58.3	21	20.7
1992	16	70.7	22	7.3	15.4	45.9	25	29.1
1993	16.8	55.9	27.9	16.2	17.4	42	22.8	35.1
1994	17.9	65.9	20.3	13.8	15.9	41	22.5	36.5
1995	17.3	66.4	23	10.7	14.9	47.1	21.9	31
1996	18.3	68.3	22.5	9.2	14	50.2	19.9	30
1997	17.7	68.1	20.1	11.8	12.5	55.4	17.7	26.8
1998	16.6	74.4	18	7.5	11.3	62.6	16.9	20.5

	25 - 49				50 +			
	Unemployment	Percentage unemployed			Unemployment	Percentage unemployed		
	Rate	< 6 months	6–12 months	> 1 year	Rate	< 6 months	6–12 months	> 1 year
1984	9.9	32.6	16.7	50.7	8.5	21.8	17.5	60.7
1985	9.9	31.9	16.1	52	8	21.9	13.9	64.1
1986	9.7	34.5	14.9	50.6	8	23.8	13.5	62.7
1987	9.6	35	14.8	50.2	8.6	24.2	12.8	62.9
1988	7.6	39.9	15.2	44.9	7.9	26.3	11.8	61.9
1989	6.2	45.1	16.4	38.5	6.9	27.4	12.1	60.5
1990	5.9	49.8	17.1	33.1	6.1	30.1	12.7	57.2
1991	7.2	54.1	17.6	28.3	6.9	37.8	15.3	46.9
1992	8.6	41.7	20.8	37.5	7.7	30.4	21	48.6
1993	8.8	35.2	19	45.8	8.9	28.7	19.5	51.8
1994	8.3	35.5	16.3	48.2	8.2	25.9	15.7	58.4
1995	7.5	36	15.6	48.4	6.7	28.5	13.9	57.6
1996	7.1	39	17.4	43.6	6.3	31.1	15.3	53.6
1997	6	41.3	15.6	43.1	5.5	33.8	13.3	52.9
1998	5.2	49.3	14.7	36	4.6	35.8	11.5	52.7

TABLE A.4.1.1 : BASIS POINT CHANGE IN UNEMPLOYMENT EXPLAINED BY INDICES OF DEMOGRAPHIC CHANGE

	Age adjustment to unemployment		Age-driven change in unemployment		Chain-weighted index	
Base year	2 groups	5 groups	2 groups	5 groups	2 groups	5 groups
1984	-55	-51	-77	-69	-48	-40
1985	-54	-50	-63	-54	-48	-40
1986	-55	-49	-66	-58	-48	-40
1987	-55	-48	-49	-42	-48	-40
1988	-57	-49	-38	-35	-48	-40
1989	-59	-50	-28	-26	-48	-40
1990	-61	-51	-32	-30	-48	-40
1991	-64	-54	-49	-46	-48	-40
1992	-68	-57	-54	-50	-48	-40
1993	-71	-59	-65	-62	-48	-40
1994	-73	-62	-60	-57	-48	-40
1995	-75	-64	-60	-57	-48	-40
1996	-75	-66	-59	-55	-48	-40
1997	-76	-68	-58	-54	-48	-40
1998	-77	-69	-55	-51	-48	-40
Mean	-65	-56	-54	-50		
Variance	79	58	175	143		

TABLE A.4.1.2 PERCENTAGE CHANGE IN UNEMPLOYMENT EXPLAINED BY INDICES OF DEMOGRAPHIC CHANGE BY BASE YEAR

	Age adjustment to unemployment		Age-driven change in unemployment		Chain-weighted index	
Base year	2 groups	5 groups	2 groups	5 groups	2 groups	5 groups
1984	9.7	9	13.7	12.3	8.6	7.2
1985	9.6	8.8	11.2	9.6	8.6	7.2
1986	9.7	8.6	11.7	10.2	8.6	7.2
1987	9.8	8.5	8.6	7.4	8.6	7.2
1988	10	8.7	6.6	6.1	8.6	7.2
1989	10.3	8.8	4.9	4.7	8.6	7.2
1990	10.9	9.1	5.6	5.4	8.6	7.2
1991	11.4	9.5	8.7	8.1	8.6	7.2
1992	12	10.1	9.5	8.8	8.6	7.2
1993	12.5	10.4	11.4	11	8.6	7.2
1994	12.9	10.9	10.6	10.1	8.6	7.2
1995	13.2	11.3	10.6	10	8.6	7.2
1996	13.3	11.6	10.5	9.7	8.6	7.2
1997	13.5	12	10.2	9.5	8.6	7.2
1998	13.7	12.3	9.7	9	8.6	7.2
Mean	11.5	10	9.6	8.8		
Variance	2.5	1.8	5.6	4.5		

TABLE A.6.1.1 BASIS POINT CHANGE IN INDICES OF DEMOGRAPHIC CHANGE, HOLDING ACTIVITY RATES CONSTANT BY BASE YEAR

	Age adjustment to unemployment		Age-driven change in unemployment		Chain-weighted index	
Base year	2 groups	5 groups	2 groups	5 groups	2 groups	5 groups
1984	-44	-42	-62	-59	-41	-38
1985	-46	-43	-52	-48	-41	-38
1986	-46	-43	-54	-51	-41	-38
1987	-46	-43	-40	-38	-41	-38
1988	-48	-44	-31	-31	-41	-38
1989	-50	-45	-23	-23	-41	-38
1990	-51	-45	-26	-26	-41	-38
1991	-53	-46	-40	-39	-40	-37
1992	-53	-45	-42	-40	-39	-36
1993	-54	-46	-50	-50	-39	-36
1994	-55	-48	-46	-45	-38	-35
1995	-56	-50	-46	-44	-38	-35
1996	-58	-53	-46	-44	-39	-36
1997	-59	-54	-44	-42	-38	-35
1998	-59	-55	-42	-39	-38	-35
Mean	-52	-47	-43	-41	-40	-37
Variance	26	18	107	90	2	2

TABLE A.6.1.2 PERCENTAGE CHANGE IN INDICES OF DEMOGRAPHIC CHANGE, HOLDING ACTIVITY RATES CONSTANT BY BASE YEAR

	Age adjustment to unemployment		Age-driven change in unemployment		Chain-weighted index	
Base year	2 groups	5 groups	2 groups	5 groups	2 groups	5 groups
1984	8	7.6	11.2	10.6	7.3	6.8
1985	8.2	7.7	9.3	8.6	7.4	6.9
1986	8.3	7.7	9.7	9.1	7.4	6.9
1987	8.2	7.7	7.2	6.7	7.4	6.9
1988	8.7	7.9	5.5	5.5	7.4	6.9
1989	9	8	4.1	4.2	7.4	6.9
1990	9.2	8.1	4.7	4.7	7.3	6.8
1991	9.5	8.3	7.1	7	7.3	6.8
1992	9.5	8.2	7.6	7.4	7.1	6.6
1993	9.8	8.4	9.1	9.1	7.1	6.5
1994	10.1	8.7	8.3	8.3	7	6.4
1995	10.3	9.1	8.4	8.1	7	6.4
1996	10.6	9.6	8.3	8	7.1	6.5
1997	10.7	9.9	8	7.7	7	6.5
1998	10.7	10	7.6	7.2	7	6.4
Mean	9.4	8.5	7.7	7.5	7.2	6.7
Variance	0.9	0.7	3.6	2.9	0	0

TABLE A.6.2.1 BASIS POINT CHANGE IN INDICES OF DEMOGRAPHIC CHANGE, USING UNEMPLOYED TO WORKING POPULATION RATIOS BY BASE YEAR

	Age adjustment to unemployment		Age-driven change in unemployment		Chain-weighted index	
Base year	2 groups	5 groups	2 groups	5 groups	2 groups	5 groups
1984	-28	-27	-48	-45	-28	-25
1985	-29	-26	-40	-36	-28	-25
1986	-30	-26	-42	-38	-28	-25
1987	-30	-26	-31	-28	-28	-25
1988	-31	-26	-24	-23	-28	-25
1989	-33	-27	-18	-17	-28	-25
1990	-35	-28	-20	-19	-28	-25
1991	-37	-30	-30	-28	-28	-25
1992	-39	-31	-28	-26	-28	-25
1993	-41	-33	-33	-32	-28	-25
1994	-43	-36	-29	-28	-28	-25
1995	-45	-38	-30	-28	-28	-25
1996	-46	-41	-31	-29	-28	-25
1997	-47	-43	-30	-28	-28	-25
1998	-48	-45	-28	-27	-28	-25
Mean	-38	-32	-31	-29		
Variance	51	46	61	50		

TABLE A.6.2.2 PERCENTAGE CHANGE IN UNEMPLOYED TO WORKING POPULATION RATIOS EXPLAINED BY INDICES OF DEMOGRAPHIC CHANGE, BY BASE YEAR.

	Age adjustment to unemployment		Age-driven change in unemployment		Chain-weighted index	
Base year	2 groups	5 groups	2 groups	5 groups	2 groups	5 groups
1984	6.47	6.07	10.92	10.25	6.34	5.6
1985	6.71	5.9	9.1	8.26	6.34	5.6
1986	6.81	5.85	9.58	8.78	6.34	5.6
1987	6.87	5.86	7.02	6.39	6.34	5.6
1988	7.12	6.03	5.46	5.2	6.34	5.6
1989	7.55	6.22	4.11	3.97	6.34	5.6
1990	8.03	6.46	4.53	4.33	6.34	5.6
1991	8.52	6.78	6.75	6.41	6.34	5.6
1992	8.9	7.11	6.37	5.94	6.34	5.6
1993	9.42	7.61	7.51	7.22	6.34	5.6
1994	9.89	8.16	6.65	6.38	6.34	5.6
1995	10.24	8.73	6.76	6.42	6.34	5.6
1996	10.54	9.34	6.96	6.57	6.34	5.6
1997	10.77	9.87	6.83	6.49	6.34	5.6
1998	10.92	10.25	6.47	6.07	6.34	5.6
Mean	8.58	7.35	7	6.58		
Variance	2.64	2.41	3.18	2.59		

TABLE A.6.3 UNEMPLOYED TO WORKING POPULATION RATIOS BY AGE GROUP : 1984-1998.

	16+	16-17	18-24	16-24	25+	25-34	35-49	50+	16-59/64
1984	9.26	13.03	15.49	14.95	7.45	9.75	6.83	6.01	9.26
1985	8.89	12.49	13.95	13.63	7.38	9.80	6.87	5.61	8.89
1986	8.87	13.21	14.05	13.87	7.30	9.82	6.58	5.63	8.87
1987	8.57	12.04	12.31	12.25	7.43	9.77	6.57	6.13	8.57
1988	7.03	9.30	10.07	9.91	6.16	7.81	5.26	5.63	7.03
1989	5.80	7.00	8.23	7.98	5.16	6.54	4.28	4.88	5.80
1990	5.53	7.05	8.18	7.96	4.85	6.05	4.20	4.42	5.53
1991	6.76	9.22	10.69	10.41	5.78	7.32	5.07	4.99	6.76
1992	7.78	8.91	11.81	11.26	6.88	8.60	6.20	5.81	7.78
1993	8.24	8.45	13.29	12.37	7.21	8.72	6.42	6.59	8.24
1994	7.68	9.37	11.84	11.36	6.80	8.27	6.03	6.18	7.68
1995	6.88	9.04	11.07	10.65	6.01	7.45	5.48	5.09	6.88
1996	6.51	10.02	10.53	10.42	5.64	7.12	5.12	4.67	6.51
1997	5.64	9.89	9.37	9.49	4.80	5.82	4.50	4.06	5.64
1998	4.88	9.11	8.36	8.53	4.09	5.32	3.68	3.35	4.88

TABLE A.7.1 PROJECTIONS OF THE LABOUR FORCE, ACTIVITY RATES AND WORKING AGE POPULATION BY AGE : 1998 –2011.

	% of Labour Force			Activity Rates			% of Working Age Population		
Year	16-24 yrs.	25-34 yrs.	35+ yrs.	16-24 yrs.	25-34 yrs.	35+ yrs.	16-24 yrs.	25-34 yrs.	35+ yrs.
1998	15.40	26.24	58.35	71.18	84.06	55.22	17.54	25.30	57.16
1999	15.38	25.50	59.12	71.60	84.45	55.73	17.49	24.58	57.93
2000	15.37	24.68	59.95	71.66	84.65	56.18	17.50	23.78	58.71
2001	15.54	23.82	60.64	71.91	84.76	56.52	17.64	22.95	59.40
2002	15.81	22.99	61.21	72.13	84.83	56.64	17.88	22.11	60.00
2003	16.07	22.26	61.67	72.36	84.91	56.70	18.12	21.39	60.49
2004	16.22	21.71	62.08	72.47	85.01	56.74	18.26	20.84	60.90
2005	16.25	21.33	62.42	72.48	85.10	56.76	18.30	20.46	61.24
2006	16.31	20.92	62.78	72.56	85.20	56.81	18.35	20.04	61.60
2007	16.48	20.62	62.90	72.74	85.28	56.66	18.53	19.78	61.70
2008	16.62	20.47	62.91	72.85	85.33	56.45	18.68	19.64	61.68
2009	16.72	20.46	62.82	72.95	85.40	56.20	18.78	19.63	61.59
2010	16.76	20.59	62.65	73.17	85.47	55.94	18.78	19.76	61.46
2011	16.73	20.82	62.45	73.32	85.51	55.67	18.72	19.98	61.30

CHAPTER 3

A MATCH MADE IN HEAVEN ? THE IMPACT OF DEMOGRAPHIC CHANGE ON THE DEMAND FOR, AND THE SUPPLY OF, SKILLS IN THE LABOUR MARKET

1. INTRODUCTION

In the media and academia alike, the causes and consequences of skill biased technological change have been discussed at length. It is widely believed that one result of this phenomenon has been that the labour markets of the developed world have experienced a skill biased shift in demand which has led to a deterioration in the fortunes of the unskilled members of the workforce on either side of the Atlantic, albeit manifested in different ways – or as Krugman (1994) so famously put it : 'the European unemployment problem and the U.S. inequality problem are two sides of the same coin' (Krugman (1994) p.71). Yet, together with this infamous shift in demand away from the unskilled, it is also common knowledge that there has been an unambiguous shift in the relative supply of skilled workers in the economy. There has been a clear rise in the level of educational attainment of successive cohorts entering the post-war labour markets, which has led to an ever increasing fraction of skilled workers in the labour force. What really matters then is whether there has been a *net* shift in demand – i.e. whether the growth in demand for the skilled members of the workforce has outstripped the increase in their supply.

This chapter is based on the hypothesis that there has been a second relative supply shock which may have altered the relative balance between the demand for, and supply of skills in the labour market, other than the rise in educational participation. Since the Second World War most nations of the developed world have experienced considerable fluctuations in their birth rate; most countries, although to different degrees, experienced a huge surge in their birth rate in the 1960's (in what became known as the 'baby boom') which was followed by a slump (or 'baby bust') in the decade that followed. These fluctuations in the birth rate inevitably repeated themselves in the age structure of the labour force some fifteen to twenty years later. Since youths lack the labour market experience that older workers have gained over time at the workplace, they can be considered relatively unskilled compared to an adult with similar academic qualifications, and therefore demographic change also has the potential to shift the relative supply of skilled workers in the labour force.

This chapter uses the established 'mismatch' theoretical framework to clarify the exact nature of the net shift in demand towards the skilled that occurred in the U.K. economy since 1979, and to understand how any such net shift in demand might have affected the labour market, and in particular the aggregate unemployment rate. Layard et. al. (1991) develop two stylised arguments to explain how the level of mismatch in the economy might explain the level of aggregate unemployment in the economy. The first relies on the presence of non-linearities in wage setting, so that an increase in the dispersion of unemployment across groups leads to an increase in aggregate unemployment, since :

> "wages are more sensitive to unemployment when unemployment is low than when it is high. (Layard *et. al.* (1991) p.47)"

so that in sectors of the labour market where unemployment is low, wage pressure is proportionately greater than wage restraint in groups where unemployment is high - requiring the "extra" unemployment to bring consistency between wage and price setters at the aggregate level. Greater mismatch in the group specific unemployment rates therefore requires higher unemployment on average to restrain wages.

The second argument is based upon the existence of a 'leading sector' – the tightest labour market in the economy, which enjoys the lowest sector specific unemployment rate. Wage pressure in this model depends only on conditions in the leading sector, so whenever unemployment rates in the other sectors of the economy exceed that in the leading sector, then that unemployment can be deemed to be of no useful purpose – since 'extra' unemployment in the sectors that 'follow' exerts no downward pressure on wages. Greater mismatch in the sector specific unemployment rates will therefore once again lead only to higher unemployment on average. The conclusions which we shall draw from this chapter should therefore be judged in the context of the empirical evidence to support each of these arguments – either non-linearities or an asymmetry in the wage setting process.

The literature provides a number of alternative approaches to measuring mismatch in the demand for, and the supply of skills is the economy. The first approach is to use simple 'outcomes-based' statistics which are based on the variance of either the unemployment rates or the wages of the different skill groups in the economy. Effectively these mismatch measures abstract away from the underlying balance between the demand for and supply of each skill group and instead focus directly on their relative labour market performance. So, for example, a deterioration in the unskilled labour market either through either a fall in the unskilled wage, or an increase in the unskilled unemployment rate relative to skilled labour, is taken as prima facie evidence of increased skill mismatch. However, irrespective of whether his parable as to the common cause of North American wage inequality and European unemployment was correct or not, Krugman's basic premise that a net shift in demand away from one group may result in either a realignment of wages or unemployment rates underlines the futility of relying on mismatch measures which garner information from only one of these sources. If wages are sufficiently flexible a net demand shift away from the unskilled may be worked through entirely in terms of higher wage inequality; alternatively if wages are rigid, this shift may result only in changes in the groups' unemployment rates. A mismatch measure based on the variance of the wages of each skill group will only report increased mismatch in the former scenario; a measure based on the variance of their unemployment rates will report increased mismatch only in the latter.

The approach of Manacorda and Petrongolo (1999) provides a framework which utilises both wage and employment outcomes to identify net demand shifts. Abstracting from the role of capital and land in the production process, they consider a stylised economy where the only input to production is labour, but where there exists a heterogeneity in the productivity, or level of skill, of the labour force. They then derive a measure of the relative demand for, and supply of each input, allowing them to define a 'true' measure of skill mismatch. They then show that if we make assumptions on the wage setting process in this stylised economy, the change in the aggregate unemployment rate can be decomposed into that generated by a shift in the composition of the labour force across skill inputs, that caused by a change in wage pressure and that caused by a change in the degree of mismatch across skill groups. This is the basic framework which we adopt in this chapter[16].

This research aims to quantify both the evolution of skill mismatch in the U.K. labour market between 1979 and 1996, and the role that mismatch can play in explaining the path of the aggregate unemployment rate over that period. In Section 2 we construct a simple definition of skill based on both the age and highest level of educational attainment of an individual, and then categorise the labour force according to our definition. We then illustrate in broad brush terms how each of our different skill groups fared in the labour market, and summarise the degree of skill mismatch in the U.K. labour market over the period as reported by the standard 'outcomes' based mismatch measures. Section 3 provides a description of the framework used in the chapter to derive a measure of skill mismatch based on the underlying shifts in the demand for, and the supply of, different skills in the labour market, which under certain assumptions can then be used to quantify the role changes in the degree of skill mismatch played in determining the path

[16] An alternative class of mismatch measure are those which draw upon information on vacancies, to estimate the degree of mismatch between the stocks of unemployed people and vacant jobs in the economy (see for example, Jackman and Roper (1987)). However, given the paucity of reliable data on vacancies,

taken by the aggregate unemployment rate over the period. Section 4 presents the key results of the chapter, and tests their sensitivity to alternative assumptions on the parameters of our model; and finally, Section 5 concludes.

2 SKILL MISMATCH : PRELIMINARIES

There appears to be a fairly broad consensus that in recent years there has been both a demand and supply shift away from the unskilled in O.E.C.D. labour markets. However, it is the extent to which one of these forces has outpaced the other which will determine whether there have been any macroeconomic consequences. Typically, attempts to quantify the role of net shifts in the demand for skilled labour on the aggregate unemployment rate have tended to focus on a rather narrow definition of skill – an individual's level of educational attainment[17]. While academic qualifications are certainly a good signal of ability and hence productivity in the workplace, it is difficult to argue that they give a complete description of an individual's level of skill. It must be the case that the knowledge an individual acquires through experience at the workplace, both of an informal kind through increased familiarity with work practices and the use of capital, but also more formal training programmes must all contribute to the level of skill of a worker. Of course finding accurate information of this kind in the data is not straightforward. However, we argue there is one variable that does act as a good proxy for at least an individual's experience of work: his age. We know that there are marked differences in the experiences of different age groups in the labour market: the differential in wages and unemployment rates by age are as least as large as those by educational attainment[18]. We argue that these differences reflect, in part, the fact that older workers are more productive than their younger counterparts, or in other words they are more highly skilled (despite the fact that on average they have fewer academic

and in particular the difficulty of categorising vacancies according to the age of their intended occupant, we do not consider this alternative class of mismatch measure.

[17] After completion of this chapter I was made aware of a paper by Jimeno and Rodriguez-Palenzuela (2001) which does indeed use a workers age as a proxy of his level of productivity.

[18] For example in 1998, the unemployment rate of those aged 35 to 49 years of age (who enjoyed the lowest age-specific unemployment rate) was about a quarter of the unemployment rate of those aged 16 to 17 (who

qualifications). We therefore develop a measure of skill which incorporates information on both the educational attainment and the experience (proxied by the age) of members of the labour force. Typically then we shall sub-divide the labour force into a number of sub-groups: collecting together within a given skill group those who are both of a similar age and share a similar level of educational attainment. This method is not altogether new; Card and Lemieux (2001) use the same conceptual approach when explaining the change in the return to acquiring qualifications. However, they proceed under the assumption that the relative unemployment rates of the separate groups are exogenous, which intuitively is entirely at odds with the approach we are taking here; for mismatch to have a role in explaining changes in the aggregate unemployment rate, net demand shifts must have an effect on the unemployment rates of each group. We shall proceed as follows: first, we give some simple descriptive statistics to illustrate the relative performance of the labour markets for these different skill groups over the period, then we turn to analyse some simple mismatch measures to establish the broad trends in the growth of mismatch between the demand and supply of skill in the U.K. labour market.

2.1 THE U.K. LABOUR MARKET FOR SKILL : 1979-1996.

We argue that a more complete definition of the skill composition of the labour force must rely not only on the level of educational attainment on the workforce but also their level of labour market experience, which we proxy by their age. Therefore, to begin with we shall describe how the educational and age composition of the labour force has changed over time. For the sake of simplicity, we shall divide the labour force into four separate groups by qualification and age respectively: in the case of qualifications, we divide individuals into four groups according to their highest level of educational attainment: less than O level (or equivalent),O Level, A Level (or equivalent) and finally degree or higher[19]. In the case of age, we divide the labour force into those aged 24 or less, those between 25 and 34 years of age, those aged 35 to 49 years of age and finally

suffered the age specific unemployment highest unemployment rate) while the unemployment rate of those with a degree was also about a quarter of those with no qualifications (Nickell (1999)).

those 50 years and above. Data on wages is taken from the General Household Survey (or G.H.S.), while labour force data is drawn from the Labour Force Survey (or L.F.S.)[20].

Figures 2.1 [a]-[c] overleaf reveal the broad developments in the labour markets for the separate qualification and age groups we have defined. They also underline the importance of tracking developments in both the market for qualifications and experience (or age); simply put, focusing on only one of these separate components of skill can give rise to misleading (and even contradictory) interpretations[21].

These figures graphically illustrate the impact of the benign supply shocks that have hit the U.K. labour market. Since 1979 there has been a marked fall in the fraction of the workforce with no qualifications, and a gradual increase in the proportion with each level of qualification (O Level, A Level and Degree (and above)). Although between 1979 and 1985, the fraction of youths (those aged 24 or less) in the workforce increased rapidly as the baby boomers arrived in the labour market, thereafter in relative terms, their numbers declined both as a result of the baby bust and the fact that the baby boomers themselves were entering middle age. By the end of the period, there were thus fewer youths and more mature adults in the labour force.

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[19] A complete description of our classification of the different qualifications held by members of the U.K. labour force into the four separate groups is given in Appendix 2, and follows the practice adopted by, among others, Dearden *et. al.* (2000).

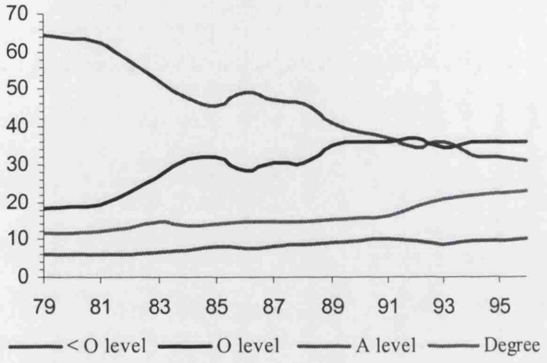
[20] Given that the L.F.S. was biannual between 1979 and 1983, labour force data for 1980 and 1982 was approximated as the average of the years immediately before and after.

[21] For example, between 1979 and 1985, the fraction of the labour force with no qualifications fell dramatically– from about 69% to a little over 50% – which implies a massive fall in the numbers of unskilled members of the workforce. However, over the same period, the fraction of the labour force below the age of 25 actually increased, which implies that, certainly in terms of their experience at the workplace, the labour force was becoming more unskilled.

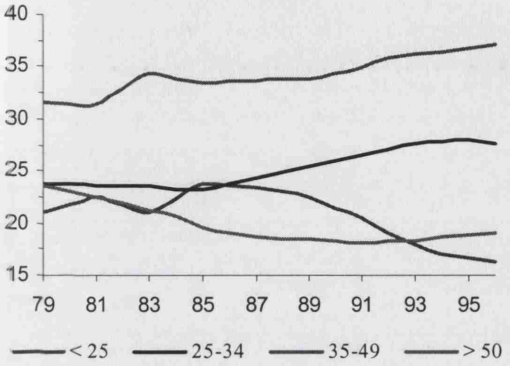
Figure 2.1 : Summary Statistics

[a] Labour Force Shares

Qualifications

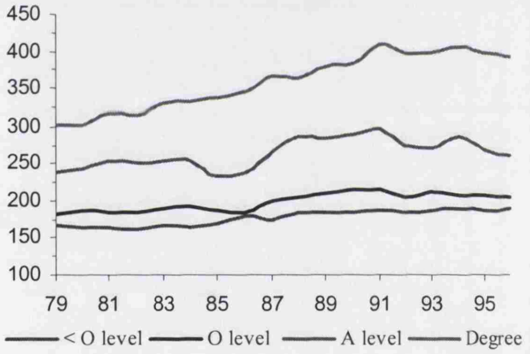


Age Groups

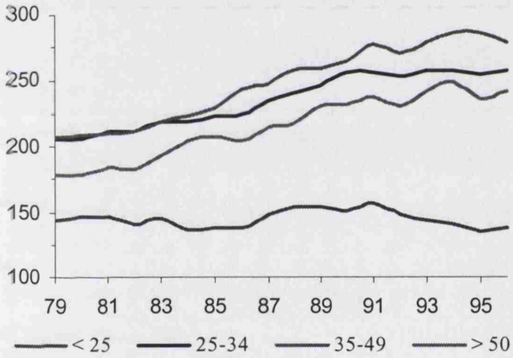


[b] Wages

Qualifications

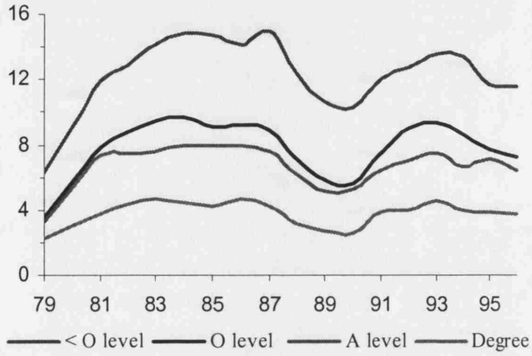


Age Groups

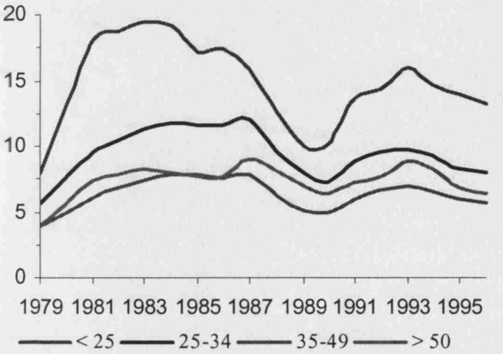


[c] Unemployment Rates

Qualifications



Age Groups



Figures 2.2 [a] – [c] reveal how each of sub-groups fared in the labour market, we find that across the different qualification groups, those with degrees stand out for they enjoyed a relative improvement in their fortunes – their wages rose faster, and their unemployment rate fell further, than those with less qualifications. Conversely, in terms of their experience in the labour market, it was the least skilled workers – the young – whose experiences contrasted most with the rest of the labour force. Indeed, between 1979 to 1996 the youth labour market appeared to stagnate – their real wages actually fell over the period, and their unemployment rate remained far higher than all other age groups in the economy.

However, in order to develop a coherent picture of how the demand and supply for skill has evolved in the U.K. labour market since 1979 we need to integrate developments in each of these labour markets. Therefore, we repeat the exercise, now modeling the labour force as the sum of sixteen sub-groups, according to the age and level of educational attainment of the worker. The figures above reveal that certainly in terms of their wages, and to a lesser extent in terms of their unemployment rates, the experiences of youths (i.e. those aged 24 or less) in the labour market are quite distinct from their older counterparts, who within the same qualification group, have broadly similar experiences. We argue that these differences in the wages earned by individuals with similar qualifications but who differ in age must at least in part reflect differences in their productivity and hence their level of skill. The fact that the age differential in wages for individuals with similar qualifications diminishes the older they get may well reflect that age becomes an increasingly poor signal of the human capital an individual has acquired at the workplace the older he gets; in other words, its not the number of years you have been in the labour market but what you have done with them that matters. When we turn to translate this information on the outcomes of these disparate sub-groups in the labour market into a single statistic on the degree of skill mismatch, we shall also consider a simplified model of the labour force where in terms of individuals' ages we distinguish only between youths and adults, together with the full decomposition into sixteen separate skill groups.

FIGURE 2.2 [A] : AGE COMPOSITION OF THE LABOUR FORCE BY QUALIFICATION GROUP

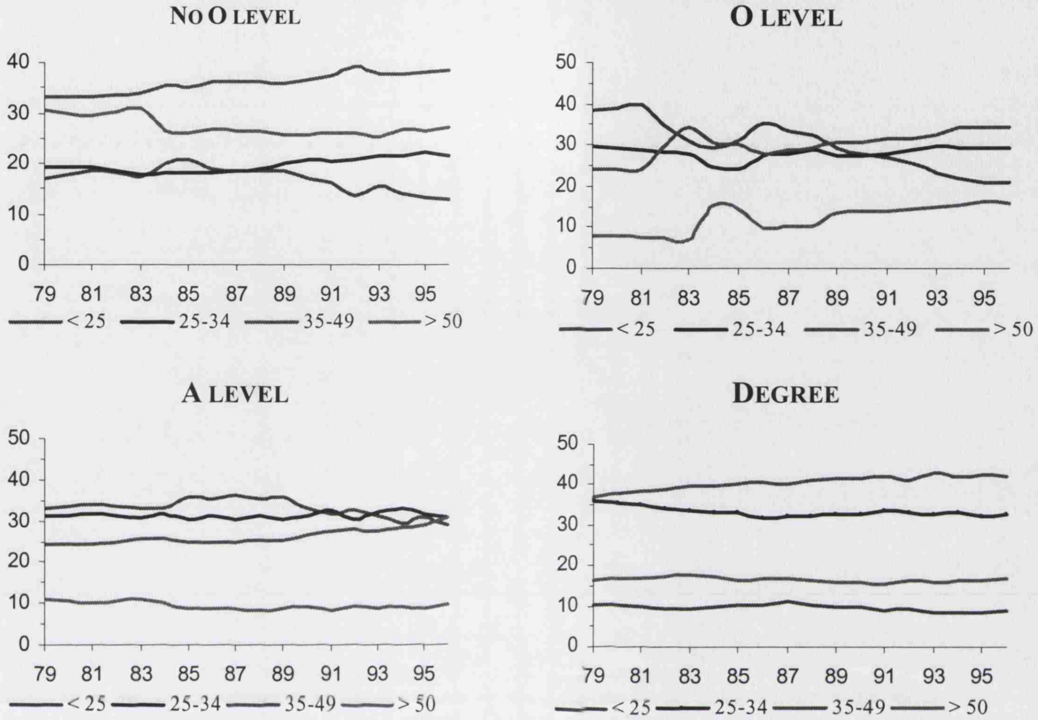


FIGURE 2.2 [B] : AGE DISTRIBUTION OF WAGES, BY QUALIFICATION GROUP

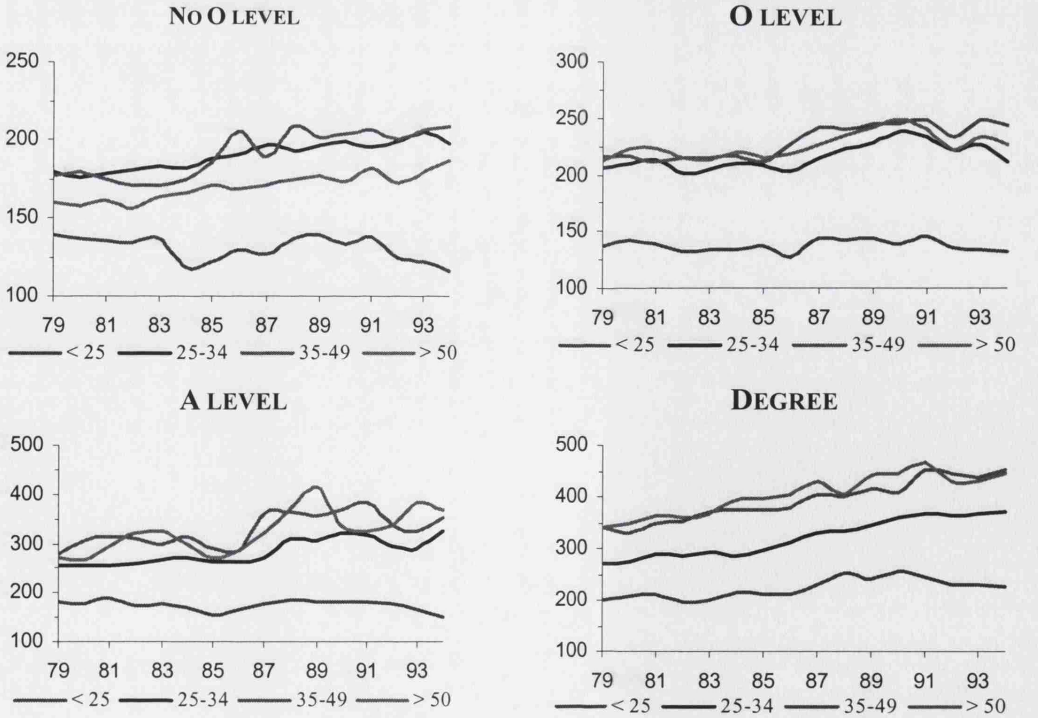
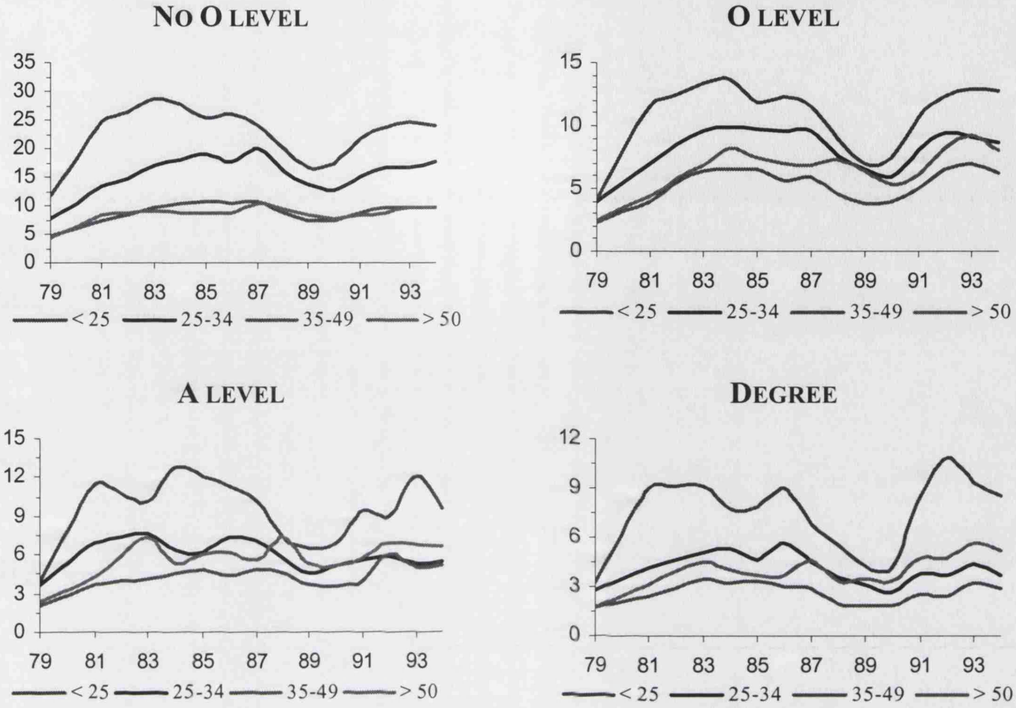


FIGURE 2.2 [C] : AGE SPECIFIC UNEMPLOYMENT RATES, BY QUALIFICATION GROUP



2.2 CONSTRUCTING AN INDEX OF SKILL MISMATCH.

The most straightforward approach to measuring the degree of mismatch between the demand and supply of different skills has proved to be to focus on outcomes in the labour markets for different skills – in other words, to compare how the wages and the unemployment rates of the different skill groups have evolved over time. The logic behind this approach is that if the wages or unemployment rates of the groups diverge then this can be taken as evidence of an increased mismatch between the demand for and supply of different skills in the economy. Obviously, this argument is most convincing when both measures give a consistent story – i.e. both the relative wages and unemployment rates of the different groups are diverging.

In order to provide a quantitative measure of the degree of mismatch in the economy, information on outcomes in these separate labour markets is usually condensed into a single index, typically based on the dispersion of the relative or absolute wage or unemployment rates of each of the groups. Of course, not all shifts in demand and supply are *skill biased* – i.e. in favour of one group at the expense of another – and the wages and unemployment rates of each of the groups will therefore move for reasons other than shifts in relative demand and supply. Any outcomes based measure of mismatch must therefore distinguish between those movements in prices and quantities in the skill-specific labour markets which are driven by skill biased shocks and those driven by skill neutral shocks.

Absolute measures of wage [AWM] and unemployment mismatch [AUM] can be calculated as follows:

$$AWM = \mathrm{var}(w_i) = \sum_i n_i (w_i - \mathrm{E}(w_i))^2 = \sum_i n_i (w_i - w)^2 \qquad [2.1]$$

$$AUM = \mathrm{var}(u_i) = \sum_i l_i (u_i - \mathrm{E}(u_i))^2 = \sum_i l_i (u_i - u)^2 \qquad [2.2]$$

where n_i is the employment share of group i, w_i is the average wage earned by members of group i, w is the average wage earned in the economy, l_i is the labour force share of group i and u is the weighted average of the age specific unemployment rates u_i – in other words, the aggregate unemployment rate. Absolute mismatch measures implicitly assume that skill neutral shocks have equivalent impacts on skill-specific wages and unemployment rates, so for example if a skill neutral shift in demand away from labour caused an equal percentage point increase in the unemployment rates of all skill groups the AUM index remains unchanged.

Similarly, indices of relative mismatch [RWM,RUM] can be calculated as follows:

$$RWM = \mathrm{var}\left(\frac{w_i}{w}\right) = \sum_i n_i \left(\frac{w_i}{w} - \mathrm{E}\left(\frac{w_i}{w}\right)\right)^2 = \sum_i n_i \left(\frac{w_i}{w} - 1\right)^2 \qquad [2.3]$$

$$RUM = \mathrm{var}\left(\frac{u_i}{u}\right) = \sum_i l_i \left(\frac{u_i}{u} - \mathrm{E}\left(\frac{u_i}{u}\right)\right)^2 = \sum_i l_i \left(\frac{u_i}{u} - 1\right)^2 \qquad [2.4]$$

since the weighted average of the groups' relative wages or unemployment rates must be one by definition. Relative mismatch measures are based on the assumption that skill neutral shocks have equi-proportionate effects on the wages and unemployment rates of each of the skill groups, so the ratio of their wages and unemployment rates (and thus the RWM and RUM indices) remain unchanged.

In the following figures we illustrate the evolution of these different mismatch measures over the period: 1979 – 1996, for both the simplified and full decompositions of the labour force.

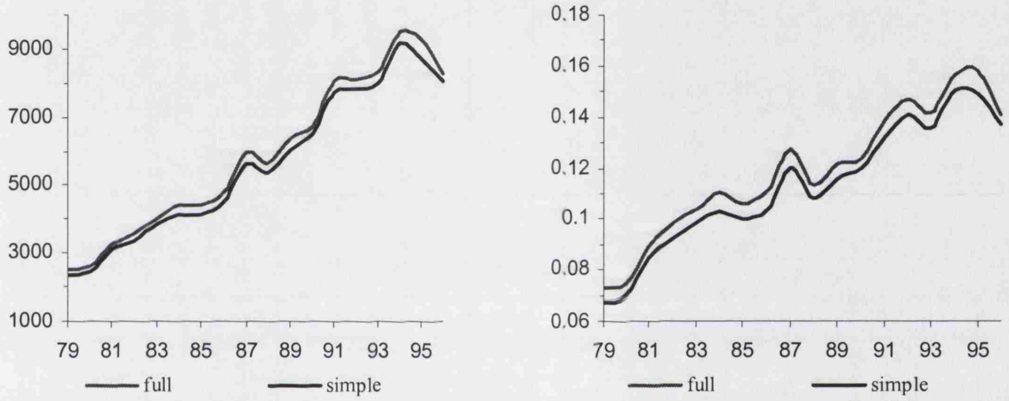
2.3 EVIDENCE FROM WAGES

Figure 2.3 overleaf reveals a clear and consistent account of the degree of mismatch between the wages earned by the separate age and qualification groups earned in the economy. Broadly speaking, as average wages in the economy have grown over time, so has the dispersion of the group-specific wages around that average, as reported by either measure. Nonetheless, this dispersion in wages has become more volatile over time, as has been found elsewhere in the case of the dispersion of wages across qualification groups alone (Burriel-Llombart and Thomas (2001)). As such, there appears to be some evidence of a growth in skill mismatch on the basis of this increase in wage dispersion; nonetheless, the data does reveal that given that the increase in wage dispersion has been fairly constant across the period that the implied *rate of growth* of skill mismatch has fallen.

Finally, we note that there is little discrepancy between the wage mismatch measures constructed from the simple and full decompositions of the labour force, implying that any further distinction between individuals according to their age beyond youths and adults adds little to our understanding of mismatch, at least as far as wages are concerned. However, this is not to say that age does not matter whatsoever; if we consider those wage mismatch measures generated from a decomposition of the labour force based solely upon individuals' level of educational attainment, we find that, measure for measure, mismatch is approximately three quarters of the level reported in the figures below.

FIGURE 2.3 : SKILL MISMATCH: EVIDENCE FROM WAGES

A.W.M. **R.W.M.**



2.4 EVIDENCE FROM UNEMPLOYMENT RATES

At first glance, the first thing that strikes the reader about Figure 2.4 overleaf is the volatility of both measures, and in particular the absolute mismatch measure. Within the space of two years (between 1979 and 1981) absolute mismatch quadrupled in value while relative mismatch increased by a about a quarter. Thereafter the two series appear to diverge somewhat; with relative mismatch falling far further in proportionate terms over the following five years and from 1987 onwards in all but one year the two mismatch measures move in opposite directions. It also appears that both unemployment measures of mismatch are sensitive to the business cycle – witness the fall in both through the recovery of the 1980's. In actual fact, this result has been established in a number of other studies; for example, Entorf (1996), discussing the relationship between the aggregate Spanish unemployment rate and a relative measure of mismatch, finds that:

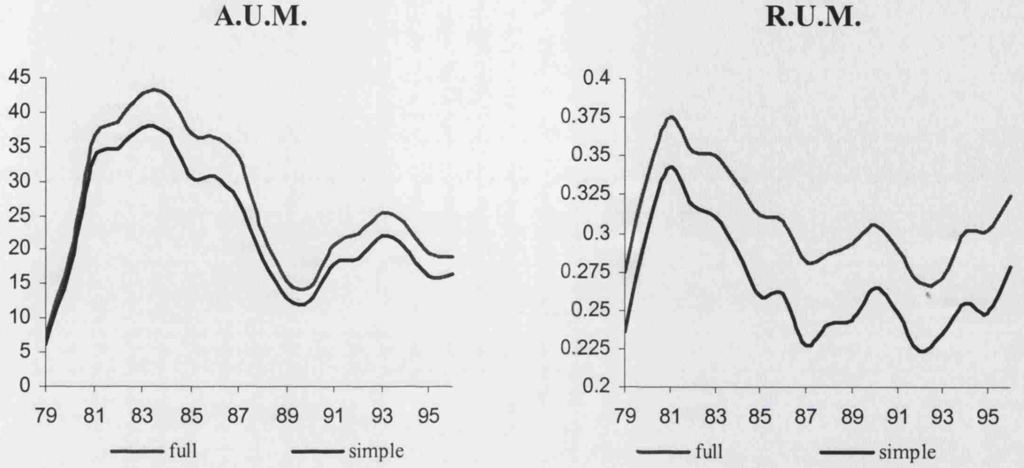
"After Franco's death and the start of the new political institutions in 1975, the negative correlation was almost perfect ...At a first glance, one again gets the impression that [relative] mismatch is more or less the inverse of unemployment (Entorf (1996) p.6)"

In summary it appears that neither of the mismatch indices based on the group-specific unemployment rates are able to strip out the effect of cyclical, skill neutral shocks to demand and supply. We know that equi-proportionate increases in all the skill-specific unemployment rates leave the relative unemployment rates unchanged but results in an increase in the variance of the absolute unemployment rates. Conversely, if each unemployment rate increases by the same amount, then the variance of the absolute rates will be unchanged, but the variance of the relative unemployment rates will decrease. Therefore, where the co-movements in the group specific unemployment rates lie between linearity and proportionality, we will inevitably see our measures of absolute and relative mismatch moving in opposite directions.

Burriel-Llombart and Thomas (2001) argue that a growth in aggregate wage pressure – the gap between the growth in wage pressure in the economy and the *feasible* growth in real wages – generates a rise in the variance of the absolute unemployment rates, but a fall in the variance of the relative rates, and vice versa. There are therefore reasons to suspect that changes in aggregate wage pressure might be the root cause of the divergent behaviour of our two series over the latter half of the period.

We also note that once again the finer decomposition of the labour force appears to add little to our measures of mismatch although the displacement between the series is certainly greater than that obtained with the wage mismatch measures. Once again it is important to point out that this in no way implies that distinguishing between individuals who hold similar qualifications according to their age is a worthless exercise; unemployment mismatch measures based solely on a decomposition of the labour force by qualification are typically a third to a half the value of those presented here.

FIGURE 2.4 : SKILL MISMATCH: EVIDENCE FROM UNEMPLOYMENT RATES



Had the wage and unemployment mismatch measures indicated a common trend in the developments in the labour markets for different skills over the period – i.e. either a convergence or divergence in the wages earned and the unemployment rates suffered by each of these groups – then we might have reasonable grounds to claim that there had been a definite change in the degree of skill mismatch in the U.K. labour market, based on the outcomes in the individual markets. However, it is apparent that our mismatch measures do not provide a compelling, nor even consistent, description of the evolution of skill mismatch over the period. While the measures based on wages indicate an increased dispersion of the group specific wages (albeit at a declining rate) the unemployment measures fluctuate considerably over the period. Furthermore, there is some concern that aggregate developments in the labour market might have been the driving force behind changes in the unemployment measures. Nonetheless, what is clear is that mismatch is demonstrably higher when we take account of an individual's age when we classify his level of skill.

3 SKILL MISMATCH : A THEORETICAL FRAMEWORK

The mismatch indices we have presented in the previous section suggest that based on outcomes in the labour market, that there may well have been a change in the degree of imbalance between the demand for, and supply of the different skill groups in the labour market. However, as was discussed earlier, the limitations of these mismatch measures are now well understood: they focus solely on either prices or quantities and are therefore to some extent theoretically flawed, and in practice the measures based on the group-specific unemployment rates appear to be unreliable, being highly collinear with changes in the aggregate labour market. In order to provide a more compelling analysis of the effect of skill mismatch on the aggregate labour market, we therefore need to integrate both wage and unemployment outcomes into our analysis.

Manacorda and Petrongolo (1999) provide just such a framework, assuming that production is Cobb-Douglas in separate skill inputs in order to define the demand for each input, and wages are set according to an "own sector" double logarithmic wage setting function. In the following work we generalise their analysis in three ways. First, we assume that technology is now defined by a Constant Elasticity of Substitution – or *C.E.S.* – production function, which allows us to test how sensitive our results are to the degree of substitution between different inputs in production (which is of course fixed at one for the Cobb-Douglas production function). Second, we allow for the fact that amongst workers with a common level of educational attainment, productivity can vary dramatically; specifically, older workers may have acquired considerable human capital at the workplace, so we allow for a much richer definition of skill by dividing workers not only according to the qualifications they hold, but also their age. Third, we allow for the fact that there may be an asymmetry in wage setting, so that wages are set according to the state of a "leading sector" in the economy, namely the labour market for skilled adult workers, and examine the extent to which our results are affected by this alternative assumption.

3.1 DEFINING THE TECHNOLOGY

To fix ideas, we assume that output Y is produced via a Constant Elasticity of Substitution production function in each of the separate skill inputs N_i as follows:

$$Y = A\left(\sum_i \alpha_i N_i^{\rho}\right)^{1/\rho} \qquad [3.1]$$

where for the sake of simple exposition we have chosen to illustrate the model hereafter with only four inputs[22], and where the coefficient A captures technological progress and we assume that the sum of the α 's is equal to one. The elasticity of substitution between different skill inputs in our production function is of course defined as :

$$\sigma = \frac{1}{1-\rho} \qquad [3.2]$$

A richer analysis might allow for the fact that the elasticity of substitution might vary between these different inputs so that, for example, individuals with the same level of educational attainment but from different age groups may be more substitutable in production, than those with different levels of educational attainment but who are from the same age group. This approach is most easily accomplished by way of a multi-level production process, as used by, for example Card and Lemieux (2001). This approach pioneered by, among others, Sato (1967) assumes a production function which has *n* primary inputs (classified by, say, qualification groups) each of which can then be subdivided into secondary inputs (classified by, say, age). The drawback to this approach is that obtaining tractable mismatch indices from such production functions is extremely complicated[23]. We therefore make the simplifying assumption that all inputs in the production process share the same constant elasticity of production, and proceed with the production function described in [3.1].

[22] It is straightforward to generalise our framework to a scenario with more inputs, as we will go on to do in the Section 4.

[23] Given such a production function, the elasticity of substitution between factors from different primary input groups may well then vary with the relative shares in production of those inputs, which given the mismatch measure we employ will considerably complicate the analysis. For example, in the case of a two-level C.E.S. production function (i.e. where the elasticity of substitution between different primary inputs is constant, and where there is a different constant elasticity of substitution between secondary inputs in each of the primary input group) then the elasticity of substitution between secondary inputs which are members of different primary input groups is defined as a harmonic mean of the inter- and intra- elasticities of substitution (Sato (1967)).

Now if we assume competitive factor markets, then it can be shown[24] that the wage of a given skill input w_i is given by its marginal product:

$$w_i = \alpha_i . A^{\sigma - 1/\sigma} . \left(\frac{Y}{N_i} \right)^{1/\sigma} \qquad [3.3]$$

where [3.3] can be thought of as a standard labour demand function for skill input i, so that (as we would expect) the wage of a particular group will rise given either a positive shift in demand in favour of that group – which we argue below is captured by α_i – or an increase in total factor productivity. Leaving shifts in demand and technology aside, we then have that a group's wage is a function of its average product. From the law of diminishing returns, as a group is used more intensively in production, its marginal product – and hence, its average product – falls, and therefore so does its wage (of course this result follows automatically from our assumption that the groups' wages are set equal to their respective marginal products). Conversely, an increase in the employment of the other factors of production raises output, and therefore, indirectly, the group's average product, and thus its wage. Therefore, as we shall see later, where the labour force is unchanged both in size and composition, then a rise in the unemployment rate of all other factors of production will lead to a fall in output, a fall in the productivity of the remaining factor, and therefore a fall in their wage too. Furthermore, the lower the value of the elasticity of substitution between different skill inputs in production, the stronger these effects from the average product of the input onto its wage become.

3.2 DEFINING THE MISMATCH INDEX

Now, rearranging equation [3.3] we have that :

[24] See Appendix 3 for a comprehensive derivation of all expressions used in this section.

$$\alpha_i = w_i . A^{1-\sigma/\sigma} . \left(\frac{N_i}{Y}\right)^{\sigma} \qquad [3.4]$$

so that the term α_i is defined as the wage bill share of group i adjusted for the elasticity of substitution between the different labour inputs, and can therefore be thought of as an ideal measure of the demand for the i^{th} input (Burriel-Llombart and Thomas (2001)). The supply of an input is of course given by its share of the labour force l_i(or L_i/L). However, following Nickell and Bell (1996) we adjust relative supply by the elasticity of substitution to reflect the ease with which firms can switch between available inputs in production; so for example, if the separate inputs are near perfect substitutes then the supply of a particular input will become increasingly irrelevant to the firm. We can therefore construct an absolute measure of the mismatch between the demand for and the supply of skill input i, written below in terms of logarithms:

$$\ln M_i = \ln \alpha_i - \frac{1}{\sigma} \ln l_i \qquad [3.5]$$

However, as Jackman et. al. (1999) argue, such an absolute measure of mismatch may prove misleading since it makes no reference to developments in the markets for other skills. It is possible that using such measures we might find that demand has grown faster than supply for *all* skill groups if there has been (net) skill neutral shift in demand. We are interested here in whether there has been any discernible net shift in demand in favour of a given (set of) skills, at the expense of others – in short whether the relative demand and supply of the different skills has become increasingly mismatched over the period. We therefore require a definition of mismatch which compares the evolution of demand and supply *across* skill groups; we define the level of relative mismatch between the demand and supply of inputs i and j as :

$$MM_{ij} = \frac{M_i}{M_j} = \frac{\alpha_i/\alpha_j}{\left(l_i/l_j\right)^{1/\sigma}} \qquad [3.6]$$

or expanding our index we have that :

$$MM_{ij} = \frac{w_i/w_j.(N_i/N_j)^{1/\sigma}}{(l_i/l_j)^{1/\sigma}} = \frac{w_i}{w_j}\left(\frac{1-u_i}{1-u_j}\right)^{1/\sigma} \qquad [3.7]$$

Within this framework, (skill-) neutral shifts in relative demand and supply are assumed to imply no resultant pressure on relative wages or unemployment rates (Jackman et. al. (1999)). Of course, our mismatch index is such that the degree of mismatch between inputs i and j is equal to the reciprocal of the mismatch between j and i. Alternatively written in logarithmic form, our index then shares the appealing feature of Manacorda and Petrongolo's index – that the log of the mismatch between the demand and supply of skill-group i relative to that for skill-group j is of opposite sign but equal in absolute value to the log of mismatch between the demand and supply of skill-group j relative to that for skill-group i.

When the number of separate skill inputs in the production function [3.1] becomes large we are left with a huge number of separate mismatch indices between each pair of inputs. In order to clarify the underlying trends in the supply of, and demand for each of these inputs we select a fixed reference skill group against which we compare the relative demand and supply of the remaining n –1 skill inputs[25]. We shall follow the convention in the literature by defining as our reference group j the least skilled group in the labour force.

[25] Of course, given these n - 1 mismatch indices it is straightforward to calculate the level of mismatch between any pair of inputs k and i given a reference group j, using the following rule:

3.3 Writing Labour Demand in terms of the level of Mismatch

In logarithmic form, we can express the labour demand curve for, say, the 1st skill input [3.2] as[26] :

$$\ln w_1 = \ln\alpha_1 + \ln A - (1-\rho)\ln N_1 +$$

$$\frac{(1-\rho)}{\rho}\ln\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}\right) \qquad [3.8]$$

which we can expand and rearrange to give:

$$\ln w_1 = \ln\alpha_1 + \ln A - (1-\rho)(1-\alpha_1)\ln(1-u_1) + (1-\rho).\alpha_2.\ln(1-u_2) +$$

$$(1-\rho).\alpha_3.\ln(1-u_3) + (1-\rho).\alpha_4.\ln(1-u_4) +$$

$$(1-\rho).\alpha_2.\ln\frac{l_2}{l_1} + (1-\rho).\alpha_3.\ln\frac{l_3}{l_1} + (1-\rho).\alpha_4.\ln\frac{l_4}{l_1} +$$

$$\frac{(1-\rho)}{\rho}\ln\left(\frac{\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}}{\left(N_1^{\alpha_1} N_2^{\alpha_2} N_3^{\alpha_3} N_4^{\alpha_4}\right)^{\rho}}\right) \qquad [3.9]$$

Then the total differential of the labour demand curve for the 1st input can be defined as :

$$d\ln w_1 = d\ln\alpha_1 + d\ln A - (1-\rho)(1-\alpha_1)d\ln(1-u_1) +$$

$$MM_{ki} = \frac{\alpha_k/\alpha_i}{(l_k/l_i)^{1/\sigma}} = \frac{\alpha_k/\alpha_j}{(l_k/l_j)^{1/\sigma}} \Big/ \frac{\alpha_i/\alpha_j}{(l_i/l_j)^{1/\sigma}} = \frac{MM_{kj}}{MM_{ij}}$$

[26] In order to simplify the exposition of our model we shall write our expressions in terms of ρ as opposed to the elasticity of substitution itself, although of course, we can always rewrite in terms of σ using [3.2].

$$(1-\rho).\alpha_2.d\ln(1-u_2)+(1-\rho).\alpha_3.d\ln(1-u_3)+$$

$$(1-\rho).\alpha_4.d\ln(1-u_4)+(1-\rho).\ln(1-u_1).d\alpha_1+$$

$$(1-\rho).\ln(1-u_2).d\alpha_2+(1-\rho).\ln(1-u_3).d\alpha_3+$$

$$(1-\rho).\ln(1-u_4).d\alpha_4+(1-\rho).\alpha_2.\ln\frac{l_2}{l_1}+(1-\rho).\alpha_3.\ln\frac{l_3}{l_1}+$$
$$(1-\rho).\alpha_4.\ln\frac{l_4}{l_1}+\frac{(1-\rho)}{\rho}d\ln\left(\frac{\Sigma}{\Pi}\right) \qquad [3.10]$$

where we denote:

$$\Sigma = \alpha_1 N_1^{\rho}+\alpha_2 N_2^{\rho}+\alpha_3 N_3^{\rho}+\alpha_4 N_4^{\rho} \qquad [3.11]$$

$$\Pi = \left(N_1^{\alpha_1}N_2^{\alpha_2}N_3^{\alpha_3}N_4^{\alpha_4}\right)^{\rho} \qquad [3.12]$$

From [3.10] if we compare the relative demand for the i[th] and j[th] inputs in total differentiated form we have (for small values of u_i and u_j):

$$d\ln w_i - d\ln w_j \approx d\ln MM_{ij}+\frac{1}{\sigma}\left(du_i-du_j\right) \qquad [3.13]$$

so that, a net demand shift in favour of the i[th] input relative to the j[th] input will, to a first approximation, result in either an increase in i[th]'s group relative wage, or an increase in the difference between their unemployment rates, or both[27].

[27] In practice, the consequences of a net relative demand shift are determined by the functional form of the wage setting curve, which closes the model (Manacorda and Petrongolo (1999)).

In order to quantify the effect of changes in the relative mismatch between the demand and supply of the separate skill inputs on the aggregate unemployment rate we need to specify the nature of the wage setting function. As we discussed in Section 1, a change in the extent of mismatch has the potential to affect the aggregate unemployment rate in two scenarios: where the wage setting function is convex, or where wage setting is asymmetric (i.e. there exists a leading sector which determines wage setting behaviour throughout the labour market). We take each of these scenarios in turn.

3.4 THE SUPPLY SIDE : CONVEX WAGE SETTING

Taking the standard[28] double logarithmic wage function, (the log of) a group's wages is a linear function of (the log of) their unemployment rate, so that the change in the wage caused by an increase in the unemployment rate of a group falls as their unemployment rate increases. In other words we have:

$$\ln w_i = z_i - \gamma \ln u_i \qquad [3.14]$$

where the term z_i captures exogenous wage pressure specific to the group, and γ is the absolute value of the elasticity of group's real wage with respect to its unemployment rate. We explicitly assume that the value of this elasticity is common across all skill inputs.

The convexity of this double log wage setting function implies that when the (own group) unemployment rate is low, a fall in wages can be achieved through a relatively small rise in unemployment; conversely, when the (own group) unemployment rate is already high, a fall in wages can only be bought at the heavy price of large increases in the unemployment rate. Therefore we might expect a skill biased shift in demand to increase the unemployment rate at the aggregate level since the required fall in the wage of the unskilled may result in large increases in unskilled unemployment while there is only a

[28] See, for example, Layard et. al. (1991).

small counterbalancing fall in the skilled unemployment rate. This is one mechanism through which skill biased shifts in demand can lead to rising aggregate unemployment.

So for the first group, the wage setting function in totally differentiated form is:

$$d\ln w_1 = dz_1 - \frac{\gamma}{u_1}du_1 \qquad [3.15]$$

Substituting [3.10] into [3.15] we have, after rearranging terms, that :

$$\left(\frac{\Phi_1}{(1-u_1).\Sigma}+\frac{\gamma}{u_1}\right)du_1 - \left(\frac{(1-\rho).\alpha_2.l_2{}^{\rho}.(1-u_2)^{\rho}}{(1-u_2).\Sigma}\right)du_2 -$$

$$\left(\frac{(1-\rho).\alpha_3.l_3{}^{\rho}.(1-u_3)^{\rho}}{(1-u_3).\Sigma}\right)du_3 - \left(\frac{(1-\rho).\alpha_4.l_4{}^{\rho}.(1-u_4)^{\rho}}{(1-u_4).\Sigma}\right)du_4 =$$

$$dz_1 - d\ln A + \alpha_2.d\ln MM_{21} + \alpha_3.d\ln MM_{31} + \alpha_4.d\ln MM_{41} -$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1{}^{\rho}.d\alpha_1 + N_2{}^{\rho}.d\alpha_2 + N_3{}^{\rho}.d\alpha_3 + N_4{}^{\rho}.d\alpha_4\right)+$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1{}^{\rho}.d\alpha_1 + N_2{}^{\rho}.d\alpha_2 + N_3{}^{\rho}.d\alpha_3 + N_4{}^{\rho}.d\alpha_4\right)+$$

$$\frac{(1-\rho)}{\Sigma}\left(\left(\frac{\alpha_1\left(\Sigma-(1-u_1)^{\rho}.l_1{}^{\rho}\right)}{l_1}\right).dl_1 + \left(\frac{\alpha_2\left(\Sigma-(1-u_2)^{\rho}.l_2{}^{\rho}\right)}{l_2}\right).dl_2 +\right.$$

$$\left(\left(\frac{\alpha_3\left(\Sigma-(1-u_3)^{\rho}.l_3^{\rho}\right)}{l_3}\right).dl_3+\left(\frac{\alpha_4\left(\Sigma-(1-u_4)^{\rho}.l_4^{\rho}\right)}{l_4}\right).dl_4\right) \qquad [3.16]$$

where we denote :

$$\Phi_1=(1-\rho).\left(\Sigma-\alpha_1.l_1^{\rho}.(1-u_1)^{\rho}\right) \qquad [3.17]$$

and:

$$d\ln MM_{j1}=d\ln\frac{\alpha_j}{\alpha_1}-(1-\rho).d\ln\frac{l_j}{l_1} \qquad \forall\, j \qquad [3.18]$$

It can be shown that a similar expression can be derived for the second input of the form :

$$-\left(\frac{(1-\rho).\alpha_1.l_1^{\rho}.(1-u_1)^{\rho}}{(1-u_1).\Sigma}\right)du_1+\left(\frac{\Phi_2}{(1-u_2).\Sigma}+\frac{\gamma}{u_2}\right)du_2-$$

$$\left(\frac{(1-\rho).\alpha_3.l_3^{\rho}.(1-u_3)^{\rho}}{(1-u_3).\Sigma}\right)du_3-\left(\frac{(1-\rho).\alpha_4.l_4^{\rho}.(1-u_4)^{\rho}}{(1-u_4).\Sigma}\right)du_4=$$

$$dz_2-d\ln A+(\alpha_2-1).d\ln MM_{21}+\alpha_3.d\ln MM_{31}+\alpha_4.d\ln MM_{41}-$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1^{\rho}.d\alpha_1+N_2^{\rho}.d\alpha_2+N_3^{\rho}.d\alpha_3+N_4^{\rho}.d\alpha_4\right)+$$

$$\frac{(1-\rho)}{\Sigma}\left(\left(\frac{\alpha_1\left(\Sigma-(1-u_1)^{\rho}.l_1^{\rho}\right)}{l_1}\right).dl_1+\left(\frac{\alpha_2\left(\Sigma-(1-u_2)^{\rho}.l_2^{\rho}\right)}{l_2}\right).dl_2+\right.$$

$$\left(\frac{\alpha_3\left(\Sigma-(1-u_3)^\rho.l_3^{\ \rho}\right)}{l_3}\right).dl_3+\left(\frac{\alpha_4\left(\Sigma-(1-u_4)^\rho.l_4^{\ \rho}\right)}{l_4}\right).dl_4\Bigg) \qquad [3.19]$$

where :

$$\Phi_2=(1-\rho).\left(\Sigma-\alpha_2.l_2^{\ \rho}.(1-u_2)^\rho\right) \qquad [3.20]$$

In essence then we have a system of equations – one for each of the separate skill inputs to the production function – which may be written in matrix notation as follows:

$$\Theta.\begin{pmatrix} du_1 \\ du_2 \\ du_3 \\ du_4 \end{pmatrix}=\begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix}-\begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}d\ln A-\begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}\Psi+$$

$$\begin{pmatrix} \alpha_2 \\ \alpha_2-1 \\ \alpha_2 \\ \alpha_2 \end{pmatrix}.d\ln MM_{21}+\begin{pmatrix} \alpha_3 \\ \alpha_3 \\ \alpha_3-1 \\ \alpha_3 \end{pmatrix}.d\ln MM_{31}+\begin{pmatrix} \alpha_4 \\ \alpha_4 \\ \alpha_4 \\ \alpha_4-1 \end{pmatrix}.d\ln MM_{41} \qquad [3.21]$$

Where we define :

$$\Theta = \begin{pmatrix} \frac{\Phi_1}{(1-u_1)\Sigma}+\frac{\gamma}{u_1} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{-\lambda_4}{(1-u_4)\Sigma} \\ \frac{-\lambda_1}{(1-u_1)\Sigma} & \frac{\Phi_2}{(1-u_2)\Sigma}+\frac{\gamma}{u_2} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{-\lambda_4}{(1-u_4)\Sigma} \\ \frac{-\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{\Phi_3}{(1-u_3)\Sigma}+\frac{\gamma}{u_3} & \frac{-\lambda_4}{(1-u_4)\Sigma} \\ \frac{-\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\Phi_4}{(1-u_4)\Sigma}+\frac{\gamma}{u_4} \end{pmatrix} \qquad [3.22]$$

such that :

$$\lambda_i = (1-\rho).\alpha_i.l_i^{\rho}.(1-u_i)^{\rho} \qquad [3.23]$$

and :

$$\Psi = \frac{(1-\rho)}{\rho.\Sigma}\left(N_1^{\rho}.d\alpha_1 + N_2^{\rho}.d\alpha_2 + N_3^{\rho}.d\alpha_3 + N_4^{\rho}.d\alpha_4\right) +$$

$$\frac{(1-\rho)}{\Sigma}\left(\left(\frac{\alpha_1\left(\Sigma-(1-u_1)^{\rho}.l_1^{\rho}\right)}{l_1}\right).dl_1 + \left(\frac{\alpha_2\left(\Sigma-(1-u_2)^{\rho}.l_2^{\rho}\right)}{l_2}\right).dl_2 +\right.$$

$$\left.\left(\frac{\alpha_3\left(\Sigma-(1-u_3)^{\rho}.l_3^{\rho}\right)}{l_3}\right).dl_3 + \left(\frac{\alpha_4\left(\Sigma-(1-u_4)^{\rho}.l_4^{\rho}\right)}{l_4}\right).dl_4\right) \qquad [3.24]$$

Now if we assume that the matrix Θ is nonsingular, we can rewrite [3.21] as :

$$\begin{pmatrix} du_1 \\ du_2 \\ du_3 \\ du_4 \end{pmatrix} = \Theta^{-1}\begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix} - \Theta^{-1}\begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} d\ln A - \Theta^{-1}\begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix}\Psi +$$

$$\Theta^{-1}\begin{pmatrix}\alpha_2\\ \alpha_2-1\\ \alpha_2\\ \alpha_2\end{pmatrix}.d\ln MM_{21}+\Theta^{-1}\begin{pmatrix}\alpha_3\\ \alpha_3\\ \alpha_3-1\\ \alpha_3\end{pmatrix}.d\ln MM_{31}+\Theta^{-1}\begin{pmatrix}\alpha_4\\ \alpha_4\\ \alpha_4\\ \alpha_4-1\end{pmatrix}.d\ln MM_{41} \quad [3.25]$$

We know that the aggregate unemployment rate u is a weighted average of the unemployment rates of the separate labour inputs, so we have that

$$du = l_1.du_1 + l_2.du_2 + l_3.du_3 + l_4.du_4 +$$

$$dl_1.u_1 + dl_2.u_2 + dl_3.u_3 + dl_4.u_4 \quad [3.26]$$

Therefore, if we define the matrix Ξ as :

$$\Xi = \begin{pmatrix} l_1 & l_2 & l_3 & l_4\end{pmatrix}.\Theta^{-1} \quad [3.27]$$

Then, finally, we have that the change in the aggregate unemployment rate can be expressed as follows :

$$du = \Xi.\begin{pmatrix}dz_1\\ dz_2\\ dz_3\\ dz_4\end{pmatrix} - \Xi.\begin{pmatrix}1\\1\\1\\1\end{pmatrix}d\ln A - \Xi.\begin{pmatrix}1\\1\\1\\1\end{pmatrix}\Psi + \Xi.\begin{pmatrix}\alpha_2\\ \alpha_2-1\\ \alpha_2\\ \alpha_2\end{pmatrix}.d\ln MM_{21} + \Xi.\begin{pmatrix}\alpha_3\\ \alpha_3\\ \alpha_3-1\\ \alpha_3\end{pmatrix}.d\ln MM_{31} +$$

$$\Xi.\begin{pmatrix}\alpha_4\\ \alpha_4\\ \alpha_4\\ \alpha_4-1\end{pmatrix}.d\ln MM_{41} + \begin{pmatrix}u_1 & u_2 & u_3 & u_4\end{pmatrix}\begin{pmatrix}dl_1\\ dl_2\\ dl_3\\ dl_4\end{pmatrix} \quad [3.28]$$

We can thus identify three potential sources of pressure on the aggregate unemployment rate within our model. The first is an increase in 'wage push', a nebulous term which in this framework is interpreted as any growth in wage pressure, captured by dz_i, over and above that implied by the increase in T.F.P. and the impact on total output (and therefore indirectly on the marginal product and hence wage of each group) of a shift in the productivity of any factor. This latter point can be best illustrated in the case of the Cobb Douglas production function, since using L'Hôpital's rule it can be shown that:

$$\lim_{\rho = 0} \Psi = \ln\frac{N_2}{N_1}.d\alpha_2 + \ln\frac{N_3}{N_1}.d\alpha_3 + \ln\frac{N_4}{N_1}.d\alpha_4 \qquad [3.29]$$

The second cause can be thought of as the *pure* demographic component of the change in the unemployment rate – i.e. that part of the change caused directly by a change in the composition of the labour force between skill groups with different group specific unemployment rates – captured by the final term in [3.28]. The third and final source of pressure on the unemployment rate within our model is the impact of net shifts in the relative demand for skills, which will be captured here by the mismatch terms.

3.5 THE SUPPLY SIDE RECONSIDERED : ASYMMETRIC WAGE SETTING

We now assume that all wages in the economy are set subject to conditions in a leading sector, so that in all other sectors of the economy "excess" unemployment (i.e. any unemployment over and above that in the leading sector) is inefficient since it exerts no downward pressure on wages. In the context of our model where skill groups are defined both in terms of age and educational attainment, asymmetric wage setting requires that wages in the economy must be set according to conditions in, say, the market for middle-aged graduates[29]. So, if we denote the fourth sector as the leading sector in our stylised economy, then [3.14] becomes:

[29] The analysis in this section hinges on this assumption. While it might be reasonable to argue that in a world of only four skill groups (adults and youths, with or without an A Level or above) more educated

$$\ln w_i = z_i - \gamma \ln u_4 \qquad [3.30]$$

Although wages in the leading sector are still set according to a convex wage setting function so that wages respond more to the unemployment rate in the leading sector when that unemployment rate is low, wages elsewhere in the economy are completely unresponsive to the particular conditions that prevail in their respective sub-sections of the labour market. For all other skill inputs in the production function, equilibrium is now determined by the intersection of their labour demand curve and a wage setting function which is horizontal in (log) wage – (log) employment space; in fact, the precise position of each of these skill specific wage setting functions is defined by the level of exogenous wage pressure and conditions in the leading sector.

Now consider the impact of a skill biased shift in demand – towards the leading skill group. Absent any change in wage pressure, a fall in unemployment in the leading sector will cause wages to rise both in the leading sector itself and elsewhere in the economy too and thus employment to fall in the remaining sectors of the labour market. However, a fall in the employment of all the other factors of production will lead to a fall in the marginal product of the leading skill group, causing its wage and employment to fall back. In fact, for the leading sector these two forces exactly cancel out[30] so that a shift in demand in favour of the leading sector actually has no effect on either the wage or the employment of that group. However, the other skill groups in the economy are disadvantaged by this shift in demand suffering higher unemployment rates as a result. Therefore, within such a model of asymmetric wage setting, skill biased shifts in demand once again have the potential to affect the aggregate unemployment rate.

We can express [3.30] in total differentiated form as:

adults play a key role in setting wages, in the case of the finer decompositions of the labour force into up to 16 different skill groups our assumption appears more tenuous.

[30] This result can be verified from the solution of [3.32] which first requires the inversion of the matrix Ω.

$$d \ln w_i = dz_i - \frac{\gamma}{u_4} du_4 \qquad [3.31]$$

so that our set of equations is now of the form :

$$\Omega . \begin{pmatrix} du_1 \\ du_2 \\ du_3 \\ du_4 \end{pmatrix} = \begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} d \ln A - \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \Psi +$$

$$\begin{pmatrix} \alpha_2 \\ \alpha_2 - 1 \\ \alpha_2 \\ \alpha_2 \end{pmatrix} . d \ln MM_{21} + \begin{pmatrix} \alpha_3 \\ \alpha_3 \\ \alpha_3 - 1 \\ \alpha_3 \end{pmatrix} . d \ln MM_{31} + \begin{pmatrix} \alpha_4 \\ \alpha_4 \\ \alpha_4 \\ \alpha_4 - 1 \end{pmatrix} . d \ln MM_{41} \qquad [3.32]$$

where we define the matrix Ω as:

$$\Omega = \begin{pmatrix} \frac{\Phi_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} - \frac{\lambda_4}{(1-u_4)\Sigma} \\ -\frac{\lambda_1}{(1-u_1)\Sigma} & \frac{\Phi_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} - \frac{\lambda_4}{(1-u_4)\Sigma} \\ -\frac{\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{\Phi_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} - \frac{\lambda_4}{(1-u_4)\Sigma} \\ -\frac{\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} + \frac{\Phi_4}{(1-u_4)\Sigma} \end{pmatrix} \qquad [3.33]$$

Once again if we assume that the matrix Ω is nonsingular, then if we define the matrix Γ as :

$$\Gamma = (l_1 \quad l_2 \quad l_3 \quad l_4) . \Omega^{-1} \qquad [3.34]$$

Then finally we have that :

$$du = \Gamma.\begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix} - \Gamma.\begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} d\ln A - \Gamma.\begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \Psi + \Gamma.\begin{pmatrix} \alpha_2 \\ \alpha_2 - 1 \\ \alpha_2 \\ \alpha_2 \end{pmatrix} .d\ln MM_{21} + \Gamma.\begin{pmatrix} \alpha_3 \\ \alpha_3 \\ \alpha_3 - 1 \\ \alpha_3 \end{pmatrix} .d\ln MM_{31} +$$

$$\Gamma.\begin{pmatrix} \alpha_4 \\ \alpha_4 \\ \alpha_4 \\ \alpha_4 - 1 \end{pmatrix} .d\ln MM_{41} + \begin{pmatrix} u_1 & u_2 & u_3 & u_4 \end{pmatrix} \begin{pmatrix} dl_1 \\ dl_2 \\ dl_3 \\ dl_4 \end{pmatrix} \qquad [3.35]$$

Our framework thus enables us to establish the role that net shifts in demand towards the skilled played in the behaviour of the aggregate unemployment rate over recent times, given suitable values of our key parameters – namely : γ the (absolute value) of the elasticity of a group's real wage with respect to its unemployment rate and : σ the elasticity of substitution between the different skill inputs, and an assumption on the nature of wage setting in the economy. In the following section we quantify the effect of any change in the degree of skill mismatch in the labour market on the unemployment rate, using reasonable values of our two key parameters taken from the literature.

4. RESULTS

We proceed as follows: first we calculate the behaviour of the demand for and the supply of skills in the labour force over the period 1979-1996, which in turn enables us to directly quantify the change in skill mismatch over the period. We then estimate directly the effect of changes in the degree of skill mismatch on the aggregate unemployment rate, using the mean values of the variables of our model, under both the assumptions that wage setting is convex, or follows a leading sector.

4.1 PRELIMINARY RESULTS : THE GROWTH IN SKILL MISMATCH

We now turn to directly quantify the effect of any change in the degree of skill mismatch in the U.K. labour market between 1979 and 1996. In order to test how sensitive our results are to the particular form of the model we apply we calculate the impact of changes in the degree of skill mismatch in the economy using four alternative decompositions of the labour force. The first two are based purely on individuals' level of educational attainment, dividing the labour force into two and four groups respectively[31]. The final two decompositions divide each of the four qualification groups into two and four sub-groups according to the age of the individuals in that group (in the case of the former differentiating between youths – those under 25 years of age – and adults; and in the latter into the following categories: below 25, 25-34, 35-49 and 50 years and above). In the model presented in the previous sections it is apparent that it is the change in the level of the logarithm of our mismatch index that drives changes in the aggregate unemployment rate, so we shall therefore focus on the growth rate of mismatch over the period. Our results are detailed in Tables 4.4 – 4.15, where we denote each group in ascending order according to their level of educational attainment, and then by their age group; so for example, when we divide the labour force into sixteen skill groups, group 8 refers to those whose highest level of educational attainment falls in the category O Level or equivalent and who are aged 50 years and above.

It appears to be an incontrovertible fact that there has been a growth in the level of mismatch between the demand for and supply of skilled workers relative to the unskilled since 1979 in the U.K. labour force – as can be gauged for example from Table 4.4. However, it is the aim of this research to investigate whether this broad growth in skill mismatch at the aggregate level masks more complex behaviour at the disaggregate level. When we adopt a more comprehensive definition of the level of skill of a worker to include not only his level of educational attainment, but also his age (as a proxy for his experience at the workplace) it becomes apparent that the evolution of the demand and supply of these separate skills in the labour market has varied dramatically. Of course, the diverse behaviour of the relative supply of each of these groups should come as no great surprise given the large rise in educational attainment and the fluctuations in the age composition of the workforce which we detailed in Section 2. However, the shifts in the relative demand for skills has been equally varied across skill groups, and as a result the growth of mismatch has also varied widely across different skills (see for example Table 4.7). Even before we take any account of the age composition of the workforce we find that the annual growth rate of mismatch for individuals holding degrees relative to those with no O Levels (or its equivalent) has grown far faster than that between either those with A or O Levels and the most unqualified members of the workforce (see Table 4.5). Moreover, for individuals who share the same level of educational attainment but whose age differ we find that mismatch has grown to varying degrees over the period.

In the following figures and tables (Figures and Tables 4.1 – 4.3) we present the time-series behaviour and average annual growth rates of the relative demand, relative supply and mismatch in the UK economy when we use our most disaggregated decomposition of the workforce into sixteen separate skill groups. We assume an elasticity of substitution between skill inputs of one (i.e., technology is Cobb Douglas) so the demand for one skill input relative to another is given by the ratio of their wage bill shares, the supply of one input relative to another is given by the ratio of their labour force shares, and finally, the mismatch between them is given by the ratio of demand and supply. If one believed that controlling for changes in the age distribution of the workforce would add little to our understanding of the evolution of skill mismatch in the labour market then it ought to be the case that *within these qualification groups* the growth rates of skill mismatch should be to a first approximation equivalent. To test this hypothesis, when calculating relative demand, relative supply and mismatch we have chosen to use a separate reference group (the youngest age group) for each qualification group to isolate these differences. Of course, since we do not use a common reference group across each all the different qualification groups, our figures and tables do not illustrate the growth in mismatch

[31] The first decomposition follows Manacorda and Petrongolo (1999) and classifies individuals as either skilled or unskilled according to whether their highest level of educational attainment is an A Level (or its

between skill groups who belong to different qualification groups. Our results suggest that the evolution of the demand and supply for individuals within the same level of educational attainment does indeed vary according to their age. This is most evident amongst the least qualified members of the workforce where the growth rate of mismatch between those aged 50 and above and our reference group is more than 2.5 percentage points greater than that between those aged 25 to 34 and our reference group. For the most qualified members of the workforce, mismatch between the youngest and oldest graduates has declined while it has grown between 25 and 34 year olds and our reference group. In other words, as far as skill mismatch is concerned, the age distribution of the workforce matters.

The statement that skill mismatch has grown on average across the period is however somewhat misleading. If we focus on the profile of skill mismatch it appears that while mismatch grew throughout the first few years of the 1980's, thereafter any significant growth in skill mismatch is far harder to discern. For that reason we have calculated the rate of growth of mismatch over these two separate sub periods: 1979-1984 and 1985-1996, as well as over the period as a whole to illustrate this point. Our results confirm our suspicions – while skill mismatch grew at a rate of over 10 percent per year for some of our finer definitions of skill in the early 1980's, in the period that followed the growth in skill mismatch died on its feet, and in many cases mismatch fell back[32]. The fact that changes in the sample period appear to have such a significant impact on the magnitude and even direction of the growth in skill mismatch is of potential concern[33]. As a result, the estimated impact of the growth in skill mismatch on the aggregate unemployment rate is also highly dependent on the sample period chosen (as we shall go on to discuss).

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equivalent) or higher; the latter follows the more comprehensive classification given in Appendix 2.

[32] Of course, our choice of the dividing line between these two sub-periods is somewhat arbitrary, since several of our mismatch indices experienced uninterrupted growth beyond 1984; nevertheless, given that the majority of the mismatch indices fell in the years that followed 1984, and in certain instances did not return to their peak level in that year during the remainder of the period, we find our choice of dividing line as convincing as any other.

[33] It might be the case that this sensitivity of our estimates of the growth in skill mismatch to the sample period reflects the fact that, as with the 'outcomes' measures described above, we are not completely stripping out the effect of the cycle.

FIGURE 4.1: RELATIVE DEMAND FOR SKILLS ASSUMING COBB-DOUGLAS TECHNOLOGY : 1979-1996

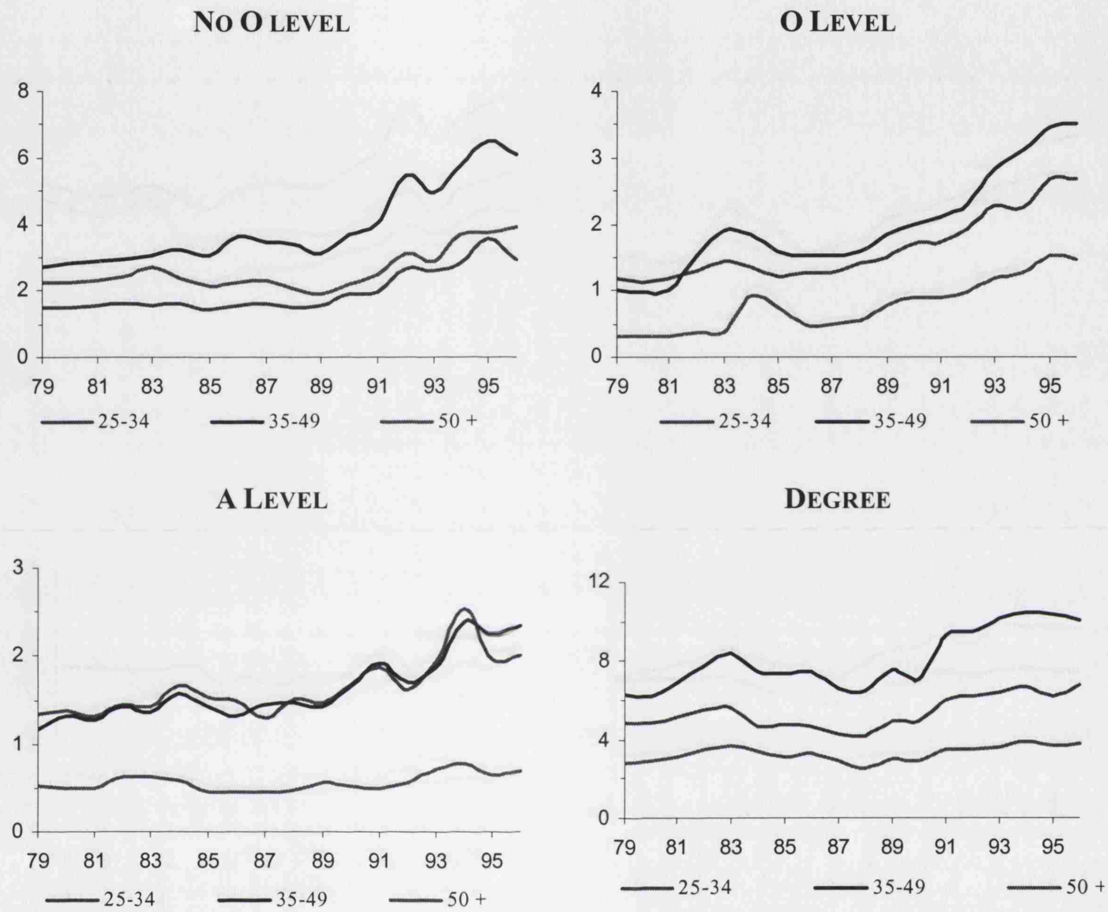

TABLE 4.1 : THE AVERAGE ANNUAL GROWTH RATE OF RELATIVE DEMAND (%)

Age Group	No O level	O level	A level	Degree
25-34	4.60	5.29	3.31	2.42
35-49	5.49	8.54	4.73	3.31
50 +	3.99	13.16	2.54	2.22

FIGURE 4.2 : RELATIVE SUPPLY OF SKILLS ASSUMING COBB-DOUGLAS TECHNOLOGY : 1979-1996

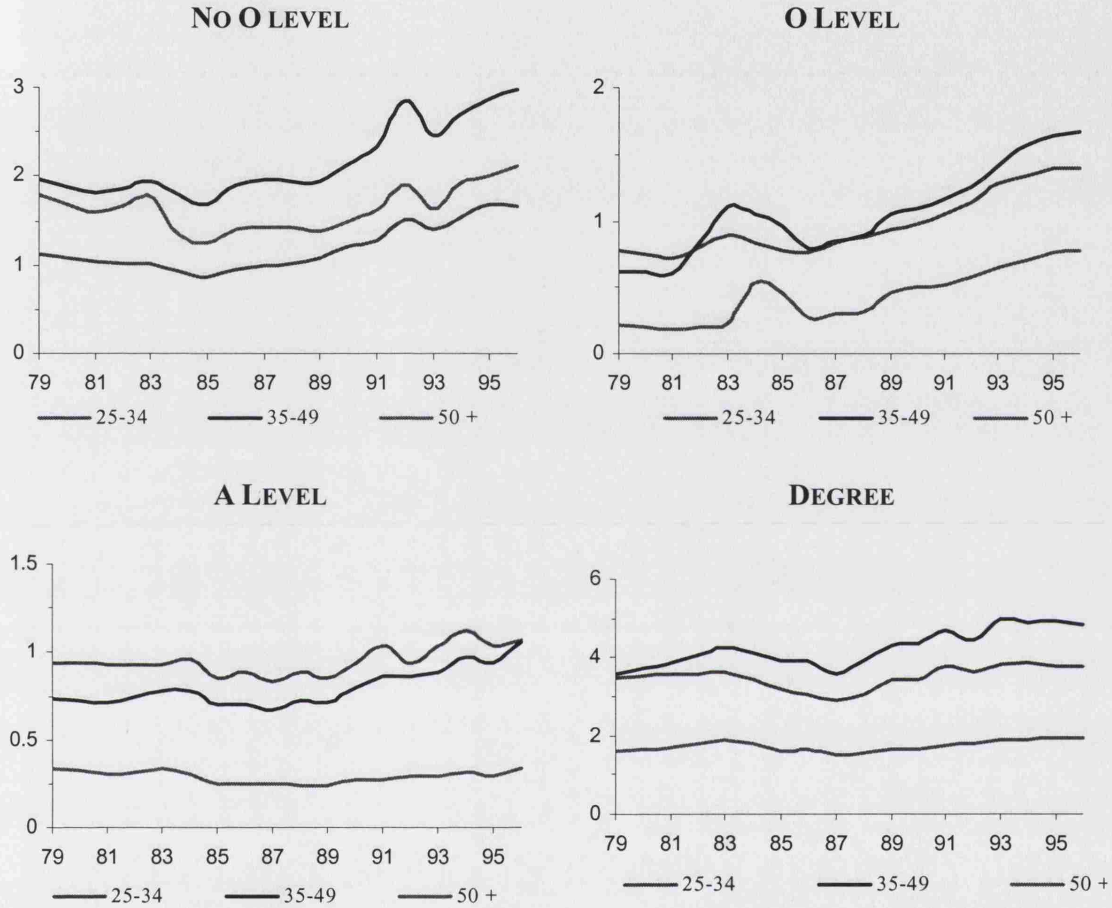

TABLE 4.2 : THE AVERAGE ANNUAL GROWTH RATE OF RELATIVE SUPPLY (%)

Age Group	No O level	O level	A level	Degree
25-34	2.54	3.72	0.95	0.57
35-49	2.85	6.76	2.36	1.90
50 +	1.53	11.99	0.17	1.17

FIGURE 4.3 : THE DEGREE OF MISMATCH OF SKILLS ASSUMING COBB-DOUGLAS TECHNOLOGY : 1979-1996

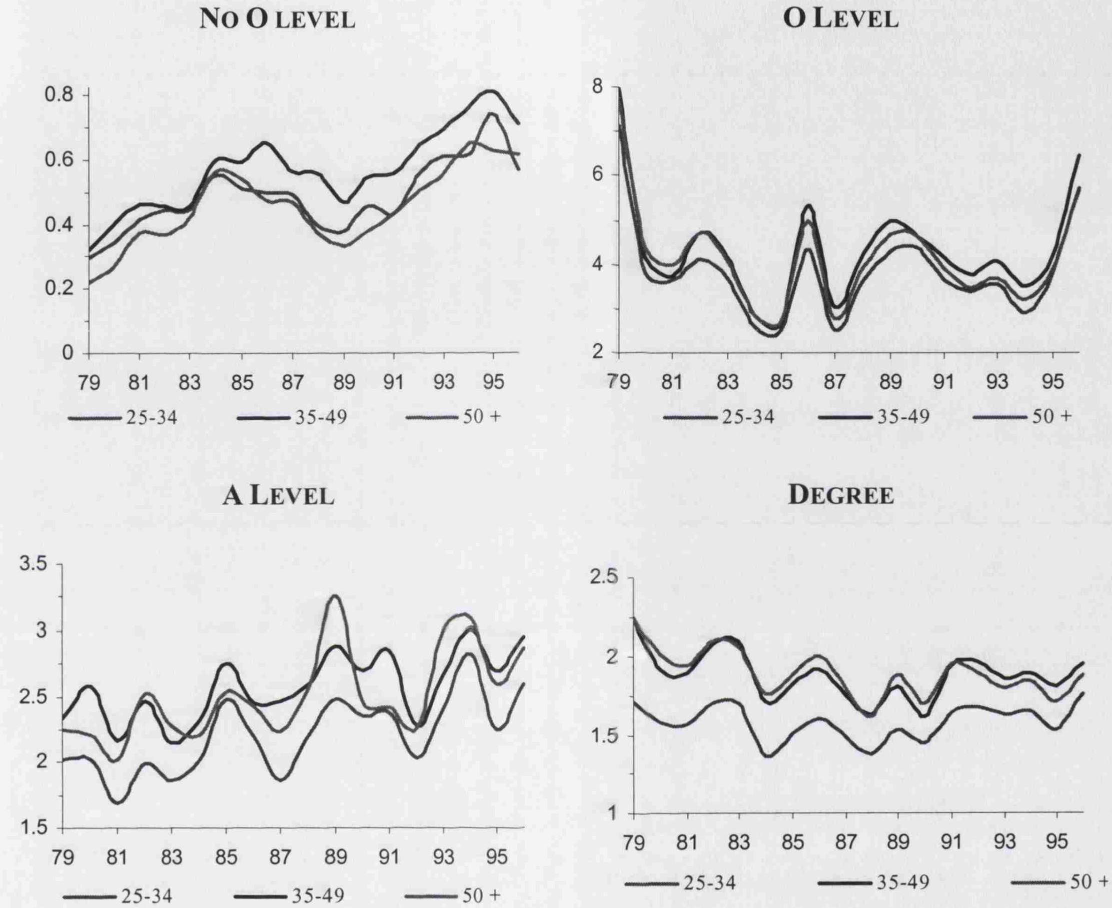

TABLE 4.3 : THE AVERAGE ANNUAL GROWTH RATE OF MISMATCH (%)

Age Group	No O level	O level	A level	Degree
25-34	4.95	3.44	2.50	0.59
35-49	5.59	4.20	2.16	-0.31
50 +	7.51	2.94	2.60	-0.58

It is tempting to attribute this decline in the rate of growth, and in some instances, the level, of skill mismatch to benign supply shocks generated by expansion of further and higher education and the 'baby bust', which together reduced the proportion of the labour force who were both unqualified and young. However, it is not quite that simple – any story of the evolution of mismatch is incomplete without a reference to both the behaviour of supply *and* demand. It also appears that a fall in the rate of growth of the relative demand for skills may also have played some part in reducing the rate of growth of skill mismatch through the late 1980's and into the 1990's. Of course, these two periods refer to very different labour markets: in the early 1980's the U.K. labour market suffered a deep slump and the unemployment rate rose sharply, but from the mid- to late 1980's onwards the trend at least in the unemployment rate was downwards, and the fall in the rate of growth of the relative demand for skills might reflect this to some extent. Nevertheless, it does appear that the growth in educational attainment and the aftershock of the collapse in the birth rate in the 1970's on the age composition of the labour force together restrained the growth in skill mismatch into the 1990's.

Of course, there is one other supply shock that might have had a similar effect on the relative supply of skilled labour – and that is the well documented growth in economic inactivity[34]. To the extent that the rise in inactivity has been concentrated amongst the least skilled members of the workforce then this will have also contributed to a fall in the share of the workforce who have little or no qualifications, and will therefore reduce the level of mismatch, *ceteris paribus*. However, exits out of the labour force were not solely restricted to the young nor even the unskilled. For example, the rise in 'early retirement' documented by Disney (1999) encompassed both voluntary exits among typically skilled members of the workforce who had amassed sufficient wealth to support themselves in retirement and quasi-involuntary exits by those typically unskilled members of the labour force who were unemployed and who realistically faced little prospect of future unemployment. Nonetheless, to the extent that the unskilled bore the brunt of the rise in inactivity, this phenomenon can be thought of a beneficial supply shock, at least as far the level of mismatch is concerned.

[34] For a detailed analysis of this phenomenon see Gregg and Wadsworth (1999).

Burriel-Llombart and Thomas (2000) take a different approach to this issue of inactivity distinguishing instead between the employed and the non-employed, and thereby including the inactive within analysis, treating them explicitly as equivalent to the unemployed. In some respects, given that we know that there are significant flows between inactivity and employment, this treatment makes a good deal of sense; however since our focus is on explaining the observed behaviour of the aggregate unemployment rate it does not seem appropriate here.

[i] Average Annual Growth Rates for the Relative Demand and Relative Supply of Skills and the level of Skill Mismatch: 1979-1996

Table 4.4 2 Skill Groups

Measure	Relative Demand			Relative Supply			Mismatch		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	11.7	5.8	3.1	11.0	5.3	2.6	0.7	0.6	0.5

Table 4.5 4 Skill Groups

Measure	Relative Demand			Relative Supply			Mismatch		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	22.3	9.8	4.6	21.5	9.4	4.4	0.2	0.1	0.1
MM_{31}	19.0	8.5	4.0	18.5	8.4	4.0	0.2	0.1	0.0
MM_{41}	21.3	10.3	5.4	19.5	9.0	4.3	1.4	1.1	0.9

Table 4.6 8 Skill Groups

Measure	Relative Demand			Relative Supply			Mismatch		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	8.5	4.7	3.1	5.4	2.3	1.0	3.0	2.4	2.1
MM_{31}	17.5	8.0	3.9	16.0	7.1	3.4	1.1	0.7	0.5
MM_{41}	35.4	15.9	8.1	31.9	13.5	6.2	2.8	2.1	1.8
MM_{51}	23.4	10.3	4.9	21.7	9.6	4.5	1.3	0.6	0.3
MM_{61}	29.2	13.9	7.5	25.0	10.9	5.1	3.4	2.6	2.2
MM_{71}	27.3	12.8	6.9	24.0	10.4	4.8	2.9	2.3	2.1
MM_{81}	32.2	15.4	8.6	26.2	11.5	5.4	4.4	3.4	3.0

TABLE 4.7 16 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	8.4	4.6	3.0	5.7	2.5	1.2	2.3	1.9	1.7
MM_{31}	10.1	5.5	3.6	6.5	2.8	1.3	3.2	2.5	2.2
MM_{41}	7.5	4.0	2.8	4.2	1.5	0.6	3.4	2.6	2.2
MM_{51}	17.5	8.0	3.9	16.0	7.1	3.4	1.1	0.7	0.5
MM_{61}	28.4	13.3	7.0	25.4	11.1	5.2	2.8	2.1	1.7
MM_{71}	40.0	17.2	8.6	36.3	14.8	6.7	3.0	2.2	1.9
MM_{81}	66.4	23.5	10.5	60.1	20.3	8.4	2.5	1.8	1.5
MM_{91}	23.4	10.3	4.9	21.7	9.6	4.5	1.3	0.6	0.3
MM_{101}	27.9	13.3	7.1	23.3	10.3	4.9	3.2	2.4	2.0
MM_{111}	32.5	15.4	8.4	28.0	12.2	5.7	3.8	3.0	2.6
MM_{121}	27.0	12.6	7.0	23.7	9.9	4.5	3.6	2.8	2.5
MM_{131}	27.3	12.8	6.9	24.0	10.4	4.8	2.9	2.3	2.1
MM_{141}	31.1	15.0	8.5	24.7	10.8	5.0	4.7	3.7	3.2
MM_{151}	33.3	16.0	8.8	27.3	12.1	5.7	4.3	3.3	2.9
MM_{161}	32.2	14.9	8.1	27.2	11.6	5.4	3.9	3.0	2.6

[ii] AVERAGE ANNUAL GROWTH RATES FOR THE RELATIVE DEMAND AND RELATIVE SUPPLY OF SKILLS AND THE LEVEL OF SKILL MISMATCH: 1979-1984

TABLE 4.8 2 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	13.5	7.0	3.9	10.3	4.9	2.4	3.0	2.0	1.5

TABLE 4.9 4 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$
MM_{21}	45.6	20.8	10.5	42.2	18.7	8.8	2.4	1.8	1.5
MM_{31}	27.5	13.5	7.3	23.6	10.9	5.3	3.3	2.4	1.9
MM_{41}	28.1	14.1	7.9	22.1	10.2	4.9	5.2	3.6	2.9

Table 4.10 8 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$
MM_{21}	1.5	2.2	2.8	-6.6	-3.6	-1.9	9.2	6.3	4.9
MM_{31}	26.0	13.7	8.2	18.3	8.6	4.2	7.0	4.9	3.9
MM_{41}	56.8	26.3	14.2	45.2	19.1	8.8	10.1	6.8	5.2
MM_{51}	23.5	11.7	6.6	16.5	7.5	3.6	6.5	4.2	3.0
MM_{61}	31.1	16.9	10.8	17.7	7.9	3.7	12.8	8.9	7.0
MM_{71}	24.4	13.8	9.3	13.0	5.7	2.7	11.9	8.5	6.9
MM_{81}	31.5	16.7	10.6	17.5	7.5	3.5	13.2	9.1	7.1

TABLE 4.11 16 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	-1.5	0.9	2.3	-7.8	-4.0	-2.0	7.0	5.3	4.4
MM_{31}	4.8	3.8	3.4	-3.4	-1.8	-0.9	9.0	6.0	4.5
MM_{41}	0.3	1.3	2.5	-8.8	-5.1	-2.8	10.7	7.4	5.8
MM_{51}	26.0	13.7	8.2	18.3	8.6	4.2	7.0	4.9	3.9
MM_{61}	35.0	17.3	10.0	25.7	11.1	5.2	9.5	6.4	5.0
MM_{71}	71.9	30.4	15.5	59.6	23.3	10.4	10.1	6.6	5.0
MM_{81}	147.5	50.6	23.4	124.8	39.2	16.0	10.3	7.1	5.6
MM_{91}	23.5	11.7	6.6	16.5	7.5	3.6	6.5	4.2	3.0
MM_{101}	30.4	16.5	10.4	17.2	7.8	3.7	12.1	8.3	6.5
MM_{111}	33.8	18.5	11.9	20.1	8.9	4.2	13.8	9.8	7.9
MM_{121}	27.5	15.0	9.8	14.3	5.9	2.7	12.9	8.9	7.1
MM_{131}	24.4	13.8	9.3	13.0	5.7	2.7	11.9	8.5	6.9
MM_{141}	25.3	13.4	8.5	13.0	5.6	2.6	11.9	7.9	6.0
MM_{151}	35.1	18.1	11.2	20.4	8.8	4.1	13.3	9.1	7.1
MM_{161}	34.7	18.5	12.0	20.4	8.7	4.0	14.2	10.2	8.2

[iii] AVERAGE ANNUAL GROWTH RATES FOR THE RELATIVE DEMAND AND RELATIVE SUPPLY OF SKILLS AND THE LEVEL OF SKILL MISMATCH : 1985-1996

TABLE 4.12 2 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	11.0	5.4	2.7	11.3	5.4	2.7	-0.3	-0.1	0.1

TABLE 4.13 4 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	12.5	5.2	2.1	12.8	5.6	2.6	-0.6	-0.6	-0.5
MM_{31}	15.4	6.5	2.7	16.3	7.3	3.5	-1.1	-0.9	-0.9
MM_{41}	18.4	8.6	4.3	18.4	8.5	4.1	-0.2	0.0	0.1

TABLE 4.14 8 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	11.5	5.7	3.3	10.3	4.7	2.3	0.5	0.7	0.9
MM_{31}	14.0	5.6	2.1	15.1	6.5	3.0	-1.4	-1.1	-1.0
MM_{41}	26.4	11.5	5.6	26.3	11.1	5.1	-0.2	0.1	0.3
MM_{51}	23.3	9.8	4.2	23.9	10.5	4.9	-0.9	-0.8	-0.8
MM_{61}	28.4	12.6	6.1	28.0	12.2	5.7	-0.5	0.0	0.2
MM_{71}	28.5	12.4	5.9	28.6	12.3	5.7	-0.9	-0.3	0.0
MM_{81}	32.5	14.9	7.7	29.8	13.1	6.2	0.7	1.0	1.2

TABLE 4.15 16 SKILL GROUPS

MEASURE	RELATIVE DEMAND			RELATIVE SUPPLY			MISMATCH		
	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
MM_{21}	12.5	6.1	3.3	11.3	5.3	2.5	0.3	0.5	0.6
MM_{31}	12.3	6.2	3.7	10.6	4.8	2.3	0.8	1.1	1.3
MM_{41}	10.5	5.1	2.9	9.6	4.3	2.0	0.3	0.6	0.8
MM_{51}	14.0	5.6	2.1	15.1	6.5	3.0	-1.4	-1.1	-1.0
MM_{61}	25.6	11.6	5.7	25.2	11.1	5.2	0.0	0.2	0.4
MM_{71}	26.7	11.7	5.8	26.6	11.2	5.1	0.1	0.4	0.6
MM_{81}	32.6	12.2	5.1	33.2	12.4	5.2	-0.7	-0.4	-0.3
MM_{91}	23.3	9.8	4.2	23.9	10.5	4.9	-0.9	-0.8	-0.8
MM_{101}	26.8	11.9	5.8	25.9	11.3	5.3	-0.5	-0.1	0.2
MM_{111}	31.9	14.2	7.0	31.3	13.6	6.3	-0.3	0.2	0.4
MM_{121}	26.8	11.6	5.8	27.5	11.6	5.3	-0.3	0.3	0.6
MM_{131}	28.5	12.4	5.9	28.6	12.3	5.7	-0.9	-0.3	0.0
MM_{141}	33.5	15.7	8.5	29.6	12.9	6.1	1.7	1.9	2.1
MM_{151}	32.6	15.0	7.8	30.1	13.4	6.3	0.5	0.9	1.1
MM_{161}	31.2	13.4	6.5	30.0	12.9	6.0	-0.5	0.0	0.3

4.2 ESTIMATING THE IMPACT OF THE GROWTH OF MISMATCH ON THE UNEMPLOYMENT RATE

We now turn directly to estimate the effect of the growth in skill mismatch documented above on the aggregate unemployment rate over the period: 1979 – 1996. We follow the approach taken by Jackman et. al. (1999) and substitute the average values over the whole period of the variables that appear as coefficients in our model, and then calculate the total impact of skill mismatch on the average change in the aggregate unemployment rate over the entire period. In the case of asymmetric wage setting – i.e., where one leading sector determines wage setting throughout the economy as a whole – we select the skill group which enjoys the lowest average unemployment rate over the period for each of the decompositions we apply[35] as the leading sector of the model.

Before we can move to quantifying the part skill mismatch played in driving developments in the labour market over recent years, we first need to select reasonable values for our two key variables: the elasticity of substitution between the different skill inputs and the (absolute value) of the elasticity of a group's real wage with respect to its unemployment rate. We shall then proceed directly to simulating our stylised model of the economy given these parameter values.

4.2.1 ESTIMATING "σ" IN THE C.E.S. PRODUCTION FUNCTION.

Following Burriel-Llombart and Thomas (2001) we can rearrange [3.5] such that we have that the relative demand for the second, third and fourth inputs can be written :

$$\left(\frac{N_k}{N_1}\right)^{1/\sigma} = \frac{w_1}{w_k}.\frac{\alpha_k}{\alpha_1} \qquad \forall k \neq 1 \qquad [4.1]$$

and therefore we have that :

$$\ln\left(\frac{N_k}{N_1}\right) = -\sigma.\ln\frac{w_k}{w_1} + \sigma.\ln\frac{\alpha_k}{\alpha_1} \qquad [4.2]$$

Now if we assume that relative wages are exogenously determined, then the k relative demand equations in [4.2] can be estimated using Seemingly Unrelated Regression Estimation (or SURE). Katz and Murphy (1992) argue that we can estimate the common elasticity of substitution σ by assuming that the evolution of relative demand shifts (i.e. the quotient of the α 's) can be proxied by a linear trend. Of course the assumption that

[35] These leading sectors are the markets for groups **2** (A Level and above; all ages), **4** (Degree; all ages), **8** (Degree; aged 25 and above) and **15** (Degree; aged 35 to 49 years) respectively for the 2, 4, 8 and 16 group

relative wages are exogenous is far from innocuous. However, if we are prepared to ignore any dynamic effects in [4.1] we can use lagged wages as instruments to circumvent this endogeneity problem

The results from estimation of [4.2] are however far from convincing. In practice we cannot obtain significant estimates of σ. Previous research in the literature[36] has produced a range of alternative estimates of the elasticity of substitution between different skill inputs in such a production function as [3.1]. Therefore, given that our estimation of the elasticity of substitution in our production function is at best inconclusive, and that an elasticity of zero (implying a Leontief technology where inputs are not substitutable at all) is implausible, we shall proceed instead by testing the sensitivity of our results to alternative values of σ – which we a half, one and two[37].

4.2.2 The Elasticity of the Real Wage with respect to the (Own Group-) Unemployment Rate.

Krugman's parable that high European unemployment and high American wage inequality are flip sides of the same coin teaches us that the degree of flexibility in the labour market is crucial in determining the outcome of any skill biased shift in demand. Previous research (see, for example, Blanchflower and Oswald (1994)) as to the magnitude of the parameter: γ has typically produced estimates that lie in the range: 0.035 to 0.1 (Manacorda and Petrongolo (1999)). In the analysis that follows we shall present results from three alternative scenarios: where (real) wages are flexible (γ=0.1), where they are not (γ=0.035), and finally, an intermediate case (γ=0.07).

4.3 Simulation Results

decompositions.

[36] For a comprehensive survey, see Hammermesh (1993).

[37] Nickell and Bell (1995) argue that since under a Cobb Douglas technology it is impossible to produce any output unless one employs a positive quantity of every input, then the elasticity of substitution must logically be greater than one because such a state of affairs implausible. Nonetheless, given both our own inconclusive results and the lack of consensus in the literature, we experiment with values of σ both above and below one.

The thing that strikes one most about the results of our simulations presented in Tables 4.16-4.21 overleaf[38] is the extent to which changing the key parameters of our model affects the magnitude of the effect of the growth in skill mismatch on the aggregate unemployment rate. If we assume that the wage setting function is convex, our results suggest that the growth in skill mismatch over the period can explain an average annual increase in the unemployment rate of anything from two basis points to a third of a percentage point, depending on the number of separate skill groups we define, and the particular parameter values we choose. In fact, our results depend both on **two key issues**: whom we should aggregate together as members of the same skill group, and the functional form of the wage setting function – and on the **magnitude of two key parameters**: the elasticity of substitution between different skill inputs in production and the elasticity of the wages with respect to the unemployment rate (or the slope of the double-log wage setting function). Finally, we have established above that the rate of growth of skill mismatch over the period was far from constant, and therefore we shall also investigate whether skill mismatch was a more important factor in driving the observed changes in the aggregate unemployment rate in either the period when mismatch rose sharply (1979-1984) or the period where mismatch stabilised (1985-1996). We shall address the role each of these issues plays in shaping our results in turn.

That the growth in skill mismatch between 1979 and 1996 contributed to the rise in the unemployment rate over that period seems irrefutable. However, the magnitude of the effect of rising skill mismatch on the unemployment rate under the assumption of a convex wage setting function appears to vary considerably depending on how we measure skill (or equivalently, the number of separate skill groups we identify in the labour force). It is certainly the case that when we restrict our attention to qualifications – based measures of skill, we find that the finer our definition, the greater the proportion of the increase in the aggregate unemployment rate we can explain. Furthermore, when our definition of skill is adjusted to differentiate between individuals according to their age as well as their qualifications our results are larger still : the growth in mismatch can now explain between half to twice the observed rise in unemployment over the period ! However, it is not the case that further division of the labour force into yet smaller skill groups inevitably leads to a greater aggregate impact. When we turn to our most comprehensive decomposition of the labour force into sixteen skill groups, our results are now approximately a third to a half of the magnitude of those obtained when we used only eight skill groups. Nonetheless, it appears that relying on a solely qualifications based measure of skill leads us to underestimate of the role that imbalances in the demand for and the supply of different skills in the labour market can play in determining the behaviour of aggregate unemployment. In the case of the leading sector model of wage setting we find that once again the definition of skill we use matters a great deal in terms of the magnitude of our results (although in this case, we find we can explain that the role of mismatch in explaining changes in the aggregate unemployment rate is smallest when we employ the most comprehensive definition of skill).

The literature establishes two mechanisms through which an increased imbalance in demand and supply can have an influence on the aggregate unemployment rate: where the wage setting function is convex, or where there exists a leading sector, which determines wages throughout the labour market. Our results suggest that depending on the nature of wage setting, rising skill mismatch has quite different aggregate impacts in magnitude, if not direction. Under the assumption of a convex wage setting function, mismatch can at best explain an annual increase of a third of a percentage point in the unemployment rate between 1979 and 1996; conversely in the case of asymmetric wage setting, using the same decomposition of the labour force, the effect of the same increase in skill mismatch on the unemployment rate is three times as large (and the largest effect we can find is five times as large). Put simply, if there exists a leading sector in the economy which determines wages across the labour market for all skill groups then the divergence between the relative demand for and supply of skills can explain a far greater proportion of the change in the aggregate unemployment rate over the period. We know

[38] See tables 4.16 – 4.18 for a summary of our results under the assumption of convex wage setting; and tables 4.19 - 4.21 for the results obtained under the alternative assumption of a leading sector in wage

that in the asymmetric wage setting model, net shifts in demand toward the skilled have the result of raising the unskilled unemployment rate, whilst leaving the skilled rate unchanged, generating a dispersion of the skill-specific unemployment rates solely through increases among those groups who had the highest unemployment rates to begin with. An analysis of U.K. data on group-specific unemployment rates reveals that this story appears to fit the facts quite well (see previous Figures 2.1 [c] and 2.2 [c]) and therefore mismatch might well appear to have had a greater role to play within such a leading sector model.

It is immediately obvious that the elasticity of substitution in production between the different skill inputs plays an important role in determining the role increased mismatch can play in explaining the rise in aggregate unemployment between 1979 and 1996. However, the relationship between the change in each of the skill-specific unemployment rates and the change in mismatch is highly non-linear in the elasticity of substitution. Across the period as a whole, the growth in mismatch was greatest where the elasticity of substitution in production was lowest which would imply that the impact of mismatch on the unemployment rate should also have been greatest in this instance. However, we also know that the downward shift in the demand for factor i induced by a decline in the employment of factor j is greatest where the elasticity of substitution is lowest; therefore, when the elasticity of substitution is low we should expect this counterbalancing force to any skill biased shift in demand to be greatest. Typically, in the case of convex wage setting model we find that the rise in skill mismatch had the greatest effect on the unemployment rate where we assigned the intermediate value (one) for the elasticity of substitution. Conversely in the case of asymmetric wage setting, the counterbalancing effect dominates, so that mismatch typically plays the greatest role the higher the value of the elasticity of substitution. Given that we were unable to identify a robust estimate of the elasticity of substitution in our production function at standard significance levels we would therefore argue for caution in placing too great a faith in the results obtained from any particular choice of elasticity of substitution, at least on the basis of the available data.

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setting.

The final parameter of our model : the slope of the double log wage setting function (i.e. the elasticity of a group's wage with respect to its unemployment rate) has an ambiguous effect on our results which depends on the nature of the wage setting process. If we assume that the wage setting function is convex then as we might expect the more inflexible wages are, then the greater the cost is in terms of higher aggregate unemployment when a skill biased shock hits the economy. In other words, mismatch has a greater role in explaining the rise in aggregate unemployment the lower the value of γ. Conversely, if we assume that there is a leading sector which determines wage setting throughout the labour market, then the more responsive wage setting is to a change in the leading skill group's unemployment rate the greater the proportion of the rise in the aggregate rate that can be explained by increased mismatch. The intuition for this result is fairly straightforward – what matters for the rest of the economy is the wage set by the leading sector. The more flexible is the wage setting process in the leading sector, the greater the impact of a given fall in the unemployment rate in the leading sector on wages there, and therefore the greater the consequential shift in the perfectly inelastic wage setting curves of all other skill groups. Therefore the impact of net shifts in demand will be magnified where wages are most responsive in the leading sector.

We have established that from the mid 1980's onwards there was little discernible growth in skill mismatch in the U.K. labour market. When we investigate whether mismatch played a more decisive role in shaping the path of the aggregate unemployment rate before this point we find weak circumstantial evidence in favour of this proposition. In particular, when we focus on the more comprehensive definitions of skill we find that there was still a marginal growth in skill mismatch over this latter period which should have generated a corresponding growth in the unemployment rate; in actual fact, from this point onwards the trend in the unemployment rate was downwards as the economy emerged from recession. This is no way invalidates our model, it only implies that some other cause must explain the improvement in the labour market, namely a relaxation in wage pressure or demographic change.

THE IMPACT OF SKILL MISMATCH ON THE AGGREGATE UNEMPLOYMENT RATE :

TABLE 4.16 CONVEX WAGE SETTING: 1979-1996

Number of Skill Groups	Gamma	Average Annual Change in the Unemployment Rate	Impact of the Change in Skill Mismatch			Percentage Explained		
			$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$
2	$\gamma=0.035$	0.15	0.03	0.10	0.15	17.6	68.6	101.1
	$\gamma=0.07$	0.15	0.02	0.08	0.11	14.4	51.6	75.7
	$\gamma=0.1$	0.15	0.02	0.06	0.09	12.4	42.6	62.0
4	$\gamma=0.035$	0.15	0.04	0.18	0.17	28.4	120.3	118.7
	$\gamma=0.07$	0.15	0.03	0.13	0.13	22.4	87.9	89.4
	$\gamma=0.1$	0.15	0.03	0.11	0.11	19.0	71.6	73.4
8	$\gamma=0.035$	0.15	0.09	0.33	0.20	64.4	222.6	135.3
	$\gamma=0.07$	0.15	0.08	0.25	0.17	53.9	172.9	116.4
	$\gamma=0.1$	0.15	0.07	0.22	0.15	47.6	146.6	102.1
16	$\gamma=0.035$	0.15	0.04	0.30	0.11	23.9	200.8	77.1
	$\gamma=0.07$	0.15	0.03	0.18	0.11	23.5	120.5	72.4
	$\gamma=0.1$	0.15	0.03	0.14	0.10	23.2	95.0	68.8

TABLE 4.17 CONVEX WAGE SETTING: 1979-1984

Number of Skill Groups	Gamma	Average Annual Change in the Unemployment Rate	Impact of the Change in Skill Mismatch			Percentage Explained		
			$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$
2	$\gamma=0.035$	1.23	0.10	0.35	0.49	8.2	28.2	39.9
	$\gamma=0.07$	1.23	0.08	0.26	0.36	6.6	20.9	29.5
	$\gamma=0.1$	1.23	0.07	0.21	0.29	5.6	17.0	24.0
4	$\gamma=0.035$	1.23	0.15	0.60	0.82	12.4	48.8	67.1
	$\gamma=0.07$	1.23	0.12	0.45	0.62	10.0	36.6	50.4
	$\gamma=0.1$	1.23	0.10	0.37	0.51	8.5	30.2	41.3
8	$\gamma=0.035$	1.23	0.24	0.81	0.72	19.4	66.4	59.0
	$\gamma=0.07$	1.23	0.20	0.65	0.61	16.3	53.2	49.4
	$\gamma=0.1$	1.23	0.18	0.56	0.53	14.4	45.9	43.0
16	$\gamma=0.035$	1.23	0.11	0.59	0.32	8.9	47.9	26.3
	$\gamma=0.07$	1.23	0.11	0.38	0.30	8.7	30.7	24.7
	$\gamma=0.1$	1.23	0.11	0.31	0.29	8.6	24.9	23.5

TABLE 4.18 CONVEX WAGE SETTING: 1985-1996

Number of Skill Groups	Gamma	Average Annual Change in the Unemployment Rate	Impact of the Change in Skill Mismatch			Percentage Explained		
			$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$
2	$\gamma=0.035$	-0.30	-0.02	-0.02	0.01	5.1	6.8	-2.3
	$\gamma=0.07$	-0.30	-0.01	-0.02	0.01	4.2	5.2	-1.7
	$\gamma=0.1$	-0.30	-0.01	-0.01	0.00	3.6	4.3	-1.4
4	$\gamma=0.035$	-0.30	-0.01	0.00	-0.03	3.4	0.1	9.6
	$\gamma=0.07$	-0.30	-0.01	-0.01	-0.03	3.2	2.9	9.2
	$\gamma=0.1$	-0.30	-0.01	-0.01	-0.03	3.1	3.7	8.4
8	$\gamma=0.035$	-0.30	0.03	0.13	0.02	-8.4	-44.3	-6.7
	$\gamma=0.07$	-0.30	0.02	0.10	0.02	-6.7	-32.3	-7.2
	$\gamma=0.1$	-0.30	0.02	0.08	0.02	-5.7	-26.3	-6.7
16	$\gamma=0.035$	-0.30	0.00	0.06	0.03	-1.4	-20.5	-10.9
	$\gamma=0.07$	-0.30	0.00	0.04	0.03	-1.4	-13.2	-10.2
	$\gamma=0.1$	-0.30	0.00	0.03	0.03	-1.4	-10.8	-9.7

TABLE 4.19 ASYMMETRIC WAGE SETTING: 1979-1996

Number of Skill Groups	Gamma	Average Annual Change in the Unemployment Rate	Impact of the Change in Skill Mismatch			Percentage Explained		
			$\sigma=0.5$	$\sigma=1$	$\sigma=2$	$\sigma=0.5$	$\sigma=1$	$\sigma=2$
2	$\gamma=0.035$	0.15	0.03	0.34	0.45	22.6	232.6	305.8
	$\gamma=0.07$	0.15	0.03	0.34	0.51	22.6	232.7	347.9
	$\gamma=0.1$	0.15	0.03	0.34	0.54	22.6	232.7	365.0
4	$\gamma=0.035$	0.15	0.06	0.75	0.96	38.8	506.9	649.4
	$\gamma=0.07$	0.15	0.06	0.75	1.11	38.8	507.1	754.9
	$\gamma=0.1$	0.15	0.06	0.75	1.17	38.8	507.1	795.8
8	$\gamma=0.035$	0.15	0.12	1.07	1.36	82.2	724.2	924.7
	$\gamma=0.07$	0.15	0.12	1.07	1.60	82.2	724.5	1084.8
	$\gamma=0.1$	0.15	0.12	1.07	1.69	82.2	724.6	1145.7
16	$\gamma=0.035$	0.15	0.03	0.14	0.10	22.8	96.3	71.2
	$\gamma=0.07$	0.15	0.03	0.13	0.11	22.8	91.1	76.2
	$\gamma=0.1$	0.15	0.03	0.13	0.12	22.8	89.5	80.1

TABLE 4.20 ASYMMETRIC WAGE SETTING: 1979-1984

Number of Skill Groups	Gamma	Average Annual Change in the Unemployment Rate	Impact of the Change in Skill Mismatch			Percentage Explained		
			σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
2	γ=0.035	1.23	0.13	0.35	1.59	10.8	28.2	130.1
	γ=0.07	1.23	0.13	0.26	1.81	10.8	20.9	147.7
	γ=0.1	1.23	0.13	0.21	1.90	10.8	17.0	154.8
4	γ=0.035	1.23	0.20	0.60	2.76	16.6	48.8	225.0
	γ=0.07	1.23	0.20	0.45	3.09	16.6	36.6	252.2
	γ=0.1	1.23	0.20	0.37	3.22	16.6	30.2	262.8
8	γ=0.035	1.23	0.30	2.48	2.98	24.6	202.7	242.8
	γ=0.07	1.23	0.30	2.49	3.40	24.6	203.0	277.4
	γ=0.1	1.23	0.30	2.49	3.56	24.6	203.1	290.5
16	γ=0.035	1.23	0.11	0.47	0.32	8.9	38.5	26.0
	γ=0.07	1.23	0.11	0.42	0.33	8.7	34.1	27.2
	γ=0.1	1.23	0.11	0.40	0.34	8.6	32.6	28.1

TABLE 4.21 ASYMMETRIC WAGE SETTING: 1985-1996

Number of Skill Groups	Gamma	Average Annual Change in the Unemployment Rate	Impact of the Change in Skill Mismatch			Percentage Explained		
			σ=0.5	σ=1	σ=2	σ=0.5	σ=1	σ=2
2	γ=0.035	-0.30	-0.02	-0.02	0.02	6.4	6.8	-6.6
	γ=0.07	-0.30	-0.02	-0.02	0.02	6.4	5.2	-7.6
	γ=0.1	-0.30	-0.02	-0.01	0.02	6.4	4.3	-7.9
4	γ=0.035	-0.30	-0.01	0.00	0.40	3.3	0.1	-133.3
	γ=0.07	-0.30	-0.01	-0.01	0.50	3.3	2.9	-164.7
	γ=0.1	-0.30	-0.01	-0.01	0.53	3.3	3.7	-176.9
8	γ=0.035	-0.30	0.04	0.11	-1.01	-11.7	-36.3	334.4
	γ=0.07	-0.30	0.04	0.11	-1.08	-11.7	-36.3	356.8
	γ=0.1	-0.30	0.04	0.11	-1.10	-11.7	-36.4	365.3
16	γ=0.035	-0.30	0.00	0.02	0.03	-1.4	-6.9	-8.5
	γ=0.07	-0.30	0.00	0.03	0.03	-1.4	-10.0	-10.3
	γ=0.1	-0.30	0.00	0.03	0.04	-1.4	-11.0	-11.6

Shifts in the composition of the labour force over the period towards skill groups with lower unemployment rates will also have had an impact on the aggregate unemployment rate (given by the final expressions in [3.28] and [3.35]), and we summarize these pure demographic contributions to the unemployment rate in Table 4.22 below. As was discussed previously, a series of supply shocks have led to an increase in the share of older and more qualified workers in the labour force who we know have lower unemployment rates. As a result, this has led to a fall in the aggregate unemployment rate, of up to an average of 15 basis points each year, or almost two percentage points over the whole period.

TABLE 4.22 THE IMPACT OF DEMOGRAPHIC CHANGE.

Number of Skill Groups	Average Annual Change in the Unemployment Rate			Impact of the Demographic Change			Percentage Explained		
	79-96	79-84	85-96	79-96	79-84	85-96	79-96	79-84	85-96
2	0.15	1.23	-0.3	-0.053	-0.04	-0.059	-35.8	-3.3	19.5
4	0.15	1.23	-0.3	-0.118	-0.152	-0.103	-80.5	-12.4	34
8	0.15	1.23	-0.3	-0.141	-0.131	-0.142	-95.9	-10.7	47
16	0.15	1.23	-0.3	-0.142	-0.145	-0.139	-96.3	-11.8	45.9

5. CONCLUSIONS

We have argued that previous research into the issue of the labour market consequences of any imbalance between the relative demand and supply of different skills has failed to take account of the role of labour market experience in determining the level of human capital, and therefore skill of members of the workforce. This chapter has re-examined the evidence as to whether there has been any discernible growth in the mismatch between the demand and supply of different skills in the labour market using this alternative definition of skill based on both the level of educational attainment and age of individual workers, and in the light of that evidence, the role that increased skill mismatch might have played in the rise in the aggregate unemployment rate since 1979. We find that on the basis of the 'outcomes' measures favoured in the literature there is only patchy evidence to suggest that there has been a clearly identifiable growth in the imbalance between the demand and supply of separate skills in the economy over the period. Nonetheless, we argue that when we focus on a measure of skill mismatch which identifies the underlying demand for, and supply of separate skill groups, that at least until the mid 1980's there is good reason to believe that there was a significant growth in skill mismatch. Thereafter, the evidence is far less conclusive, as a series of relative supply shocks led to a fall in the proportion of young and unqualified workers in the economy.

When we focus on the role rising skill mismatch might have played in determining the path of the unemployment rate we find that there is clear evidence that between 1979 and 1996 the growth in skill mismatch contributed to the rise in the aggregate unemployment rate. Moreover, we find that in quantitative terms our results are significantly larger than those found elsewhere (e.g. Manacorda and Petrongolo (1999)). There are two explanations for this disagreement. First, by ignoring that component of skill derived through experience at the workplace which we have proxied here by the age of individual workers, one can seriously underestimate the role that increased skill mismatch played. Second, given the behaviour of the aggregate unemployment rate over the last few decades choosing the years over which we estimate the role of skill mismatch makes a big difference. So, if we begin the analysis in the early 1970s when unemployment was low and end it in the early 1990's during recession when the unemployment rate was high, it is inevitable that the annual change in the unemployment rate will be large and the change implied by rising skill mismatch proportionately small. Furthermore, we also find that in quantitative terms, the magnitude of our estimate of the impact of skill mismatch is heavily dependent on the particular values we assign to the key parameters and structure of our model: namely the degree of substitutability in production of our different skill groups and the precise form of the wage setting function.

APPENDIX 1 : TABLES

TABLE A.2.1 [A] : THE COMPOSITION OF THE LABOUR FORCE

	Qualifications				Age Groups			
Year	< O level	O level	A level	Degree	< 25	25-34	35-49	> 50
79	64	18	6	11	21	24	32	24
80	63	19	6	12	22	24	32	23
81	63	19	6	12	22	24	32	22
82	57	23	6	13	22	24	33	22
83	52	27	7	15	21	24	34	21
84	48	31	7	14	22	23	34	21
85	46	32	8	14	24	23	34	20
86	49	28	8	15	24	24	34	19
87	47	30	8	15	23	24	34	19
88	46	30	8	15	23	25	34	18
89	41	35	9	15	22	25	34	18
90	39	36	10	16	21	26	34	18
91	37	36	10	16	20	27	35	18
92	34	37	10	19	19	27	36	18
93	36	34	9	21	18	28	36	18
94	33	36	10	22	17	28	36	19
95	32	36	10	22	17	28	37	19
96	31	36	10	23	16	28	37	19

TABLE A.2.1 [B] THE AVERAGE WAGE BY QUALIFICATION AND AGE GROUP.

	Qualifications				Age Groups			
Year	< O level	O level	A level	Degree	< 25	25-34	35-49	> 50
79	166	183	239	301	146	208	210	181
80	165	186	243	301	147	209	212	181
81	165	185	253	318	146	214	213	188
82	162	183	251	316	141	215	216	187
83	166	188	253	329	145	223	224	199
84	164	192	254	332	138	222	228	211
85	170	188	234	336	139	227	233	213
86	179	185	238	346	138	229	247	212
87	175	200	265	367	149	239	253	222
88	184	204	286	364	154	246	263	224
89	183	211	284	379	155	252	266	239
90	184	214	289	383	153	262	270	240
91	188	216	296	408	157	263	284	246
92	183	204	274	396	149	259	277	239
93	187	213	272	396	146	264	286	250
94	189	208	287	404	142	265	295	258
95	186	207	269	397	137	261	294	245
96	189	206	261	391	139	264	287	249

TABLE A.2.1 [C]:UNEMPLOYMENT RATES BY QUALIFICATION AND AGE GROUP.

	Qualifications				Age Groups			
Year	< O level	O level	A level	Degree	< 25	25-34	35-49	> 50
79	6.3	3.5	3.2	2.3	7.9	5.6	3.9	4.0
80	9.1	5.8	5.4	3.0	13.2	7.6	5.0	5.6
81	11.9	7.9	7.4	3.8	18.1	9.6	6.0	7.4
82	12.9	8.8	7.5	4.3	18.7	10.5	6.8	7.8
83	14.1	9.4	7.6	4.7	19.4	11.4	7.5	8.2
84	14.8	9.7	7.9	4.5	19.2	11.7	7.8	8.0
85	14.7	9.1	7.9	4.3	17.0	11.6	7.8	7.7
86	14.2	9.2	8.0	4.6	17.4	11.6	7.5	7.7
87	14.9	8.9	7.6	4.2	15.7	12.1	7.8	8.9
88	12.4	7.1	6.2	3.1	12.6	9.5	6.2	8.2
89	10.6	5.8	5.1	2.7	10.1	7.9	5.0	7.0
90	10.3	5.7	5.3	2.6	10.2	7.3	4.9	6.4
91	12.0	7.5	6.4	3.8	13.6	8.8	5.9	7.2
92	12.7	9.0	7.0	4.0	14.4	9.6	6.7	7.7
93	13.6	9.3	7.4	4.5	16.0	9.8	6.9	8.8
94	13.4	8.6	6.7	4.0	14.7	9.2	6.5	8.3
95	11.7	7.8	7.1	3.9	13.9	8.3	6.0	6.8
96	11.5	7.2	6.4	3.8	13.2	7.9	5.7	6.4

TABLE A.2.2 [A] AGE COMPOSITION OF THE LABOUR FORCE BY QUALIFICATION GROUP

	no O level				O level			
year	< 25	25-34	35-49	> 50	< 25	25-34	35-49	> 50
79	17	19	33	30	38	30	24	8
80	18	19	33	30	39	29	24	8
81	18	19	33	29	40	29	24	8
82	18	18	34	30	35	28	30	7
83	17	18	34	31	31	28	34	7
84	20	18	35	26	29	25	31	15
85	21	18	35	26	31	24	30	14
86	19	18	36	27	35	27	28	10
87	19	18	36	27	34	28	29	10
88	19	19	36	26	32	28	29	10
89	19	20	36	26	29	27	30	13
90	17	21	37	26	28	27	31	14
91	16	21	37	26	27	28	31	14
92	14	21	39	26	25	29	32	14
93	15	22	38	25	23	30	33	15
94	14	21	38	27	22	29	34	15
95	13	22	38	26	21	29	34	16
96	13	21	39	27	21	29	34	16

	A level				Degree			
year	< 25	25-34	35-49	> 50	< 25	25-34	35-49	> 50
79	33	31	24	11	10	36	37	17
80	34	31	24	11	10	36	38	17
81	34	32	24	10	10	35	38	17
82	33	31	25	11	10	34	39	17
83	33	31	25	11	9	33	40	18
84	33	32	25	10	10	33	40	17
85	36	30	25	9	10	33	40	16
86	35	31	25	9	10	32	41	17
87	36	30	25	9	11	32	40	17
88	35	31	25	8	10	32	41	16
89	36	30	25	9	10	33	41	16
90	33	31	27	9	10	33	42	16
91	32	33	27	8	9	34	42	16
92	32	30	28	9	9	33	41	16
93	31	32	28	9	9	33	43	16
94	29	33	29	9	9	33	42	16
95	31	32	29	9	9	32	42	17
96	29	31	31	10	9	33	42	17

TABLE A.2.2 [B] AGE DISTRIBUTION OF WAGES BY QUALIFICATION GROUP

	no O level				O level			
year	< 25	25-34	35-49	> 50	< 25	25-34	35-49	> 50
79	139	179	177	159	137	207	216	212
80	137	176	179	157	141	209	215	223
81	135	178	175	161	138	213	211	222
82	134	181	170	156	131	202	215	215
83	137	183	171	164	134	205	215	213
84	119	182	175	166	134	209	216	220
85	122	188	185	171	137	207	210	214
86	129	191	204	168	127	203	226	218
87	126	196	189	171	144	214	241	226
88	136	193	208	175	143	223	240	235
89	140	197	201	177	144	228	244	241
90	132	199	204	174	139	238	244	247
91	138	195	206	182	146	232	247	239
92	124	199	200	172	135	221	232	221
93	122	205	205	179	133	225	248	232
94	115	197	208	187	132	211	243	227
95	108	209	207	170	120	221	237	224
96	121	194	208	187	120	220	238	216

	A level				Degree			
year	< 25	25-34	35-49	> 50	< 25	25-34	35-49	> 50
79	180	255	280	272	198	271	341	342
80	177	254	305	267	207	276	328	348
81	190	256	314	294	212	289	350	364
82	173	259	308	322	197	285	351	358
83	179	266	297	327	200	294	370	365
84	169	273	315	299	215	284	372	392
85	155	264	291	270	211	298	374	395
86	165	264	286	288	211	312	379	405
87	179	269	361	321	230	331	405	429
88	184	311	366	370	253	334	400	402
89	181	307	355	414	242	345	413	441
90	182	321	367	336	255	361	407	443
91	183	319	384	326	243	367	452	467
92	177	296	337	338	230	361	446	428
93	165	291	325	385	231	367	438	429
94	151	325	353	368	224	369	451	444
95	156	276	351	340	230	353	453	421
96	152	282	322	319	220	371	430	412

TABLE A.2.2 [C] UNEMPLOYMENT RATES BY AGE GROUP BY QUALIFICATION GROUP

	no O level				O level			
year	< 25	25-34	35-49	> 50	< 25	25-34	35-49	> 50
79	11.57	7.62	4.73	4.36	4.08	3.93	2.27	2.42
80	18.30	10.41	6.08	6.22	8.01	5.50	3.15	3.44
81	24.59	13.24	7.46	8.18	11.52	7.01	3.95	4.43
82	26.30	14.81	8.47	8.56	12.45	8.45	5.47	5.73
83	28.59	16.99	9.72	9.01	13.38	9.60	6.29	6.80
84	27.76	18.09	10.32	8.83	13.59	9.85	6.48	8.21
85	25.41	19.04	10.62	8.66	11.87	9.62	6.50	7.39
86	25.85	17.79	10.27	8.74	12.32	9.55	5.61	6.97
87	24.13	19.98	10.83	10.46	11.51	9.55	5.84	6.88
88	19.88	15.87	8.79	9.44	8.94	7.50	4.53	7.20
89	16.73	13.57	7.48	8.26	7.00	6.49	3.77	6.33
90	17.20	12.75	7.33	7.77	7.44	5.92	3.94	5.28
91	21.71	14.94	8.72	8.50	10.68	8.00	4.96	6.13
92	23.61	16.63	9.50	8.57	12.23	9.44	6.53	8.12
93	24.54	16.80	9.72	9.81	12.83	9.12	6.95	9.26
94	23.86	17.51	9.69	9.83	12.70	8.66	6.24	7.97
95	22.32	15.69	8.57	7.38	11.66	7.65	5.82	6.98
96	22.93	14.92	8.69	7.43	11.01	7.34	5.24	6.26

	A level				Degree			
year	< 25	25-34	35-49	> 50	< 25	25-34	35-49	> 50
79	4.03	3.68	2.03	2.36	3.20	2.77	1.68	1.79
80	7.81	5.35	2.87	3.28	6.15	3.48	2.04	2.47
81	11.41	6.96	3.69	4.26	9.01	4.16	2.37	3.10
82	10.80	7.35	3.92	5.90	9.09	4.64	2.93	3.87
83	10.22	7.72	4.12	7.31	9.16	5.08	3.41	4.52
84	12.72	6.36	4.57	5.25	7.75	5.33	3.19	4.00
85	12.03	6.17	4.91	6.07	7.85	4.56	3.33	3.67
86	11.40	7.40	4.42	6.20	8.96	5.70	3.05	3.65
87	10.20	7.13	4.88	5.63	6.83	4.51	2.93	4.63
88	7.35	5.76	4.55	7.37	5.55	3.60	1.97	3.40
89	6.50	4.58	3.64	5.35	4.25	3.06	1.80	3.46
90	6.95	5.14	3.46	5.14	4.21	2.64	1.83	3.34
91	9.41	5.59	4.03	5.71	8.58	3.76	2.51	4.69
92	8.96	5.82	6.02	6.93	10.84	3.70	2.43	4.79
93	12.01	5.27	5.03	6.77	9.29	4.41	3.18	5.70
94	9.52	5.42	5.18	6.54	8.52	3.69	2.86	5.24
95	10.77	4.68	5.73	7.83	8.98	3.34	2.92	4.87
96	8.27	6.17	4.60	6.99	8.93	3.28	2.93	4.11

TABLE A.2.3 : SKILL MISMATCH : EVIDENCE FROM WAGES

	A.W.M.		R.W.M.	
Year	full	simple	full	simple
79	2520	2359	0.072	0.068
80	2623	2457	0.074	0.070
81	3257	3088	0.089	0.084
82	3572	3367	0.099	0.093
83	4046	3842	0.104	0.099
84	4397	4111	0.111	0.103
85	4387	4154	0.106	0.100
86	4825	4508	0.111	0.104
87	5990	5632	0.128	0.120
88	5656	5386	0.114	0.108
89	6367	6054	0.122	0.116
90	6746	6526	0.124	0.120
91	8066	7696	0.139	0.132
92	8118	7793	0.147	0.141
93	8309	7989	0.142	0.136
94	9524	9166	0.157	0.151
95	9267	8721	0.159	0.149
96	8271	8067	0.141	0.138

TABLE A.2.4 : SKILL MISMATCH : EVIDENCE FROM UNEMPLOYMENT RATES

	A.U.M.		R.U.M.	
Year	full	simple	full	simple
79	7	6	0.275	0.236
80	19	17	0.338	0.304
81	37	33	0.375	0.342
82	38	35	0.353	0.319
83	43	38	0.350	0.310
84	42	37	0.332	0.289
85	37	31	0.312	0.260
86	36	31	0.308	0.260
87	34	27	0.283	0.227
88	23	19	0.288	0.240
89	15	13	0.293	0.243
90	15	13	0.306	0.265
91	21	18	0.289	0.248
92	22	19	0.268	0.224
93	25	22	0.271	0.234
94	24	20	0.300	0.255
95	20	16	0.302	0.248
96	19	16	0.325	0.279

TABLE A.4.1 : RELATIVE DEMAND FOR SKILLS WITHIN QUALIFICATION GROUPS

	Relative Demand Index											
	21	31	41	65	75	85	109	119	129	1413	1513	1613
79	1.52	2.70	2.23	1.18	1.00	0.33	1.34	1.16	0.52	4.81	6.29	2.81
80	1.52	2.82	2.22	1.14	0.98	0.33	1.37	1.31	0.51	4.85	6.19	2.88
81	1.58	2.87	2.31	1.17	1.00	0.33	1.31	1.28	0.51	5.12	6.85	3.08
82	1.60	2.95	2.41	1.30	1.51	0.37	1.45	1.43	0.62	5.47	7.77	3.46
83	1.56	3.06	2.69	1.43	1.91	0.39	1.42	1.37	0.62	5.57	8.43	3.66
84	1.59	3.25	2.34	1.36	1.83	0.92	1.65	1.57	0.58	4.67	7.44	3.42
85	1.45	3.07	2.15	1.20	1.57	0.75	1.54	1.41	0.46	4.71	7.33	3.13
86	1.55	3.65	2.25	1.27	1.52	0.49	1.48	1.31	0.46	4.68	7.46	3.29
87	1.63	3.44	2.28	1.27	1.52	0.50	1.29	1.44	0.46	4.27	6.60	2.89
88	1.51	3.39	2.06	1.40	1.58	0.54	1.52	1.47	0.48	4.13	6.44	2.53
89	1.57	3.09	1.93	1.49	1.84	0.78	1.47	1.43	0.56	4.94	7.53	3.04
90	1.90	3.68	2.19	1.70	1.99	0.91	1.69	1.67	0.51	4.90	7.09	2.90
91	1.96	4.06	2.50	1.71	2.11	0.90	1.87	1.92	0.49	5.96	9.30	3.47
92	2.65	5.47	3.13	1.92	2.30	0.98	1.63	1.69	0.56	6.15	9.48	3.51
93	2.60	4.94	2.86	2.27	2.82	1.18	1.95	1.89	0.71	6.39	10.12	3.61
94	2.84	5.78	3.68	2.24	3.10	1.27	2.51	2.38	0.77	6.70	10.42	3.91
95	3.55	6.48	3.75	2.68	3.46	1.51	1.96	2.24	0.65	6.16	10.40	3.69
96	2.92	6.07	3.92	2.67	3.52	1.46	2.02	2.33	0.70	6.75	10.08	3.79

TABLE A.4.2 : RELATIVE SUPPLY OF SKILLS WITHIN QUALIFICATION GROUPS

	Relative Supply Index											
	21	31	41	65	75	85	109	119	129	1413	1513	1613
79	1.13	1.96	1.79	0.78	0.62	0.21	0.94	0.73	0.34	3.50	3.60	1.61
80	1.08	1.88	1.69	0.75	0.61	0.20	0.94	0.72	0.32	3.53	3.74	1.65
81	1.04	1.81	1.59	0.72	0.61	0.19	0.93	0.71	0.30	3.57	3.87	1.69
82	1.02	1.86	1.67	0.81	0.86	0.21	0.93	0.74	0.32	3.59	4.08	1.80
83	1.01	1.94	1.77	0.90	1.10	0.23	0.93	0.77	0.33	3.61	4.28	1.90
84	0.92	1.78	1.33	0.84	1.05	0.53	0.96	0.77	0.30	3.45	4.09	1.80
85	0.87	1.69	1.25	0.77	0.97	0.46	0.85	0.70	0.25	3.22	3.94	1.60
86	0.94	1.90	1.40	0.77	0.79	0.27	0.89	0.70	0.25	3.06	3.90	1.62
87	0.99	1.96	1.43	0.83	0.85	0.30	0.83	0.67	0.24	2.90	3.60	1.52
88	1.01	1.94	1.41	0.88	0.90	0.32	0.88	0.72	0.24	3.07	3.93	1.56
89	1.07	1.93	1.38	0.93	1.05	0.46	0.85	0.71	0.24	3.42	4.30	1.66
90	1.20	2.13	1.50	0.98	1.10	0.50	0.94	0.80	0.27	3.41	4.34	1.66
91	1.28	2.33	1.62	1.04	1.17	0.52	1.03	0.86	0.27	3.76	4.69	1.74
92	1.52	2.86	1.89	1.13	1.25	0.57	0.94	0.86	0.29	3.63	4.47	1.77
93	1.41	2.46	1.64	1.28	1.41	0.65	1.03	0.89	0.29	3.82	5.00	1.87
94	1.53	2.70	1.92	1.34	1.57	0.70	1.12	0.97	0.31	3.87	4.87	1.91
95	1.69	2.87	2.00	1.39	1.64	0.77	1.04	0.94	0.29	3.77	4.95	1.93
96	1.66	2.99	2.11	1.40	1.67	0.77	1.06	1.06	0.33	3.77	4.84	1.92

TABLE A.4.3 : MISMATCH OF SKILLS WITHIN QUALIFICATION GROUPS

Mismatch Index

	21	31	41	65	75	85	109	119	129	1413	1513	1613
79	0.30	0.32	0.22	7.13	8.02	7.72	2.02	2.33	2.24	1.71	2.24	2.25
80	0.34	0.40	0.27	3.80	4.16	4.37	2.01	2.57	2.21	1.58	1.92	2.02
81	0.42	0.46	0.37	3.63	3.73	3.99	1.69	2.16	2.02	1.57	1.89	1.94
82	0.45	0.46	0.37	4.11	4.73	4.72	1.99	2.46	2.52	1.71	2.08	2.10
83	0.44	0.46	0.42	3.67	4.15	4.07	1.86	2.15	2.28	1.70	2.10	2.06
84	0.55	0.60	0.57	2.61	2.85	2.84	2.02	2.32	2.21	1.36	1.71	1.76
85	0.51	0.60	0.54	2.52	2.70	2.73	2.47	2.75	2.54	1.50	1.82	1.89
86	0.50	0.65	0.47	4.34	5.33	4.99	2.19	2.45	2.43	1.60	1.92	2.01
87	0.49	0.57	0.47	2.50	3.05	2.79	1.86	2.47	2.23	1.48	1.75	1.80
88	0.40	0.56	0.37	3.64	4.24	3.96	2.21	2.60	2.56	1.38	1.63	1.62
89	0.38	0.47	0.33	4.29	4.98	4.69	2.47	2.89	3.25	1.53	1.81	1.88
90	0.46	0.54	0.38	4.36	4.64	4.63	2.34	2.70	2.45	1.45	1.61	1.70
91	0.43	0.56	0.43	3.65	4.15	3.91	2.38	2.85	2.43	1.64	1.95	1.96
92	0.56	0.65	0.50	3.39	3.75	3.46	2.04	2.28	2.26	1.68	1.97	1.89
93	0.61	0.70	0.56	3.54	4.06	3.67	2.41	2.66	3.00	1.63	1.86	1.80
94	0.62	0.76	0.65	2.91	3.53	3.21	2.83	3.02	3.08	1.65	1.89	1.85
95	0.74	0.81	0.63	3.81	4.19	3.90	2.25	2.70	2.59	1.54	1.81	1.71
96	0.57	0.71	0.62	5.73	6.46	5.69	2.59	2.96	2.87	1.76	1.96	1.89

APPENDIX 2 : A CLASSIFICATION OF U.K. QUALIFICATIONS

Any classification of individuals into separate ranked skill groups according to the academic qualifications that they hold clearly involves an implicit ranking of all the different qualifications one can obtain in the UK educational system. However, such a ranking is not straightforward – a cursory look at the data reveals the extent of the range in the type and level of academic and vocational qualifications held by different members of the workforce (leaving aside any discussion of whether the nature of the qualifications themselves have changed over time – for example, the accusation is consistently made that the standards required to achieve a particular grade in G.C.S.E. examinations have been consistently reduced). At any one time it may be straightforward to rank the different qualifications that a given cohort can obtain according to their level of complexity or the attractiveness of the skills they signal to potential employers. However, the educational system has been in a state of almost permanent revolution, where frequent educational reforms have ensured that successive generations of students enter the labour force holding different kinds of qualification (or perhaps more cynically, similar qualifications with different names). Of course individuals will often hold a number of different qualifications but they are usually ranked according to their highest level of achievement (which typically, but not always, will be the last qualification they achieve before entering the labour market).

Although there is no absolute standard for the ranking of qualifications, the majority of the literature which has drawn on educational data has tended to follow an approach similar to that adopted here, which is taken from Burriel-Llombart (2001). Effectively, we identify four separate qualification groups – those with no qualifications whatsoever or qualifications less than the standard of an O level; those holding O Levels (or their vocational equivalent); those with a Further Education qualification: an A Level or its vocational equivalent; and finally those with a qualification obtained from a Higher Education institution: a degree or its vocational equivalent. For the sake of clarity, we shall briefly outline this classification system overleaf – however, a more comprehensive description of this kind of ranking system of the various academic and vocational qualifications that exist among the U.K. labour force can be found for example in Dearden et. al. (2000)[39].

A CLASSIFICATION OF U.K. QUALIFICATIONS:

QUALIFICATION GROUP	QUALIFICATIONS
LESS THAN O LEVEL	**VOCATIONAL** : NVQ level 1, GNVQ foundation level, SCOTVEC modules, YT/YTP certificates, RSA other, City and Guilds 'other', BTEC/SCOTVEC general certificate. **ACADEMIC** : CSE below grade 1, GCSE below grade C.
O LEVEL	**VOCATIONAL** : NVQ level 2, GNVQ intermediate level, RSA diploma, City and Guilds Advanced and Craft level, BTEC/SCOTVEC general diploma and completed apprenticeship. **ACADEMIC** : O Level, CSE grade 1, GCSE grade A to C.
A LEVEL	**VOCATIONAL** : NVQ level 3, GNVQ advanced level, RSA advanced diploma, ONC, OND, BTEC/SCOTVEC national level. **ACADEMIC** : A Level, AS Level, Scottish 6th year Certificate, SCE higher level.
DEGREE	**VOCATIONAL** : Nursing qualifications, NVQ level 4-5, GNVQ advanced level, RSA higher diploma, HNC, HND, BTEC/SCOTVEC higher level. **ACADEMIC** : Graduate and Undergraduate Degree, all teaching qualifications.

[39] In fact, Dearden et. al. (2000) identify five separate qualification groups (rather than the four used here) since they sub-divide the highest qualification group into those holding degrees and those holding diplomas

APPENDIX 3 : DERIVATION OF THE RESULTS IN MAIN CHAPTER

Consider the following C.E.S. production function:

$$Y = A\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}\right)^{1/\rho} \qquad [A1]$$

The marginal product of the 1st input is defined as follows:

$$\frac{\partial Y}{\partial N_1} = \frac{1}{\rho}.\rho.\alpha_1.N_1^{\rho-1}.A\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}\right)^{1/\rho-1} \qquad [A2]$$

$$\Rightarrow \frac{\partial Y}{\partial N_1} = \alpha_1.N_1^{\rho-1}.A^{\rho}.Y^{1-\rho} \qquad [A3]$$

If we assume perfectly competitive factor markets, and profit maximisation on the part of firms:

$$w_1 = \alpha_1.A^{\rho}.\left(\frac{Y}{N_1}\right)^{1-\rho} \qquad [A4]$$

or in terms of the elasticity of substitution:

$$w_1 = \alpha_1.A^{\sigma-1/\sigma}.\left(\frac{Y}{N_1}\right)^{1/\sigma} \qquad [A5]$$

or rearranging:

---

and other Higher Education qualifications below degree level.

$$\alpha_1 = w_1.A^{1-\sigma/\sigma}.\left(\frac{N_1}{Y}\right)^{\sigma} \qquad [A6]$$

Therefore if the relative wage of the first and second skill inputs is defined as follows:

$$\frac{w_1}{w_2} = \frac{\alpha_1}{\alpha_2}.\left(\frac{N_2}{N_1}\right)^{1/\sigma} \qquad [A7]$$

which when we rearrange gives us :

$$\frac{\alpha_1}{\alpha_2} = \frac{w_1}{w_2}.\left(\frac{N_1}{N_2}\right)^{1/\sigma} \qquad [A8]$$

Now from [A5] taking logs we have:

$$\ln w_1 = \ln \alpha_1 + \rho \ln A + (1-\rho)\ln Y - (1-\rho)\ln N_1 \qquad [A9]$$

Now from [A1] we have that :

$$\ln Y = \ln A + \frac{1}{\rho}\ln\left(\alpha_1 N_1{}^{\rho} + \alpha_2 N_2{}^{\rho} + \alpha_3 N_3{}^{\rho} + \alpha_4 N_4{}^{\rho}\right) \qquad [A10]$$

$$\therefore (1-\rho)\ln Y = (1-\rho)\ln A +$$

$$\frac{(1-\rho)}{\rho}\ln\left(\alpha_1 N_1{}^{\rho} + \alpha_2 N_2{}^{\rho} + \alpha_3 N_3{}^{\rho} + \alpha_4 N_4{}^{\rho}\right) \qquad [A11]$$

so substituting back into [A9] we have that :

$$\ln w_1 = \ln\alpha_1 + \ln A - (1-\rho)\ln N_1 +$$

$$\frac{(1-\rho)}{\rho}\ln\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}\right) \qquad \text{[A12]}$$

Now adding and subtracting terms in the total labour force and the labour force of the particular group we have :

$$\ln w_1 = \ln\alpha_1 + \ln A - (1-\rho)\ln N_1 + (1-\rho)\ln L_1 - (1-\rho)\ln L_1 + (1-\rho)\ln L -$$

$$(1-\rho)\ln L + \frac{(1-\rho)}{\rho}\ln\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}\right) \qquad \text{[A13]}$$

$$\Rightarrow \ln w_1 = \ln\alpha_1 + \ln A - (1-\rho)\ln(1-u_1) - (1-\rho)\ln l_1 - (1-\rho)\ln L +$$

$$\frac{(1-\rho)}{\rho}\ln\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}\right) \qquad \text{[A14]}$$

Now if we take the log of the labour demand function for the second group from that of the first we have:

$$\ln w_1 - \ln w_2 = \ln\frac{\alpha_1}{\alpha_2} - (1-\rho)\ln\frac{l_1}{l_2} - (1-\rho)(\ln(1-u_1) - \ln(1-u_2)) \qquad \text{[A15]}$$

and taking the total differential of this expression we have:

$$d\ln w_1 - d\ln w_2 = d\ln\frac{\alpha_1}{\alpha_2} - (1-\rho)d\ln\frac{l_1}{l_2} -$$

$$(1-\rho)(d\ln(1-u_1)-d\ln(1-u_2)) \qquad [A16]$$

Now for small values of x the approximation $\ln(1+x)\approx x$ is reasonable, so we can rewrite [A15] as follows:

$$d\ln w_1 - d\ln w_2 \approx d\ln\frac{\alpha_1}{\alpha_2}-(1-\rho)d\ln\frac{l_1}{l_2}+(1-\rho)(du_1-du_2) \qquad [A17]$$

or alternatively in terms of the elasticity of substitution:

$$d\ln w_1 - d\ln w_2 = d\ln\frac{\alpha_1}{\alpha_2}-\frac{1}{\sigma}d\ln\frac{l_1}{l_2}+\frac{1}{\sigma}(du_1-du_2) \qquad [A18]$$

Consider the following rearrangement of the final term in [A13]:

$$\ln\left(\alpha_1 N_1^{\rho}+\alpha_2 N_2^{\rho}+\alpha_3 N_3^{\rho}+\alpha_4 N_4^{\rho}\right)=$$

$$\ln\left(\left(N_1^{\alpha_1}N_2^{\alpha_2}N_3^{\alpha_3}N_4^{\alpha_4}\right)^{\rho}\times\left(\frac{\alpha_1 N_1^{\rho}+\alpha_2 N_2^{\rho}+\alpha_3 N_3^{\rho}+\alpha_4 N_4^{\rho}}{\left(N_1^{\alpha_1}N_2^{\alpha_2}N_3^{\alpha_3}N_4^{\alpha_4}\right)^{\rho}}\right)\right) \qquad [A19]$$

$$=\rho.\ln\left(N_1^{\alpha_1}N_2^{\alpha_2}N_3^{\alpha_3}N_4^{\alpha_4}\right)+\ln\left(\frac{\alpha_1 N_1^{\rho}+\alpha_2 N_2^{\rho}+\alpha_3 N_3^{\rho}+\alpha_4 N_4^{\rho}}{\left(N_1^{\alpha_1}N_2^{\alpha_2}N_3^{\alpha_3}N_4^{\alpha_4}\right)^{\rho}}\right) \qquad [A20]$$

$$=\rho.(\alpha_1\ln N_1+\alpha_2\ln N_2+\alpha_3\ln N_3+\alpha_4\ln N_4)+\ln\left(\frac{\Sigma}{\Pi}\right) \qquad [A21]$$

where $\Sigma = \alpha_1 N_1^{\rho}+\alpha_2 N_2^{\rho}+\alpha_3 N_3^{\rho}+\alpha_4 N_4^{\rho}$ [A22] and $$\Pi = \left(N_1^{\alpha_1} N_2^{\alpha_2} N_3^{\alpha_3} N_4^{\alpha_4}\right)^{\rho} \qquad [A23]$$

Therefore substituting into [A13] we have :

$$\Rightarrow \ln w_1 = \ln \alpha_1 + \ln A - (1-\rho)\ln(1-u_1) - (1-\rho)\ln l_1 - (1-\rho)\ln L +$$

$$(1-\rho).\alpha_1.\ln N_1 + (1-\rho).\alpha_2.\ln N_2 + (1-\rho).\alpha_3.\ln N_3 +$$

$$(1-\rho).\alpha_4.\ln N_4 + \frac{(1-\rho)}{\rho}\ln\left(\frac{\Sigma}{\Pi}\right) \qquad [A24]$$

Now if we add and subtract terms in the labour force of each skill input we have:

$$\Rightarrow \ln w_1 = \ln \alpha_1 + \ln A - (1-\rho)\ln(1-u_1) - (1-\rho)\ln l_1 - (1-\rho)\ln L +$$

$$(1-\rho).\alpha_1.\ln(1-u_1) + (1-\rho).\alpha_2.\ln(1-u_2) + (1-\rho).\alpha_3.\ln(1-u_3) +$$

$$(1-\rho).\alpha_4.\ln(1-u_4) + \frac{(1-\rho)}{\rho}\ln\left(\frac{\Sigma}{\Pi}\right) + (1-\rho).\alpha_1.\ln L_1 +$$

$$(1-\rho).\alpha_2.\ln L_2 + (1-\rho).\alpha_3.\ln L_3 + (1-\rho).\alpha_4.\ln L_4 \qquad [A25]$$

Now given that :

$$-(1-\rho).\ln l_1 = -(1-\rho)(\alpha_1 + \alpha_2 + \alpha_3 + \alpha_4)\ln l_1 \qquad [A26]$$

and :

$$-(1-\rho).\ln L = -(1-\rho)(\alpha_1+\alpha_2+\alpha_3+\alpha_4)\ln L \qquad \text{[A27]}$$

we can rewrite [A18] as follows:

$$\Rightarrow \ln w_1 = \ln\alpha_1 + \ln A - (1-\rho)(1-\alpha_1)\ln(1-u_1) + (1-\rho).\alpha_2.\ln(1-u_2) +$$

$$(1-\rho).\alpha_3.\ln(1-u_3) + (1-\rho).\alpha_4.\ln(1-u_4) + \frac{(1-\rho)}{\rho}\ln\left(\frac{\Sigma}{\Pi}\right) +$$

$$(1-\rho).\alpha_2.\ln\frac{l_2}{l_1} + (1-\rho).\alpha_3.\ln\frac{l_3}{l_1} + (1-\rho).\alpha_4.\ln\frac{l_4}{l_1} \qquad \text{[A28]}$$

The total differential of this labour demand function is thus :

$$d\ln w_1 = d\ln\alpha_1 + d\ln A - (1-\rho)(1-\alpha_1)d\ln(1-u_1) +$$

$$(1-\rho).\alpha_2.d\ln(1-u_2) + (1-\rho).\alpha_3.d\ln(1-u_3) +$$

$$(1-\rho).\alpha_4.d\ln(1-u_4) + (1-\rho).\ln(1-u_1).d\alpha_1 +$$

$$(1-\rho).\ln(1-u_2).d\alpha_2 + (1-\rho).\ln(1-u_3).d\alpha_3 +$$

$$(1-\rho).\ln(1-u_4).d\alpha_4 + (1-\rho).\alpha_2.d\ln\frac{l_2}{l_1} + (1-\rho).\alpha_3.d\ln\frac{l_3}{l_1} +$$

$$(1-\rho).\alpha_4.d\ln\frac{l_4}{l_1} + \frac{(1-\rho)}{\rho}d\ln\left(\frac{\Sigma}{\Pi}\right) \qquad \text{[A29]}$$

Now if the wage setting curve is of the form :

$$\ln w_i = z_i - \gamma \ln u_i \qquad [A30]$$

then the total differential of the double logarithmic wage setting curve for the first input is :

$$d\ln w_1 = dz_1 - \frac{\gamma}{u_1} du_1 \qquad [A31]$$

Substituting [A31] into [A29] we have:

$$dz_1 - \frac{\gamma}{u_1} du_1 = d\ln\alpha_1 + d\ln A - (1-\rho)(1-\alpha_1)d\ln(1-u_1) +$$

$$(1-\rho).\alpha_2.d\ln(1-u_2) + (1-\rho).\alpha_3.d\ln(1-u_3) +$$

$$(1-\rho).\alpha_4.d\ln(1-u_4) + (1-\rho).\ln(1-u_1).d\alpha_1 +$$

$$(1-\rho).\ln(1-u_2).d\alpha_2 + (1-\rho).\ln(1-u_3).d\alpha_3 +$$

$$(1-\rho).\ln(1-u_4).d\alpha_4 + (1-\rho).\alpha_2.d\ln\frac{l_2}{l_1} + (1-\rho).\alpha_3.d\ln\frac{l_3}{l_1} +$$

$$(1-\rho).\alpha_4.d\ln\frac{l_4}{l_1} + \frac{(1-\rho)}{\rho} d\ln\left(\frac{\Sigma}{\Pi}\right) \qquad [A32]$$

Evaluating the final term in this expression, we know that :

$$\frac{(1-\rho)}{\rho} d\ln\left(\frac{\Sigma}{\Pi}\right) = \frac{(1-\rho)}{\rho}\left(\frac{\Pi}{\Sigma}\right) d\left(\frac{\Sigma}{\Pi}\right)$$

$$= \frac{(1-\rho)}{\rho}\left(\frac{\Pi}{\Sigma}\right)\left(\frac{\Pi d\Sigma - \Sigma d\Pi}{\Pi^2}\right)$$

$$= \frac{(1-\rho)}{\rho}\left(\frac{d\Sigma}{\Sigma} - \frac{d\Pi}{\Pi}\right) \qquad \text{[A33]}$$

Therefore differentiating and collecting terms we have :

$$\left(\frac{(1-\rho).\left(\Sigma - \alpha_1.l_1^{\rho}.(1-u_1)^{\rho}\right)}{(1-u_1).\Sigma} + \frac{\gamma}{u_1}\right)du_1 = dz_1 - d\ln A - d\ln\alpha_1 -$$

$$(1-\rho).\alpha_2.d\ln\frac{l_2}{l_1} - (1-\rho).\alpha_3.d\ln\frac{l_3}{l_1} - (1-\rho).\alpha_4.d\ln\frac{l_4}{l_1} +$$

$$\frac{(1-\rho).\alpha_2.l_2^{\rho}.(1-u_2)^{\rho}}{\Sigma.(1-u_2)}du_2 + \frac{(1-\rho).\alpha_3.l_3^{\rho}.(1-u_3)^{\rho}}{\Sigma.(1-u_3)}du_3 +$$

$$\frac{(1-\rho).\alpha_4.l_4^{\rho}.(1-u_4)^{\rho}}{\Sigma.(1-u_4)}du_4 + \frac{(1-\rho).\left(\ln l_1.\rho.\Sigma - N_1^{\rho}\right)}{\Sigma.\rho}d\alpha_1 +$$

$$\frac{(1-\rho).\left(\ln l_1.\rho.\Sigma - N_2^{\rho}\right)}{\Sigma.\rho}d\alpha_2 + \frac{(1-\rho).\left(\ln l_1.\rho.\Sigma - N_3^{\rho}\right)}{\Sigma.\rho}d\alpha_3 +$$

$$\frac{(1-\rho).\left(\ln l_1.\rho.\Sigma - N_4^{\rho}\right)}{\Sigma.\rho}d\alpha_4 + \frac{(1-\rho).\alpha_1.\left(\Sigma - (1-u_1)^{\rho}.l_1^{\rho}\right)}{\Sigma.l_1}dl_1 +$$

$$\frac{(1-\rho).\alpha_2.\left(\Sigma - (1-u_2)^{\rho}.l_2^{\rho}\right)}{\Sigma.l_2}dl_2 + \frac{(1-\rho).\alpha_3.\left(\Sigma - (1-u_3)^{\rho}.l_3^{\rho}\right)}{\Sigma.l_3}dl_3 +$$

$$\frac{(1-\rho).\alpha_4.\left(\Sigma-(1-u_4)^{\rho}.l_4^{\,\rho}\right)}{\Sigma.l_4}dl_4 \qquad [A34]$$

Now since :

$$\alpha_1+\alpha_2+\alpha_3+\alpha_4=1 \qquad [A35]$$

then :

$$d\alpha_1+d\alpha_2+d\alpha_3+d\alpha_4=0 \qquad [A36]$$

$$\therefore\left(\frac{(1-\rho).\rho.\Sigma.\ln l_1}{\rho.\Sigma}\right)(d\alpha_1+d\alpha_2+d\alpha_3+d\alpha_4)=0 \qquad [A37]$$

Furthermore :

$$\alpha_1 d\ln\alpha_1+\alpha_2 d\ln\alpha_2+\alpha_3 d\ln\alpha_3+\alpha_4 d\ln\alpha_4=0 \qquad [A38]$$

$$\therefore(1-\alpha_2-\alpha_3-\alpha_4)d\ln\alpha_1+\alpha_2 d\ln\alpha_2+\alpha_3 d\ln\alpha_3+\alpha_4 d\ln\alpha_4=0 \qquad [A39]$$

$$\Rightarrow d\ln\alpha_1=-\alpha_2 d\ln\frac{\alpha_2}{\alpha_1}-\alpha_3 d\ln\frac{\alpha_3}{\alpha_1}-\alpha_4 d\ln\frac{\alpha_4}{\alpha_1} \qquad [A40]$$

Therefore, we can simplify as

$$\left(\frac{\Phi_1}{(1-u_1)\Sigma}+\frac{\gamma}{u_1}\right)du_1-\left(\frac{(1-\rho).\alpha_2.l_2^{\,\rho}.(1-u_2)^{\rho}}{(1-u_2)\Sigma}\right)du_2-$$

$$\left(\frac{(1-\rho).\alpha_3.l_3^{\rho}.(1-u_3)^{\rho}}{(1-u_3).\Sigma}\right)du_3 - \left(\frac{(1-\rho).\alpha_4.l_4^{\rho}.(1-u_4)^{\rho}}{(1-u_4).\Sigma}\right)du_4 =$$

$$dz_1 - d\ln A + \alpha_2.d\ln MM_{21} + \alpha_3.d\ln MM_{31} + \alpha_4.d\ln MM_{41} -$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1^{\rho}.d\alpha_1 + N_2^{\rho}.d\alpha_2 + N_3^{\rho}.d\alpha_3 + N_4^{\rho}.d\alpha_4\right) +$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1^{\rho}.d\alpha_1 + N_2^{\rho}.d\alpha_2 + N_3^{\rho}.d\alpha_3 + N_4^{\rho}.d\alpha_4\right) +$$

$$\frac{(1-\rho)}{\Sigma}\left(\left(\frac{\alpha_1\left(\Sigma-(1-u_1)^{\rho}.l_1^{\rho}\right)}{l_1}\right).dl_1 + \left(\frac{\alpha_2\left(\Sigma-(1-u_2)^{\rho}.l_2^{\rho}\right)}{l_2}\right).dl_2 +\right.$$

$$\left.\left(\frac{\alpha_3\left(\Sigma-(1-u_3)^{\rho}.l_3^{\rho}\right)}{l_3}\right).dl_3 + \left(\frac{\alpha_4\left(\Sigma-(1-u_4)^{\rho}.l_4^{\rho}\right)}{l_4}\right).dl_4\right) \qquad [A41]$$

where we denote :

$$\Phi_1 = (1-\rho).\left(\Sigma - \alpha_1.l_1^{\rho}.(1-u_1)^{\rho}\right) \qquad [A42]$$

and:

$$\ln MM_{j1} = d\ln\frac{\alpha_j}{\alpha_1} - (1-\rho).d\ln\frac{l_j}{l_1} \qquad \forall\, j \qquad [A43]$$

Now from [A14] the demand function for the second input is :

$$\ln w_2 = \ln\alpha_2 + \ln A - (1-\rho)\ln(1-u_2) - (1-\rho)\ln l_1 - (1-\rho)\ln L +$$

$$\frac{(1-\rho)}{\rho}\ln\left(\alpha_1 N_1^{\rho} + \alpha_2 N_2^{\rho} + \alpha_3 N_3^{\rho} + \alpha_4 N_4^{\rho}\right) \qquad [A44]$$

or writing in terms of labour demand for the first input:

$$\ln w_2 = \ln w_1 - \ln\alpha_1 + \ln\alpha_2 + (1-\rho)\ln(1-u_1) -$$

$$(1-\rho)\ln(1-u_2) - (1-\rho)\ln\frac{l_2}{l_1} \qquad [A45]$$

and therefore substituting [A28] into [A45] :

$$\ln w_2 = \ln\alpha_2 + \ln A + (1-\rho)(1-\alpha_1)\ln(1-u_1) - (1-\rho)(1-\alpha_2)\ln(1-u_2) +$$

$$(1-\rho).\alpha_3.\ln(1-u_3) + (1-\rho).\alpha_4.\ln(1-u_4) + \frac{(1-\rho)}{\rho}\ln\left(\frac{\Sigma}{\Pi}\right) +$$

$$(1-\rho).(\alpha_2 - 1).\ln\frac{l_2}{l_1} + (1-\rho).\alpha_3.\ln\frac{l_3}{l_1} + (1-\rho).\alpha_4.\ln\frac{l_4}{l_1} \qquad [A46]$$

Thus from [A29] the total differential of this demand function is:

$$d\ln w_2 = d\ln\alpha_2 + d\ln A - (1-\rho)(1-\alpha_1)d\ln(1-u_1) -$$

$$(1-\rho).(1-\alpha_2).d\ln(1-u_2) + (1-\rho).\alpha_3.d\ln(1-u_3) +$$

$$(1-\rho).\alpha_4.d\ln(1-u_4) + (1-\rho).\ln(1-u_1).d\alpha_1 +$$

$$(1-\rho).\ln(1-u_2).d\alpha_2+(1-\rho).\ln(1-u_3).d\alpha_3+$$

$$(1-\rho).\ln(1-u_4).d\alpha_4+(1-\rho).\alpha_2.\ln\frac{l_2}{l_1}+(1-\rho).\alpha_3.\ln\frac{l_3}{l_1}+$$
$$(1-\rho).\alpha_4.\ln\frac{l_4}{l_1}+\frac{(1-\rho)}{\rho}d\ln\left(\frac{\Sigma}{\Pi}\right) \qquad \text{[A47]}$$

Now, substituting the total differential of the wage setting function [A31] into [A47] we have, after collecting terms:

$$\left(\frac{(1-\rho).\left(\Sigma-\alpha_2.l_2{}^{\rho}.(1-u_2)^{\rho}\right)}{(1-u_2).\Sigma}+\frac{\gamma}{u_2}\right)du_2=dz_2-d\ln A-d\ln\alpha_2-$$

$$(1-\rho).(\alpha_2-1).d\ln\frac{l_2}{l_1}-(1-\rho).\alpha_3.d\ln\frac{l_3}{l_1}-(1-\rho).\alpha_4.d\ln\frac{l_4}{l_1}+$$

$$\frac{(1-\rho).\alpha_1.l_1{}^{\rho}.(1-u_1)^{\rho}}{\Sigma.(1-u_1)}du_1+\frac{(1-\rho).\alpha_3.l_3{}^{\rho}.(1-u_3)^{\rho}}{\Sigma.(1-u_3)}du_3+$$

$$\frac{(1-\rho).\alpha_4.l_4{}^{\rho}.(1-u_4)^{\rho}}{\Sigma.(1-u_4)}du_4+\frac{(1-\rho).\left(\ln l_1.\rho.\Sigma-N_1{}^{\rho}\right)}{\Sigma.\rho}d\alpha_1+$$

$$\frac{(1-\rho).\left(\ln l_1.\rho.\Sigma-N_2{}^{\rho}\right)}{\Sigma.\rho}d\alpha_2+\frac{(1-\rho).\left(\ln l_1.\rho.\Sigma-N_3{}^{\rho}\right)}{\Sigma.\rho}d\alpha_3+$$

$$\frac{(1-\rho).\left(\ln l_1.\rho.\Sigma-N_4{}^{\rho}\right)}{\Sigma.\rho}d\alpha_4+\frac{(1-\rho).\alpha_1.\left(\Sigma-(1-u_1)^{\rho}.l_1{}^{\rho}\right)}{\Sigma.l_1}dl_1+$$

$$\frac{(1-\rho).\alpha_2.\left(\Sigma-(1-u_2)^{\rho}.l_2^{\rho}\right)}{\Sigma.l_2}dl_2+\frac{(1-\rho).\alpha_3.\left(\Sigma-(1-u_3)^{\rho}.l_3^{\rho}\right)}{\Sigma.l_3}dl_3+$$

$$\frac{(1-\rho).\alpha_4.\left(\Sigma-(1-u_4)^{\rho}.l_4^{\rho}\right)}{\Sigma.l_4}dl_4 \qquad [A48]$$

Now from [A40]:

$$d\ln\alpha_2=-\alpha_1 d\ln\frac{\alpha_1}{\alpha_2}-\alpha_3 d\ln\frac{\alpha_3}{\alpha_2}-\alpha_4 d\ln\frac{\alpha_4}{\alpha_2} \qquad [A49]$$

$$\Rightarrow d\ln\alpha_2=-\alpha_1 d\ln\alpha_1-\alpha_3 d\ln\alpha_3-\alpha_4 d\ln\alpha_4+ \qquad [A50]$$

$$(\alpha_1+\alpha_3+\alpha_4)d\ln\alpha_2$$

$$\Rightarrow d\ln\alpha_2=-\alpha_1 d\ln\alpha_1-\alpha_3 d\ln\alpha_3-\alpha_4 d\ln\alpha_4+(1-\alpha_2)d\ln\alpha_2 \qquad [A51]$$

Now given [A35]:

$$\therefore (1-\alpha_1-\alpha_2-\alpha_3-\alpha_4)d\ln\alpha_1=0 \qquad [A52]$$

$$\Rightarrow d\ln\alpha_2=-\alpha_3 d\ln\frac{\alpha_3}{\alpha_1}-\alpha_4 d\ln\frac{\alpha_4}{\alpha_1}+(1-\alpha_2)d\ln\frac{\alpha_2}{\alpha_1} \qquad [A53]$$

and therefore, given [A37], we can rewrite [A48], after simplification as :

$$-\left(\frac{(1-\rho).\alpha_1.l_1^{\rho}.(1-u_1)^{\rho}}{(1-u_1).\Sigma}\right)du_1+\left(\frac{\Phi_2}{(1-u_2).\Sigma}+\frac{\gamma}{u_2}\right)du_2-$$

$$\left(\frac{(1-\rho).\alpha_3.l_3^{\rho}.(1-u_3)^{\rho}}{(1-u_3).\Sigma}\right)du_3-\left(\frac{(1-\rho).\alpha_4.l_4^{\rho}.(1-u_4)^{\rho}}{(1-u_4).\Sigma}\right)du_4=$$

$$dz_2-d\ln A+(\alpha_2-1).d\ln MM_{21}+\alpha_3.d\ln MM_{31}+\alpha_4.d\ln MM_{41}-$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1^{\rho}.d\alpha_1+N_2^{\rho}.d\alpha_2+N_3^{\rho}.d\alpha_3+N_4^{\rho}.d\alpha_4\right)+$$

$$\frac{(1-\rho)}{\Sigma}\left(\left(\frac{\alpha_1\left(\Sigma-(1-u_1)^{\rho}.l_1^{\rho}\right)}{l_1}\right).dl_1+\left(\frac{\alpha_2\left(\Sigma-(1-u_2)^{\rho}.l_2^{\rho}\right)}{l_2}\right).dl_2+\right.$$

$$\left.\left(\frac{\alpha_3\left(\Sigma-(1-u_3)^{\rho}.l_3^{\rho}\right)}{l_3}\right).dl_3+\left(\frac{\alpha_4\left(\Sigma-(1-u_4)^{\rho}.l_4^{\rho}\right)}{l_4}\right).dl_4\right) \qquad [A54]$$

where :

$$\Phi_2=(1-\rho).\left(\Sigma-\alpha_2.l_2^{\rho}.(1-u_2)^{\rho}\right) \qquad [A55]$$

So we have an equation like [A55] for each of the terms du_i which all contain a term in the change in the unemployment rates of the other labour inputs, which gives us a classic system of equations, which if we define the matrix Θ :

$$\Theta = \begin{pmatrix} \frac{\Phi_1}{(1-u_1)\Sigma}+\frac{\gamma}{u_1} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{-\lambda_4}{(1-u_4)\Sigma} \\ \frac{-\lambda_1}{(1-u_1)\Sigma} & \frac{\Phi_2}{(1-u_2)\Sigma}+\frac{\gamma}{u_2} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{-\lambda_4}{(1-u_4)\Sigma} \\ \frac{-\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{\Phi_3}{(1-u_3)\Sigma}+\frac{\gamma}{u_3} & \frac{-\lambda_4}{(1-u_4)\Sigma} \\ \frac{-\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\Phi_4}{(1-u_4)\Sigma}+\frac{\gamma}{u_4} \end{pmatrix} \qquad [A56]$$

where we define :

$$\lambda_i = (1-\rho).\alpha_i.l_i^{\rho}.(1-u_i)^{\rho} \qquad [A57]$$

then we describe this system of equations as follows:

$$\Theta.\begin{pmatrix} du_1 \\ du_2 \\ du_3 \\ du_4 \end{pmatrix} = \begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} d\ln A - \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \Psi +$$

$$\begin{pmatrix} \alpha_2 \\ \alpha_2 - 1 \\ \alpha_2 \\ \alpha_2 \end{pmatrix} .d\ln MM_{21} + \begin{pmatrix} \alpha_3 \\ \alpha_3 \\ \alpha_3 - 1 \\ \alpha_3 \end{pmatrix} .d\ln MM_{31} + \begin{pmatrix} \alpha_4 \\ \alpha_4 \\ \alpha_4 \\ \alpha_4 - 1 \end{pmatrix} .d\ln MM_{41} \qquad [A58]$$

where

$$\Psi = \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \left(\frac{(1-\rho)}{\rho.\Sigma} \right) \left(N_1^{\rho}.d\alpha_1 + N_2^{\rho}.d\alpha_2 + N_3^{\rho}.d\alpha_3 + N_4^{\rho}.d\alpha_4 \right) +$$

$$\begin{pmatrix}1\\1\\1\\1\end{pmatrix}.\left(\frac{(1-\rho)}{\Sigma}\right)\left(\left(\frac{\alpha_1\left(\Sigma-(1-u_1)^{\rho}.l_1^{\rho}\right)}{l_1}\right).dl_1+\left(\frac{\alpha_2\left(\Sigma-(1-u_2)^{\rho}.l_2^{\rho}\right)}{l_2}\right).dl_2+\right.$$

$$\left.\left(\frac{\alpha_3\left(\Sigma-(1-u_3)^{\rho}.l_3^{\rho}\right)}{l_3}\right).dl_3+\left(\frac{\alpha_4\left(\Sigma-(1-u_4)^{\rho}.l_4^{\rho}\right)}{l_4}\right).dl_4\right) \qquad \text{[A59]}$$

then if we assume that the matrix Θ is nonsingular, we can rewrite [A59] as :

$$\begin{pmatrix}du_1\\du_2\\du_3\\du_4\end{pmatrix}=\Theta^{-1}\begin{pmatrix}dz_1\\dz_2\\dz_3\\dz_4\end{pmatrix}-\Theta^{-1}\begin{pmatrix}1\\1\\1\\1\end{pmatrix}d\ln A-\Theta^{-1}\begin{pmatrix}1\\1\\1\\1\end{pmatrix}\Psi+$$

$$\Theta^{-1}\begin{pmatrix}\alpha_2\\\alpha_2-1\\\alpha_2\\\alpha_2\end{pmatrix}.d\ln MM_{21}+\Theta^{-1}\begin{pmatrix}\alpha_3\\\alpha_3\\\alpha_3-1\\\alpha_3\end{pmatrix}.d\ln MM_{31}+\Theta^{-1}\begin{pmatrix}\alpha_4\\\alpha_4\\\alpha_4\\\alpha_4-1\end{pmatrix}.d\ln MM_{41} \qquad \text{[A60]}$$

Now we know that the aggregate unemployment rate u is a weighted average of the unemployment rates of the separate labour inputs, i.e. :

$$u=l_1.u_1+l_2.u_2+l_3.u_3+l_4.u_4 \qquad \text{[A61]}$$

$$\therefore du=l_1.du_1+l_2.du_2+l_3.du_3+l_4.du_4+$$

$$dl_1.u_1+dl_2.u_2+dl_3.u_3+dl_4.u_4 \qquad \text{[A62]}$$

Therefore, if we define the matrix Ξ as :

$$\Xi = \begin{pmatrix} l_1 & l_2 & l_3 & l_4 \end{pmatrix} . \Theta^{-1} \qquad [A63]$$

Then from [A60] we have that :

$$du = \Xi . \begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix} - \Xi . \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} d \ln A - \Xi . \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \Psi + \Xi . \begin{pmatrix} \alpha_2 \\ \alpha_2 - 1 \\ \alpha_2 \\ \alpha_2 \end{pmatrix} . d \ln MM_{21} + \Xi . \begin{pmatrix} \alpha_3 \\ \alpha_3 \\ \alpha_3 - 1 \\ \alpha_3 \end{pmatrix} . d \ln MM_{31} +$$

$$\Xi . \begin{pmatrix} \alpha_4 \\ \alpha_4 \\ \alpha_4 \\ \alpha_4 - 1 \end{pmatrix} . d \ln MM_{41} + \begin{pmatrix} u_1 & u_2 & u_3 & u_4 \end{pmatrix} \begin{pmatrix} dl_1 \\ dl_2 \\ dl_3 \\ dl_4 \end{pmatrix} \qquad [A64]$$

Now, if alternatively there is a leading sector, so that all wages in the economy are set subject to conditions in one sector, say for example the market for input 4, then the generic wage setting function is of the form :

$$\ln w_i = z_i - \gamma \ln u_4 \qquad [A65]$$

then the total differential of this asymmetric wage setting function is :

$$d \ln w_i = dz_i - \frac{\gamma}{u_4} du_4 \qquad [A66]$$

Therefore, we now have to rewrite [A41] as :

$$\left(\frac{\Phi_1}{(1-u_1).\Sigma}\right)du_1-\left(\frac{(1-\rho).\alpha_2.l_2^{\ \rho}.(1-u_2)^{\rho}}{(1-u_2).\Sigma}\right)du_2-$$

$$\left(\frac{(1-\rho).\alpha_3.l_3^{\ \rho}.(1-u_3)^{\rho}}{(1-u_3).\Sigma}\right)du_3+\left(\frac{\gamma}{u_4}-\frac{(1-\rho).\alpha_4.l_4^{\ \rho}.(1-u_4)^{\rho}}{(1-u_4).\Sigma}\right)du_4=$$

$$dz_1-d\ln A+\alpha_2.d\ln MM_{21}+\alpha_3.d\ln MM_{31}+\alpha_4.d\ln MM_{41}-$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1^{\ \rho}.d\alpha_1+N_2^{\ \rho}.d\alpha_2+N_3^{\ \rho}.d\alpha_3+N_4^{\ \rho}.d\alpha_4\right)+$$

$$\frac{(1-\rho)}{\rho.\Sigma}\left(N_1^{\ \rho}.d\alpha_1+N_2^{\ \rho}.d\alpha_2+N_3^{\ \rho}.d\alpha_3+N_4^{\ \rho}.d\alpha_4\right)+$$

$$\frac{(1-\rho)}{\Sigma}\left(\left(\frac{\alpha_1\left(\Sigma-(1-u_1)^{\rho}.l_1^{\ \rho}\right)}{l_1}\right).dl_1+\left(\frac{\alpha_2\left(\Sigma-(1-u_2)^{\rho}.l_2^{\ \rho}\right)}{l_2}\right).dl_2+\right.$$

$$\left.\left(\frac{\alpha_3\left(\Sigma-(1-u_3)^{\rho}.l_3^{\ \rho}\right)}{l_3}\right).dl_3+\left(\frac{\alpha_4\left(\Sigma-(1-u_4)^{\rho}.l_4^{\ \rho}\right)}{l_4}\right).dl_4\right) \qquad \text{[A67]}$$

Therefore we can define the matrix Ω:

$$\Omega = \begin{pmatrix} \frac{\Phi_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} - \frac{\lambda_4}{(1-u_4)\Sigma} \\ -\frac{\lambda_1}{(1-u_1)\Sigma} & \frac{\Phi_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} - \frac{\lambda_4}{(1-u_4)\Sigma} \\ -\frac{\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{\Phi_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} - \frac{\lambda_4}{(1-u_4)\Sigma} \\ -\frac{\lambda_1}{(1-u_1)\Sigma} & \frac{-\lambda_2}{(1-u_2)\Sigma} & \frac{-\lambda_3}{(1-u_3)\Sigma} & \frac{\gamma}{u_4} + \frac{\Phi_4}{(1-u_4)\Sigma} \end{pmatrix} \qquad [A68]$$

so that our set of equations is now :

$$\Omega . \begin{pmatrix} du_1 \\ du_2 \\ du_3 \\ du_4 \end{pmatrix} = \begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix} - \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} d \ln A - \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \Psi +$$

$$\begin{pmatrix} \alpha_2 \\ \alpha_2 - 1 \\ \alpha_2 \\ \alpha_2 \end{pmatrix} .d \ln MM_{21} + \begin{pmatrix} \alpha_3 \\ \alpha_3 \\ \alpha_3 - 1 \\ \alpha_3 \end{pmatrix} .d \ln MM_{31} + \begin{pmatrix} \alpha_4 \\ \alpha_4 \\ \alpha_4 \\ \alpha_4 - 1 \end{pmatrix} .d \ln MM_{41} \qquad [A69]$$

then if we assume that the matrix Ω is nonsingular, we can rewrite [A69] as :

$$\begin{pmatrix} du_1 \\ du_2 \\ du_3 \\ du_4 \end{pmatrix} = \Omega^{-1} \begin{pmatrix} dz_1 \\ dz_2 \\ dz_3 \\ dz_4 \end{pmatrix} - \Omega^{-1} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} d \ln A - \Omega^{-1} \begin{pmatrix} 1 \\ 1 \\ 1 \\ 1 \end{pmatrix} \Psi +$$

$$\Omega^{-1}\begin{pmatrix}\alpha_2\\ \alpha_2-1\\ \alpha_2\\ \alpha_2\end{pmatrix}.d\ln MM_{21}+\Omega^{-1}\begin{pmatrix}\alpha_3\\ \alpha_3\\ \alpha_3-1\\ \alpha_3\end{pmatrix}.d\ln MM_{31}+\Omega^{-1}\begin{pmatrix}\alpha_4\\ \alpha_4\\ \alpha_4\\ \alpha_4-1\end{pmatrix}.d\ln MM_{41} \quad [A70]$$

Therefore, if we define the matrix Γ as :

$$\Gamma=\begin{pmatrix}l_1 & l_2 & l_3 & l_4\end{pmatrix}.\Omega^{-1} \qquad [A71]$$

Then from [A62] and [A71] we have that :

$$du=\Gamma.\begin{pmatrix}dz_1\\ dz_2\\ dz_3\\ dz_4\end{pmatrix}-\Gamma.\begin{pmatrix}1\\ 1\\ 1\\ 1\end{pmatrix}d\ln A-\Gamma.\begin{pmatrix}1\\ 1\\ 1\\ 1\end{pmatrix}\Psi+\Gamma.\begin{pmatrix}\alpha_2\\ \alpha_2-1\\ \alpha_2\\ \alpha_2\end{pmatrix}.d\ln MM_{21}+\Gamma.\begin{pmatrix}\alpha_3\\ \alpha_3\\ \alpha_3-1\\ \alpha_3\end{pmatrix}.d\ln MM_{31}+$$

$$\Gamma.\begin{pmatrix}\alpha_4\\ \alpha_4\\ \alpha_4\\ \alpha_4-1\end{pmatrix}.d\ln MM_{41}+\begin{pmatrix}u_1 & u_2 & u_3 & u_4\end{pmatrix}\begin{pmatrix}dl_1\\ dl_2\\ dl_3\\ dl_4\end{pmatrix} \qquad [A72]$$

CHAPTER 4

'THE CHRONIC' - AN ANALYSIS OF THE DEGREE OF CONCENTRATION IN THE DISTRIBUTION OF CLAIMANT UNEMPLOYMENT ACROSS MEN

1. INTRODUCTION

The unemployment rate is defined as the fraction of the labour force who are out of work and claiming benefit, or seeking employment (depending on one's definition) on any given day. A time series of the unemployment rate tells us how the aggregate incidence of unemployment has varied over time. However, time series data on the rate cannot tell us how that unemployment is distributed over time – whether it is the same people who are unemployed day after day, or whether each day the stock flows out of unemployment to be replaced by a new inflow. In order to answer this question we need to look beyond the aggregate unemployment rate and focus on the long run distribution of unemployment at the micro level, and that is the focus of this chapter.

We know that experiences of unemployment vary. For some, the experience is short lived, as they rapidly exit unemployment and return to work. However, for others – *the long term unemployed* – that spell of unemployment may last months, or even years. Yet, many of those who exit unemployment at a given point in time, perhaps after only a brief spell, will also flow back within a short space of time. Thus, over the course of a number of spells separated only by ephemeral interludes of employment or inactivity, these individuals – *the recurrent unemployed* – may also spend a considerable fraction of any given period unemployed. Focusing only on the duration of particular spells of unemployment suffered by individual can therefore obscure the true incidence of unemployment among the population. To get a clearer picture of the extent of this accumulated exposure to unemployment – or what we define here as *chronic unemployment* – we need a wider perspective on outcomes in the labour market.

We might well ask what extra information do we gain from focusing on individuals' accumulated experiences of unemployment over and above observing the length of the current spell, or put another way, does a past history of unemployment matter ? We argue there are (at least) three reasons why chronic unemployment matters: because the existence of a rump of chronically unemployed individuals upon whom experience of unemployment is heavily concentrated may help us understand the relationship between wage setting and the unemployment rate at the aggregate level; because if past spells of unemployment cause (or extend) future spells then recurrent unemployment may help explain the persistence of outcomes at the individual level and unemployment at the aggregate level; and because chronic exposure to unemployment is likely to be heavily correlated with the incidence of poverty. In order to motivate this chapter we shall briefly outline each of these arguments below.

The causes and consequences of long term spells of unemployment have received a great deal of attention in the literature[40] in recent years. From the macroeconomic perspective, it has been argued[41] that the growth in long term unemployment across Europe through the late 1970's and 1980's offers an explanation for the sustained rise in the aggregate unemployment rate suffered there over the period. The long term unemployed appear particularly ineffective at filling vacancies, and therefore provide little restraint on wage behaviour – since those in jobs know that if the firm wants to replace them, there are few adequate substitutes in the unemployment pool. The shift in the Beveridge curve over the period is usually taken as strong corroborative evidence of this persistence mechanism – as the search intensity of the unemployed is said to have fallen with the rise in the average duration of unemployment. However, there is a growing realisation that the rise in long term unemployment is insufficient both in theory and in practice to explain the

[40] For example, for a survey of the existing research see Machin and Manning (1999).
[41] See Layard at. al. (1991).

hysteresis in European unemployment rates[42], and therefore high unemployment should restrain wage growth, even if that unemployment is predominantly long term in nature. Of course, once we accept that individuals vary in their probability of being unemployed, the aggregate unemployment rate may cease to be an accurate signal of the unemployment risk faced by wage setters. The least skilled members of the labour force are always going to be the most likely to both become and remain unemployed, and for a given aggregate unemployment rate, the less evenly that unemployment is spread across the population, the lower the probability that insiders will suffer any significant experience of unemployment. In other words, in order to understand how wage setters respond to the incidence of unemployment in the labour market we need to appreciate how that unemployment is distributed across the labour force, as well as just the level.

Blanchard outlines a particular form of this hypothesis: since unemployment is concentrated amongst the young, then even though adult wage setters are at risk of becoming unemployed they are certainly not at risk of becoming young – and therefore, they are not at risk of becoming chronically unemployed. Consequently, wage setters pay little regard to a high unemployment rate where it is driven by chronic youth unemployment, and so high unemployment will fail to control wage pressure. For this reason, understanding not only how much unemployment is concentrated among the few, but also whom it is concentrated on, may prove insightful in understanding the link between wage setting and the incidence of unemployment.

It often argued that there is duration dependence in unemployment – the longer a spell of unemployment lasts, the smaller the chance that a given individual will escape – as his level of motivation, human capital and even psychological well-being are eroded through exclusion from work. It seems plausible that any "scarring effect" of unemployment might not be instantly cleansed upon exit from unemployment (that any erosion of human capital is not instantly reversed); instead this damage to the individual may persist - and

[42] The evidence suggests that the mechanism does not appear to be quantitatively powerful enough to explain the degree of persistence we observe in the evolution of unemployment rates across countries, and in any case, the existence of long term unemployment should still moderate wage behaviour on the part of insiders, because one day it may be them who are long term unemployed (Blanchard (2000)).

past experiences of unemployment will continue to have an impact on current outcomes through so called *lagged duration dependence effects*[43]. The existence of significant lagged duration dependence effects would generate a further powerful persistence mechanism to that described above – not only would it be the case that those in jobs are unlikely ever to suffer much unemployment (and pay little heed to a high aggregate unemployment rate, driven by high durations of those unfortunate enough to suffer it) but moreover, those out of jobs who have suffered prolonged exposure to unemployment in the past will over time search less effectively, and provide an ever weaker restraint on wages. We return to investigate this issue in greater depth in Chapter 5.

There is also a growing literature[44] which suggests that recurrent unemployment is part of a wider phenomenon – the "low pay – no pay" cycle – where individuals are trapped in a cycle of poverty pay and unemployment – a fact observed thirty years ago by Robert Hall:

> "Changing from one low-paying, unpleasant job to another, often several times a year, is the typical pattern of some workers. The resulting unemployment can hardly be said to be the outcome of a normal process of career advancement. The true problem of hard-core unemployment is that certain members of the labor force account for a disproportionate share of unemployment because they drift from one unsatisfactory job to another, spending the time between jobs either unemployed or out of the labor force. (Hall (1970) p.389)"

The welfare implications of this "low pay – no pay" cycle are clear. Repeated exposure to unemployment may not be of great concern if between spells, individuals are earning very high wages, which in some sense compensate them for the insecurity of their work. However, if it is the case that even when the recurrent unemployed do find work, their earnings are very low, then these individuals may spend a considerable period of time on,

[43] For an excellent exposition of this concept see Heckman and Borjas (1980).
[44] See, for example, Dickens *et. al.*(2000) and Stewart (2000).

or below, the poverty line[45]. If lagged duration dependence effects are significant – so past spells of unemployment erode individual's employability and/or productivity, then this process becomes a vicious cycle – each successive spell of unemployment further reduces the individual's ability to escape by making them less and less attractive to employers offering anything other than poverty pay.

We have argued then that understanding the long run distribution of unemployment across individuals, and in particular how concentrated those experiences of unemployment are, is important. However, in order to address these issues it is first necessary to gain a clearer idea of exactly how much unemployment individuals experience in the long run. We therefore focus on experiences of unemployment ***across*** spells – aggregating the duration of each separate spell of unemployment experienced by the individual to gain an insight into the total amount of time an individual is unemployed ***over a specified period***. Inevitably this will involve censoring spells at the beginning and end of each period – so the true impact of long term unemployment will be understated – since many spells which began in the year in question will endure into following years (and sometimes, decades)[46]. This approach to measuring longer run experiences of unemployment has its antecedents in the work of Hall (1970), Clark and Summers (1979) and Disney (1979); more recently it has been suggested by Machin and Manning (1999) as a means to resolve the extent to which unemployment (and therefore poverty) is concentrated among a few individuals.

This research focuses on the distribution of unemployment across individuals within a given period; therefore a natural benchmark against which we can compare our results is

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[45] There is an alternative interpretation of the high rates of job destruction that we observe in the labour market – that contrary to Hall's claim, they reflect individuals searching through alternative careers until a suitable match is found – a process labelled as "job shopping". Nonetheless, to the extent that both interpretations imply that individuals will spend a prolonged period of time earning low or no wages, then at least on welfare grounds, there is good reason to be concerned over the amount of unemployment individuals suffer in the long run – a chronic lack of paid employment is likely to be highly correlated with the incidence of poverty and social exclusion.

[46] For this reason, we will vary the length of the 'window' over which we analyze experiences of unemployment. For simplicity's sake, we measure the total duration of unemployment suffered by an individual as a percentage of the total length of the period we are analyzing, to allow comparison across these alternative 'windows'.

the distribution of unemployment across spells in that period. Of course, if individuals did not suffer repeated spells of unemployment, then the two distributions would be identical· Therefore, in some respects, the extent to which the two distributions differ can be thought of as capturing the impact of repeat spells of unemployment on the distribution of unemployment. Consequently, we believe that the distribution of unemployment across spells constitutes a useful yardstick against which to compare developments in the labour market, and we will reference our results against those obtained with this alternative distribution. Finally, a note of caution should be made; our estimate of distribution of spell lengths in the JUVOS panel will be censored since we treat all spells as if they started no earlier than the beginning of the period, and finished no later than the end of the year.

In summary then, our research aims to describe the distribution of the total duration of unemployment across individuals, and in particular how concentrated that distribution is. The chapter proceeds as follows: Section 2 describes the data set upon which the research is based – the J.U.V.O.S. cohort panel. Section 3 reports on the distribution of unemployment across the male working age population. Section 4 focuses on those in the population who suffer the most – the *chronically unemployed* – whom we define here as those who spend at least half of a given period in unemployment, and addresses Blanchard's assertion that chronic unemployment falls on the young. We have argued that if experiences of unemployment are segregated between those who suffer very little, and those who are chronically unemployed, then we might expect to observe both extreme poverty among a small rump of the population at the micro level, and persistence in the unemployment rate at the macro level. However, it is not clear which particular feature of the distribution of unemployment across individuals drives wage setting, and Sections 5 and 6 represent alternative approaches to quantifying the variation in experiences of unemployment or the degree to which the distribution of unemployment shifts through time[47]. Section 5 focuses on the degree of inequality in the distribution of

[47] Although one could attempt to discriminate which of these concepts better describes how insiders assess their risk of being unemployed – for example, by including each of these measures in a wage curve regression – we do not pursue this line of enquiry in this thesis.

unemployment, drawing upon established tools taken from the that literature[48]; alternatively Section 6 draws upon the concept of polarisation within a distribution to examine whether there is instead any evidence of stratification in experiences of unemployment, where individuals can be separated out into separate 'clusters'. Finally, Section 7 concludes.

2. THE DATA

The JUVOS Cohort is a longitudinal data set which contains information on approximately of 5% of all claims for unemployment-related benefits paid through the National Unemployment Benefit Payments System (NUBS), which was established in October 1982 following the switch from a registrant to a claimant count basis[49]. Spells[50] are randomly selected on the basis of the National Insurance number of the claimant, which ensures that the entire spell histories (since the inception of the scheme) of those with the appropriate NI numbers are recorded. The twin virtues of the JUVOS cohort over and above other pre-existing labour market datasets are its size and length – in May 1995 the panel contained information on almost three million separate claims, and over one million separate claimants, collected over a thirteen year period[51]. Furthermore, the fact that the information is recorded in real time (information in the panel is updated on a daily basis, using information drawn directly from the local offices of the Employment Service) ensures that measurement error in recording spell information is minimized. In contrast, in those datasets where information on lifetime labour market experiences is collected retrospectively, the number of spells of both employment and unemployment tend to be under-reported (typically at the expense of those spells of only short duration) leading us to overestimate the incidence of long-term unemployment and underestimate the incidence of recurrent unemployment (see Paull (1996)). Consequently, the JUVOS

[48] For an excellent summary of this literature see Cowell (1995).
[49] Ward and Bird (1995), p.345.
[50] The results in this paper are based on a subset of the sample which includes only those spells of unemployment which last for seven days or more. Similar results are achieved when we include all spells of a day or more in length, and these may be obtained from the author on request.
[51] Ward and Bird (1996), p.346.

panel enables us to obtain an insight into individual experiences of unemployment over their lifetime at a level of detail that was not previously possible.

Essentially, the JUVOS panel records the start and end date of each separate spell of unemployment suffered by each individual; however, without any alternative data source, we have no information on the labour market status of these individuals between each spell – specifically whether they were employed or economically inactive[52]. As such, the JUVOS cohort should be thought of as delineating periods of each individual's labour market history as either *"unemployed"* or *"not-unemployed"* (as opposed to a more standard division of individuals' status as either employed or not-employed). This may be of particular concern when attempting to make inferences about the long run labour market experiences of female claimants on the basis of their spell histories, when female inactivity rates are significantly higher than those of males at all ages (although the gap has closed considerably), and when, in particular, many females completely withdraw from the labour force for an extended period of time in order to care for their children. Furthermore, relative to males, there is evidence that the claimant count definition of the female unemployment rate is particularly misleading, since there are a considerable number of women actively searching for work who are not eligible for government benefit[53]. Similarly, since those at either extreme of the working age spectrum may have only weak attachment to the labour market and may be ineligible for those benefits which imply entry into the JUVOS panel, the dataset may not accurately describe the true incidence of unemployment among these groups. For these reasons this chapter will focus only on the unemployment histories of prime age males (those between 18 and 65 years of age) in the JUVOS cohort, of which there are over half a million, with information on nearly two million separate claims. Since data was only collected on spells of

[52] From August 1996 onwards we can identify whether an individual left the claimant count for employment or inactivity. However, there is much evidence to suggest that flows between economic inactivity and employment are non trivial (see Gregg and Wadsworth (1999)) so there remains no water-tight way to discern the labour market status of individuals throughout the periods in which they are not recorded as claimant unemployed.

[53] In 1995 over a third of those women actively searching for work and defined as unemployed by the ILO measure were not registered as claimant unemployed; indeed, the abject failure of the claimant count to accurately record the incidence of female unemployment may well have been the final nail in the coffin for the claimant count as the government's measure of the unemployment rate (Nickell (1999)).

unemployment in Northern Ireland from October 1993 onwards, we have also removed all these spells from our sample, so strictly speaking our research refers to unemployment in Great Britain, rather than the United Kingdom.

Finally, two notes of caution must be made as to how to interpret results derived from the JUVOS dataset. Firstly, although a random sample of the unemployed, the panel is not a representative sample of the labour force – far from it, since in order to be included an individual must have made a claim for unemployment related benefits since October 1982. Therefore, our results refer implicitly to that subset of the labour force who at some stage experience unemployment. Secondly, as in many countries, the rules governing the level of, and eligibility for, benefit payments to the unemployed in the U.K. were subject to significant and repeated change over the period[54]. These changes will doubtless have had an impact on the distribution of claimant unemployment, and hence the nature of our sample.

3. THE DISTRIBUTION OF UNEMPLOYMENT

Our approach in describing the distribution of unemployment among prime age males in the panel focuses on three key features of that distribution: the number of individuals who are unemployed at some point in any given period – or the *domain* of the distribution; the shape – or *density* – of the distribution itself; and finally, the degree of *turbulence* within the distribution, captured by the gross flows into and out of the claimant count. The extent to which the distribution of unemployment shifts over time will be investigated in Sections 5 and 6.

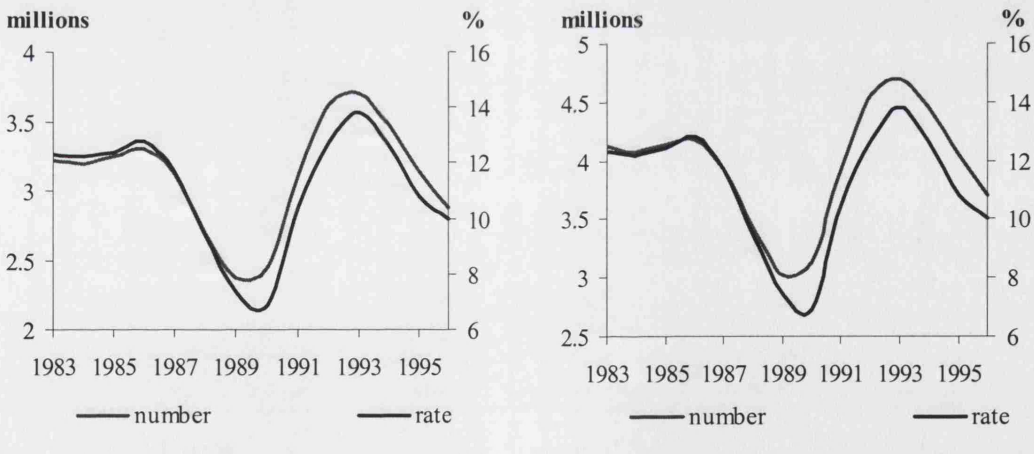
[54] See Bell and Smith (2002) for an excellent summary of the changes in entitlements within the benefit system over this period.

3.1 THE DOMAIN OF THE DISTRIBUTION OF UNEMPLOYMENT

It is straightforward to estimate on the basis of the JUVOS panel, the total number of males, between 18 and 65 years of age, who made a claim for unemployment related benefits each year. It transpires that in any given year between 1983 and 1996, two to four million prime age males had some experience of unemployment[55]. Although there is clear evidence of the cycle, that is (as expected) in a year when the unemployment rate is high, the number of men who have some experience of unemployment at some point during that year is also high, there is also circumstantial evidence that quantitatively this relationship has changed (see Figure 3.1) – while the male unemployment rate was almost identical at similar points in the cycle in 1986 and 1994[56], over 150,000 more men had some experience of unemployment in 1994[57].

FIGURE 3.1: INCIDENCE OF UNEMPLOYMENT IN A YEAR (MILLIONS) [58,59]

INDIVIDUALS **SPELLS**



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[55] All figures quoted in this Chapter are grossed up by a factor of 20 since the JUVOS cohort is a random 5% sample of the claimant unemployed.

[56] In actual fact, the male unemployment rate was slightly lower in 1994 – in June 1986 the male unemployment rate was 12.8%, while in June 1994 it was 12.6% - nonetheless approximately one hundred and seventy one thousand more men had some experience of unemployment in 1994 than in 1986.

[57] Of course, there were more men in the working-age population in 1994 than 1986. However, in proportional terms, more men had an experience of unemployment in 1994 than 1986.

[58] Strictly speaking, the male claimant unemployment rate in Great Britain for June of each year.

[59] The data underlying this figure (and all the others included in this paper) are reproduced in Appendix 2.

However, despite the fact that our panel contains information over a fourteen year period we feel that there is probably insufficient information to be able to decisively identify any change in the distribution of unemployment across successive cycles, and for that reason we shall make only tentative suggestions as to possible shifts in the distribution of unemployment *across the labour force* over time.

If we widen our perspective, to consider how many individuals are ever unemployed over a longer period of time, unsurprisingly we find the number increases – between 1993 and 1996, almost five and a half million prime aged males made at least one claim for unemployment related benefits. To put this figure in context, there were almost 18 million economically active working age males in 1996.

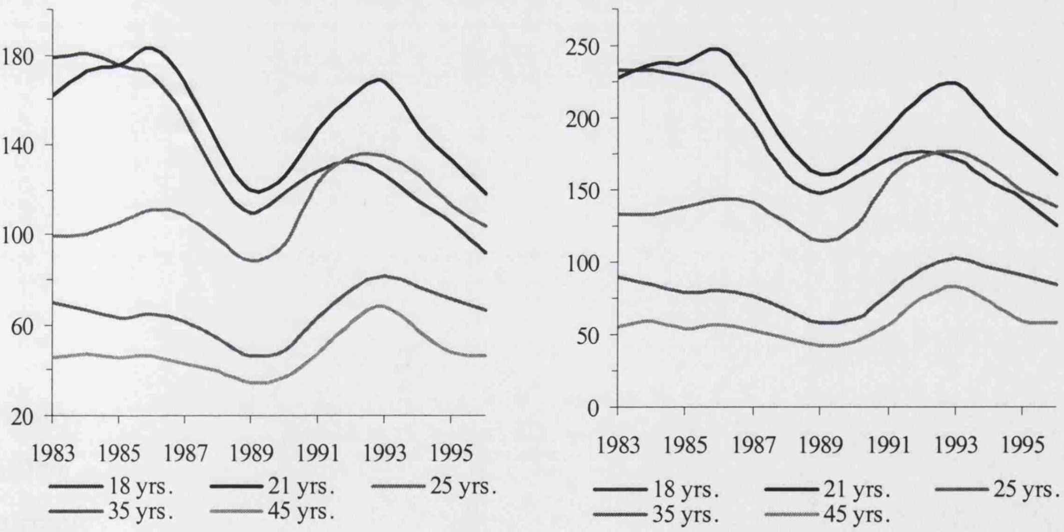
The JUVOS cohort also allows us to estimate the total number of spells of unemployment experienced by males at some point over the sample period. There were in excess of three million separate claims made for unemployment related benefits in every year between 1983 and 1996. As the figure above illustrates, the total number of spells over a year is also highly correlated with the unemployment rate in that year. Once again we find (at least circumstantial) evidence that this relationship may have changed over time – there were more than a quarter of a million more spells of unemployment over the course of 1994 than over 1986. Finally, due to the inevitable double counting of long spells, we find that as with individuals, the number of claims recorded increases less than proportionately with the size of the sample period – between 1993 and 1996 there were over ten million separate claims for benefit made by prime age males, but in each of those years there were an average of over four million claims.

When we turn to the age profile of those who have some experience of unemployment, we find that as a group they are not representative of the labour force as a whole. As Figure 3.2 illustrates, we find that in particular, the young appear more likely to have some experience of unemployment. This would seem to support Blanchard's hypothesis that unemployment is concentrated on the young: in 1983 there were about two and a half times as many 18 year olds who had some experience of unemployment as 35 year olds.

However, over time we find the number of youths who were unemployed in successive cohorts declined substantially – about half as many eighteen year olds had some experience of unemployment in 1996 as did in 1983, while for those in their thirties this figure was, broadly speaking, unchanged. Of course, over the time, the number of youths in the labour force has fallen dramatically, both as a consequence of a decline in the fertility rate some years before, but also as result of an increase in participation in tertiary education, and therefore the figure above will overstate the decline in the proportion of the youth labour force who are unemployed. However the dramatic fall in the number of youths who are unemployed each year is also likely to reflect both changes in the relative incentives and/or entitlement for youths to claim benefit when unemployed, as well as the effect of any shift in the demand for labour between different age groups.

FIGURE 3.2 : INCIDENCE OF UNEMPLOYMENT BY AGE (THOUSANDS)

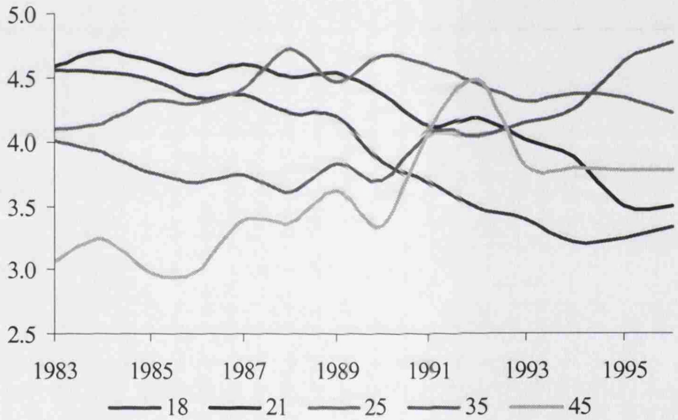
INDIVIDUALS **SPELLS**



When we turn to the distribution of unemployment across spells we find that the youth spells are also over-represented in the JUVOS sample[60], but once again, we find that this differential has narrowed over the period.

In Figure 3.3 we highlight these shifts in the age composition of the population as a result of demographic change[61]. In order to control for the impact of demographic change, we have calculated the fraction of the total population of each age group who have some experience of unemployment each year. As Figure 3.4 illustrates, although over time less youths had some experience of unemployment, they remained the age group most afflicted by unemployment.

FIGURE 3.3 : AGE COMPOSITION OF THE LABOUR FORCE [HUNDREDS OF THOUSANDS]



Finally, we turn to the number of separate experiences of unemployment each individual suffers within a given period. The vast majority of those who have some experience of unemployment in a year will only have one experience of unemployment in that year. Nonetheless, something like three quarters of a million males, suffer recurrent unemployment each year. However, experience of a large number of separate spells in a single year is rare – in all but one year (1984), less than one out of every hundred males

[60] In fact youths and their individual spells are over-represented in the JUVOS sample to roughly the same extent; for example, in 1990 there were 2.43 eighteen year olds in the JUVOS sample for every thirty five year old, and 2.59 spells experienced by eighteen year olds for spell experienced by a thirty five year old.
[61] Our estimates of the age composition of the population are taken from the annual Labour Force Survey.

who had an experience of unemployment suffered four or more separate spells of unemployment (see Figure 3.5). We find that given the preponderance of youth spells in the JUVOS panel there is remarkably little difference in the incidence of recurrent unemployment among individuals from different age groups in the labour force (see Figure 3.6). Over a four year period, it remains the case that the majority of individuals who have some experience of unemployment suffer only one spell, although now only marginally so (see Figure 3.7). Over this longer period, more than one in ten of those who entered the JUVOS panel at some point suffered four or more spells. Quite simply, the longer the period over which we estimate the distribution of unemployment, the larger the role that recurrent unemployment plays.

FIGURE 3.4 : FRACTION OF EACH AGE GROUP WHO HAVE SOME EXPERIENCE OF UNEMPLOYMENT EACH YEAR [%]

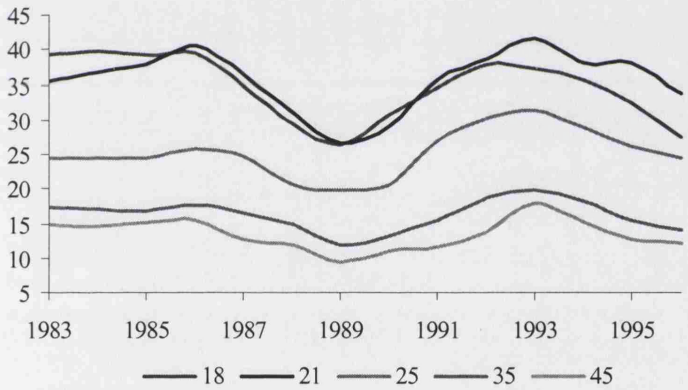


FIGURE 3.5 : THE DISTRIBUTION OF SPELLS OF UNEMPLOYMENT [1 YEAR] (%)

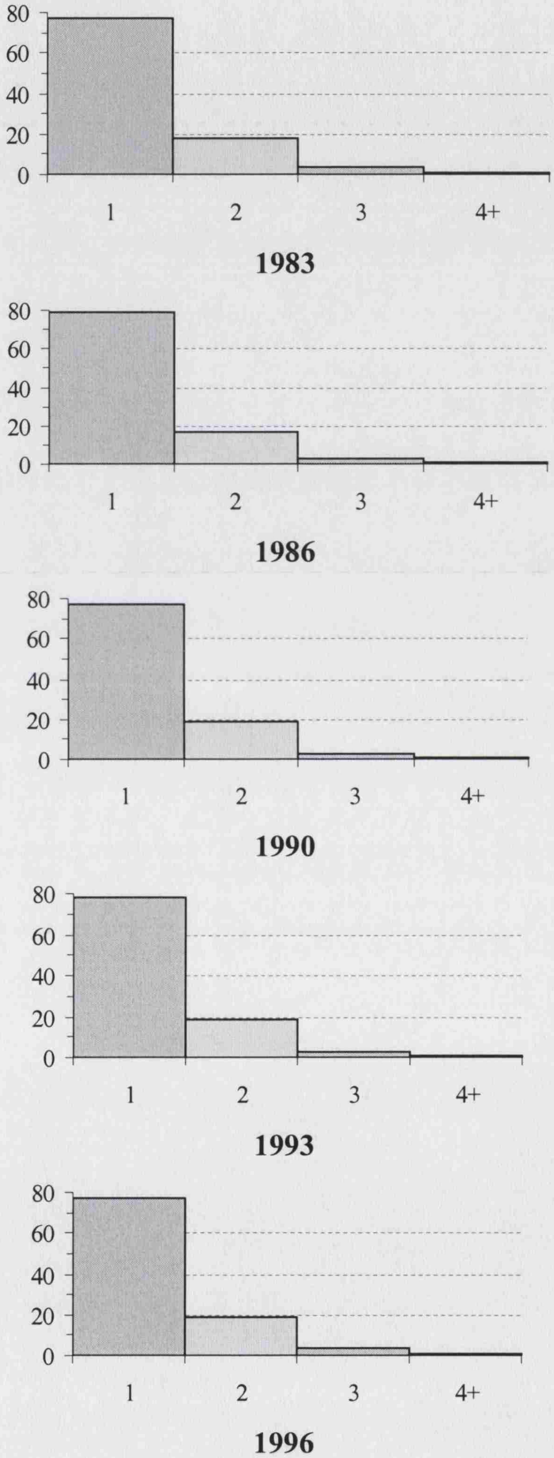
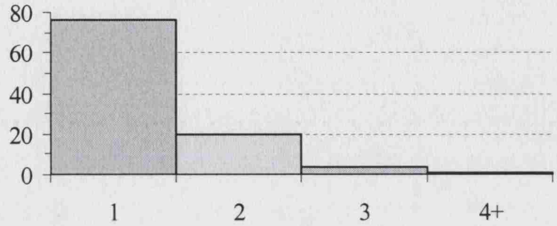
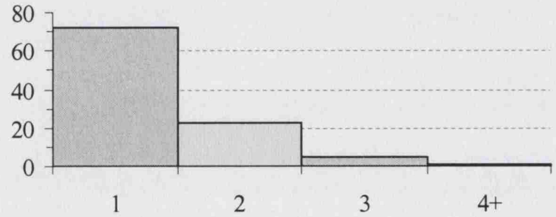


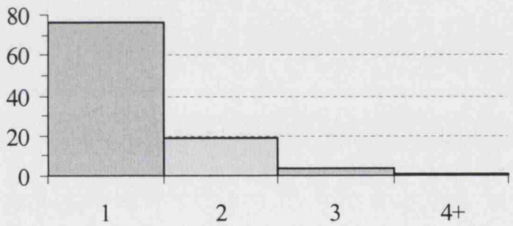
FIGURE 3.6 : THE DISTRIBUTION OF SPELLS OF UNEMPLOYMENT BY AGE [1986] (%)



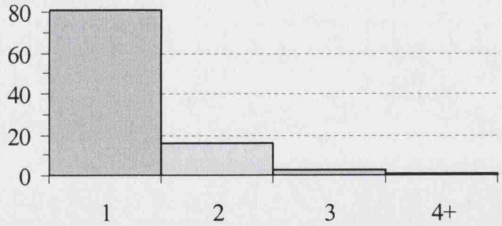
18 YEARS



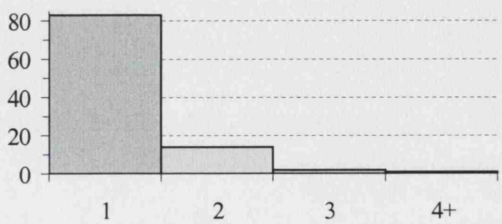
21 YEARS



25 YEARS

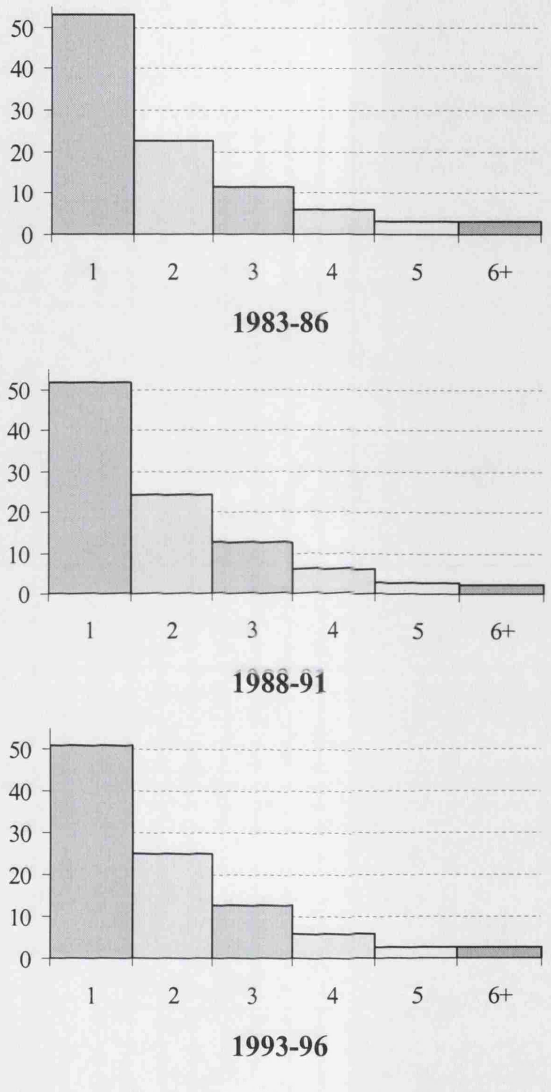


35 YEARS



45 YEARS

FIGURE 3.7 : THE DISTRIBUTION OF SPELLS OF UNEMPLOYMENT [4 YEARS] (%)



It is clear then that youths suffer more spells of unemployment than adults, although it appears that this is because experience of unemployment is spread over a larger section of the youth population rather than on an individual basis, youths suffer more spells on average than older members of the labour force. Whether either on an individual or aggregate basis, youths suffer more days of unemployment each year is not clear. In order to answer that question definitively we need to turn to the shape of the distribution of unemployment itself.

3.2 THE DENSITY OF THE DISTRIBUTION

To gain a more complete characterisation of the distribution of unemployment across individuals we now turn to techniques that capture the relative frequency of observations across the range of possible total durations of unemployment. It should be noted form the outset that we will not estimate the distribution of unemployment across the entire labour force – those who suffered no unemployment over the period are deliberately excluded[62].

Initially, to give a broad overview of the distribution of unemployment across our panel we have aggregated experiences of unemployment within the following categories – for the one year periods: less than a month, between one and four months, between four and eight months, and more than eight months; and for the four year periods: less than three months, between three and six months, between six months and a year, between one and three years, and more than three years.

Figures 3.8-3.10 reveal the sharp contrast in experiences of unemployment in the JUVOS panel: about two in five men who have some experience of unemployment suffer less than four months of unemployment in total in a given year, while a roughly similar proportion spend eight months or more of that year in unemployment. Of course these proportions vary over the cycle – in 1990, more than a half of those who experienced unemployment suffered less than four months of unemployment, yet in 1993 this fraction fell to a third. It appears that a far smaller proportion of youths (who have some experience of unemployment) suffer long accumulated durations of unemployment in any year, and a higher fraction suffer less than a month of unemployment. When we extend the length of our period we find that while a quarter of the sample suffer three months or

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[62] One solution to this problem would be to try supplement the dataset to create a 5% sample of the entire labour force and then we could calculate the distribution of unemployment over (a representative sample of) the entire labour force. However, in doing so we would be simply adding a relatively large number of individuals all of whom had no experience of unemployment whatsoever over the period creating a frequency distribution with about 75% of the entire population concentrated at a point mass at one extreme of the distribution. It is not apparent what this would add to our understanding of how unemployment is distributed among those who suffer it, although in itself the percentage of the labour force who are never unemployed in any given period is clearly a meaningful statistic (of course, estimates of the proportion of the labour force who are never unemployed in a given period can of course be interpolated directly from the results presented above on the number of individuals who have some experience of unemployment).

less of unemployment, one in ten of those with some experience of unemployment suffer more than three years out of four out of work.

When we turn to the distribution of unemployment across spells, we find as we would expect, that short durations of unemployment are more common among spells, than among people. In proportional terms, almost twice as many spells as individuals involve a duration of unemployment less than a month over the course of a year. Figures 3.8-3.10 also illustrate how a far greater proportion of individuals suffer very long durations of unemployment than spells last a similar length – as a proportion, between three to four times as many people suffer two years or more of unemployment over a four year period as there are spells of unemployment which last for that length[63]. Clearly, the number of long term spells of unemployment can be deceiving as to the true incidence of chronic unemployment. The length of the average spell experienced by different age groups also varies significantly – about one in ten spells suffered by eighteen year olds in 1986 lasted more than eight months, but for twenty five year olds this figure was three in ten and for forty five year olds it was nearly four in ten.

[63] Of course, in any period there are more spells than individuals who experience them so this will tend to overstate the point.

FIGURE 3.8 : THE DISTRIBUTION OF UNEMPLOYMENT IN MONTHS [1 YEAR] (%)

INDIVIDUALS **SPELLS**

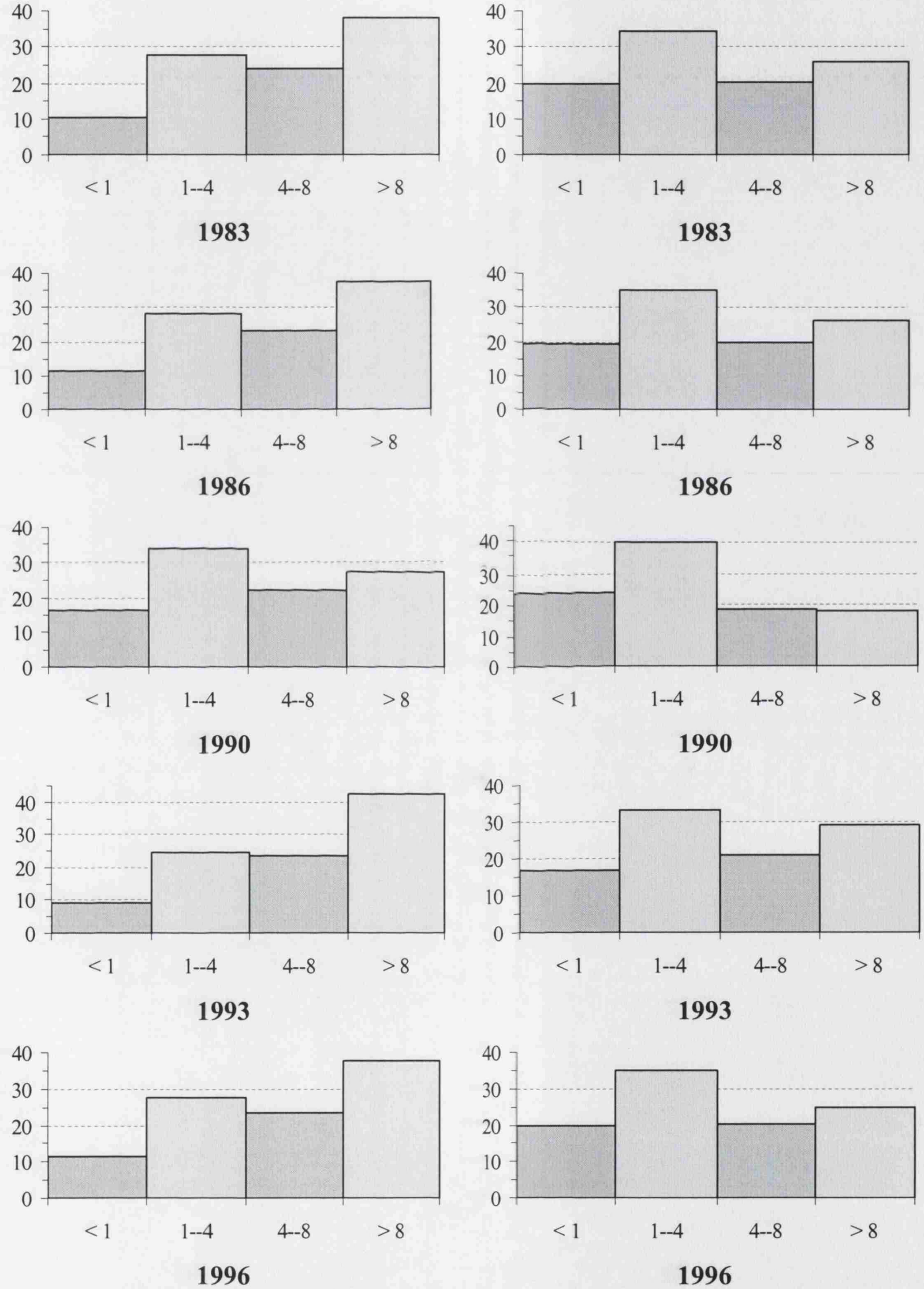


FIGURE 3.9 : THE DISTRIBUTION OF UNEMPLOYMENT IN MONTHS BY AGE [1986] (%)

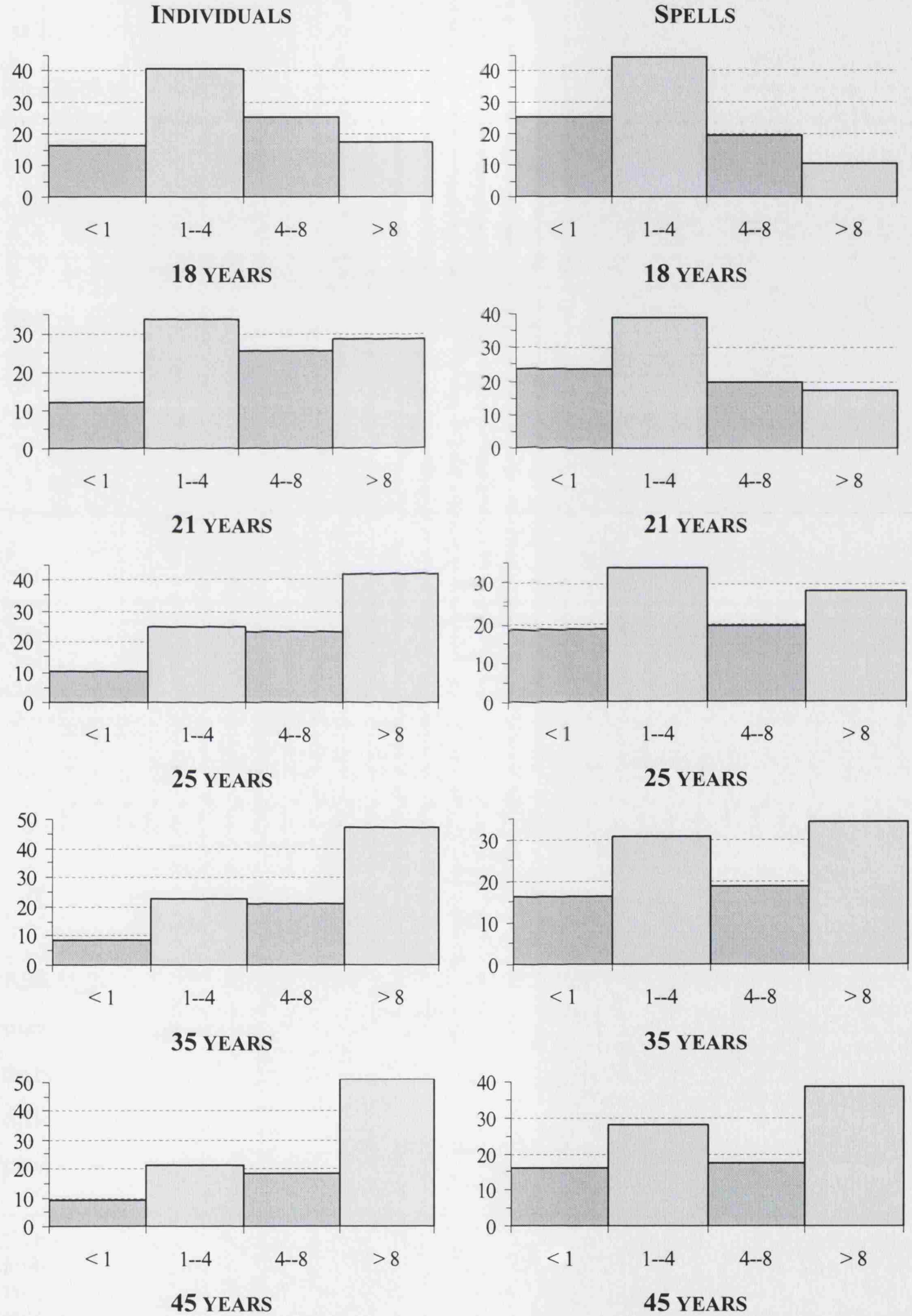
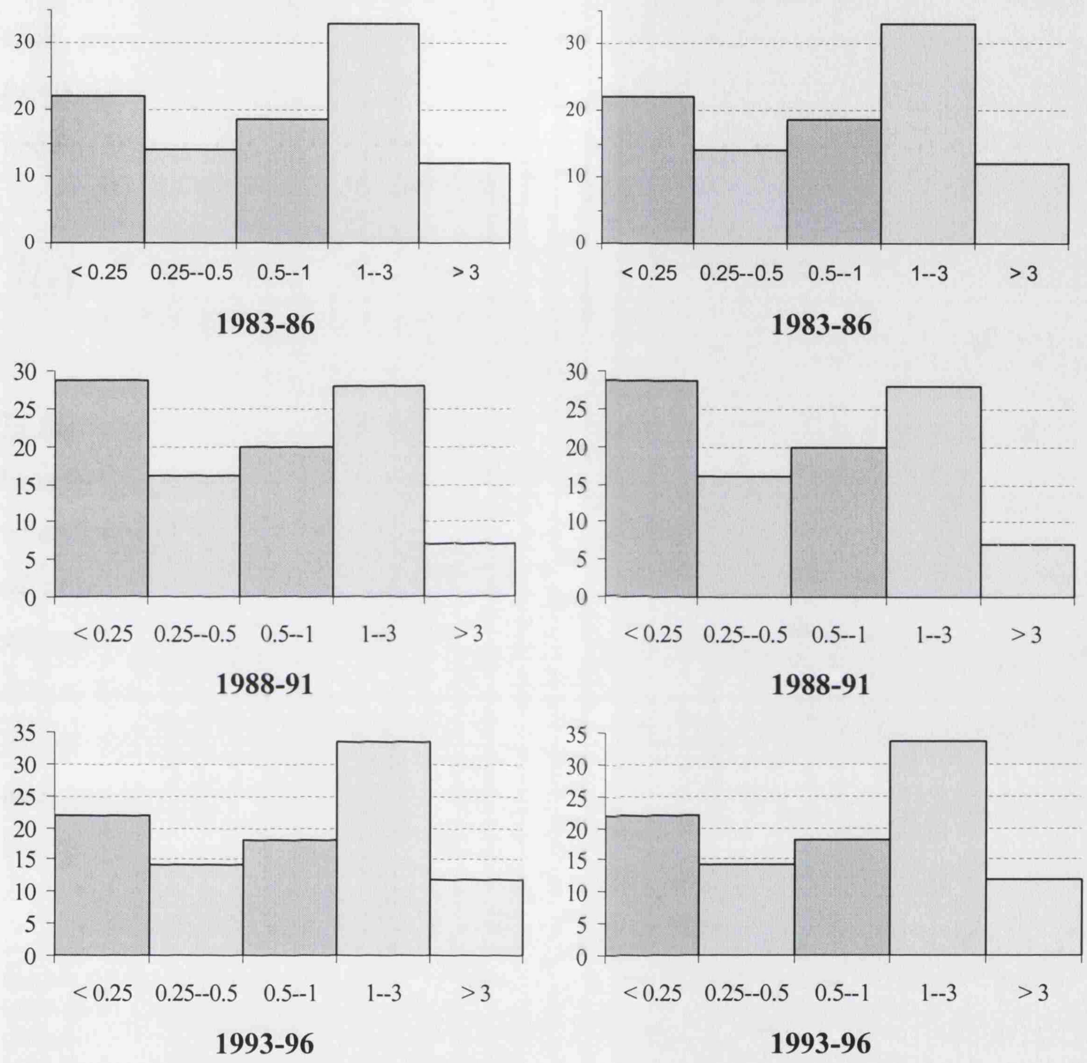


FIGURE 3.10 : THE DISTRIBUTION OF UNEMPLOYMENT IN YEARS [4 YEARS] (%)

INDIVIDUALS | SPELLS



Although it provides a useful broad brush description of the distribution of unemployment, the histogram is inevitably a crude instrument with which to illustrate a distribution in any detail. In effect, these histograms aggregate together individuals with different experiences of unemployment according to essentially arbitrary criteria, producing a discrete frequency distribution[64]. An alternative approach is to construct a

[64] Of course, since the total duration of unemployment experienced is in itself discrete, this may not be a problem. We could construct a histogram with a number of bins equal to the total number of days across the period we are studying, so that within each bin all individuals will have an identical total duration of unemployment – giving the *probability mass function* - which could with some justification be considered the true distribution of unemployment in a given year. However, this approach is unlikely to lead to a

smoothed representation of the frequency distribution using kernel density estimation techniques[65]. Essentially this non-parametric approach involves estimating the density at each point by counting the number of observations within a specified interval $(x-h, x+h)$, and weighting each according to how close they are to that point, using a known, well behaved (i.e. symmetric) density function[66,67], as follows :

$$\hat{f}(x) = \frac{1}{n.h} \sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right) \qquad [3.1]$$

In the final analysis, the kernel density and the histogram characterise a distribution in broadly the same fashion (although at varying level of mathematical complexity) – estimating the relative frequency of observations at a given point according to the number of observations that lie within a specified neighbourhood around that point. These estimates of the distribution of unemployment are presented in Appendix 1 and their salient features are discussed in the following section. To illustrate how the implied form of the distribution of unemployment varies according to the precision with which we measure the relative frequency of observations across all possible durations we vary the bandwidth of the kernel density, and the bin-width of the histograms[68]. We shall focus on

smooth frequency distribution, since in every period, chance is likely to lead to disproportionate numbers of individuals sharing certain numbers of days of total unemployment, producing a series of irregular spikes throughout the distribution. As a result, at the microscopic level, such probability mass functions are likely to be highly unstable over time. On a more aesthetic level, a histogram with 365 bins is unlikely to be a useful descriptive tool.

[65] For a comprehensive summary of these techniques see Silverman (1986).

[66] The kernel density functions estimated here are calculated using the standard Epanechnikov kernel, which weights observations as follows:

$$K(t) = \frac{3}{4\sqrt{5}}\left(1 - \frac{t^2}{5}\right) \qquad \text{if } |t| < \sqrt{5}$$
$$= 0 \qquad \text{otherwise.}$$

[67] The result is a smoother representation of the underlying frequency distribution, although the degree to which the microscopic irregularities in the data are removed will depend on the width of the interval used to estimate the kernel (Silverman (1986)).

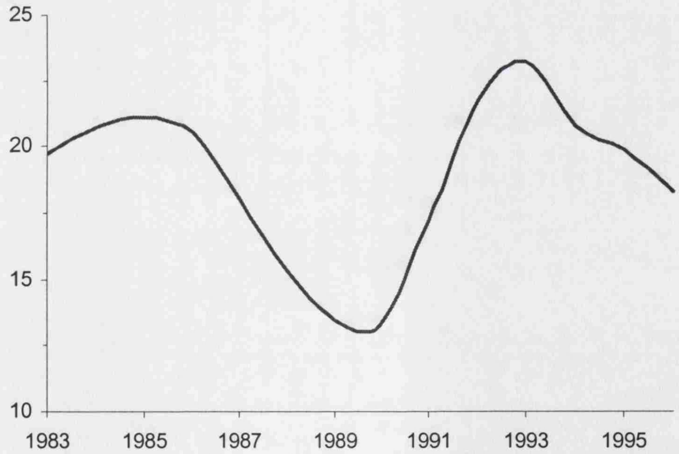
[68] In particular, in the case of histograms, we use three alternative specifications, with 12, 25 and 50 bins respectively (so in the case where we are describing the distribution of unemployment over the course of a year, they correspond approximately to aggregating together those individuals who share the same number of months, fortnights and weeks of unemployment respectively).

two key features of the distribution: the 'spike' (representing those who are permanently unemployed) and the interior of the distribution.

3.2.1 THE 'SPIKE' IN THE DISTRIBUTION OF UNEMPLOYMENT

Irrespective of the sample we use, and the period over which we estimate it, the distribution of unemployment always exhibits a common feature : a large point mass at the extreme end of the distribution, indicating the large number of individuals who are permanently unemployed throughout the period. About one in five of those who have some experience of unemployment each year will spend the entire year unemployed. Although this fraction varies anticyclically (see Figure 3.11) it does not appear that the incidence of permanent unemployment at a given point in the economic cycle has changed over time[69].

FIGURE 3.11 : THE INCIDENCE OF PERMANENT UNEMPLOYMENT
[AS A PERCENTAGE OF THOSE WHO HAVE SOME EXPERIENCE OF UNEMPLOYMENT]



When we extend the period over which we estimate the distribution of unemployment we find that the relative importance of this spike in the distribution diminishes. Obviously,

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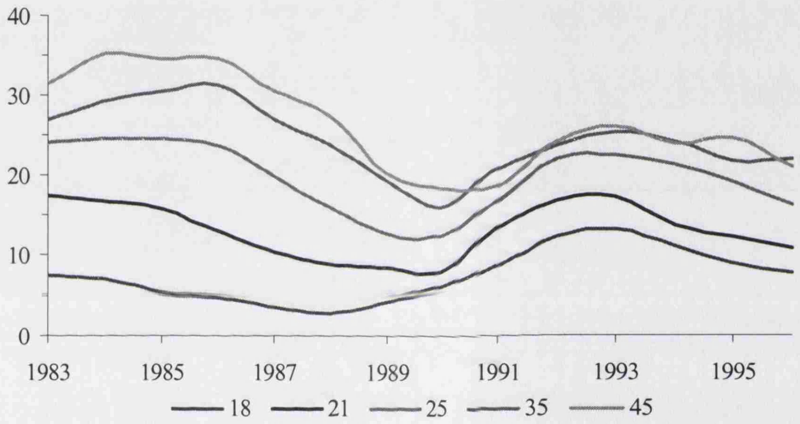
[69] This result is somewhat surprising. We might have expected the introduction of the Restart programme to have reduced the fraction of the sample who are permanently unemployed from 1986 onwards by removing the long-term unemployed from the benefit rolls.

the fraction of all those who have some experience of unemployment over a four year period who are unemployed throughout that period will be far lower than the corresponding figure in any of the individual years. Depending on the state of the labour market, between two to four per cent of those who have an experience of unemployment during a four year period will spend that entire period unemployed. However, this still implies that between one and two hundred thousand men are permanently unemployed over a four year period.

FIGURE 3.12 : THE INCIDENCE OF PERMANENT UNEMPLOYMENT BY AGE [%]



If we concentrate on the distribution of unemployment for specific age groups in the sample, then we find that the incidence of permanent unemployment is considerably lower among younger members of the workforce (see Figure 3.12). For example, in 1984 of those who had some experience of claimant unemployment less than 7 % of eighteen year olds were unemployed throughout the year, while 25 % of twenty five year olds and 35 % of forty five year olds were permanently unemployed.

3.2.2 THE INTERIOR OF THE DISTRIBUTION

Self evidently, wherever the relative importance of this spike in the distribution of unemployment is low, there is more mass present in the main body of the distribution. However, the distribution of total duration of unemployment is far from uniform across this interval. The relative frequency of observations clearly appears to decrease as the total duration of unemployment increases, although this trend is not monotone[70]. Indeed, as the length of the period which we estimate the distribution over increases, we find that a second spike emerges in the distribution at the other extreme – representing the increasing number of frictionally unemployed individuals who typically suffer a single, brief experience of unemployment which constitutes only a tiny fraction of the total period. However, those individuals who suffer either less than a month, or more than 47 months of unemployment in a four year period still represent less than a fifth of all those with some experience of unemployment.

Finally, when we turn to the distribution of unemployment **across spells**, we find that, as expected, short durations of unemployment are more frequent among spells than among individuals. About a fifth of all spells that occurred at some point in 1983 lasted less than a month, while only about a tenth of those who had some experience of unemployment suffered less than a month of unemployment in total. Similarly, about 15% of spells last more than 51 weeks, while over 20% of individuals suffer this much unemployment.

3.3 THE DEGREE OF TURBULENCE WITHIN THE DISTRIBUTION

The previous analysis has established the key features of the distribution of unemployment across the range of possible cumulative durations of unemployment. In this section of the Chapter we focus on one final feature of the distribution – the size of the flows into and out of claimant unemployment. However, it must be stressed that we shall not attempt the gargantuan task of explicitly *explaining* the distribution of unemployment itself by analysing the underlying gross inflows into the claimant count and outflow at each spell duration, in every separate day of the year.

The fact that the JUVOS database records information (collected in 'real time' rather than retrospectively) on the start and end dates of all the spells of unemployment experienced

[70] See, for example, the kernel density estimates produced using the narrower bandwidths which illustrate the finer detail in the data and the inherent variation in the incidence of unemployment.

by a random 5 % sample of that part of the population who are eligible for unemployment related benefits provides an unprecedented opportunity to examine the flows of individuals into and out of the claimant count. Previous research has been forced to rely on longitudinal data to approximate these flows from the numbers of individuals who are observed to have changed labour market status within a given interval (typically a quarter).

Although information exists on the destination of those who flow out of the claimant count for the last five months of our fourteen year sample period, we have no information on the labour market state from which individuals exited to flow into unemployment. Therefore, we shall abstract away from the source of inflows and destination of outflows from the claimant count and focus simply on the gross flows into and out of unemployment each week[71]. We follow convention by normalising these flows relative to their respective stocks to give us the *gross inflow* and *gross outflow rates*. Finally, in order to abstract away from the stochastic variation in these gross flows from week to week we also calculate a smoothed representation of each series using the Hodrick-Prescott filter (1997)[72].

[71] Given that the small number of spells of unemployment which were less than seven days in length were dropped from the analysis, we can be certain that no transitions into and out of the claimant count will be censored by focusing on the weekly flows.

[72] The Hodrick-Prescott filter decomposes a series y_t into its trend μ_t and stationary components $y_t - \mu_t$ by selecting the time series of the trend μ_t which minimises the following expression (Enders (1995)):

$$\frac{1}{T}\sum_{t=1}^{T}(y_t - \mu_t)^2 + \frac{\lambda}{T}\sum_{t=2}^{T-1}[(\mu_{t+1} - \mu_t) - (\mu_t - \mu_{t-1})]^2$$

The value of λ defines the extent to which the trend in the series is smoothed: when λ equals zero the trend is equal to the series itself, when λ tends to infinity the trend will approach linearity.

FIGURE 3.13 : THE WEEKLY INFLOW RATE INTO THE CLAIMANT COUNT [%][73]

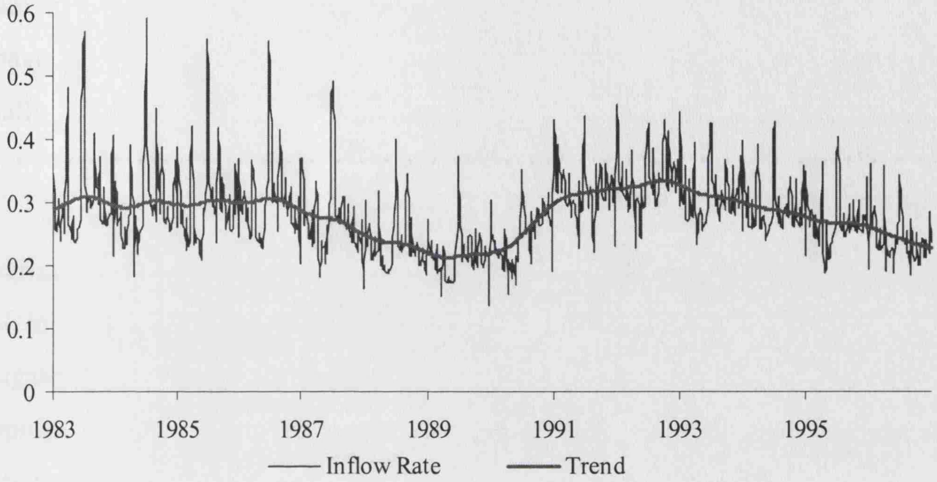
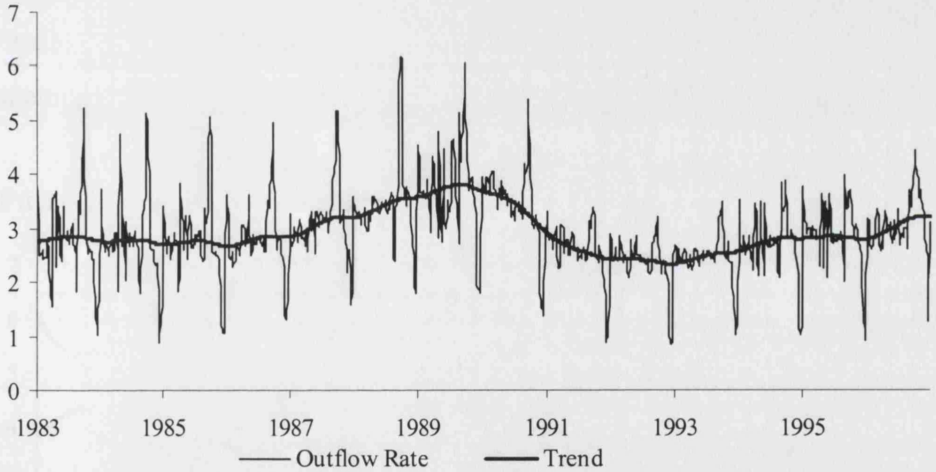


FIGURE 3.14 : THE WEEKLY OUTFLOW RATE FROM THE CLAIMANT COUNT



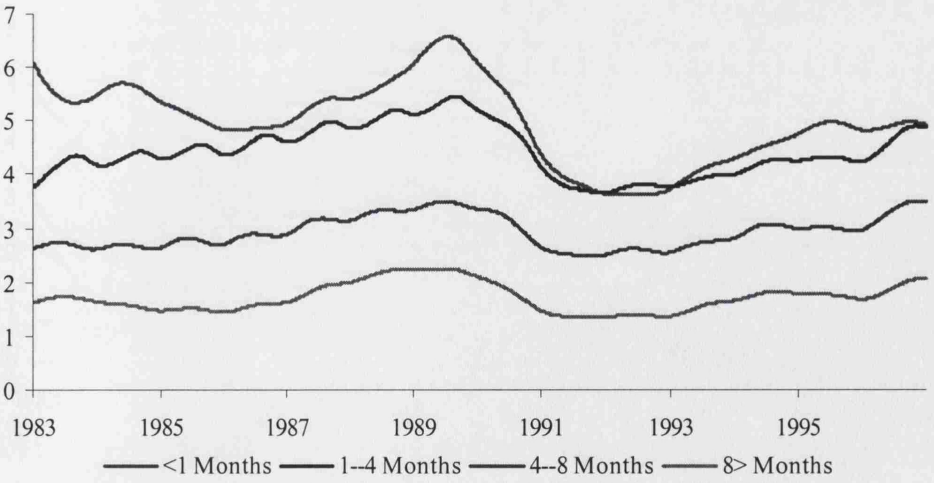
On average, about 45,000 working age men flow in and out of claimant unemployment each week, but the net flow from the claimant count over the period averages just over a thousand men each week. In terms of the underlying stocks, about a third of a per cent of the stock of working age men who are not claimant unemployed become unemployed each week and about three per cent of the stock of claimant count flow out of

[73] Given the size of the underlying data, information on the weekly gross flows presented in the following figures is not recorded in the tables in the Appendix.

unemployment each week (see Figures 3.13 and 3.14 above). It is transparently clear that both the inflow to and outflow from the claimant count each week are noisy series – they both have a standard deviation of about 10,000. Nonetheless, the weekly gross flows are unusually low in the final week of the year and unusually high in the first week of the year.

The variation in the flows off the claimant count at different spell durations will be crucial in determining the final shape of the distribution of unemployment. We can investigate this issue by focusing on the gross flows out of unemployment normalising by the appropriate stock at various spell durations (which will approximate very crudely the discrete-time hazard function). Given the noise in our gross flows data we focus only on the trend in each of the underlying weekly series obtained from a Hodrick-Prescott filter. Unsurprisingly we find that the outflow rate from very short term unemployment (defined here as less than a month) is far higher than that from longer spells (see Figure 3.15). Nevertheless, even at long durations between one and two per cent of the stock of long term unemployed men exit unemployment each week.

FIGURE 3.15 : WEEKLY OUTFLOW RATES AT VARYING SPELL DURATIONS [%]



Finally, if we focus on the gross flows among different age groups in the population we find that the flows both into and out of the claimant count are far larger among youths. On average about two and a half thousand eighteen and twenty one year old men flow in and out of the claimant count each week, whereas only about five hundred men aged forty five do likewise (see Figures 3.16 – 3.17). This reflects our findings that a larger proportion of the youth population flow into unemployment each period, but on average they tend to suffer shorter spells, and thus flow out of unemployment more rapidly.

FIGURE 3.16 : WEEKLY INFLOW RATES BY AGE [%]

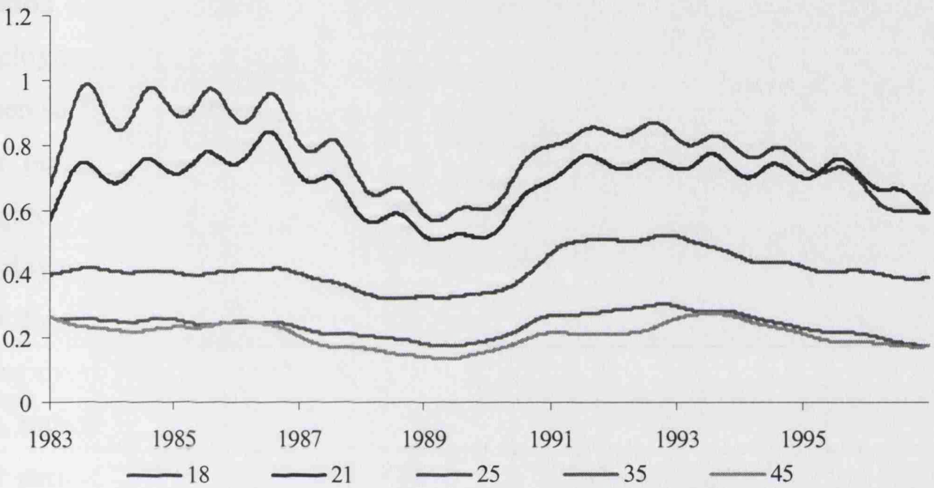
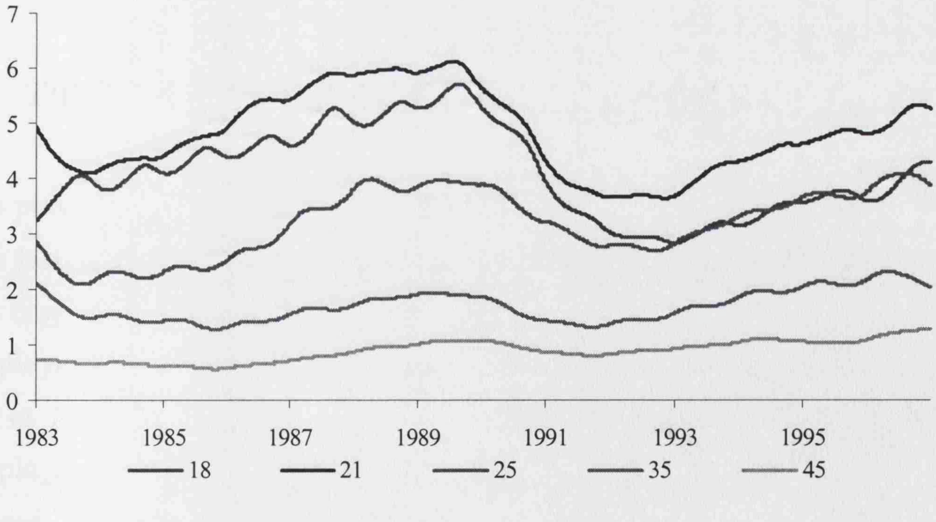


FIGURE 3.17 : WEEKLY OUTFLOW RATES BY AGE [%]



To conclude, we have found that in any given year, a significant fraction of the male labour force have some experience of unemployment. Relative to their share of the working age population, young men are over represented in the JUVOS panel, although this gap has closed considerably over time reflecting the demographic shift in the composition of the population away from the young. Among those who are unemployed at some point in any period, experiences of unemployment differ greatly: while many suffer only very brief spells, a sizeable fraction of those who have some experience of unemployment are permanently unemployed throughout the period (although the size of this spike in the distribution of unemployment varies inversely with age and the length of the period over which we estimate the distribution). Over the course of a year, recurrent unemployment is not a significant phenomenon: about three quarters of a million working age men suffer more than one spell of unemployment in any given year; however, over a longer period of time recurrent unemployment becomes more pervasive. When we aggregate across spells, it appears that those youths who have some experience of unemployment will suffer less days of unemployment in total than older members of the labour force. Therefore, it seems that youths have higher unemployment rates simply because they flow into unemployment in larger numbers (although not more often) than adults, rather than because those youths who do enter unemployment remain there for a longer period of time. The gross flows into and out of the claimant count dwarf the net changes in the stock – each week approaching fifty thousand men become unemployed, and a similar number leave the claimant count.

4. THE INCIDENCE OF CHRONIC UNEMPLOYMENT

In the previous section we detailed how unemployment is distributed across individuals in the labour force over a given period of time when we aggregate across each of the spells they suffer. In particular we noted the fraction of those who have an experience of unemployment in a given year who are unemployed throughout that year. However, if we want to focus more generally on those who suffer long accumulated durations of unemployment in a given year – whom we define here as the ***chronically unemployed***[74] – we need a slightly more inclusive definition than this. The definition of chronic

[74] This is by no means the first use of the expression '*chronically unemployed*'; indeed the term appears to have been almost ever-present in the vocabulary of those concerned with the rise in unemployment since the 1970's. However, we believe that this is perhaps the first practical definition of who actually is

unemployment we use here is based on the proportion of a given period that an individual is unemployed[75] so that an individual who spends more than half of any period on unemployment benefit we label as chronically unemployed.

We argued in Section 1 that there are (at least) three reasons why the concentration of unemployment on a number of chronically unemployed individuals matters: because their existence may help us understand the persistence in the aggregate unemployment rate; because through lagged duration dependence effects, prolonged exposure to unemployment may scar the individual having long-term consequences for their prospects; and because chronic exposure to unemployment is likely to be heavily correlated with the incidence of poverty. We therefore believe that these unfortunate individuals are worthy of special attention. In this section of the Chapter we therefore briefly discuss four issues: how many chronically unemployed individuals are there in the labour force at any one time; how much of the total duration of unemployment do they account for; are the chronically unemployed and the long term unemployed one in the same; and finally, are the chronically unemployed representative of the labour force as a whole. To conclude this section we offer an alternative definition of chronic unemployment based on the relative experiences of those who suffer unemployment in any given period.

4.1 THE INCIDENCE OF CHRONIC UNEMPLOYMENT

In Section 3 we described how between two and four million prime age males have some experience of unemployment each year between 1983 and 1996. Of these, about one to two million are chronically unemployed ! The fraction of all those who have some experience of unemployment in a given year who are chronically unemployed varies anti-cyclically (see Figure 4.1). Yet, even in 1989 when the labour market was over-heating it remains true that two out of every five men who were ever unemployed in that year spent six months or more unemployed. When we investigate whether the chronically

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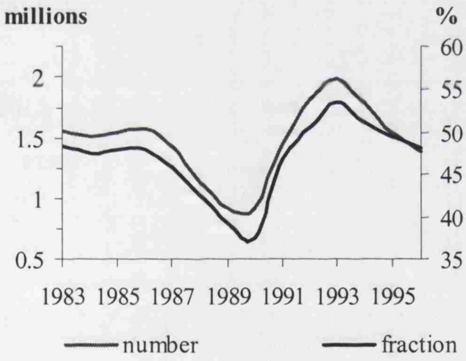
chronically unemployed, and in particular, the first definition which encompasses both the recurrent and the long term unemployed.

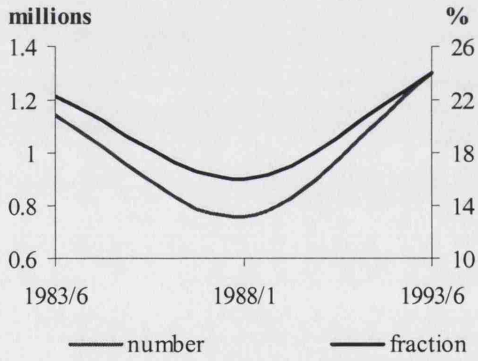
unemployed are growing in size across the economic cycles, we find tentative evidence that this is indeed the case . There were almost two hundred thousand more chronically unemployed males in 1994 than in 1986 (when the unemployment rate was approximately the same).

Finally, when we estimate the distribution of unemployment over a longer period of time, we find that the chronically unemployed are far fewer in number; over the average four year period about one million men are unemployed for two years or more. As a proportion, the chronically unemployed now comprise between one in seven to one in four of all those who are ever unemployed during that four year period.

FIGURE 4.1 : THE CHRONICALLY UNEMPLOYED : THEIR TOTAL [MILLIONS] AND AS A FRACTION OF ALL THOSE WHO HAVE SOME EXPERIENCE OF UNEMPLOYMENT.



1 YEAR



4 YEARS

4.2 HOW IMPORTANT ARE THE CHRONICALLY UNEMPLOYED ?

We have established that about a half of all those who have some experience of unemployment in any year spend a half of that year unemployed. We might then ask how much of the total days lost to unemployment in any given year is accounted for by the chronically unemployed. It transpires that on average the chronically unemployed account for about three quarters of the total number of days of unemployment suffered

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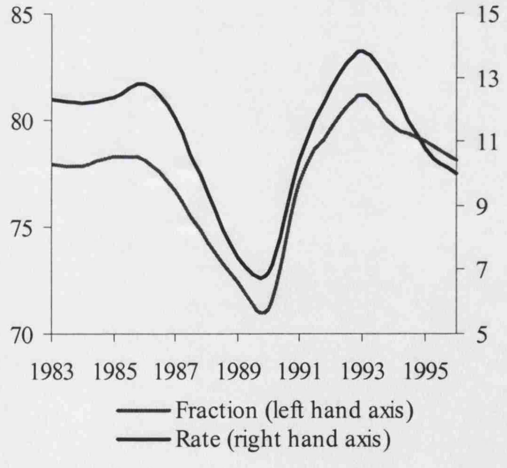
[75] See Section 4.4 for an alternative definition.

over the course of a given year (see Figure 4.2). When we estimate the distribution of unemployment over a longer time period we know that the chronically unemployed are a far smaller fraction of those who ever experience unemployment – nonetheless, they now account for a disproportionate fraction of the total number of days of unemployment suffered over that period. For example, between 1993 and 1996 the quarter of those who have some experience of unemployment who were chronically unemployed accounted for almost three fifths of the total days of unemployment experienced in that period.

The aggregate unemployment rate is typically thought of as a 'worker discipline device'. If workers understand that the majority of the unemployment they observe in the labour market is suffered by outsiders then they are unlikely to be constrained in their wage setting behaviour by the presence of this reserve army of workers, because their levels of skill (or demographic characteristics given the presence of discriminating employers) makes it unlikely they will ever join the ranks of the outsiders.

FIGURE 4.2 : THE FRACTION OF THE TOTAL DAYS OF UNEMPLOYMENT ACCOUNTED FOR BY THE CHRONICALLY UNEMPLOYED AND THE UNEMPLOYMENT RATE [%]



4.3 LONG TERM UNEMPLOYMENT AND CHRONIC UNEMPLOYMENT.

Despite the distinctions we have already drawn between the distributions of unemployment across individuals and spells in the previous section the sceptical reader may still question whether in fact the chronically unemployed and the long term unemployed are simply one in the same. It is certainly true that when the distribution of unemployment is defined over a one year interval something like three quarters of the chronically unemployed suffer only one spell of unemployment in that year (see Figure 4.3) – in other words they are long term unemployed. However, there remains the final quarter of those who spend more than half a given year unemployed who are recurrent unemployed – some half a million men. It seems reasonable to assume that the typical chronically unemployed male will have a low exit rate from unemployment, and therefore on average when they enter unemployment we would expect them to have to endure a significant spell out of work. We might therefore expect then that the probability of observing a chronically unemployed individual who suffers more than a couple of spells of unemployment in any given year is likely to be low. Nonetheless, there are something of the order of ten thousand working age men who over the course of four or more spells of unemployment in a year spend more than six months of that year unemployed. So, although long term unemployment is the prime cause of chronic unemployment, it is by no means the only cause, and policy initiatives aimed at those excluded from the workplace which focus on long term spells alone may do so at the expense of the many thousands of men who suffer recurrent unemployment.

When we estimate the distribution of unemployment over a longer time period the recurrent unemployed are now the majority of the chronically unemployed (see Figure 4.4). Only about three out of every ten of those who suffer more than two years of unemployment over a four year period suffer a single long term spell of unemployment. Conversely, about one in eight of the chronically unemployed suffer five or more spells.

FIGURE 4.3 : THE NUMBER OF SPELLS EXPERIENCED BY THE CHRONICALLY UNEMPLOYED [1YEAR] (%)

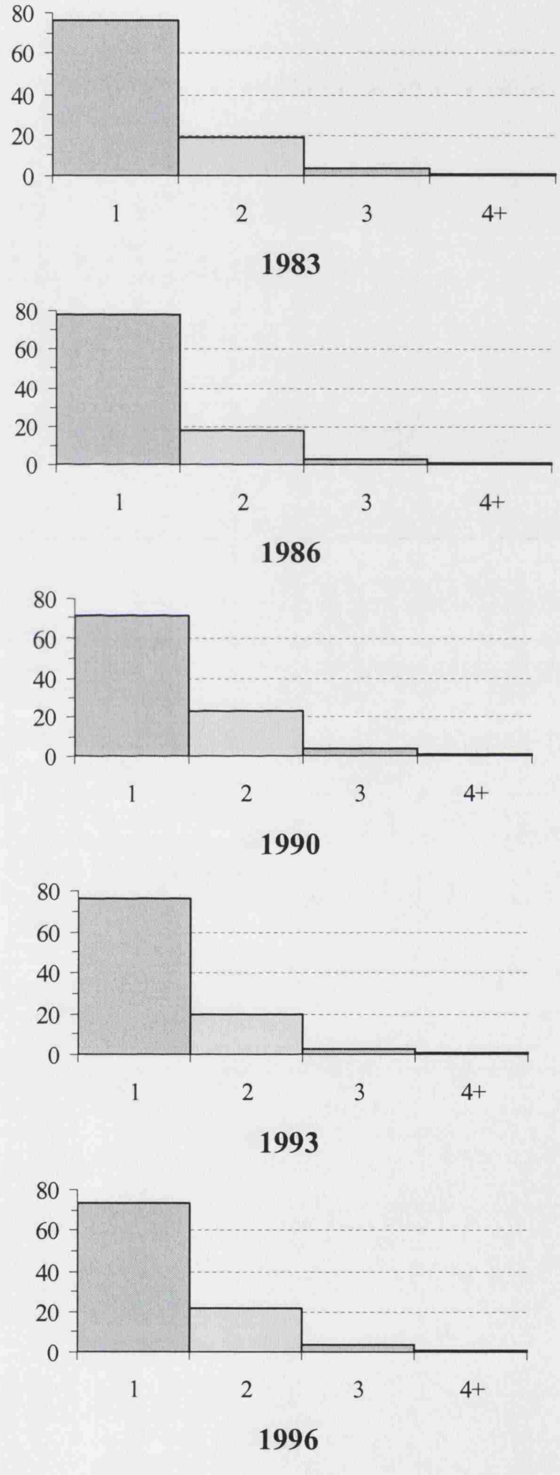
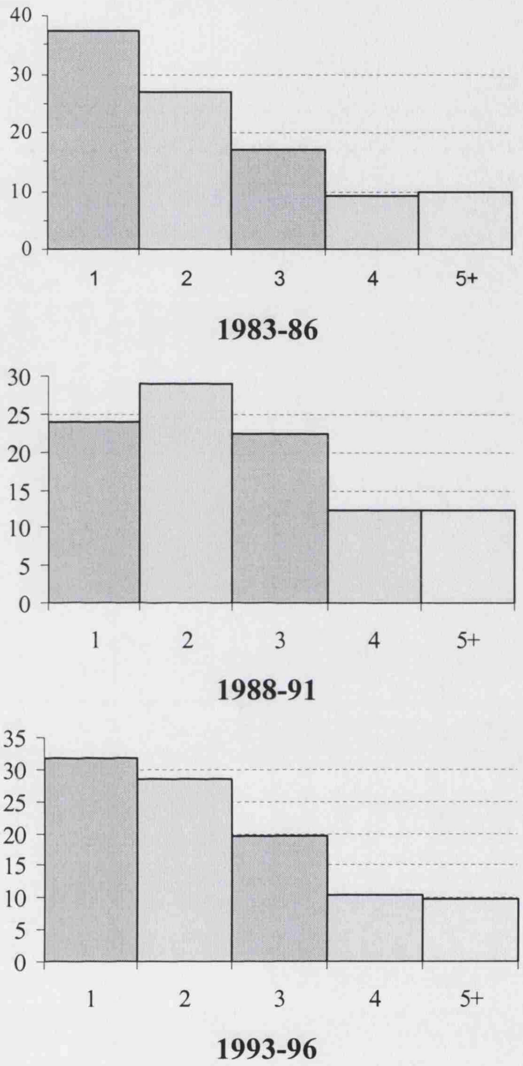


FIGURE 4.4 : THE NUMBER OF SPELLS EXPERIENCED BY THE CHRONICALLY UNEMPLOYED [4 YEAR] (%)



4.4 WHO ARE THE CHRONICALLY UNEMPLOYED ?

We know that youths are over represented among those who have some experience of unemployment; however, we also know that on average their spells of unemployment seem to be shorter. In fact there are more youths who are chronically unemployed than adults (see Figure 4.5). As the following figures demonstrate, relative to their share of the working age population, youths are over represented among the chronically unemployed;

however, relative to their share of those who have some experience of unemployment they are under represented (see Figure 4.6).

FIGURE 4.5 : THE INCIDENCE OF CHRONIC UNEMPLOYMENT BY AGE [THOUSANDS]

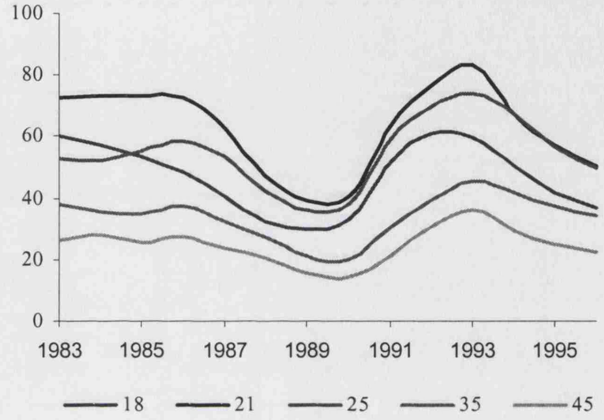
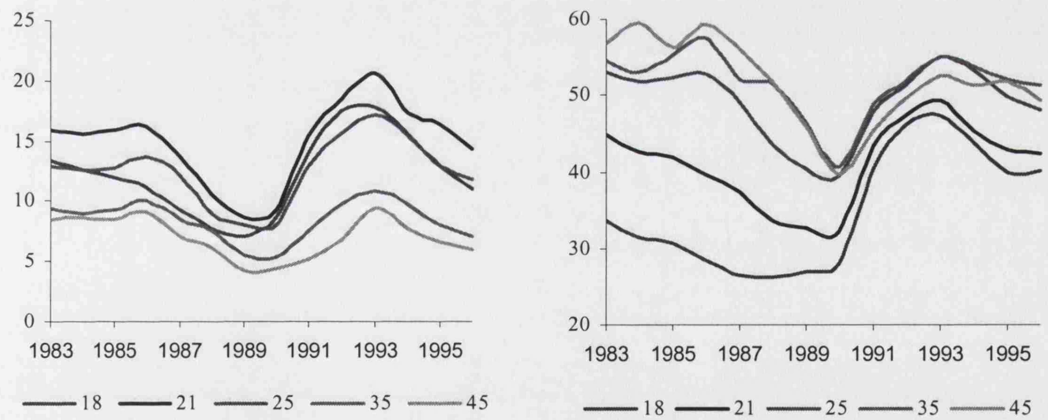


FIGURE 4.6 : THE RELATIVE INCIDENCE OF CHRONIC UNEMPLOYMENT BY AGE [%]



AS A PROPORTION OF THEIR COHORT

AS A PROPORTION OF THOSE WHO HAVE SOME EXPERIENCE OF UNEMPLOYMENT

Blanchard's hypothesis hinges upon whether the chronically unemployed are overwhelmingly young. The evidence we have presented above casts doubt on this conjecture. It is still the case that the younger members of the labour force are more likely to be chronically unemployed than their elders. However, about 70% of the chronically unemployed are above 25 years of age, and about 40% are above 35 years of age. Although we believe that youth unemployment may not act as a restraint upon adult insiders who set wages, we do not believe there is any evidence that chronic unemployment is heavily concentrated upon the young, and therefore, by itself youth unemployment will not be able to explain the persistence in the unemployment rate.

4.5 A RELATIVE DEFINITION OF CHRONIC UNEMPLOYMENT

In the analysis above the chronically unemployed are defined on an *absolute basis*, i.e. according to the total duration of unemployment they suffer over a given period. Finally, in this section we briefly explore an alternative definition of chronic unemployment based on the experience of individuals *relative to others in the population.* A natural choice for such a relative measure is to define the chronically unemployed as those individuals whose accumulated experiences of unemployment place them among the highest (arbitrarily defined) quantile of the distribution of unemployment[76].

The number of chronically unemployed men is then defined straightforwardly by the total number of individuals who have some experience of unemployment in a period. For example, if we define the chronically unemployed as those in the highest quartile of the distribution of unemployment in any given year, then by definition, one in four of all those who have some experience of unemployment are chronically unemployed. A natural question to ask is how much unemployment would one have to suffer in order to be defined chronically unemployed using this alternative definition. Of course, given that our definition is now relative the answer will vary from year to year, and it can be read off from Figures 5.1 and 5.2 (see later) since these percentile plots define the lower bound on the experiences of unemployment of the chronically unemployed according to the corresponding definition.

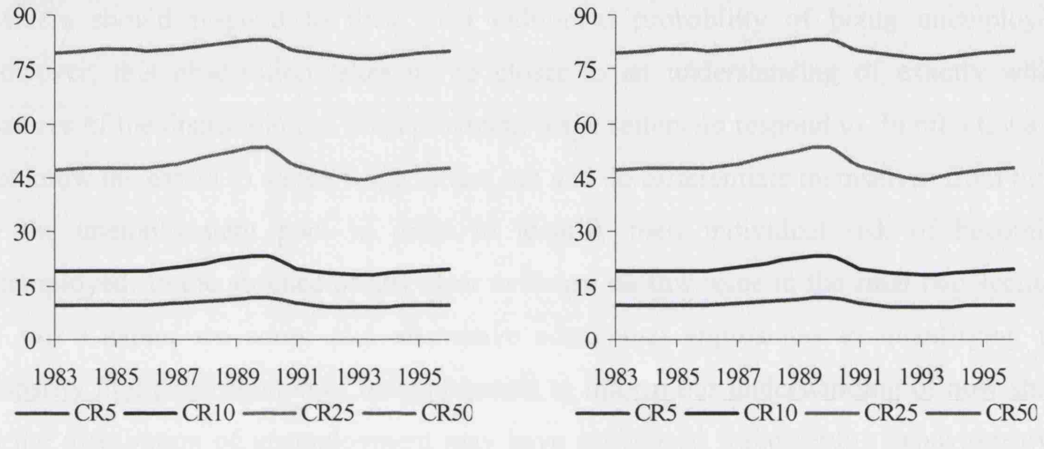
[76] In this section of the chapter we offer only the briefest description of the distribution using concentration ratios. However, for a more in depth analysis of the inequalities in the distribution of unemployment based on this approach see Dickens *et. al.* (2000).

The advantage of this relative definition is that it lends itself to answering the question: how much of the total duration of unemployment suffered by the population is accounted for by the chronically unemployed ? If we define the chronically unemployed in relative terms then the answer to this question is given by the concentration ratio which measures the fraction of the total duration of unemployment accounted for by the subset of the panel which contains those who experienced the most unemployment. So, for example, CR10 and CR50 indicate the fraction of the total number of days of unemployment suffered by the tenth and the half of the sample which suffered the most unemployment in a given year respectively.

The results indicate that the degree of concentration of unemployment is anti-cyclical – by 1993 the degree of concentration of unemployment had fallen back to between 77 and 94% of its level in 1990 (see Figure 4.7) depending on the particular ratio. In quantitative terms, the degree of concentration of unemployment on the chronically unemployed is quite severe. About 10% of the total duration of unemployment suffered by all individuals in the panel can be attributed to the 5% of the sample with the longest cumulative durations, and the half of the sample who suffer the most unemployment can always account for more than three quarters of the total days of unemployment suffered in any year. It is also the case, that all the concentration ratios are lower in 1994 than in 1986 for both the distribution of unemployment across individuals and spells – indicating that the burden of the chronically unemployed may have fallen over time.

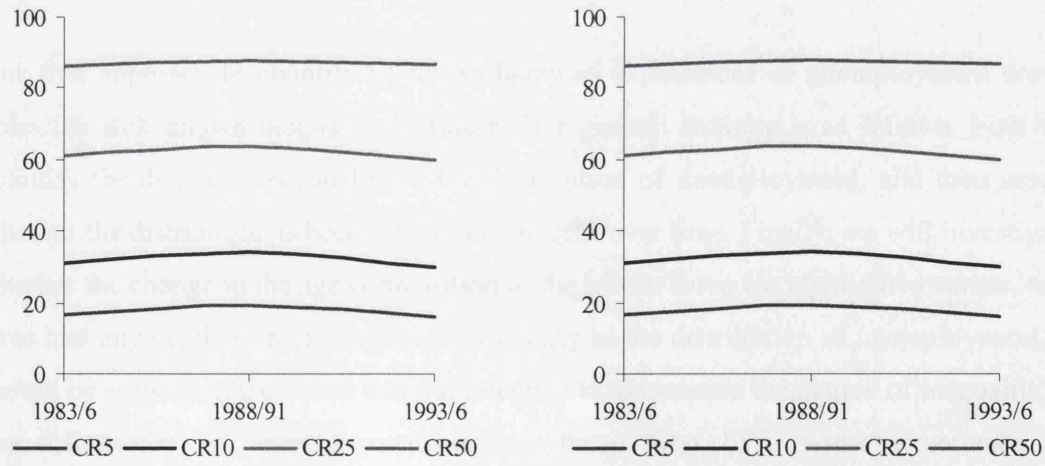
When estimated over a longer period of time, the degree of concentration on the chronically unemployed appears, if anything, to increase (see Figure 4.8). The experiences of the quarter of the population who suffer the most unemployment now account for over three fifths of the total duration of unemployment. This should not come as any great surprise – while the identity of those suffering only brief experiences of unemployment changes from year to year (which leads to growth in the size of the sample over which we estimate the distribution of unemployment), the identity of those who suffer the most unemployment is often the same from year to year. Inevitably then, the chronically unemployed end up accounting for an increasing share of the total duration of unemployment suffered as the lengthen the period over which we define the distribution of unemployment.

FIGURE 4.7 : CONCENTRATION RATIOS FOR THE DISTRIBUTION [1 YEAR]



INDIVIDUALS **SPELLS**

FIGURE 4.8 : CONCENTRATION RATIOS FOR THE DISTRIBUTION [4 YEARS]



INDIVIDUALS **SPELLS**

5. INEQUALITY IN THE DISTRIBUTION AND WAGE PRESSURE

In the Section 3, we outlined the disparity in experiences of unemployment among those who are unemployed at some point in a given period. In Section 1 we argued that this disparity in experiences may have implications for wage setting behaviour, because insiders should respond to their own individual probability of being unemployed. However, this observation takes us no closer to an understanding of exactly which features of the distribution of unemployment wage setters *do* respond to. In effect, we do not know the extent to which wage setters can and do differentiate themselves from those in the unemployment pool in order to identify their individual risk of becoming unemployed. In the absence of any clear evidence on this issue in the final two sections of this Chapter we adopt two alternative conceptual approaches to quantifying the disparity in the distribution of unemployment to inform our understanding of how shifts in the distribution of unemployment may have influenced wage setting behaviour over the period.

5.1 MEASURING INEQUALITY

Our first approach to quantifying the variation in experiences of unemployment draws upon the well known inequality literature. Our general strategy is as follows. First we quantify the degree of inequality in the distribution of unemployment, and then assess whether the distribution is becoming more unequal over time. Finally, we will investigate whether the change in the age composition of the labour force we highlighted earlier, will have had any bearing on the degree of inequality in the distribution of unemployment. It should be stressed at the outset that our intention is to measure the degree of inequality in the distribution of unemployment among those who have some experience of unemployment in that given period. In particular we are not going to describe the degree of inequality in the distribution of unemployment across the labour force. Typically, in any given year, only something of the order of a sixth of the labour force have some experience of unemployment (although as we have shown this figure is sensitive to the cycle). It seems there are two separate issues : the proportion of the labour force who have any experience of unemployment, and among those who are unemployed at some point, the degree of inequality in its distribution across that group. It is not clear that attempting to investigate these two issues using a single measure is particularly informative[77].

Unfortunately it is not readily apparent exactly which inequality measure provides the closest approximation to the perceptions of wage setters of their relative risk of becoming unemployed. We therefore employ a more general approach to measuring the degree of inequality in the distribution, surveying the broad trends in inequality from two separate perspectives. The first approach to measuring inequality involves the percentiles of the distribution which we can use to isolate relative shifts in the distribution of unemployment at specific points in that distribution. The second approach draws upon two established inequality measures: the Gini and Theil indices, which condense all the information on the distribution of unemployment into a single statistic to describe the degree of inequality in that distribution. Although these indices are more conducive to definitive conclusions they do not lend themselves to any easy interpretation of the cause of any change in inequality. We therefore believe our two approaches are natural complements.

Consider comparing the relative position of the percentiles of the distribution over time. If these percentiles move apart then there is evidence that experiences of unemployment are becoming more disperse, or unequal. For example, an oft-quoted statistic is the ratio of the 90th and the 10th percentiles of a given distribution, which measures the relative experiences of unemployment of those at either extremes of the distribution. If this statistic increases over time then there is evidence that the distribution of unemployment

[77] For example, consider a situation where the proportion of people who have some experience of unemployment in a given year falls, but that among those who suffer some experience of unemployment, the total number of days lost to unemployment are distributed more equally. On the one hand, the distribution of unemployment could be said to have become more unequal, since the experience of unemployment is now concentrated among a smaller minority of the labour force; yet on the other hand, within that small minority, unemployment is distributed is more equally. A single statistic measuring the degree of inequality across the whole labour force cannot illustrate both of these opposing forces, only their net effect, and in all probability, any interesting change in the inequality of the distribution of unemployment among the tenth of the population who have some experience of unemployment will be dominated by fluctuations in the fraction of the labour force who suffer no unemployment whatsoever.

has become more unequal, since either those who experience very little unemployment are suffering even less, or those who experience a lot of unemployment are suffering even more, or some combination of the two. There are two obvious problems with such an approach. Firstly, it is not often clear *why* the quantile ratios have changed (i.e. which of the above explanations is the correct one). Secondly, and potentially of more concern, is that these statistics only speak of what is happening at specific (and arbitrary) points in the distribution, and one can easily construct examples where the movement of a particular percentile ratio can be particularly misleading as to overall changes in the dispersion of observations. The obvious solution is to calculate a number of percentile ratios for a number of different pairs of points through the distribution of unemployment – and that is what we have done in the following figures. However, there is a drawback to this approach, and that is there is nothing which guarantees that all the percentile ratios will move in the same direction.

The Gini coefficient is perhaps the most well known inequality measure, and is defined as the average difference between all possible pairs of durations of unemployment in the population as a fraction of the total duration of unemployment experienced [78], i.e. :

$$G = \frac{1}{2n^2 \bar{u}} \sum_{i=1}^{n} \sum_{j=1}^{n} \left| u_i - u_j \right| \qquad [5.1]$$

where u_i is the duration of unemployment of each individual, and $\bar{u}$ is the mean duration of unemployment across the sample of n individuals[79].

[78] Cowell (1995) , p.23.

[79] Of course, the Gini coefficient is also equal to exactly twice the area between the Lorenz curve and a hypothetical Lorenz curve defined for a population where the distribution of unemployment is absolutely equal (all individuals have an identical experience of unemployment). Therefore, perhaps a more appealing method of comparing the degree of inequality in two identically sized populations might be to plot their respective Lorenz curves. If one lies completely inside the other, then that population must certainly suffer less inequality than its rival. However, the fact that our samples are often over a hundred thousand individuals in size will typically mitigate against the occurrence of this event; instead the Lorenz curves will generally intersect, so we must use the Gini coefficient instead to differentiate between the samples. For an example of such an approach see Disney (1979) who uses the Lorenz curve of the distribution of unemployment to estimate the concentration of unemployment, and how that distribution is affected by recurrent unemployment.

The other inequality measure we employ is the Theil index, which is a specific member of the family of modified information theoretic measures. The Theil index is defined as follows :

$$T = \frac{1}{n} \sum_{i=1}^{n} \frac{u_i}{\bar{u}} \log\left(\frac{u_i}{\bar{u}}\right) \qquad [5.2]$$

The reader might reasonably ask what value this extra inequality measure adds to the analysis over and above the familiar Gini coefficient. The answer to this question will depend on the properties we require of our inequality index. Cowell (1995) considers five properties that a desirable index of inequality might satisfy. Both the Theil index and Gini coefficient satisfy the weak principle of transfers (where, for a given total duration of unemployment, if the Lorenz curve of one sample lies entirely inside that of another, then the measure ranks inequality as being higher in the latter than the former) and independence of the measure both to the total duration of unemployment, and the number of individuals in the sample (change all durations by the same proportion, and inequality should remain unchanged). However, the Theil index exhibits two further properties that favour it as a measure of inequality. Firstly, we cannot decompose the Gini coefficient to provide an explanation of changes in inequality in the sample as a whole in terms of the degree of inequality between, say, different age groups in the sample, and that to inequality within each of those age groups[80]. Conversely, for the Theil index, total inequality is exactly equal to the sum of within and between group inequality. Secondly, with the Theil index, the effect of a transfer of a small amount of unemployment [Δu] from one individual to another on total inequality depends only on a function (specifically, their quotient) of their relative shares of the total duration of unemployment (the strong principle of transfers). With the Gini coefficient, the effect of such a transfer depends on the relative location of the individuals, not the amount of unemployment they each experience, nor their share of total unemployment- so that transfers happen to have a

[80] Unless, each age group can be strictly ordered in terms of their experience of unemployment (Cowell (1995), p.150), which will, of course, never be the case.

much larger effect on measured inequality if that transfer is between individuals near the median of the cumulative distribution function [F(u)][81]. Consequently, if we rely on either one of these measures to describe changes in inequality in the distribution of unemployment over time then our conclusions may be very sensitive to where changes in the density of observations occur across the range of all possible durations of unemployment. We now turn to an analysis of the extent of any inequality in the distribution of unemployment over time, initially in the full sample, and then for particular age groups, in order to explain how changes in the age composition of the labour force might have impacted upon the level of inequality in the sample as a whole.

5.2 INEQUALITY IN THE DISTRIBUTION OF UNEMPLOYMENT ACROSS THE WHOLE SAMPLE

The percentile plots overleaf (Figures 5.1-5.2) indicate that, above all, inequality in the distribution of unemployment appears to be greater when the economy is in a boom, and this fact is most strikingly illustrated by the ratio of the 90th to the 10th percentile, which falls by almost two fifths (38%) in value between 1990 and 1993. If we turn to the ratio of the percentiles to the median (see Figure 5.3), then we find a similar picture – the ratio of the 90th percentile to the median falls proportionately even further (40%) between 1990 and 1993 (the ratio of the 10th percentile to the median fell only by about 3% in the same period). The explanation of this dramatic increase in inequality, as measured by the ratio of 90th to the 10th percentile, seems to lie almost exclusively in the (lack of) movement of the 90th percentile. In fact at least one in ten of those who are unemployed in every year are unemployed throughout that year – so the 90th percentile is equal to unity throughout the period. However, when the labour market begins to tighten experiences of unemployment tend to fall so the ratio inevitably increases, indicating greater inequality. The same outcome is observed with the other percentile ratios, although in quantitative terms the changes in inequality are less pronounced, and that is because the other percentiles at the upper end of the distribution (the 80th, 75th and 66th) respond to the change in the labour market and also track downwards.

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[81] Cowell (1995), p.23.

FIGURE 5.1 : PERCENTILES OF THE DISTRIBUTION [MONTHS] – 1 YEAR

INDIVIDUALS **SPELLS**

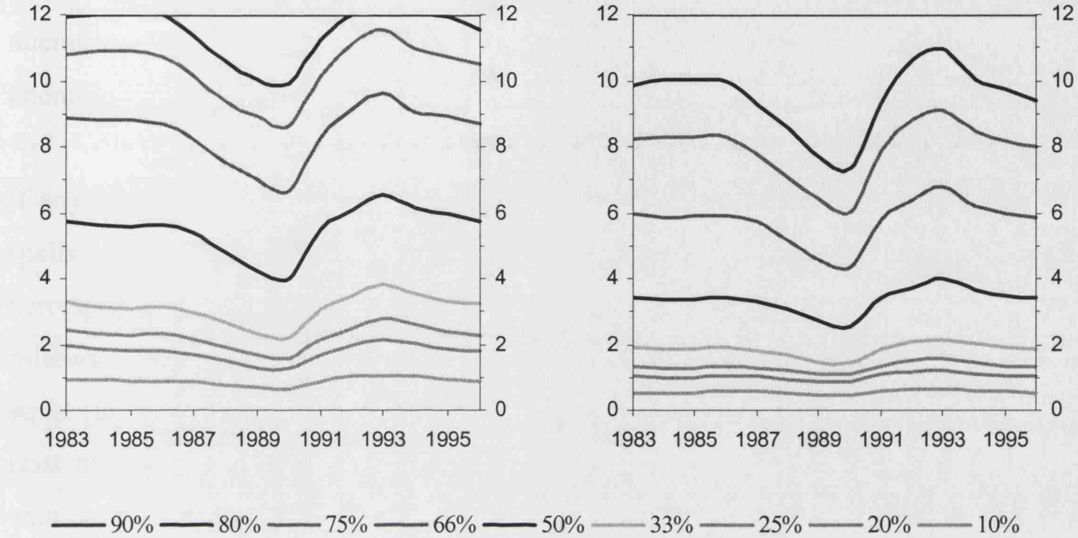
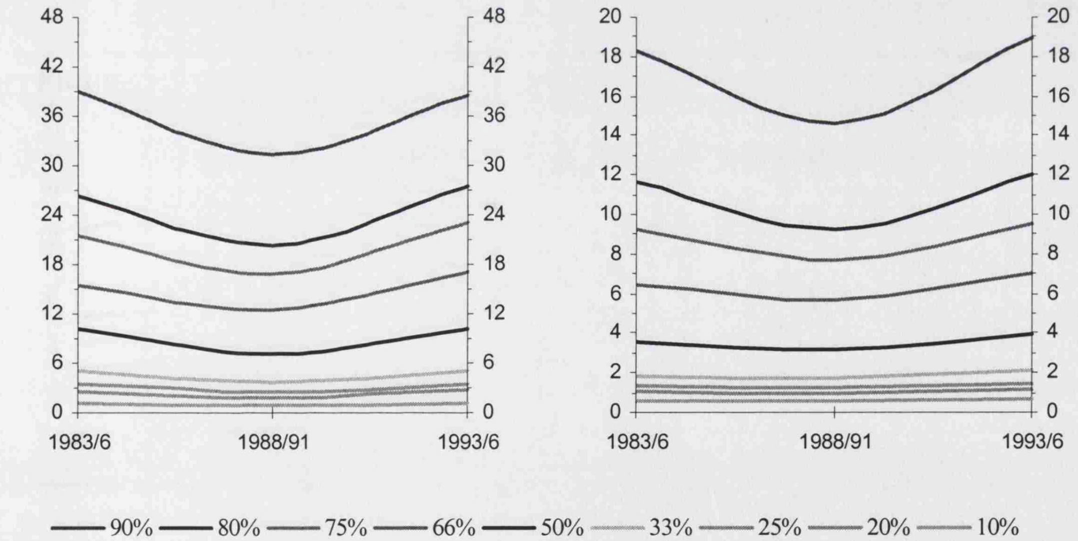


FIGURE 5.2 : PERCENTILES OF THE DISTRIBUTION [MONTHS] – 4 YEARS

INDIVIDUALS **SPELLS**



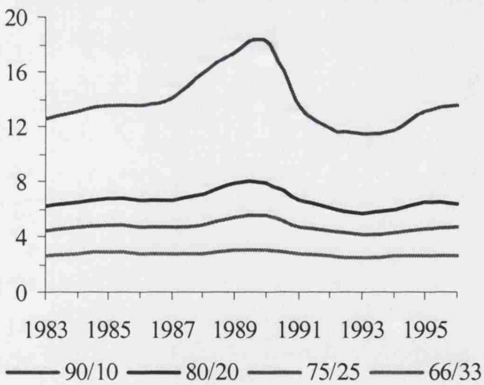
The underlying message remains the same – the fortunes of those at the upper end of the unemployment distribution are less responsive in *proportional terms* to improvements in the aggregate labour market[82]; even the least volatile ratio presented below, that of the

[82] As we noted in the previous section, in *absolute terms* the opposite is the case – between 1990 and 1993, the 25th percentile increased by just over a month, but by a staggering 75%, while the 75th percentile increased by nearly three months but increased by only a third.

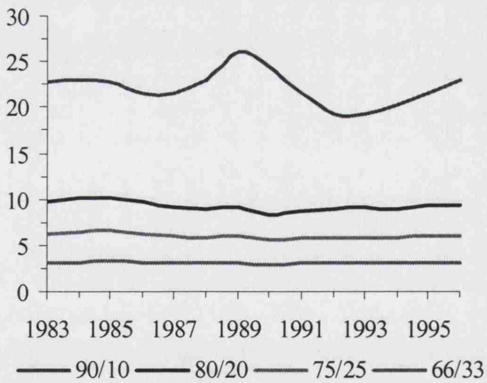
66th to the 33rd percentile, falls by a sixth between 1990 and 1993. It is also the case that each of the percentile ratios we calculated were lower in 1994 than in 1986 when the unemployment rate was all but identical which suggests that over time the distribution of unemployment might have become less unequal.

If anything, the distribution of unemployment appears to be even more unequal across spells (see figure 5.3) – the ratio of the 90th and the 10th percentiles approached twice the corresponding value for the distribution of unemployment across individuals. This result follows directly from the fact that while the 90th percentiles of both distributions are equal (to 100%), the total duration of unemployment experienced by those who suffer the least still exceeds the length of the shortest spells. The obvious inference is that those who suffer the shortest spells over the course of a year typically suffer more than one spell in that year[83], which will tend to equalise experiences of unemployment across individuals, compared to across spells.

FIGURE 5.3 : RATIOS OF THE PERCENTILES OF THE DISTRIBUTION [1 YEAR PERIOD]



INDIVIDUALS



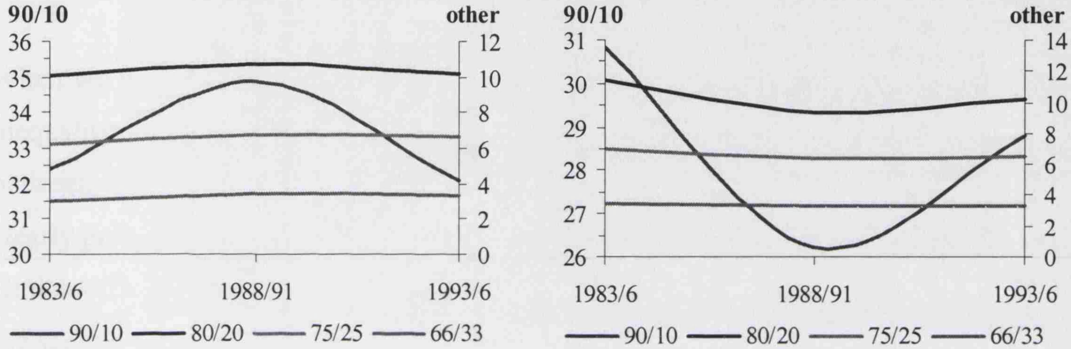
SPELLS

As we widen the period over which we estimate the distribution of unemployment, it appears that the distribution becomes even more unequal. Over the period 1983 to 1986, the ratio of the 90th and 10th percentiles is more than two and a half times the average of the same ratio calculated on an annual basis. However, when we turn to the ratio of the

[83] Of course, if the period over which we measure experiences is too short, this result is almost inevitable, since if an individual is to suffer multiple spells in a short space of time, each constituent spell must by definition be short (OECD (1985)).

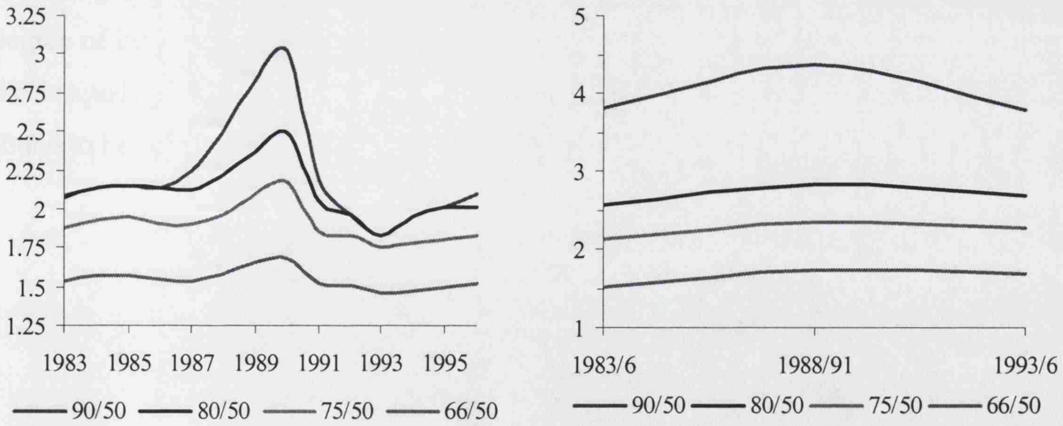
66th and 33rd percentiles calculated on the basis of the distribution estimated over one and four year periods, we find that they are approximately equal. Therefore, we find evidence that around the median of the distribution of unemployment, the degree of inequality is largely unchanged as we widen the period over which we estimate the distribution. However, at the extremes of the distribution, we do find evidence that the distribution has become more extreme as the window of estimation widens.

FIGURE 5.4 : RATIOS OF THE PERCENTILES OF THE DISTRIBUTION [4 YEAR PERIOD]



INDIVIDUALS **SPELLS**

FIGURE 5.5 : RATIOS OF THE UPPER PERCENTILES TO THE MEDIAN (INDIVIDUALS)



1 YEAR **4 YEAR**

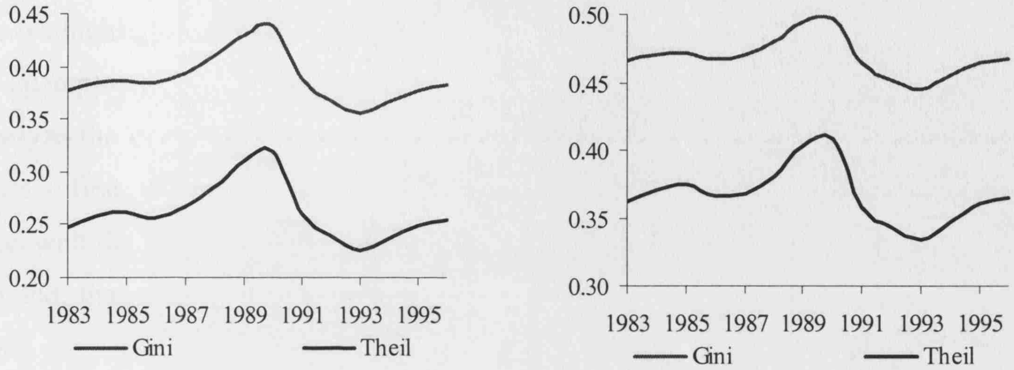
As we extend the period over which we estimate the distribution of unemployment, an increasing number of individuals are included. Now many of these individuals (whom we could conveniently label the frictionally unemployed) will typically suffer a very brief spell of unemployment. As a result the numerical value of the 10th percentile of the distribution will rise only marginally as we extend the length of the period[84] (see Figure 5.5). Furthermore, as we extend the period over which we estimate the distribution of unemployment, the extent to which we censor the number of spells suffered by the recurrent unemployed and the length of spells suffered by the long term unemployed will diminish, so unsurprisingly, the experiences of these unfortunate few diverge from those of the many. Indeed, in the four year period 1983-6, the ratio of the 90th percentile to the median was approximately 3.8; in any of the component years, this ratio calculated on the basis of the distribution of unemployment in a single year was only about 2.1.

When we turn to those measures which condense all the information about the degree of inequality in the population into a single statistic we find once again the clear link between the cycle and the degree of inequality in the distribution – both measures are clearly pro-cyclical (see Figure 5.6). Furthermore, our findings appear unambiguous – the Gini coefficient and the Theil index both give identical rankings of the fourteen years in the sample period in terms of the inequality in the distribution of unemployment. There is therefore very strong evidence to suggest that inequality in the distribution of unemployment across the unemployed varies procyclically[85]. When we compare the degree of inequality in the distribution of unemployment across cycles we find that for all the inequality measures we have used inequality in the distribution of unemployment is found to be lower in 1994 than in 1986 both across individuals and spells

[84] The tenth percentile of the distribution of unemployment over the four year period: 1983-1986 is 1.2 months; the average of the tenth percentile of the distribution when estimated separately over each of those four years is 0.9 months.

[85] Given that the proportion of the labour force who have some experience of unemployment in a given year varies pro-cyclically, we might expect that the degree of inequality in the distribution of unemployment will also be procyclical – since both 'forces' are working in the same direction – in a boom, unemployment becomes more concentrated among a smaller proportion of the labour force, among whom the distribution of unemployment becomes more unequal.

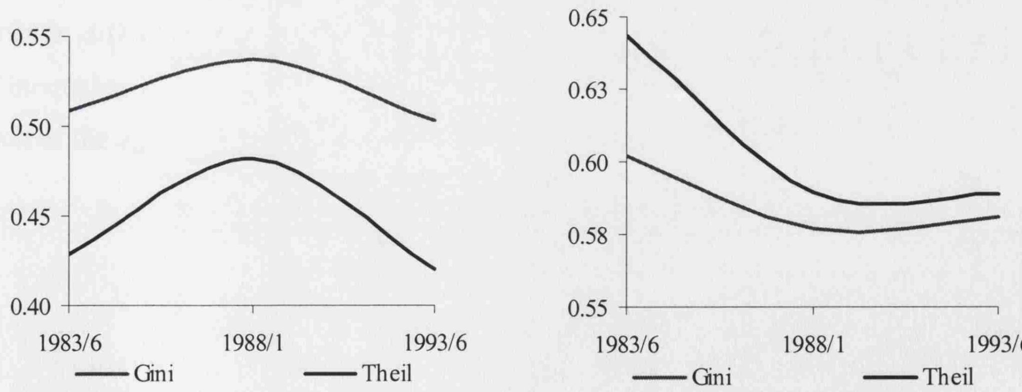
FIGURE 5.6 : INEQUALITY IN THE DISTRIBUTION OF UNEMPLOYMENT [1 YEAR PERIOD]



INDIVIDUALS **SPELLS**

When we turn to an analysis of the degree of inequality in the distribution of unemployment over a longer time-scale then we find that once again our measures are consistent with our findings using the percentile ratios – that measured inequality is higher in the distribution of unemployment when it is estimated over a longer time period (see Figure 5.7).

FIGURE 5.7 : INEQUALITY IN THE DISTRIBUTION OF UNEMPLOYMENT [4 YEAR PERIOD]



INDIVIDUALS **SPELLS**

5.3 INEQUALITY IN THE DISTRIBUTION OF UNEMPLOYMENT BY AGE.

As we highlighted in Sections 3 and 4, there are significant differences in the distribution of unemployment across different age groups (see Figures 5.8 - 5.9). When we turn to the analyze the degree of inequality in these age-specific distributions we find two striking facts – first, that inequality in the distribution of unemployment varies significantly by age, with the young typically suffering a more unequal distribution of unemployment; but second, that there has been a significant convergence in this variation in inequality by age.

Experiences of unemployment are most unequal among youths when we compare the 90th and 10th percentiles of the distribution – although this pattern was reversed through the recession in the early 1990's. This result is a consequence of the fact that relative to adults, those youths who experience the least unemployment over the period suffer very little unemployment indeed. However, we find the opposite result when we turn to the distribution of unemployment across spells – where, for example, there is less inequality in the length of spells suffered by those in their teens compared to those in their twenties, because so few of the former suffer long spells. The figures illustrate graphically the significant differences in the degree of inequality in the distribution of unemployment for those at different points in their working life. However, they also reveal that the pattern of inequality in the distribution of unemployment evolves in broadly the same fashion for each of the age groups.

FIGURE 5.8 : PERCENTILES OF THE DISTRIBUTION BY AGE [MONTHS] – 1 YEAR

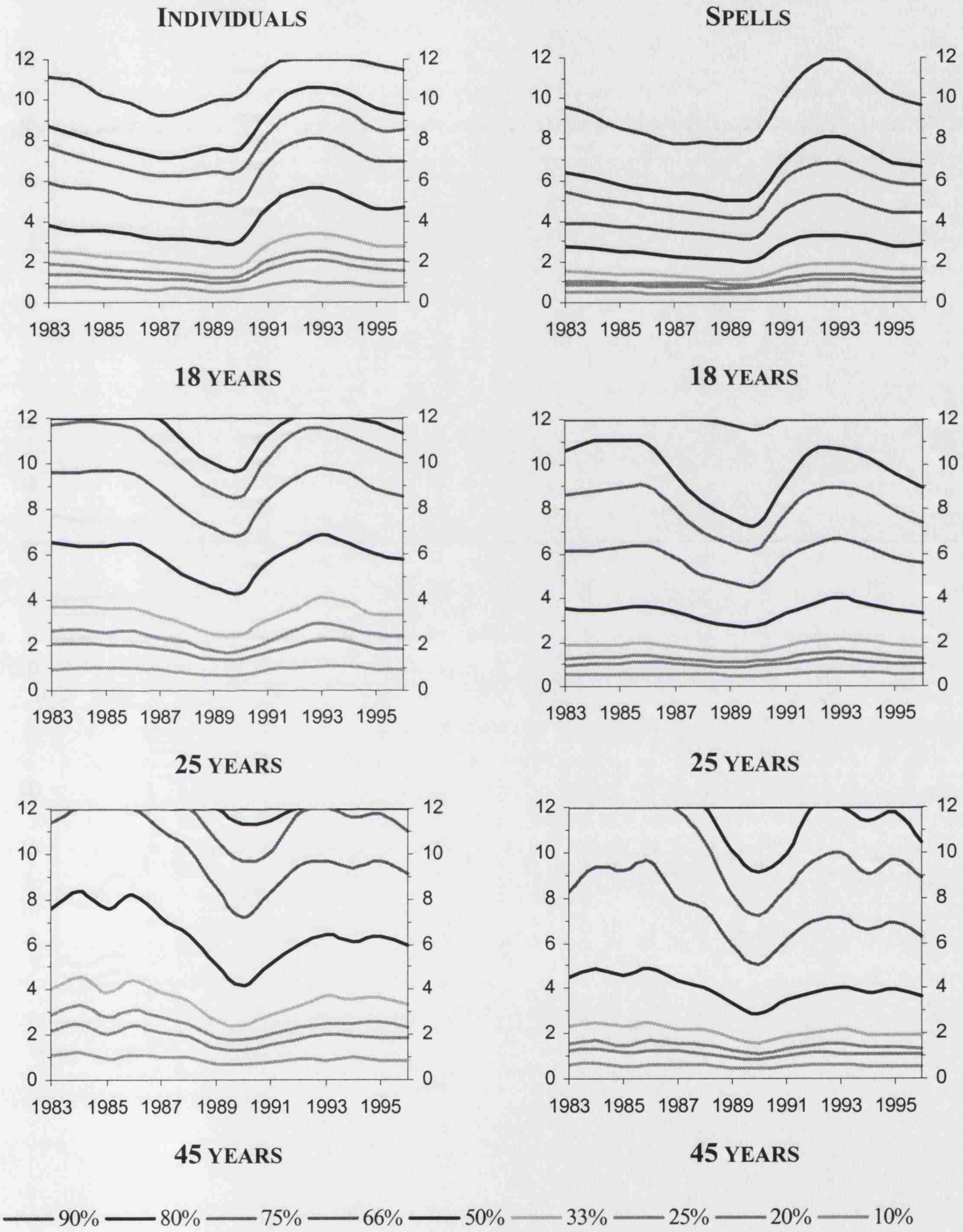
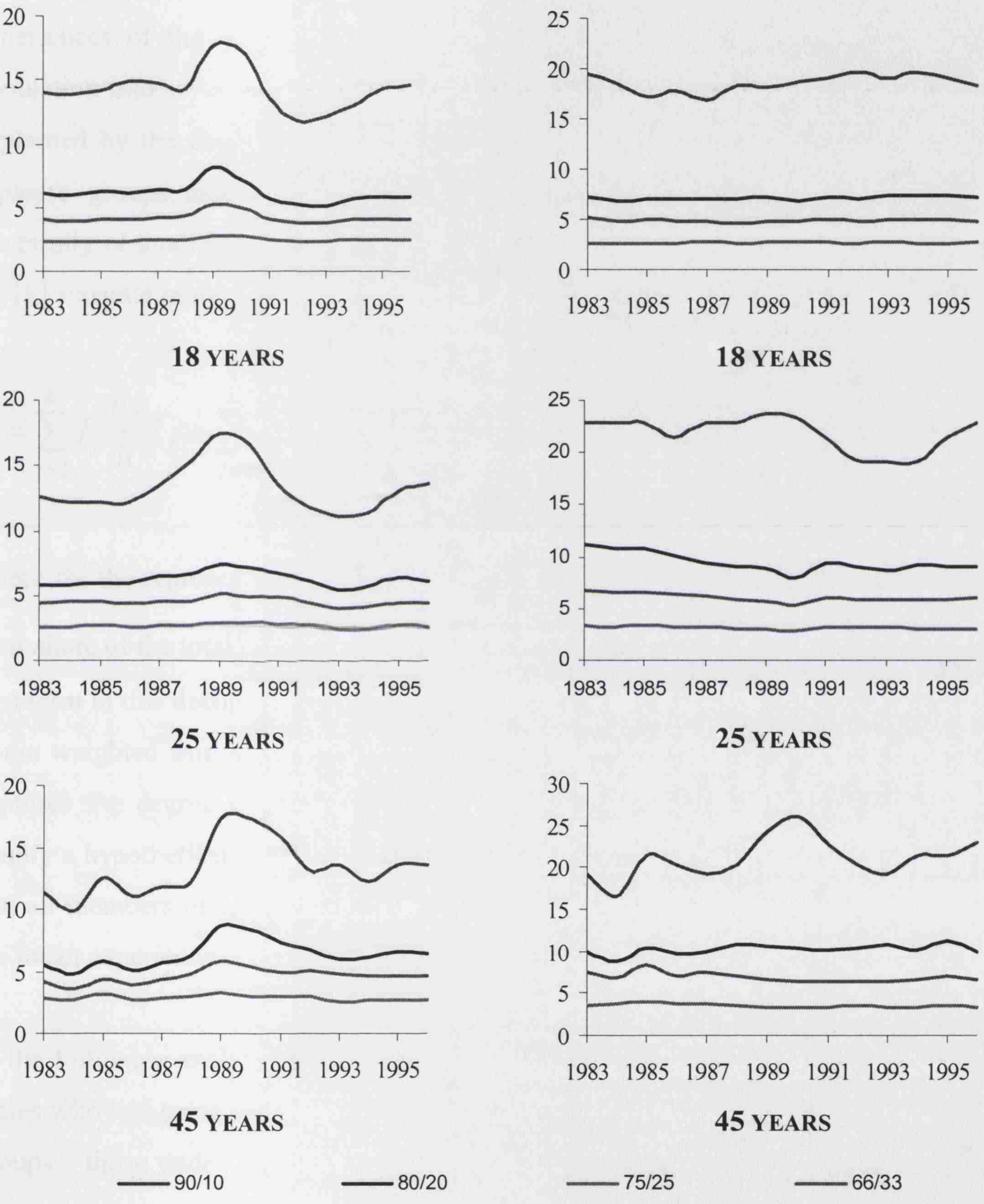


FIGURE 5.9 : RATIO OF THE PERCENTILES OF THE DISTRIBUTION [1 YEAR]

INDIVIDUALS SPELLS



Casual inspection of Figure 5.10 below also reveals the extent of the convergence in the inequality in the distribution of unemployment within different age groups. In 1984, the degree of inequality in the distribution of unemployment among 45 year olds was almost exactly two thirds of that in the distribution of 18 year olds, as measured by the Theil index; by 1996, any gap had all but disappeared. Unfortunately, these figures do not allow us to directly investigate the extent to which inequality in the distribution of unemployment across the labour force is driven by this inequality between the experiences of the different age groups. Ideally, we would like to divide the entire population into several distinct sub-groups and decompose measured inequality into that explained by the degree of inequality between the typical experience of each of these separate groups, and that within each of these groups. The Theil index (as a member of the family of modified information theoretic measures) allows just such a decomposition for [k] separate mutually exclusive groups as follows[86]:

$$T = \sum_{j=1}^{k} f_j \frac{\overline{u}_j}{\overline{u}} I_j + \sum_{j=1}^{k} f_j \frac{\overline{u}_j}{\overline{u}} \log\left(\frac{\overline{u}_j}{\overline{u}}\right) \qquad [5.3]$$

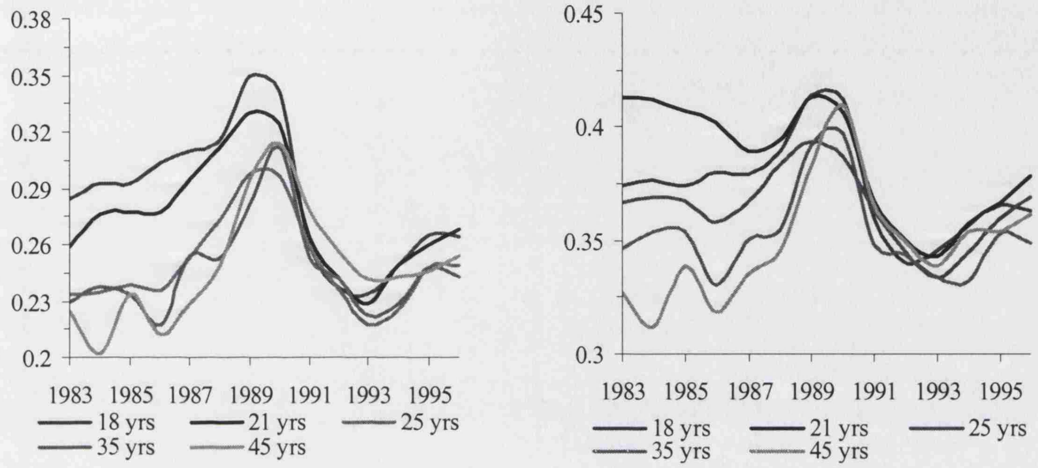
where for the representative j[th] group, their mean duration of unemployment is $\overline{u}_j$, f_j is their share of the total sample and I_j is the degree of inequality within that sub-group. The first term in this decomposition captures the degree of inequality within each group – and is the weighted sum of the Theil index calculated for each sub group; the second term captures the degree of inequality between the separate groups in the sample, and is simply a hypothetical Theil index calculated over the entire sample under the assumption that all members of each group have an identical experience of unemployment (equal to the mean experience of their group).

In the following analysis we perform just such a decomposition, dividing the sample of males who had some experience of unemployment in a given year into five separate age-groups - those under 22 years of age, those between 22 and 29, 30 and 39, 40 and 49 years, and those over 49 years of age. The results are illustrated in Figure 5.11, with the inequality between groups graphed on a separate axis for greater clarity:

[86] Cowell (1995), p.151.

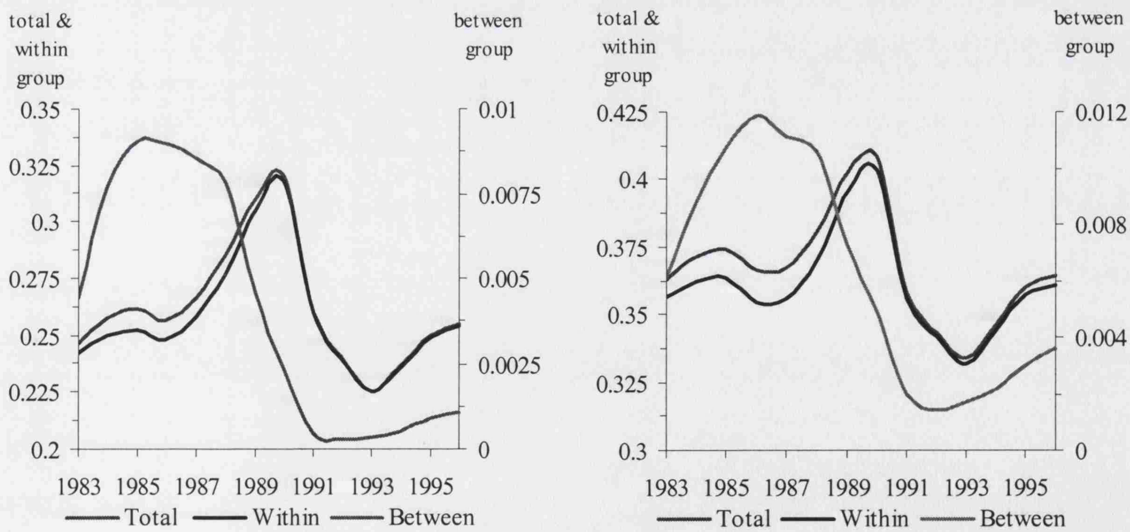
FIGURE 5.10 : INEQUALITY IN THE DISTRIBUTION OF UNEMPLOYMENT BY AGE

[THEIL INDEX]



INDIVIDUALS **SPELLS**

FIGURE 5.11 : INEQUALITY - WITHIN AND BETWEEN AGE GROUPS



INDIVIDUALS **SPELLS**

The decomposition highlights that inequality in the experience of unemployment is driven almost exclusively by the degree of inequality within each of the age-groups – or, in other words, we gain very little by decomposing the panel into separate groups when trying to explain inequality in the distribution of unemployment. Between 1983 and 1996, inequality between these age groups never explains more than 3.5% of total measured inequality in the whole sample. This result is robust to alternative age decompositions – for example, between youths and adults (i.e. between those aged under 25 years, and those aged 25 years and above).

The other striking result is that in a very short period of time – between 1986 and 1990 – the proportion of total inequality explained by inequality between the experiences of these separate age groups falls from this peak to 0.1% - which underscores the convergence in the inequality measures we graphed in the previous figures. When we repeat the decomposition for the distribution of unemployment across spells, we find broadly the same picture – that differences in the degree of inequality in the distribution of unemployment between age groups are not significant. Simply put, different age groups in the labour force never were that different in terms of the inequality in the distribution of unemployment among them, and any differences that did exist almost disappeared over the period.

To conclude then, we have established five key results. First, that the degree of inequality in the distribution of unemployment among those males who have some experience of it varies pro-cyclically (i.e. increases in a boom when unemployment falls), and therefore since the number of people who have some experience of unemployment also falls in a boom, we expect that inequality in the distribution of unemployment across the entire labour force will also vary pro-cyclically. Second, that as we widen the period over which we estimate the distribution of unemployment, the degree of inequality in that distribution increases. Third, that the distribution of unemployment is even more unequal across spells than individuals so that recurrent unemployment appears if anything to equalise experiences of unemployment across individuals. Fourth, that over time, there is at least some circumstantial evidence to suggest that the degree of inequality in the distribution of unemployment has fallen. Fifth, that although the degree of inequality in the distribution of unemployment differs for separate age groups in the sample, these differences explain a small and decreasing fraction of the overall level of inequality in the sample.

In terms of the implications of the above for wage setting behaviour results one and four deserve particular attention; the fact that the distribution of unemployment becomes more unequal in a recovery is likely to increase the elasticity of the wage setting function with respect to the unemployment rate, since as the aggregate unemployment rate falls experiences of unemployment become increasingly concentrated on the chronically unemployed. However, if the distribution of unemployment has become more equal over time than this might suggest that insiders will show increasing restraint in future when they set wages.

6. POLARISATION IN THE DISTRIBUTION AND WAGE PRESSURE

In the previous section we analyzed the degree of inequality in the distribution of unemployment, arguing that an unequal distribution may lead to lower wage restraint on the part of insiders than we would otherwise expect at a given unemployment rate. However, recent work by Esteban and Ray (1994) argues that the axioms that underpin the inequality literature may not be wholly appropriate as a logical framework to analyze a situation of social conflict[87] which, at least in a metaphorical sense, seems an apt description of the 'leapfrogging' behaviour which characterizes decentralized wage setting. Instead, they argue that conflict is most likely to occur within a *polarised* (rather than an unequal) population, which they define as one in which there are a relatively small number of distinct clusters, in which experiences are relatively similar, but between which experiences differ sharply. In other words, a polarised population exhibits both *intra-group homogeneity* and *inter-group heterogeneity*.

[87] For example, a survey by Amiel and Cowell (1992) found that most non-economists do not even rank income distributions according to how unequal they are in a manner consistent with the Lorenz ordering – that is if at every level of income, a smaller proportion of population A than population B have that income or less, then income is distributed more unequally among population A than among B (Esteban and Ray (1994)).

Although similar concepts, Esteban and Ray argue that polarisation and inequality are fundamentally different phenomena, and therefore focusing on the degree of polarisation in the distribution of unemployment might offer us an alternative insight into the determinants of aggregate wage setting. They argue inequality measures fail to differentiate between shifts in a distribution that could be loosely thought of as convergence to the global mean and those shifts which entail convergence towards a local mean, or 'clustering'[88]. In either case the level of inequality in the distribution of unemployment may fall which we might argue should lead to greater wage restraint; however in the latter case, the degree of polarisation in the population has clearly increased[89]. It may well be that it is only where individuals are able to clearly distinguish between different groups in the labour market each of whom suffer different experiences of unemployment that they can distinguish between their own individual risk of becoming and remaining unemployed from the average risk across the labour force. Indeed the stylized argument we presented in Section 1 in terms of a society inhabited by insiders who control wage setting (in their own interests) and outsiders who bear the brunt of unemployment is couched in terms of a polarised society. Since any conclusions we might draw regarding the behaviour of wage setters will be predicated on the assumption of what matters when insiders assess their risk of becoming (and remaining) unemployed, we now focus on the degree of polarisation in the distribution of unemployment in order to examine whether or not this alternative approach produces broadly consistent conclusions regarding wage setting behaviour to those developed in Section 5.

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[88] So that, for example, while in the economic growth literature, *conditional convergence* – the convergence in the per capita growth rates of the developed and developing nations to separate means – will lead eventually to a sharp polarisation in standards of living around the world, on any measure of inequality based on growth rates, inequality will be found to have fallen (Esteban and Ray (1994)).

[89] The distinction here is quite subtle – since the degree to which the distribution of unemployment is polarised into distinct cluster points will certainly affect the level of inequality in that distribution. Nonetheless, polarisation and inequality are conceptually distinct from each other. As a case in point consider two alternative unemployment distributions: a uniform distribution over the domain of all possible durations, and a bimodal distribution, where all individuals spend either one third or two thirds of any period unemployed. The former distribution is very unequal, but unpolarised; the latter is highly polarised

6.1 DEFINING THE DEGREE OF POLARISATION IN A POPULATION

In their seminal paper, Esteban and Ray (1994) give an axiomatic derivation of a class of polarisation measures of the general form:

$$P(\pi,u)=\sum_{i}^{n}\sum_{j}^{n}\pi_i\pi_j.T(i,a) \qquad [6.1]$$

so that for a distribution (π,u)[90], polarisation is dependent on the sum of all *'effective antagonisms'* between each individual and all others in the sample, according to some function $T(i(\cdot),a(\cdot))$ where the degree of antagonism between any pair of individuals, is in turn defined by the distance between their experiences. Antagonism can take one of two forms: individuals who have similar experiences of unemployment are said to *identify* with each other according to some function: $i(\cdot)$; conversely, individuals whose experiences of unemployment differ are said to be *alienated* from each other according to some function $a(\cdot)$. The degree of polarisation in a distribution is thus defined by the extent to which individuals both identify with certain individuals in the distribution (capturing the existence of clusters of individuals who share common experiences) and distinguish themselves from others (capturing the degree to which the experiences of individuals in a particular cluster are distinct from those in other clusters).

In order to make this generalised polarisation measure operational we need to specify the particular form of the identification and alienation functions. Following Esteban and Ray (1994), we assume that identification occurs over an interval, so that individuals identify with not only those who have identical experiences of unemployment, but also with those who share 'similar' experiences to their own. The limit of identification can then be defined by some (arbitrary) constant D, so that a cluster is now defined as interval of width 2D. Within that cluster, total identification for individual i is defined as:

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but not very unequal. For a detailed discussion of the distinction between these two concepts see Esteban and Ray (1994).

[90] Where u = {u1,u2,.....,un} is the set of all possible durations of unemployment, over which individuals are distributed across the range of [n] cluster points with frequency πi , where πi >0 ∀ n.

$$i_i = \sum_{j:\left|u_j - u_i\right| \le D} \pi_j . w(u_i, u_j) \qquad [6.2]$$

where the function $w(u_i, u_j)$ defines the level of identification between individuals i and j which depends on their respective experiences of unemployment. It then remains to define a particular functional form for our identification function. Once again, following Esteban and Ray, we argue that any reasonable choice of identification function should satisfy three properties: first, that it should be symmetric so that the i's identification with j should equal j's identification with i; second, that, identification should depend only on the difference between their experiences of unemployment; and finally, third, that the level of identification should be monotonically decreasing in the difference between their experiences, below the limit of identification. A suitable candidate for the identification function is therefore:

$$i_i = \sum_{j:\left|u_j - u_i\right| \le D} \pi_j . \left(\frac{D - \left| u_i - u_j \right|}{D} \right) \qquad [6.3]$$

which ensures that identification is linearly decreasing in the difference between individuals' experience of unemployment, and is bounded between zero and one.

Of course, by the same token, any reasonable alienation function should also satisfy the same three criteria we applied to the identification function above, except that our third condition would now require that alienation is monotonically increasing in the difference between the experiences of i and j, beyond the limit of identification. Therefore, for those individuals whose experiences of unemployment differ by more than D, the degree of alienation felt by individual i is defined as :

$$a_i = \sum_{j:\left|u_i - u_j\right| > D}^{n} \pi_j \left(\frac{\left|u_i - u_j\right| - D}{1 - D} \right) \qquad [6.4]$$

so that alienation, beyond the threshold [D], is linearly increasing in the distance between two individuals. For the sake of consistency, we have also normalised the degree of alienation so that it too is bounded between zero and one. Given these functional forms, we can specify our polarisation measure[91] so that across a population, containing k distinct cluster points, polarisation is defined as :

$$P(\pi,u) = \sum_{k=1}^{n} \sum_{i=1}^{n_k} \pi_{ik} \cdot \left[\sum_{j:\left|u_{ik} - u_j\right| \le D}^{n} \pi_j \left(\frac{D - \left|u_{ik} - u_j\right|}{D} \right) \times \sum_{j:\left|u_{ik} - u_j\right| > D}^{n} \pi_j \left(\frac{\left|u_{ik} - u_j\right| - D}{1 - D} \right) \right] \qquad [6.5]$$

An intuitive explanation for the polarisation measure is as follows – for any pair of individuals, the measure will return the greatest numerical value where their experiences are either very similar, or very different from each other.

Of course, in the measure above the parameter [D], which determines the point at which individuals cease to identify and begin to feel animosity, remains to be specified. If this

[91] By way of comparison, Esteban and Ray define the level of polarisation across i cluster groups as follows:

$$P(\pi,u) = K.\sum_{i=1}^{n} \sum_{j=1}^{n} \pi_i^{1+\alpha} \pi_j . \left|u_i - u_j\right|$$

where K is simply a multiplicative constant, and α captures the degree of 'polarisation sensitivity'. In equation [6.5] we have set the constant: K and α equal to one (although we will go on to define K as the inverse of the cube of the sample size to normalize our polarisation measure). If, alternatively, α is set equal to zero our polarisation measure is equivalent to the Gini index.

parameter is relatively large then the measure will be dominated by the extent of identification in the sample - in other words, the degree of homogeneity within clusters; if it is relatively small, the measure is dominated by the degree of animosity in the sample – i.e. the degree of heterogeneity between clusters[92]. We therefore calculate this particular polarisation measure for a range of possible values for this parameter, to examine the sensitivity of our results. However, as the figures below demonstrate, irrespective of whether we define the point at which individuals with different experiences of unemployment cease to identify with each other as a number of days equivalent to 0.02, 0.05 or 0.1 percent of the period[93] our results are not materially affected.

However, the polarisation measure we have defined here is not independent of the size of the sample, and *ceteris paribus*, polarisation is lower among a small population than a large one (Esteban and Ray (1994) p.847). However, the measure may be normalised in population size by dividing by the cube of the sample size[94], and to illuminate 'genuine' changes in the degree of polarisation in the data, over and above any change in population size, both the standard and normalised measures will be considered.

Clearly, our results may be highly dependent on the particular functional form we have chosen for the identification and alienation functions. We have argued that it is logical to assume that identification must monotonically decrease (and alienation monotonically increase) as the difference between individuals' experiences increase. In [6.3] and [6.4] we have assumed that the rate of change of identification and alienation with the difference between individuals' experiences is constant. However, it is not clear that any restriction ought to be placed on the second derivative of the identification or alienation functions. In order to illustrate the sensitivity of our results to the specification of these

[92] Specifically, as D increases each individual will identify with a larger fraction of the population, and among the remainder of the population from whom he is alienated, he will feel a lower level of alienation than he previously did.

[93] When calculating the degree of polarization in the distribution of unemployment estimated over a single year, these alternative choices of the value of the parameter D imply that individuals identify with each other if the total duration of unemployment they suffer differs by less than approximately a week, a fortnight or a month respectively.

[94] Which is effectively equivalent to re-defining the population weights π_i as population frequencies (Esteban and Ray (1994)).

functions, we therefore consider two alternative functional forms for the identification and alienation functions: where both the identification and alienation functions are either convex or concave respectively. Simple concave and convex transformations of the identification function [6.3] are respectively:

$$i_i' = \sum_{j:\left|u_j - u_i\right| \leq D} \pi_j \cdot \left(\frac{D - \left| u_i - u_j \right|}{D} \right)^{1/2} \qquad [6.6]$$

$$i_i'' = \sum_{j:\left|u_j - u_i\right| \leq D} \pi_j \cdot \left(\frac{D - \left| u_i - u_j \right|}{D} \right)^{2} \qquad [6.7]$$

The intuitive interpretation of these identification functions is that the individual identifies strongly with all those but at the extremes of the cluster in the case of concave identification [6.6]; conversely, given convex identification [6.7] identification is only significant within a small fraction of the total width of the cluster. Consequently, it is clear that measured identification is higher in the former case than in the latter. Similarly, for our alienation function [6.4], we now have:

$$a_i' = \sum_{j:\left|u_i - u_j\right| > D}^{n} \pi_j \left(\frac{\left| u_i - u_j \right| - D}{1 - D} \right)^{1/2} \qquad [6.8]$$

$$a_i'' = \sum_{j:\left|u_i - u_j\right| > D}^{n} \pi_j \left(\frac{\left| u_i - u_j \right| - D}{1 - D} \right)^{2} \qquad [6.9]$$

In the former case (concave alienation [6.8]), an individual feels considerable alienation towards a large section of the population, whereas in the latter case (convex identification

[6.9]), individuals feel alienated only from those whose experiences are utterly different to their own. Once again, measured alienation is greater in the former case than in the latter. The resulting polarisation functions are respectively:

$$P'(\pi,u)=\sum_{k=1}^{n}\sum_{i=1}^{n_k}\pi_{ik}\cdot\left[\sum_{j:\left|u_{ik}-u_j\right|\leq D}^{n}\pi_j\left(\frac{D-\left|u_{ik}-u_j\right|}{D}\right)^{1/2}\times\right.$$

$$\left.\sum_{j:\left|u_{ik}-u_j\right|>D}^{n}\pi_j\left(\frac{\left|u_{ik}-u_j\right|-D}{1-D}\right)^{1/2}\right] \qquad [6.10]$$

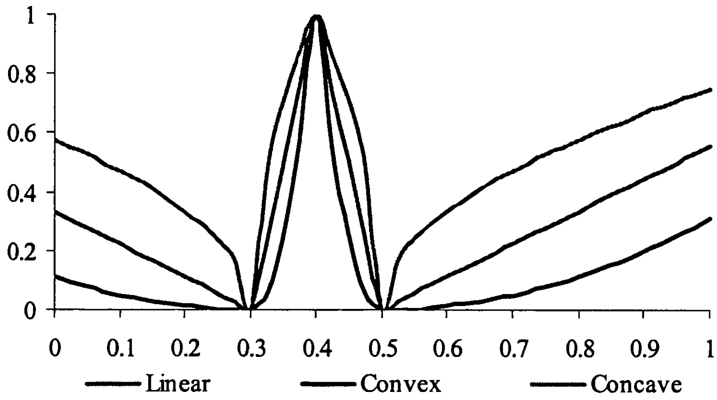
$$P''(\pi,u)=\sum_{k=1}^{n}\sum_{i=1}^{n_k}\pi_{ik}\cdot\left[\sum_{j:\left|u_{ik}-u_j\right|\leq D}^{n}\pi_j\left(\frac{D-\left|u_{ik}-u_j\right|}{D}\right)^{2}\times\right.$$

$$\left.\sum_{j:\left|u_{ik}-u_j\right|>D}^{n}\pi_j\left(\frac{\left|u_{ik}-u_j\right|-D}{1-D}\right)^{2}\right] \qquad [6.11]$$

In Figure 6.1 below we give a simple graphical illustration of our three generic polarisation measures; in the particular example we consider an individual who spends 40% of a given period unemployed, where the limit of identification is considered to be a number of days of unemployment equivalent to 10% of the whole period [D=0.1].

Therefore, given concave identification and alienation functions, we will always measure a higher level of polarisation in a given distribution than if we had used convex functions instead. The issue we investigate is the extent to which varying the form of what are ultimately arbitrary functions affects the time series profile of polarisation in our sample.

FIGURE 6.1 : LINEAR, CONVEX AND CONCAVE POLARISATION FUNCTIONS



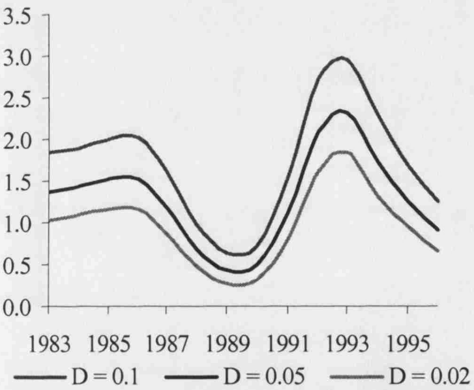
6.2 POLARISATION IN THE DISTRIBUTION OF UNEMPLOYMENT

If we first consider the standard polarisation measure we observe that the distribution of unemployment becomes markedly more polarised when the labour market enters a slump – between 1990 and 1993 there was a four fold increase in polarisation, as measured by our standard measure where identification occurs over a range equivalent to just over a fortnight [D=0.05]. The results obtained are remarkably similar for the distribution of unemployment across spells. In short, polarisation in the distribution of unemployment appears to be highly anti-cyclical (see Figure 6.2).

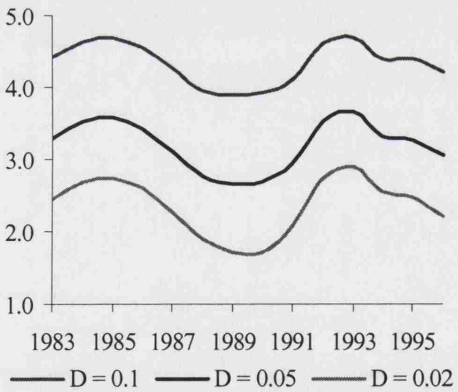
Of course more people have some experience of unemployment during a slump and this will increase measured polarisation. Nonetheless, when we turn to the polarisation measure which is normalised by the size of the sample, our results are qualitatively, if not quantitatively, unchanged. Polarisation is now weakly anti-cyclical – between 1990 and 1993 polarisation in the distribution of unemployment now increases by between a fifth to two thirds depending on the measure we use. We see a very similar pattern when we turn to the distribution of unemployment across spells (see Figure 6.3), where the rate at which polarisation increases during a slump is muted once we control for the increase in the number of spells that results from a downturn in the labour market. Before normalisation, the distribution of unemployment appears more polarised across spells than individuals, but inevitably this is a result of the fact that there are more spells of unemployment in any period than people who suffer them. After controlling for this, we find the distribution of unemployment is less polarised across spells than individuals. Finally, when we focus on the extent to which the degree of polarisation in the distribution has changed over time we find that before controlling for the size of the sample in those two years, polarisation is higher in 1994 than in 1986, yet after normalisation, polarisation is lower in 1994.

As Figures 6.4 - 6.5 show our results are robust to alternative specification of the polarisation measure – although polarisation is increasing in the range of identification, and greater when both identification and alienation are concave rather than convex – the underlying trend in polarisation remains the same.

FIGURE 6.2 : POLARISATION OF THE DISTRIBUTION ACROSS INDIVIDUALS VARYING THE LIMIT OF 'IDENTIFICATION' [D]



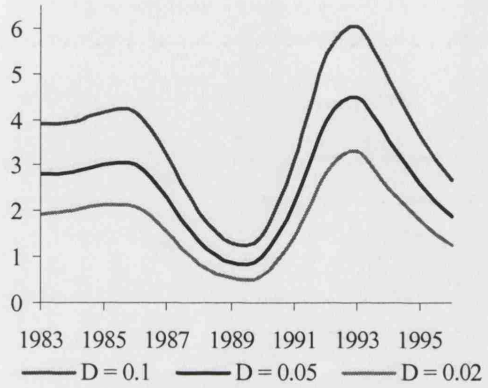
STANDARD : 1 x 10^{14}



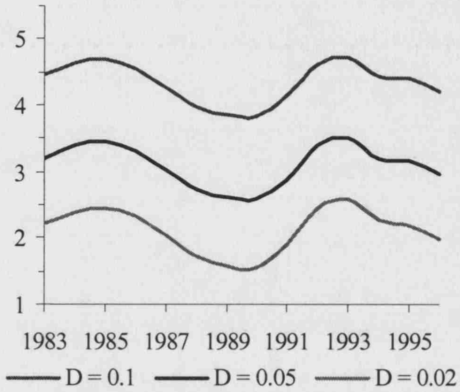
NORMALISED : 1 x 10^{-2}

FIGURE 6.3 : POLARISATION OF THE DISTRIBUTION ACROSS SPELLS

VARYING THE LIMIT OF 'IDENTIFICATION' [D]



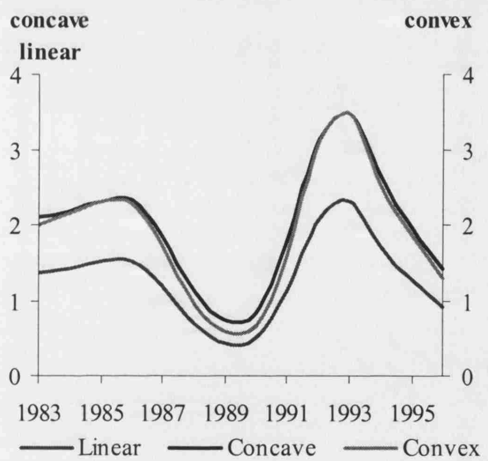
STANDARD : 1×10^{14}



NORMALISED : 1×10^{-2}

FIGURE 6.4 : POLARISATION OF THE DISTRIBUTION ACROSS INDIVIDUALS

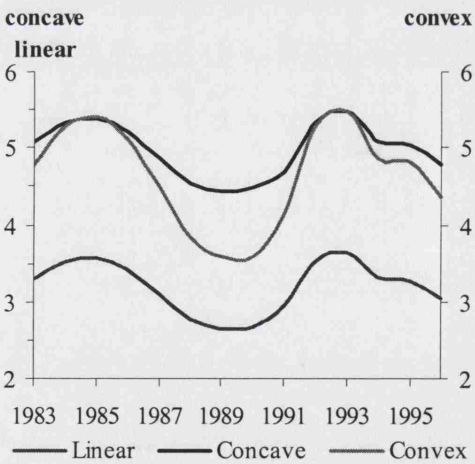
VARYING THE FUNCTIONAL FORM OF 'IDENTIFICATION' AND 'ALIENATION' [D=0.05]



STANDARD:

LINEAR, CONCAVE: 1×10^{14} ;

CONVEX: 1×10^{11}



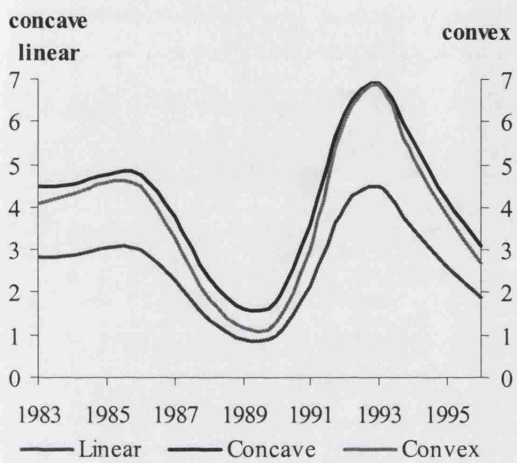
NORMALISED :

LINEAR, CONCAVE: 1×10^{-2} ;

CONVEX: 1×10^{-5}

FIGURE 6.5 : POLARISATION OF THE DISTRIBUTION ACROSS SPELLS

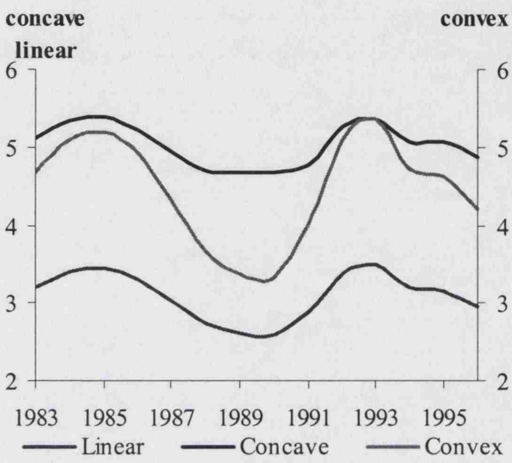
VARYING THE FUNCTIONAL FORM OF 'IDENTIFICATION' AND 'ALIENATION' [D=0.05]



STANDARD:

LINEAR, CONCAVE: 1 X 10^14 ;

CONVEX: 1 X 10^11



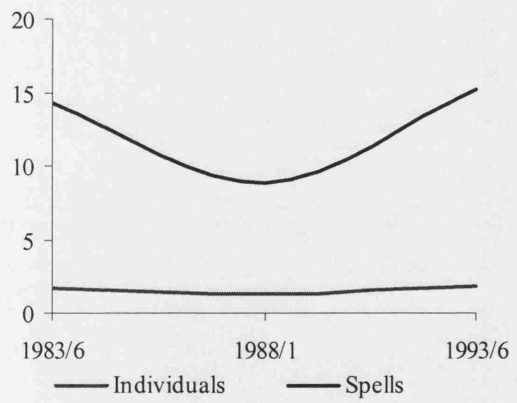
NORMALISED :

LINEAR, CONCAVE: 1 X 10^-2 ;

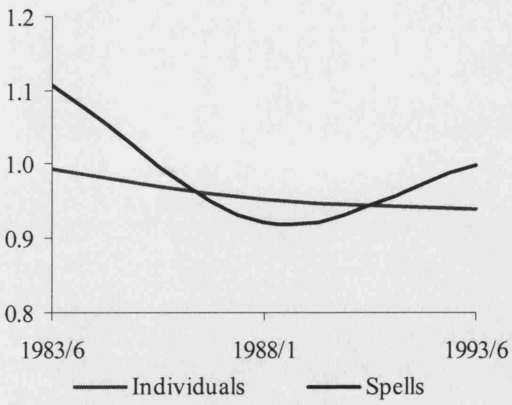
CONVEX: 1 X 10^-5

FIGURE 6.6 : POLARISATION OF THE DISTRIBUTION ACROSS INDIVIDUALS AND SPELLS

FOUR YEAR PERIOD [D=0.02]



STANDARD : 1 x 10^14



NORMALISED : 1 x 10^-2

After controlling for changes in the size of our sample it appears that polarisation is driven by the relative size of the spike in the distribution of unemployment – in a slump a larger proportion of those who experience unemployment are permanently unemployed which will not only increase identification among those who are unfortunate enough to suffer such long durations but also increase alienation as a greater proportion of the sample move to one extreme of the distribution. This process can be "eye-balled" from either the percentile plots of the distribution given in figure 3.6, or from the estimates of the distribution itself given in Appendix 1. When we turn to consider how the degree of polarisation in the distribution of unemployment has changed over time, we find that both across individuals and spells, there has been a marginal fall in polarisation, once we control for the fact that more people now have some experience of unemployment than they did a decade ago.

Finally, when we estimate the distribution of unemployment over a longer period of time, the degree of polarisation in that distribution is higher[95] before we control for the fact that more people have some experience of unemployment over a longer time period (see Figure 6.6). However, once we control for the fact that a far larger number of people have some experience of unemployment over a four year period, we find that the distribution of unemployed is far less polarised when estimated over a longer period. This is due in no small part to the fact that when the distribution of unemployment is defined over a longer time period, the relative importance of the 'spike' at the far extreme of the distribution diminishes and as a result the distribution appears less polarised.

6.3 POLARISATION IN THE DISTRIBUTION OF UNEMPLOYMENT BY AGE

We have already established in the previous section that the degree of inequality in the distribution of unemployment does not vary significantly by age. When we turn to detail the variation in the degree of polarisation in the distribution of unemployment by age, we find a broadly similar picture (see Figures 6.7 – 6.8). Before normalising by the number of each of the respective age groups in the sample, the distribution of unemployment

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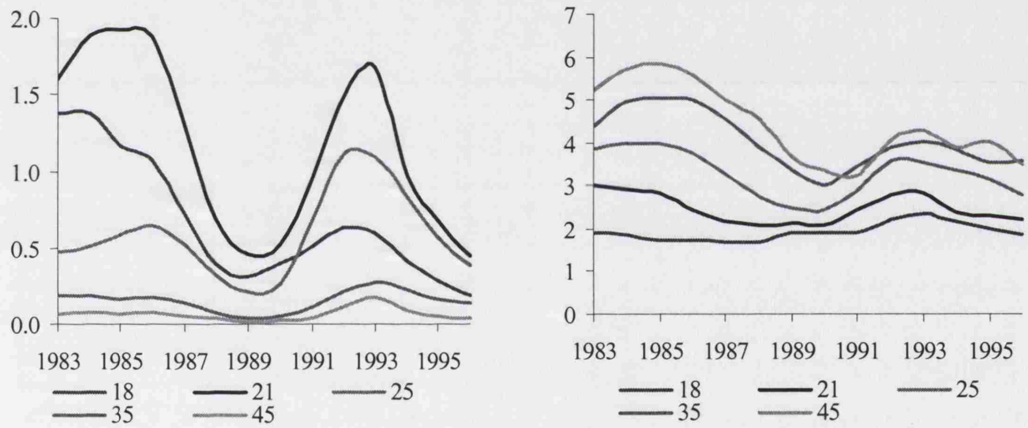
[95] When the distribution of unemployment is estimated over the four year period 1983-1986 we measure polarisation as 1.68 x1014 when identification occurs in an interval of 2% of the period either side of the individual. When estimated separately over each of those years, the highest value of polarisation we record using the same choice of the parameter D is 1.17 x10^{14} (see Appendix tables A.6.2 and A.6.6).

appears most polarised among the young but to a decreasing extent over the course of the period. However, as we detailed in Section 3 there are a disproportionately large number of youths among those who have some experience of unemployment and this is likely to have increased our measure of polarisation. Furthermore, we also know that the age-composition of the sample has changed dramatically over time – in particular, the number of youths who have some experience of unemployment in a given period has fallen relative to adults; *ceteris paribus,* this will have reduced the degree of polarisation in the distribution of unemployment among the young.

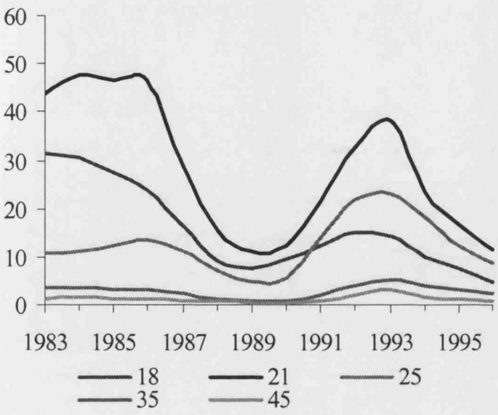
FIGURE 6.7 : POLARISATION OF THE DISTRIBUTION ACROSS INDIVIDUALS BY AGE [D=0.05]



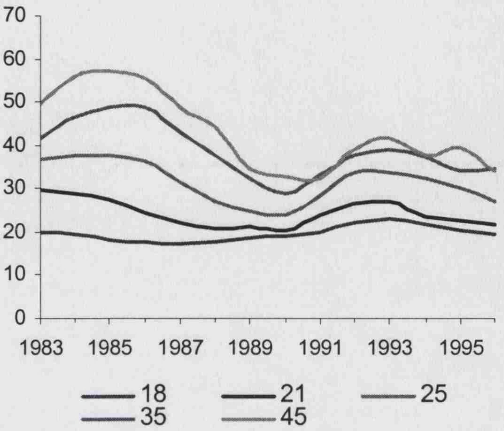
STANDARD : 1 x 10^{10} **NORMALISED : 1 x 10^{-2}**

Once we control for the relative numbers of each group who have some experience of unemployment, we find that the distribution of unemployment is least polarised among the young, and once again there is clear evidence of convergence in experiences across age groups. Increasing polarisation in the distribution of unemployment by age appears to be a direct consequence of the fact that the proportion of the age group who are permanently unemployed throughout the period also increases with age.

FIGURE 6.8 : POLARISATION OF THE DISTRIBUTION ACROSS SPELLS BY AGE [D=0.05]



STANDARD : 1 x 10^{10}



NORMALISED : 1 x 10 $^{-2}$

This section has focused upon a specific feature of the distribution of unemployment – the extent of the polarisation in that distribution, arguing that this, rather than the overall level of inequality in the distribution, may be a factor taken into account by wage setters. At first glance, it appears our results here are in direct contrast to those we obtained in the previous section (the degree of inequality in the distribution of unemployment is pro-cyclical, and the distribution is most unequal among the young). We now find that the degree of polarisation in the distribution of unemployment is anti-cyclical, since during a boom there are relatively fewer people who experience very high durations of unemployment so the importance of this key cluster group diminishes in size. We also find that the distribution of unemployment is least polarised among the young, although once again this differential is small and has diminished markedly over time. These results suggest that if the degree of polarisation of the distribution of unemployment is taken into account by wage setters, then during a recession wage setters will not moderate their claims in the face of a high aggregate unemployment rate.

It must be remembered that the polarisation measures we have adopted is defined in terms of the absolute distance (or difference) between individuals' experiences of unemployment; whereas, the inequality measures we adopted in the previous section are typically defined in terms of one individual's experience as a fraction of another's. This distinction proves crucial: in a boom the gap between those suffering the most and the least unemployment narrows in *absolute terms* and polarisation falls; but in *proportionate terms* the opposite is the case, the gap widens and inequality increases. Whether insiders view their exposure to unemployment relative to those of outsiders in proportionate or absolute terms is unclear. However, if insiders take their relative risk of becoming unemployed into consideration when setting wages, this distinction may matter over the course of the economic cycle.

7. CONCLUSIONS

This chapter has analyzed how experiences of unemployment vary across the labour force in the long run – an issue which, until recently, has not been the subject of much research, due in large part to the lack of data. The JUVOS cohort dataset, upon which this research is based, includes exhaustive information on the spell histories of a random five percent sample of all those who have some experience of unemployment since October 1982. By aggregating across these spells we have been able to construct a detailed account of the total duration of unemployment suffered by those individuals in the panel over the long run.

In any given year, between two to four million men of prime working age have some experience of unemployment over the course of three to five million separate spells. Across a four year period, something of the order of five million men make at least one claim for unemployment related benefits over the course of nearly ten million spells. However, experiences of unemployment are far from uniform among these men. Of those who have some experience of unemployment in any given year, about one in ten will spend less than four weeks in unemployment over the course of a year, yet one in five will spend the entire year unemployed. Over the course of a year, recurrent unemployment is rare – about one in five of those men who will claim unemployment related benefits in a given year will suffer more than one spell of unemployment in that year, and less than one in a hundred will suffer four or more spells. Over a four year period, recurrent unemployment becomes a much more pervasive phenomenon – the majority of individuals who experience unemployment during the period will suffer more than one spell, and one in ten will suffer four or more spells. Spells suffered by youths are over-represented in the JUVOS panel. However, the data establishes that youths suffer higher unemployment rates because a larger fraction of their cohort in the labour force flow into unemployment each year, rather than because those youths who do experience unemployment suffer more or longer spells than adults do. Given that the level of the claimant count varies little from week we might expect that the distribution of unemployment is quite static in the sense that it is the same individuals who are unemployed from week to week. However, this is not the case – the gross flows onto and off of the claimant count dwarf the net changes in the stock: while the claimant count changes by an average of a thousand men each week, some forty five thousand men will enter and exit unemployment each week.

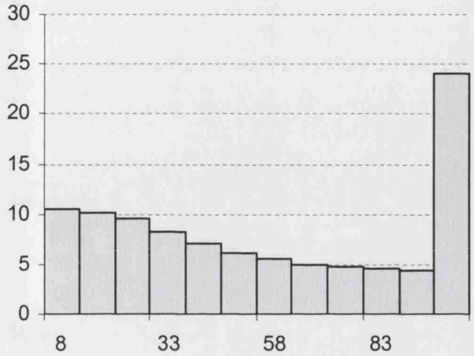
The chronically unemployed – those who spend the majority of any period claiming unemployment benefit – account for about a half of all those who ever enter unemployment in the space of a year and about three quarters of the total days lost to unemployment in that year. Over a four year period, they represent a smaller fraction of all those who experience unemployment, but still account for a large fraction of the total duration of unemployment suffered. It is not the case that long term unemployment and chronic unemployment are one in the same; over a one year period the recurrent unemployed make up about a quarter of the chronically unemployed, and over a four year period they are in the majority. Policy initiatives which focus on the long term unemployed alone may therefore do so at the expense of the hundreds of thousands of recurrent unemployed individuals who over the course of a number of spells spend the majority of their time unemployed. Relative to their share of the labour force youths are over represented among the chronically unemployed, although nothing like to the extent that they are among the pool of all those who have some experience of unemployment.

It is a fact of life that certain individuals – typically the more skilled and productive members of the workforce – are always going to be at a lower risk of becoming unemployed and enjoy a higher probability of escaping unemployment than others. It seems plausible that the more disproportionately that the total burden of unemployment falls upon the chronically unemployed the less restrained wage setters will feel in pushing for higher wages. Blanchard (2000) has voiced a particular form of this argument: that adult wage setters will not be concerned with a high unemployment rate which is concentrated on the young. Given the evidence presented above we do not feel there is overwhelming support for this proposition in the data. It is more plausible to believe that it is the incidence of chronic unemployment per se that might be the root cause of this persistence mechanism. Unfortunately our data does not allow us to directly investigate this alternative hypothesis since we have no information on the distribution of unemployment before the sharp rise in unemployment in the late 1970's and early 1980's.

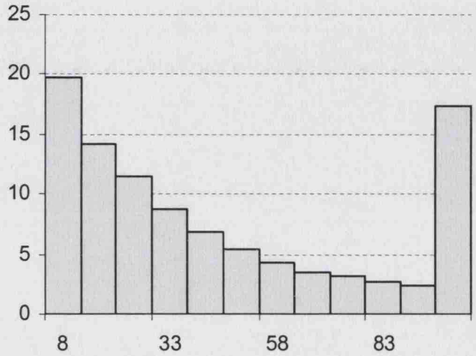
However, we can analyze the degree of imbalance in the distribution of unemployment across individuals since the depths of the recession in the mid 1980's and this potentially offers us new insights into wage-setting behaviour. We have focused on two alternative frameworks which attempt to measure this variation in experiences of unemployment across the labour force: the first draws upon the established inequality literature, the second from the work of, among others, Esteban and Ray (1994) who have pioneered the concept of polarisation. Unfortunately, these two frameworks offer different interpretations on the degree of imbalance in the distribution of unemployment – over the cycle: the distribution is most polarised during a slump and yet most unequal in a boom. This contradiction results from alternative interpretations of the same phenomenon: that in a boom the gap between those suffering the most and the least unemployment narrows in *absolute terms*, but widens in *proportionate terms*. Understanding whether wage setters consider their relative risk of becoming and remaining unemployed relative to outsiders in absolute or proportionate terms is therefore of crucial importance, and could at least potentially be decided on the basis of empirical research – perhaps through survey. Certainly putting some flesh on the bones of the hypothesis that we have outlined here – that wage setters respond to certain features of the distribution of unemployment– is clearly necessary. However, there is at least one point of consensus between our measures: between the cycles of the 1980's and 1990's the degree of both inequality and polarisation in the distribution of unemployment has fallen and so other things equal, we might expect greater restraint on the part of wage setters who can now expect to suffer a greater (if not equal) share of the burden of unemployment.

APPENDIX 1 : THE DISTRIBUTION OF UNEMPLOYMENT :

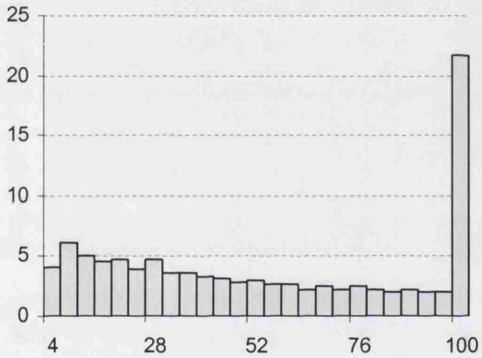
[A] HISTOGRAMS [X AXIS ~ PERCENTAGE OF PERIOD]



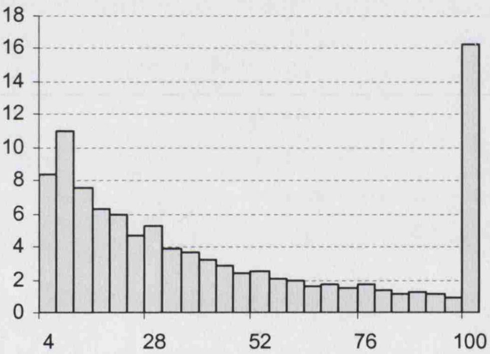
1983 – INDIVIDUALS [12 BINS]



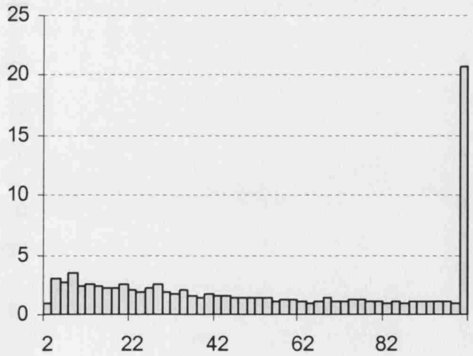
1983 – SPELLS [12 BINS]



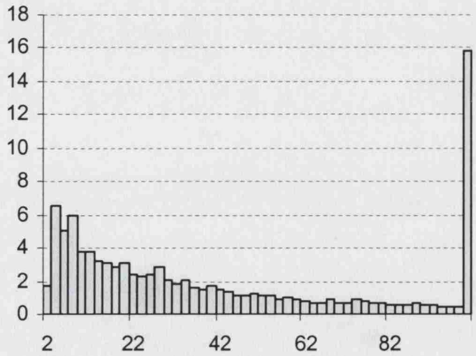
1983 – INDIVIDUALS [25 BINS]



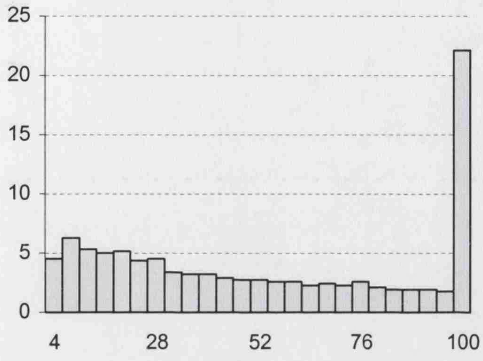
1983 – SPELLS [25 BINS]



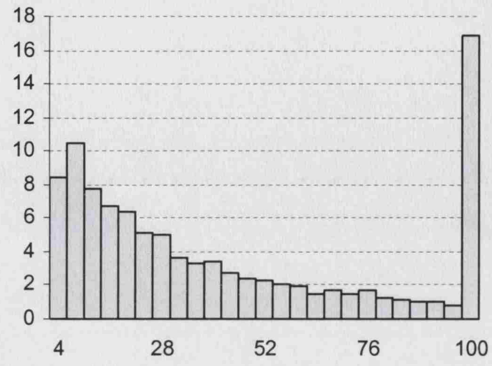
1983 – INDIVIDUALS [50 BINS]



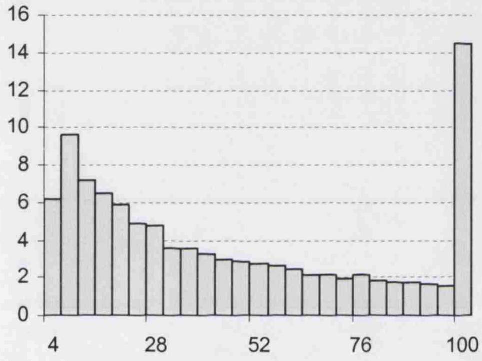
1983 – SPELLS [50 BINS]



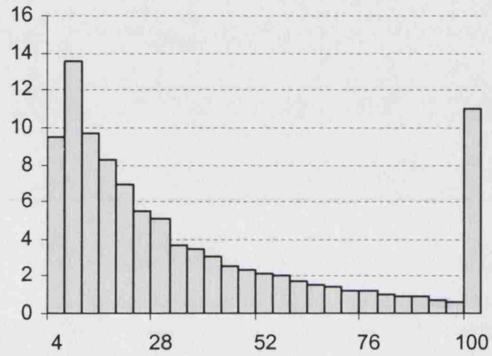
1986 – INDIVIDUALS [25 BINS]



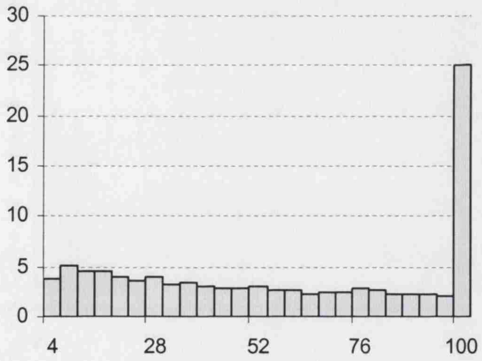
1986 – SPELLS [25 BINS]



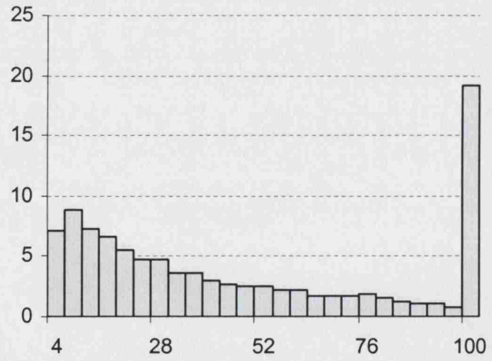
1990 – INDIVIDUALS [25 BINS]



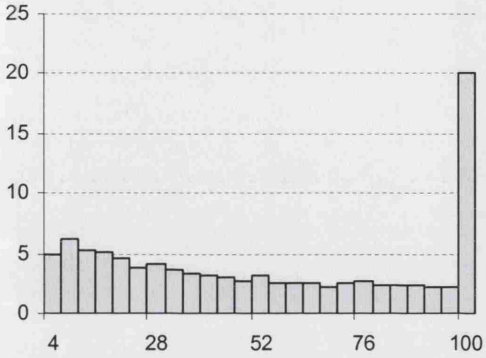
1990 – SPELLS [25 BINS]



1993 – INDIVIDUALS [25 BINS]



1993 – SPELLS [25 BINS]



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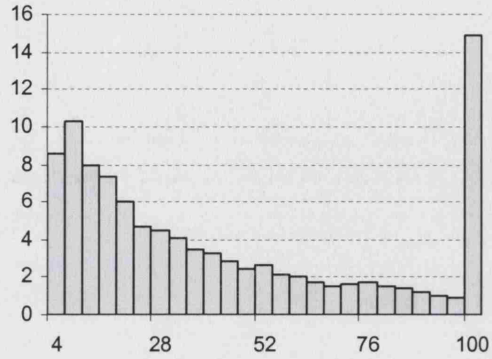

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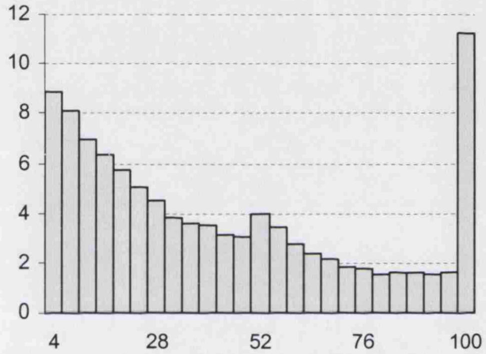

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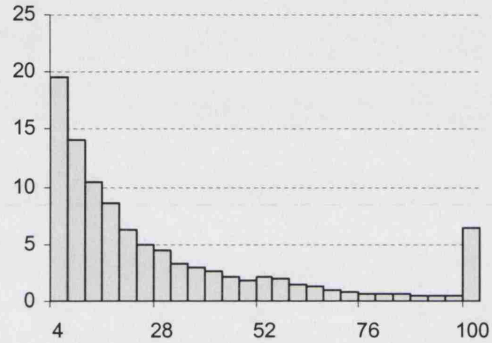

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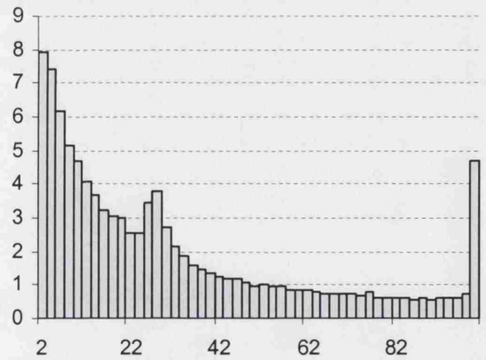
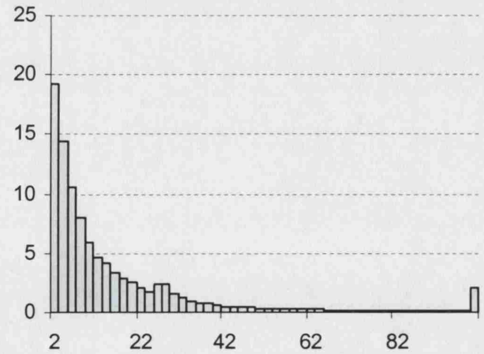


1983/6 – INDIVIDUALS [50 BINS]



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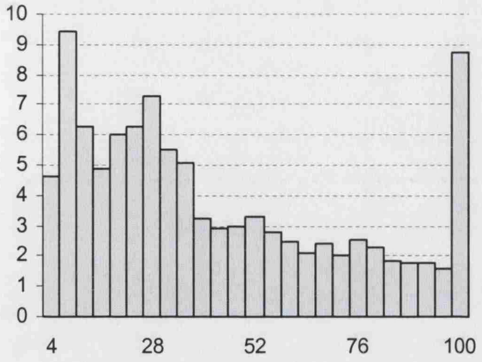

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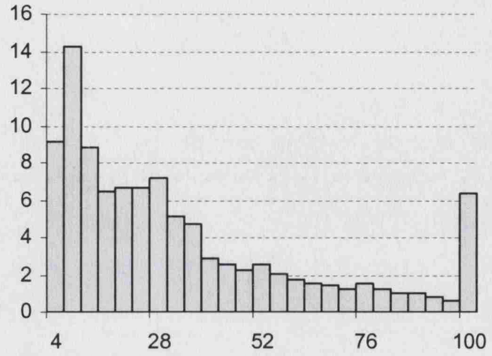

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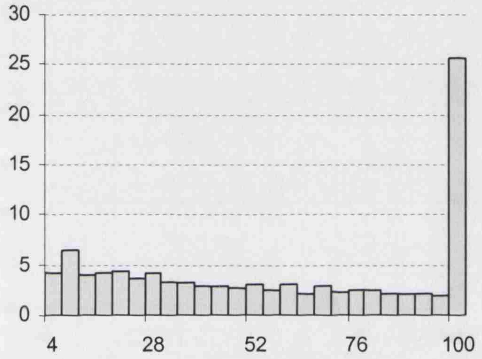

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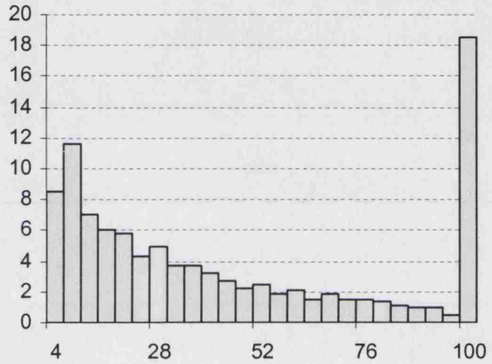
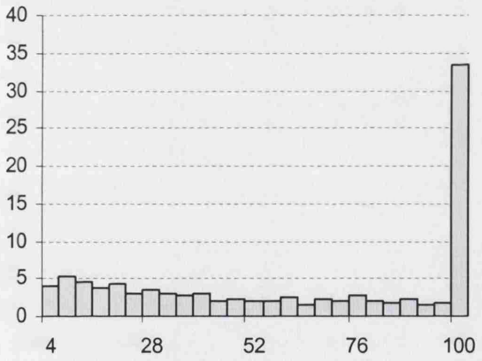
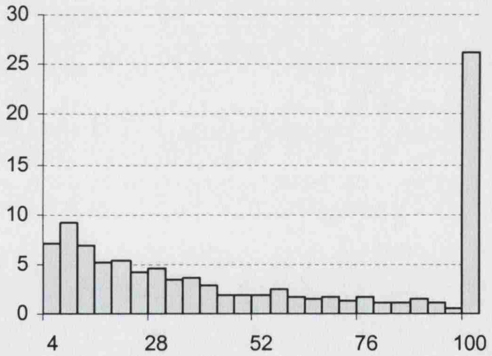


1983 – 25 YEAR OLDS - SPELLS [25 BINS]

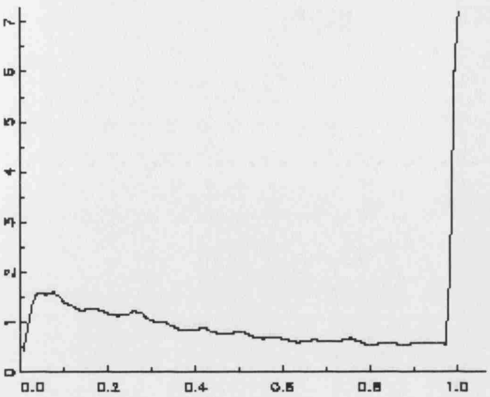


1983 – 45 YEAR OLDS [25 BINS]



1983 – 45 YEAR OLDS - SPELLS [25 BINS]

[B] KERNEL DENSITY PLOTS [X AXIS ~ FRACTION OF PERIOD][96]



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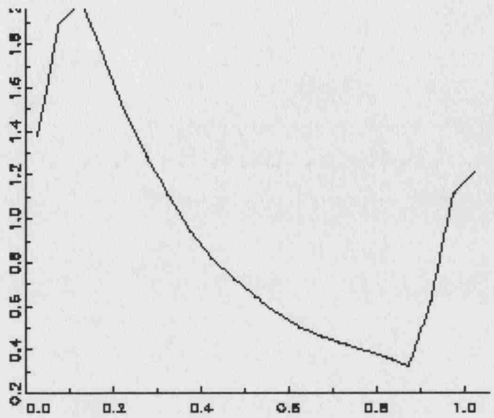

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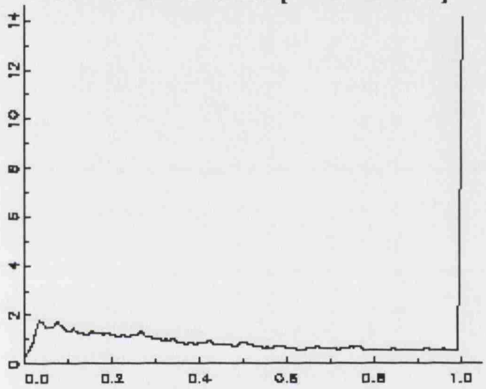

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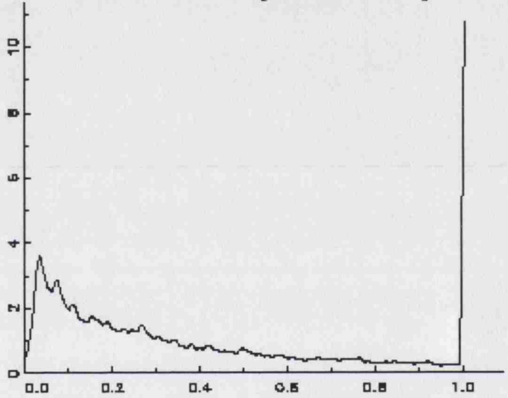

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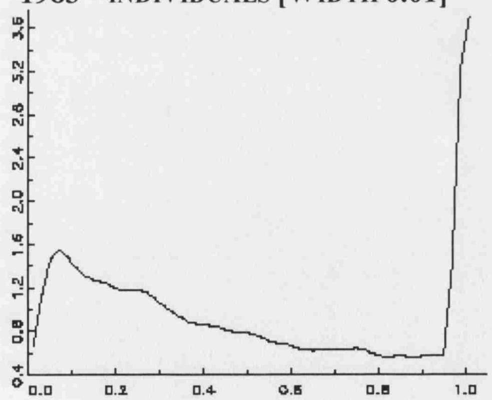

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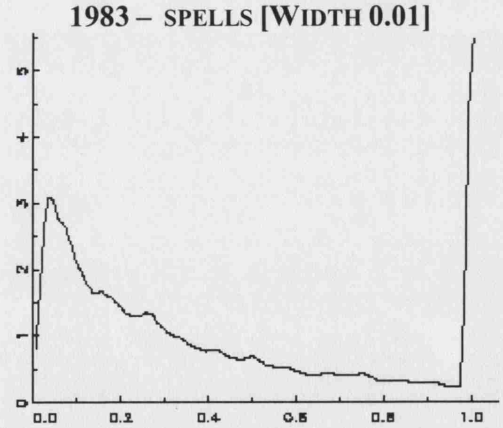
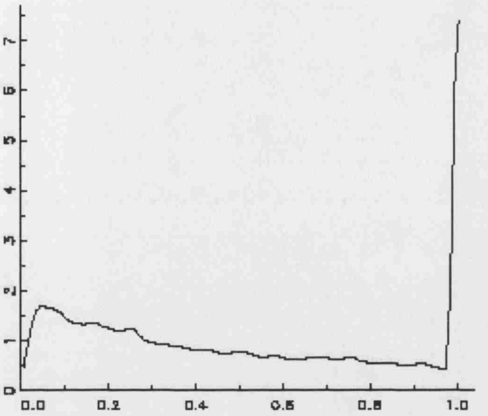


1983 – SPELLS [WIDTH 0.005]

96 I would like to thank Sandra Bulli for making available the GAUSS programmes which were used to generated the kernel density functions presented here.



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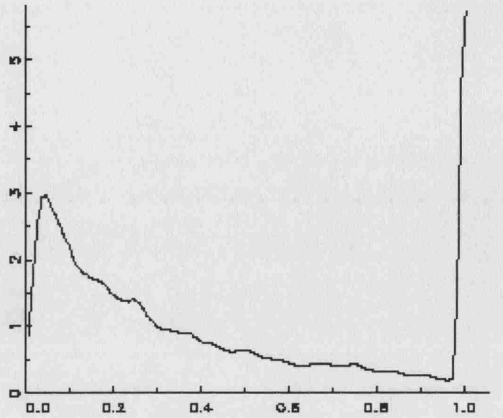

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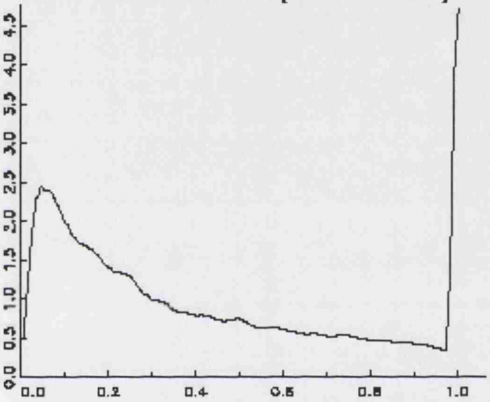

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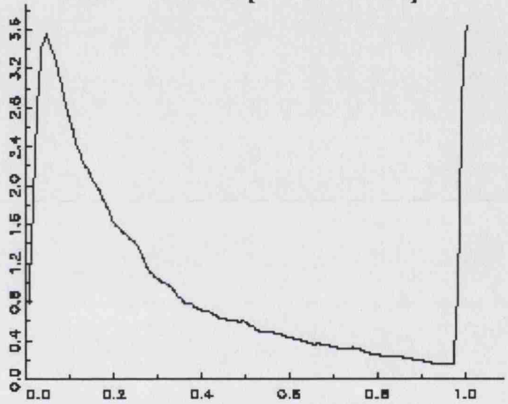

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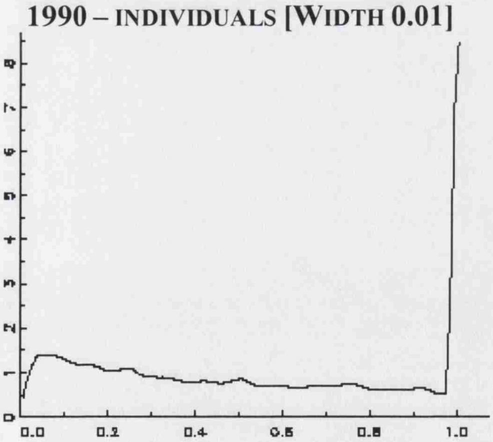

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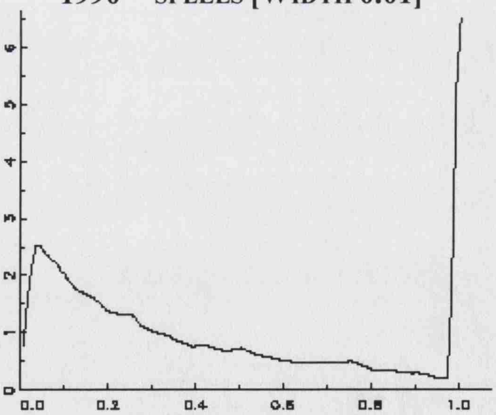

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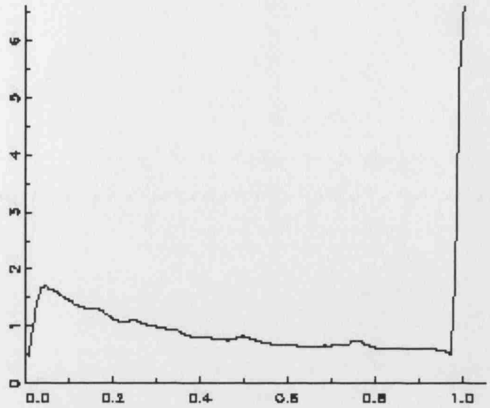

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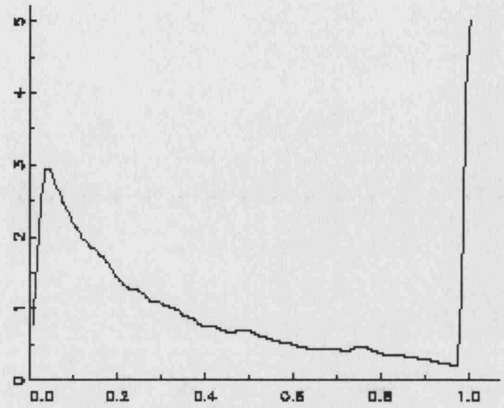

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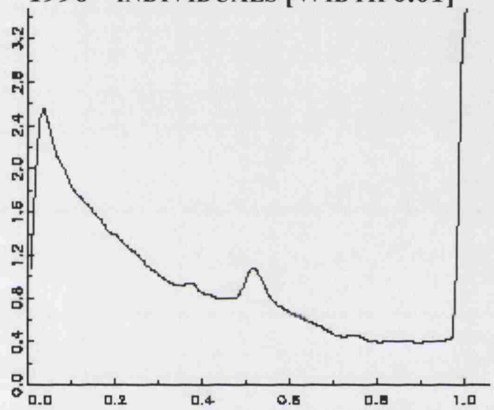
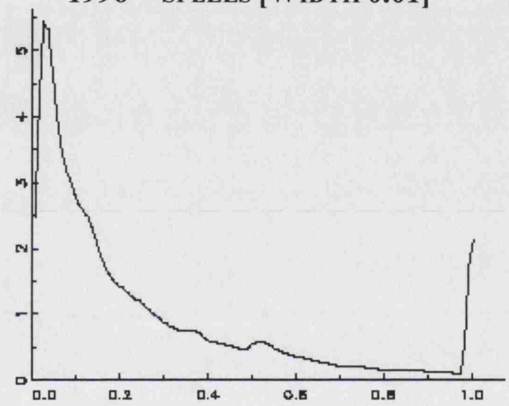


1983/4 – INDIVIDUALS [WIDTH 0.01]



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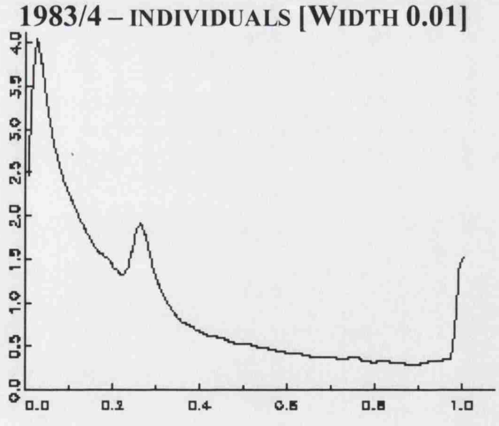
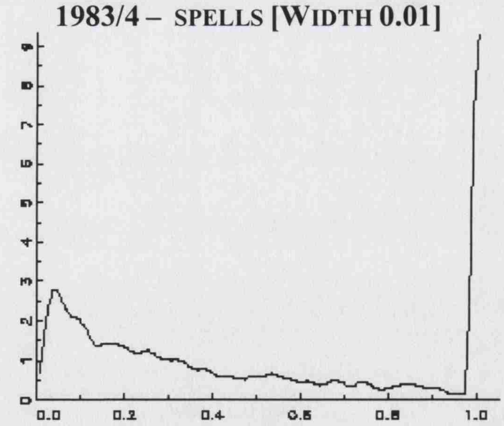


1983/6 – INDIVIDUALS [50 BINS]



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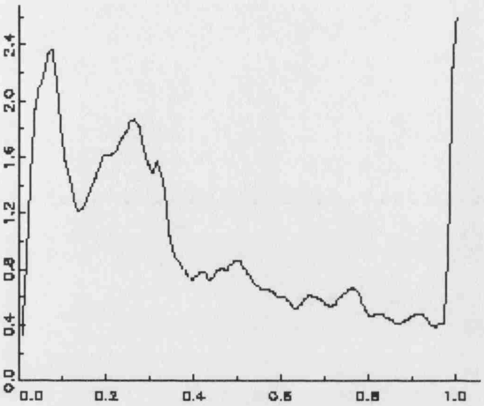

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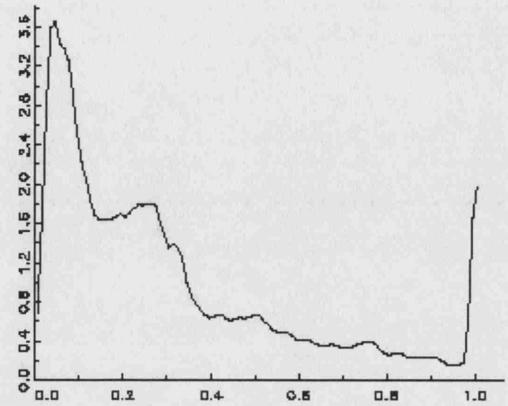

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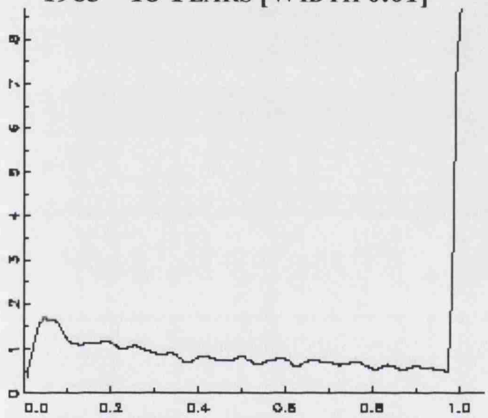

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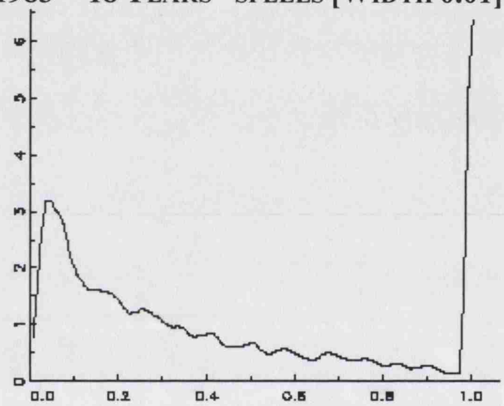
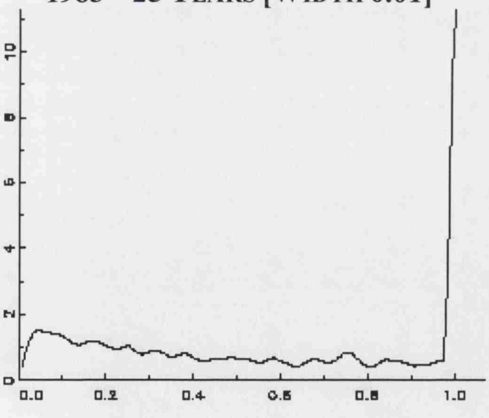
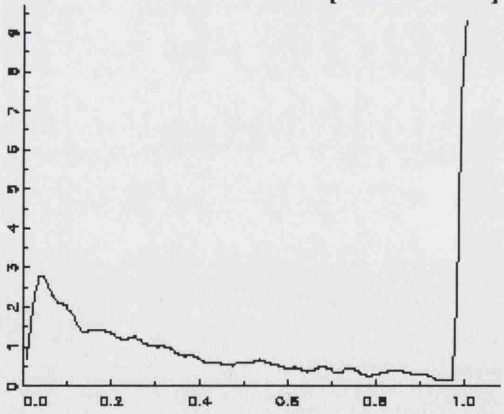


1983 – 25 YEARS - SPELLS [WIDTH 0.01]



1983 – 45 YEARS [WIDTH 0.01]



1983 – 45 YEARS - SPELLS [WIDTH 0.01]

APPENDIX 2 : TABLES FOR FIGURES IN THE CHAPTER

TABLE 3.1 : INCIDENCE OF UNEMPLOYMENT IN A YEAR (MILLIONS)

	Rate (%)	individuals	spells
1983	12.3	3.21	4.12
1984	12.2	3.19	4.08
1985	12.4	3.25	4.13
1986	12.8	3.30	4.17
1987	11.7	3.12	3.93
1988	9.4	2.70	3.41
1989	7.4	2.36	3.01
1990	6.9	2.46	3.14
1991	10.4	3.11	3.91
1992	12.7	3.62	4.55
1993	13.8	3.70	4.68
1994	12.6	3.47	4.44
1995	10.8	3.14	4.04
1996	10	2.88	3.70

TABLE 3.2 : INCIDENCE OF UNEMPLOYMENT BY AGE (THOUSANDS)

	Individuals					Spells				
	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.
1983	179.3	162.2	99.4	69.8	45.5	232.4	228.1	132.3	89.0	55.9
1984	180.6	172.7	100.7	66.6	47.4	233.0	236.6	133.3	83.8	58.6
1985	175.5	175.7	105.4	62.9	45.0	229.5	238.6	138.1	79.4	54.5
1986	170.7	182.9	111.2	65.1	46.2	220.6	247.8	143.9	80.8	56.4
1987	151.7	167.6	108.9	61.6	42.7	194.7	218.9	141.3	75.7	52.5
1988	123.8	139.4	97.6	53.4	39.7	160.9	181.9	127.6	66.6	47.8
1989	110.0	120.1	88.3	46.0	34.2	0.0	160.9	114.4	58.4	42.2
1990	118.7	126.3	95.8	48.9	36.6	158.2	169.3	123.7	61.0	44.7
1991	128.2	146.7	123.2	62.9	47.0	171.1	192.6	158.0	77.9	56.4
1992	132.0	161.8	134.9	76.0	61.4	176.1	213.9	172.8	94.1	74.4
1993	126.7	168.0	135.1	81.7	68.2	171.2	223.5	176.1	102.9	83.2
1994	114.4	147.5	126.1	77.0	57.3	155.2	199.7	165.3	95.8	72.2
1995	105.1	133.2	113.2	71.2	47.9	143.3	180.0	148.0	90.5	59.8
1996	91.7	118.1	103.7	66.6	45.9	125.2	161.2	138.0	84.1	57.6

TABLE 3.3 : AGE-COMPOSITION OF THE POPULATION (HUNDREDS OF THOUSANDS)

	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.
1983	4.56	4.58	4.09	4.02	3.07
1984	4.53	4.71	4.14	3.93	3.25
1985	4.48	4.63	4.31	3.76	2.98
1986	4.33	4.51	4.29	3.69	3.00
1987	4.37	4.60	4.40	3.75	3.40
1988	4.22	4.50	4.72	3.62	3.38
1989	4.19	4.52	4.46	3.84	3.64
1990	3.85	4.36	4.66	3.70	3.34
1991	3.69	4.11	4.58	4.06	4.07
1992	3.48	4.18	4.45	4.05	4.48
1993	3.39	4.02	4.32	4.15	3.81
1994	3.21	3.88	4.37	4.26	3.79
1995	3.25	3.49	4.35	4.63	3.78
1996	3.34	3.50	4.23	4.77	3.79

TABLE 3.4 :FRACTION OF EACH AGE GROUP WHO HAVE SOME EXPERIENCE OF UNEMPLOYMENT (%)

	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.
1983	39.35	35.38	24.32	17.35	14.81
1984	39.84	36.70	24.33	16.98	14.60
1985	39.20	37.97	24.42	16.71	15.08
1986	39.41	40.58	25.91	17.63	15.44
1987	34.74	36.46	24.73	16.42	12.57
1988	29.36	31.00	20.66	14.76	11.74
1989	26.28	26.56	19.82	11.97	9.41
1990	30.82	29.01	20.59	13.22	10.95
1991	34.72	35.70	26.93	15.50	11.54
1992	37.88	38.70	30.32	18.75	13.71
1993	37.41	41.82	31.31	19.69	17.88
1994	35.62	38.04	28.82	18.08	15.12
1995	32.34	38.17	26.01	15.36	12.70
1996	27.47	33.73	24.53	13.96	12.12

TABLE 3.5 : THE DISTRIBUTION OF SPELLS OF UNEMPLOYMENT – 1 YEAR PERIOD (%)

	1983	1986	1990	1993	1996
1	77.61	78.61	77.31	78.11	76.81
2	17.74	17.23	18.71	18.17	18.94
3	3.67	3.32	3.27	3.00	3.40
4+	0.99	0.84	0.72	0.73	0.86

TABLE 3.6 : THE DISTRIBUTION OF SPELLS OF UNEMPLOYMENT BY AGE [1986] PERIOD (%)

	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.
1	76.17	71.65	76.54	80.89	82.83
2	19.39	22.37	18.53	15.42	13.88
3	3.62	4.94	4.08	2.89	2.38
4+	0.82	1.04	0.85	0.80	0.91

TABLE 3.7 : THE DISTRIBUTION OF SPELLS OF UNEMPLOYMENT – 4 YEAR PERIOD (%)

	1983/6	1988/91	1993/6
1	53.01	51.51	50.69
2	22.70	24.37	24.95
3	11.73	12.70	12.66
4	6.14	6.08	6.10
5	3.20	2.87	2.88
6+	3.22	2.46	2.73

TABLE 3.8 : THE DISTRIBUTION OF UNEMPLOYMENT IN MONTHS 1 YEAR PERIOD (%)

	1983		1986		1990		1993		1996	
	individuals	spells	individuals	spells	individuals	spells	individuals	spells	individuals	spells
< 1	10.57	19.81	11.12	19.45	16.25	23.64	9.39	16.80	11.55	19.70
1--4	27.72	34.37	28.33	34.99	33.78	40.09	24.71	33.19	27.43	35.11
4--8	23.77	20.08	23.06	19.60	22.30	18.17	23.45	20.88	23.35	20.17
> 8	37.94	25.73	37.48	25.97	27.68	18.11	42.45	29.13	37.67	25.02

TABLE 3.9 : THE DISTRIBUTION OF UNEMPLOYMENT BY AGE – 1 YEAR PERIOD (%)

	18 yrs.		21 yrs.		25 yrs.		35 yrs.		45 yrs.	
	individuals	spells	individuals	spells	individuals	spells	individuals	spells	individuals	spells
< 1	16.33	25.30	12.18	23.56	10.13	18.67	8.63	16.18	9.17	16.19
1--4	40.71	44.36	33.58	39.25	25.13	33.96	22.95	30.66	21.37	28.07
4--8	25.40	19.83	25.63	19.95	23.19	19.27	21.26	18.81	18.30	17.26
> 8	17.55	10.51	28.61	17.24	41.55	28.10	47.16	34.35	51.17	38.48

TABLE 3.10: THE DISTRIBUTION OF UNEMPLOYMENT IN YEARS – 4 YEAR PERIOD (%)

	1983/6		1988/91		1993/6	
	individuals	spells	individuals	spells	individuals	spells
< 0.25	22.20	45.28	28.72	48.38	22.05	42.29
0.25--0.5	14.19	18.64	16.18	19.29	14.11	19.07
0.5--1	18.54	16.78	20.01	18.28	18.23	18.56
1--3	33.06	15.51	28.02	12.41	33.62	16.98
> 3	12.02	3.80	7.08	1.64	11.99	3.10

TABLE 3.11: THE INCIDENCE OF CHRONIC UNEMPLOYMENT (1 YEAR PERIOD)

	Per cent
1983	19.74
1984	20.77
1985	21.14
1986	20.49
1987	18.10
1988	15.35
1989	13.43
1990	13.29
1991	17.18
1992	21.76
1993	23.17
1994	20.74
1995	19.91
1996	18.27

TABLE 3.12 : THE INCIDENCE OF CHRONIC UNEMPLOYMENT BY AGE

	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.
1983	7.32	17.34	23.98	26.86	31.34
1984	6.86	16.63	24.60	29.35	35.34
1985	5.30	15.66	24.51	30.37	34.46
1986	4.85	12.95	23.46	31.15	34.60
1987	3.49	10.30	19.67	26.95	30.44
1988	2.97	8.47	15.62	23.56	27.18
1989	4.29	8.14	12.45	18.93	20.05
1990	5.61	7.66	12.17	15.78	18.21
1991	8.58	13.42	16.73	20.74	18.53
1992	12.30	16.95	22.03	23.79	24.38
1993	13.36	17.49	22.57	25.56	26.12
1994	11.30	13.76	21.49	24.35	23.95
1995	9.04	12.32	19.17	21.83	24.66
1996	7.96	11.01	16.48	22.17	21.24

TABLE 4.1 : INCIDENCE OF CHRONIC UNEMPLOYMENT (MILLIONS)

	1 Year		4 Years	
	Total	Fraction	Total	Fraction
1983	1.56	48.43	1.14	22.29
1984	1.52	47.60		
1985	1.55	47.85		
1986	1.58	47.91		
1987	1.44	45.93		
1988	1.15	42.53	0.75	16.03
1989	0.93	39.20		
1990	0.92	37.51		
1991	1.46	46.80		
1992	1.83	50.68		
1993	1.98	53.47	1.30	24.01
1994	1.77	51.17		
1995	1.55	49.45		
1996	1.39	48.23		

TABLE 4.2 : FRACTION OF TOTAL UNEMPLOYMENT ACCOUNTED FOR BY CHRONIC UNEMPLOYMENT

	Rate	Fraction
1983	12.30	77.96
1984	12.20	77.89
1985	12.40	78.33
1986	12.80	78.11
1987	11.70	76.71
1988	9.40	74.32
1989	7.40	72.42
1990	6.90	71.20
1991	10.40	77.08
1992	12.70	79.62
1993	13.80	81.18
1994	12.60	79.70
1995	10.80	79.01
1996	10.00	78.12

TABLE 4.3 : THE DISTRIBUTION OF SPELLS AMONG THE CHRONICALLY UNEMPLOYED 1 YEAR PERIOD (%)

	1983	1986	1990	1993	1996
1	76.34	77.60	71.36	76.55	73.66
2	18.95	18.15	23.42	19.65	21.66
3	3.82	3.42	4.29	3.09	3.78
4+	0.89	0.83	0.94	0.71	0.90

TABLE 4.4 THE DISTRIBUTION OF SPELLS OF UNEMPLOYMENT AMONG THE CHRONICALLY UNEMPLOYED – 4 YEAR PERIOD (%)

	1983/6	1988/91	1993/6
1	37.41	23.97	31.87
2	26.75	29.09	28.47
3	16.91	22.38	19.63
4	9.21	12.29	10.33
5+	9.70	12.27	9.70

TABLE 4.5 : THE INCIDENCE OF CHRONIC UNEMPLOYMENT BY AGE ['000S]

	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.
1983	60.54	72.6	52.76	38.1	25.86
1984	56.84	73.58	52.14	35.34	28.24
1985	53.72	73.5	55.22	34.78	25.34
1986	48.4	72.68	58.56	37.42	27.44
1987	40.28	62.58	53.42	32.08	23.9
1988	32.6	47.08	42.54	27.52	20.5
1989	29.64	39.16	35.74	21.24	15.68
1990	33.04	40.5	37.64	19.92	14.48
1991	51.66	63.46	58.86	30.74	21.32
1992	60.86	76.68	69.36	39.34	30.46
1993	59.92	83	74.22	45.06	35.9
1994	50.02	66.78	67.18	41.44	29.4
1995	41.82	57.04	56.3	37.12	24.8
1996	36.7	50.14	49.96	34.12	22.64

TABLE 4.6 : THE RELATIVE INCIDENCE OF CHRONIC UNEMPLOYMENT BY AGE

	% OF POPULATION					% OF UNEMPLOYED				
	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.	18 yrs.	21 yrs.	25 yrs.	35 yrs.	45 yrs.
1983	13.29	15.84	12.91	9.47	8.42	33.77	44.77	53.07	54.55	56.84
1984	12.54	15.64	12.60	9.00	8.70	31.47	42.60	51.80	53.03	59.55
1985	12.00	15.89	12.80	9.24	8.50	30.61	41.83	52.41	55.29	56.34
1986	11.17	16.13	13.65	10.13	9.16	28.35	39.75	52.67	57.48	59.34
1987	9.23	13.61	12.13	8.55	7.04	26.56	37.33	49.06	52.08	55.97
1988	7.73	10.47	9.01	7.60	6.07	26.32	33.78	43.59	51.54	51.69
1989	7.08	8.66	8.02	5.53	4.31	26.95	32.61	40.47	46.21	45.82
1990	8.58	9.30	8.08	5.38	4.33	27.83	32.06	39.27	40.72	39.58
1991	13.99	15.44	12.86	7.58	5.24	40.30	43.26	47.76	48.89	45.40
1992	17.46	18.34	15.59	9.71	6.81	46.10	47.39	51.42	51.76	49.64
1993	17.70	20.67	17.20	10.86	9.42	47.31	49.42	54.93	55.15	52.67
1994	15.58	17.22	15.36	9.74	7.76	43.74	45.26	53.28	53.85	51.33
1995	12.87	16.34	12.94	8.01	6.57	39.80	42.81	49.74	52.13	51.73
1996	10.99	14.32	11.82	7.15	5.98	40.01	42.46	48.20	51.25	49.37

TABLE 4.7 : CONCENTRATION RATIOS – 1 YEAR PERIOD

	CR5		CR10		CR25		CR50	
	individuals	Spells	individuals	spells	individuals	spells	individuals	spells
1983	9.53	12.23	19.06	24.46	47.13	57.04	79.42	84.75
1984	9.61	12.27	19.23	24.55	47.69	57.63	80.14	85.12
1985	9.65	12.28	19.29	24.56	47.87	57.71	80.34	85.27
1986	9.65	12.22	19.30	24.44	47.76	57.25	80.07	84.93
1987	10.00	12.58	20.00	25.17	48.88	57.48	80.56	84.88
1988	10.60	13.39	21.21	26.78	50.64	58.66	81.46	85.08
1989	11.27	14.37	22.54	28.73	52.67	60.24	82.76	85.66
1990	11.58	14.78	23.16	29.56	53.73	60.88	83.18	85.59
1991	9.92	12.46	19.84	24.92	48.34	56.85	80.11	84.5
1992	9.26	11.66	18.51	23.31	46.05	55.57	78.98	84.11
1993	8.93	11.3	17.86	22.61	44.57	54.47	77.94	83.86
1994	9.26	11.87	18.52	23.75	45.92	55.79	78.60	84.17
1995	9.50	12.24	19.00	24.47	46.93	56.84	79.53	84.71
1996	9.68	12.45	19.36	24.91	47.50	57.07	79.80	84.82

TABLE 4.8 : CONCENTRATION RATIOS – 4 YEAR PERIOD

	CR5		CR10		CR25		CR50	
	individuals	Spells	individuals	spells	individuals	spells	individuals	spells
1983/6	16.33	28.31	30.95	44.02	61.02	70.02	86.17	89.88
1988/91	19.19	26.89	34.20	41.23	63.60	67.37	87.68	88.53
1993/6	15.84	26.10	29.77	41.16	60.01	67.94	86.39	88.94

TABLE 5.1 : PERCENTILES OF THE DISTRIBUTION – 1 YEAR PERIOD (MONTHS)

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90%	individuals	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
	spells	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
80%	individuals	11.9	12.0	12.0	12.0	11.4	10.6	10.1	9.9	11.2	12.0	12.0	12.0	12.0	11.5
	spells	9.9	10.0	10.1	10.0	9.3	8.6	7.7	7.4	9.3	10.6	11.0	10.1	9.7	9.4
75%	individuals	10.8	10.9	10.9	10.7	10.2	9.4	8.9	8.6	10.2	11.1	11.5	10.9	10.7	10.5
	spells	8.2	8.3	8.3	8.3	7.8	7.0	6.4	6.0	7.9	8.8	9.1	8.4	8.1	8.0
66%	individuals	8.8	8.8	8.8	8.7	8.2	7.5	7.0	6.7	8.3	9.2	9.6	9.1	8.9	8.7
	spells	6.0	5.9	5.9	5.9	5.7	5.2	4.6	4.3	5.8	6.4	6.8	6.2	6.0	5.8
50%	individuals	5.7	5.6	5.6	5.6	5.4	4.8	4.2	4.0	5.5	6.1	6.6	6.1	6.0	5.7
	spells	3.4	3.3	3.3	3.4	3.3	3.0	2.7	2.6	3.4	3.7	4.0	3.6	3.5	3.4
33%	individuals	3.3	3.1	3.1	3.1	3.0	2.7	2.3	2.2	3.1	3.5	3.8	3.6	3.3	3.2
	spells	1.9	1.8	1.8	1.9	1.8	1.7	1.5	1.5	1.9	2.1	2.2	2.0	1.9	1.8
25%	individuals	2.4	2.3	2.3	2.3	2.2	1.9	1.7	1.6	2.2	2.5	2.8	2.6	2.4	2.3
	spells	1.3	1.3	1.2	1.3	1.3	1.2	1.1	1.1	1.3	1.5	1.5	1.5	1.3	1.3
20%	individuals	1.9	1.8	1.8	1.8	1.7	1.5	1.3	1.2	1.7	2.0	2.1	2.0	1.8	1.8
	spells	1.0	1.0	1.0	1.0	1.0	0.9	0.9	0.9	1.1	1.2	1.2	1.1	1.1	1.0
10%	individuals	0.9	0.9	0.9	0.9	0.9	0.8	0.7	0.7	0.9	1.0	1.1	1.0	0.9	0.9
	spells	0.5	0.5	0.5	0.6	0.6	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.5

TABLE 5.2 : PERCENTILES OF THE DISTRIBUTION – 4 YEAR PERIOD (MONTHS)

		1983/6	1988/91	1993/6
90 %	individuals	38.9	31.4	38.5
	spells	18.2	14.7	18.9
80 %	individuals	26.2	20.4	27.4
	spells	11.7	9.2	12.1
75 %	individuals	21.6	16.8	23.1
	spells	9.3	7.7	9.6
66 %	individuals	15.5	12.4	17.1
	spells	6.5	5.7	7.0
50 %	individuals	10.2	7.2	10.2
	spells	3.5	3.2	3.9
33 %	individuals	5.2	3.6	5.2
	spells	1.9	1.7	2.1
25 %	individuals	3.5	2.5	3.5
	spells	1.3	1.2	1.5
20 %	individuals	2.6	1.9	2.7
	spells	1.0	1.0	1.2
10 %	individuals	1.2	0.9	1.2
	spells	0.6	0.6	0.7

TABLE 5.3 : RATIOS OF THE PERCENTILES – 1 YEAR PERIOD

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90/10	individuals	12.6	13.1	13.5	13.5	14.0	15.9	17.4	18.3	13.5	11.8	11.4	11.8	13.0	13.6
	spells	22.8	22.9	22.8	21.5	21.5	22.9	26.1	24.3	21.5	19.3	19.2	20.3	21.5	22.9
80/20	individuals	6.2	6.5	6.8	6.6	6.7	7.0	7.8	7.9	6.6	6.1	5.6	6.0	6.5	6.4
	spells	9.7	10.2	10.2	9.8	9.1	9.0	9.0	8.3	8.6	9.0	9.0	9.0	9.3	9.3
75/25	individuals	4.4	4.7	4.8	4.7	4.7	4.9	5.3	5.5	4.7	4.4	4.2	4.2	4.5	4.6
	spells	6.3	6.5	6.6	6.3	6.1	5.8	5.9	5.5	5.9	5.8	5.9	5.8	6.0	6.0
66/33	individuals	2.7	2.8	2.8	2.8	2.8	2.8	3.0	3.0	2.7	2.6	2.5	2.6	2.7	2.7
	spells	3.1	3.2	3.2	3.1	3.2	3.1	3.1	3.0	3.1	3.1	3.1	3.0	3.1	3.2

TABLE 5.4 : RATIOS OF THE PERCENTILES – 4 YEAR PERIOD

		1983/6	1988/91	1993/6
90/10	individuals	32.4	34.9	32.1
	spells	30.8	26.2	28.8
80/20	individuals	10.1	10.7	10.1
	spells	11.5	9.3	10.2
75/25	individuals	6.2	6.7	6.6
	spells	7.1	6.4	6.5
66/33	individuals	3.0	3.4	3.3
	spells	3.5	3.3	3.3

TABLE 5.5 : RATIOS OF THE PERCENTILES TO THE MEDIAN

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90/10	1 year	2.1	2.1	2.1	2.1	2.2	2.5	2.8	3.0	2.2	2.0	1.8	2.0	2.0	2.1
	4 year		3.8					4.4						3.8	
80/20	1 year	2.1	2.1	2.1	2.1	2.1	2.2	2.4	2.5	2.0	2.0	1.8	2.0	2.0	2.0
	4 year		2.6					2.8						2.7	
75/25	1 year	1.9	1.9	1.9	1.9	1.9	2.0	2.1	2.2	1.9	1.8	1.8	1.8	1.8	1.8
	4 year		2.1					2.3						2.3	
66/33	1 year	1.5	1.6	1.6	1.5	1.5	1.6	1.7	1.7	1.5	1.5	1.5	1.5	1.5	1.5
	4 year		1.5					1.7						1.7	

TABLE 5.6 : INEQUALITY MEASURES – 1 YEAR PERIOD

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
gini	individuals	0.38	0.38	0.39	0.38	0.39	0.41	0.43	0.44	0.39	0.37	0.35	0.37	0.38	0.38
	spells	0.47	0.47	0.47	0.47	0.47	0.48	0.49	0.50	0.46	0.45	0.44	0.46	0.46	0.47
theil	individuals	0.25	0.26	0.26	0.26	0.27	0.28	0.31	0.32	0.26	0.24	0.23	0.24	0.25	0.25
	spells	0.36	0.37	0.37	0.37	0.37	0.38	0.40	0.41	0.36	0.34	0.33	0.35	0.36	0.36

TABLE 5.7 : INEQUALITY MEASURES – 4 YEAR PERIOD

		1983/6	1988/1	1993/6
gini	Individuals	0.51	0.54	0.50
	Spells	0.60	0.58	0.58
theil	Individuals	0.43	0.48	0.42
	Spells	0.64	0.59	0.59

TABLE 5.8 : PERCENTILES OF THE DISTRIBUTION – 1 YEAR PERIOD (MONTHS)

18 YEAR OLDS:

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90%	individuals	11.1	10.9	10.2	9.8	9.2	9.4	9.9	10.2	11.6	12.0	12.0	12.0	11.7	11.5
	spells	9.6	9.1	8.5	8.2	7.8	7.8	7.8	8.0	10.1	11.6	11.9	11.0	10.1	9.6
80%	individuals	8.7	8.3	7.9	7.5	7.1	7.2	7.5	7.6	9.3	10.4	10.7	10.2	9.6	9.3
	spells	6.4	6.1	5.8	5.5	5.4	5.2	5.0	5.2	6.9	7.9	8.1	7.5	6.8	6.7
75%	individuals	7.7	7.2	6.9	6.5	6.2	6.2	6.4	6.5	8.4	9.3	9.6	9.3	8.5	8.5
	spells	5.5	5.1	4.9	4.7	4.5	4.3	4.1	4.3	6.0	6.7	6.8	6.3	5.9	5.8
66%	individuals	6.0	5.7	5.5	5.1	4.9	4.8	4.8	5.0	6.9	7.9	8.1	7.6	7.0	7.0
	spells	3.9	3.9	3.7	3.6	3.5	3.3	3.2	3.2	4.6	5.2	5.2	4.8	4.4	4.4
50%	individuals	3.8	3.6	3.6	3.4	3.1	3.1	3.0	3.1	4.7	5.5	5.7	5.1	4.6	4.7
	spells	2.7	2.7	2.5	2.4	2.3	2.2	2.1	2.1	2.9	3.3	3.3	3.1	2.8	2.8
33%	individuals	2.6	2.4	2.3	2.2	2.0	1.9	1.7	1.8	2.8	3.3	3.4	3.1	2.8	2.8
	spells	1.5	1.5	1.4	1.3	1.3	1.2	1.2	1.2	1.6	1.9	1.9	1.8	1.6	1.6
25%	individuals	1.9	1.8	1.7	1.6	1.5	1.4	1.2	1.3	2.1	2.5	2.5	2.3	2.1	2.1
	spells	1.1	1.0	1.0	1.0	1.0	0.9	0.9	0.9	1.2	1.4	1.3	1.3	1.2	1.2
20%	individuals	1.4	1.4	1.3	1.2	1.1	1.1	0.9	1.1	1.6	2.0	2.1	1.8	1.6	1.6
	spells	0.9	0.9	0.8	0.8	0.8	0.8	0.7	0.8	1.0	1.1	1.1	1.0	0.9	0.9
10%	individuals	0.8	0.8	0.7	0.7	0.6	0.7	0.6	0.6	0.9	1.0	1.0	0.9	0.8	0.8
	spells	0.5	0.5	0.5	0.5	0.5	0.4	0.4	0.4	0.5	0.6	0.6	0.6	0.5	0.5

25 YEAR OLDS

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90%	individuals	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
	spells	12.0	12.0	12.0	12.0	12.0	12.0	11.7	11.5	12.0	12.0	12.0	12.0	12.0	12.0
80%	individuals	12.0	12.0	12.0	12.0	11.9	10.8	10.0	9.7	11.2	12.0	12.0	12.0	11.7	11.3
	spells	10.6	11.0	11.1	10.9	9.5	8.3	7.6	7.3	9.2	10.6	10.7	10.3	9.5	8.9
75%	individuals	11.7	11.9	11.8	11.6	10.7	9.6	8.9	8.5	10.2	11.3	11.5	11.2	10.7	10.2
	spells	8.6	8.8	8.9	9.0	8.0	7.0	6.4	6.2	7.7	8.8	8.9	8.6	7.9	7.4
66%	individuals	9.6	9.6	9.7	9.5	8.7	7.8	7.1	6.8	8.4	9.3	9.8	9.5	8.9	8.6
	spells	6.1	6.1	6.3	6.3	5.8	5.0	4.7	4.6	5.8	6.3	6.6	6.3	5.8	5.5
50%	individuals	6.6	6.4	6.4	6.4	5.9	5.0	4.5	4.3	5.6	6.3	6.9	6.5	6.0	5.7
	spells	3.6	3.4	3.5	3.6	3.4	3.0	2.7	2.7	3.3	3.7	4.0	3.7	3.4	3.3
33%	individuals	3.7	3.7	3.6	3.6	3.2	2.9	2.5	2.5	3.1	3.5	4.1	3.8	3.3	3.3
	spells	1.9	1.9	1.9	2.0	1.8	1.7	1.5	1.6	1.8	2.0	2.1	2.0	1.9	1.8
25%	individuals	2.6	2.7	2.6	2.6	2.3	2.1	1.7	1.8	2.1	2.6	2.9	2.7	2.4	2.4
	spells	1.3	1.3	1.3	1.4	1.3	1.2	1.1	1.2	1.3	1.5	1.5	1.5	1.3	1.2
20%	individuals	2.1	2.1	2.0	2.0	1.8	1.6	1.3	1.4	1.7	2.0	2.2	2.1	1.8	1.9
	spells	1.0	1.0	1.0	1.1	1.0	0.9	0.9	0.9	1.0	1.2	1.2	1.1	1.1	1.0
10%	individuals	1.0	1.0	1.0	1.0	0.9	0.8	0.7	0.7	0.9	1.0	1.1	1.1	0.9	0.9
	spells	0.5	0.5	0.5	0.6	0.5	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.6	0.5

45 YEAR OLDS

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90%	individuals	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
	spells	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0	12.0
80%	individuals	12.0	12.0	12.0	12.0	12.0	12.0	12.0	11.3	11.5	12.0	12.0	12.0	12.0	12.0
	spells	12.0	12.0	12.0	12.0	12.0	12.0	10.0	9.2	9.9	12.0	12.0	11.3	11.7	10.4
75%	individuals	12.0	12.0	12.0	12.0	12.0	12.0	10.6	9.7	10.1	11.8	12.0	11.6	11.7	11.0
	spells	12.0	12.0	12.0	12.0	11.8	10.5	8.1	7.2	8.4	9.6	10.0	9.1	9.7	8.9
66%	individuals	11.4	12.0	12.0	12.0	11.0	10.2	8.5	7.2	8.3	9.4	9.7	9.4	9.7	9.1
	spells	8.3	9.3	9.2	9.6	8.0	7.5	5.9	5.1	6.1	7.0	7.1	6.6	6.9	6.3
50%	individuals	7.6	8.3	7.6	8.2	7.2	6.4	5.1	4.2	5.1	6.0	6.4	6.1	6.3	5.9
	spells	4.5	4.9	4.5	4.9	4.3	4.0	3.3	2.9	3.5	3.8	4.0	3.8	3.9	3.6
33%	individuals	4.0	4.6	3.8	4.4	3.8	3.5	2.6	2.4	2.8	3.2	3.7	3.6	3.6	3.3
	spells	2.3	2.5	2.3	2.5	2.2	2.1	1.7	1.6	1.9	2.0	2.2	2.0	2.0	1.9
25%	individuals	2.9	3.3	2.8	3.1	2.8	2.5	1.8	1.8	2.0	2.3	2.5	2.5	2.5	2.4
	spells	1.6	1.7	1.4	1.7	1.6	1.5	1.2	1.1	1.3	1.5	1.5	1.4	1.4	1.3
20%	individuals	2.2	2.5	2.0	2.4	2.1	1.9	1.4	1.3	1.6	1.8	2.0	1.9	1.8	1.9
	spells	1.2	1.3	1.2	1.2	1.2	1.1	1.0	0.9	1.0	1.1	1.1	1.1	1.1	1.0
10%	individuals	1.1	1.2	1.0	1.1	1.0	1.0	0.7	0.7	0.8	0.9	0.9	1.0	0.9	0.9
	spells	0.6	0.7	0.6	0.6	0.6	0.6	0.5	0.5	0.5	0.6	0.6	0.6	0.6	0.5

TABLE 5.9 : RATIOS OF THE PERCENTILES – 1 YEAR PERIOD

18 YEAR OLDS

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90/10	individuals	14.1	13.9	14.1	14.9	14.7	14.3	17.7	17.2	13.5	11.8	12.2	13.0	14.2	14.6
	spells	19.4	18.6	17.3	17.8	16.9	18.4	18.2	18.8	19.1	19.7	19.1	19.7	19.1	18.4
80/20	individuals	6.2	6.0	6.2	6.2	6.4	6.4	8.2	7.2	5.6	5.3	5.1	5.7	5.8	5.8
	spells	7.2	6.9	7.0	7.0	7.1	7.0	7.3	6.9	7.3	7.1	7.5	7.4	7.4	7.3
75/25	individuals	4.0	4.0	4.1	4.1	4.2	4.4	5.3	5.0	4.0	3.8	3.8	4.1	4.1	4.1
	spells	5.2	4.9	5.0	4.7	4.7	4.7	4.8	4.8	4.9	4.8	5.1	4.9	4.9	4.9
66/33	individuals	2.3	2.4	2.4	2.4	2.5	2.5	2.8	2.7	2.5	2.4	2.4	2.4	2.5	2.5
	spells	2.6	2.6	2.7	2.7	2.7	2.7	2.8	2.7	2.8	2.7	2.7	2.7	2.7	2.7

25 YEAR OLDS

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90/10	individuals	12.6	12.2	12.2	12.2	13.5	15.2	17.4	16.6	13.5	11.8	11.1	11.4	13.0	13.6
	spells	22.8	22.9	22.8	21.5	22.8	22.9	23.8	23.4	21.5	19.3	19.2	19.2	21.5	22.9
80/20	individuals	5.8	5.8	6.0	6.0	6.6	6.7	7.4	7.0	6.7	6.1	5.4	5.6	6.4	6.0
	spells	11.1	10.9	10.9	10.1	9.3	9.1	8.9	8.0	9.3	9.0	8.8	9.2	9.1	9.1
75/25	individuals	4.4	4.5	4.6	4.4	4.6	4.5	5.1	4.8	4.8	4.4	4.0	4.1	4.4	4.3
	spells	6.7	6.5	6.6	6.4	6.2	5.9	5.7	5.4	6.0	5.8	5.8	5.8	5.9	5.9
66/33	individuals	2.6	2.6	2.7	2.6	2.7	2.7	2.9	2.8	2.7	2.7	2.4	2.5	2.7	2.6
	spells	3.3	3.3	3.3	3.2	3.2	3.0	3.0	2.9	3.2	3.1	3.1	3.1	3.1	3.1

45 YEAR OLDS

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
90/10	individuals	11.4	9.9	12.6	11.1	11.8	12.2	17.4	17.4	15.9	13.1	13.5	12.2	13.5	13.6
	spells	19.2	16.6	21.5	20.3	19.2	20.3	24.3	26.1	22.8	20.3	19.2	21.5	21.5	22.9
80/20	individuals	5.5	4.8	5.9	5.1	5.7	6.3	8.7	8.4	7.3	6.7	6.0	6.2	6.5	6.4
	spells	9.9	8.9	10.4	9.6	9.9	10.8	10.5	10.3	10.1	10.5	10.7	10.1	11.2	9.9
75/25	individuals	4.2	3.6	4.3	3.8	4.3	4.8	5.7	5.4	5.0	5.1	4.8	4.6	4.6	4.7
	spells	7.6	6.9	8.3	7.2	7.5	7.1	6.7	6.4	6.4	6.4	6.4	6.6	7.0	6.6
66/33	individuals	2.8	2.6	3.1	2.7	2.9	2.9	3.3	3.0	2.9	2.9	2.6	2.6	2.6	2.8
	spells	3.6	3.7	4.0	3.9	3.7	3.5	3.4	3.2	3.3	3.4	3.2	3.3	3.5	3.2

TABLE 5.10 : INEQUALITY MEASURES BY AGE – 1 YEAR PERIOD

		Individuals					spells				
		18	21	25	35	45	18	21	25	35	45
1983	Gini	0.42	0.39	0.36	0.35	0.34	0.48	0.50	0.47	0.45	0.43
	Theil	0.28	0.26	0.23	0.23	0.22	0.37	0.41	0.37	0.35	0.33
1984	Gini	0.42	0.40	0.36	0.36	0.32	0.48	0.50	0.47	0.45	0.42
	Theil	0.29	0.28	0.23	0.24	0.20	0.38	0.41	0.37	0.35	0.31
1985	Gini	0.42	0.41	0.36	0.35	0.35	0.48	0.50	0.47	0.45	0.43
	Theil	0.29	0.28	0.24	0.23	0.23	0.37	0.41	0.37	0.35	0.34
1986	Gini	0.43	0.41	0.36	0.34	0.33	0.48	0.49	0.46	0.43	0.42
	Theil	0.30	0.28	0.24	0.22	0.21	0.38	0.40	0.36	0.33	0.32
1987	Gini	0.44	0.42	0.38	0.37	0.35	0.48	0.49	0.47	0.45	0.44
	Theil	0.31	0.29	0.25	0.25	0.23	0.38	0.39	0.37	0.35	0.34
1988	Gini	0.44	0.44	0.40	0.37	0.37	0.49	0.49	0.48	0.46	0.45
	Theil	0.32	0.31	0.27	0.25	0.25	0.39	0.39	0.38	0.35	0.35
1989	Gini	0.46	0.45	0.42	0.40	0.41	0.50	0.50	0.49	0.48	0.48
	Theil	0.35	0.33	0.30	0.28	0.29	0.41	0.41	0.39	0.39	0.38
1990	Gini	0.46	0.45	0.42	0.43	0.43	0.50	0.50	0.49	0.49	0.49
	Theil	0.34	0.32	0.30	0.31	0.31	0.41	0.41	0.39	0.40	0.41
1991	Gini	0.40	0.40	0.39	0.38	0.40	0.47	0.47	0.47	0.46	0.47
	Theil	0.26	0.26	0.26	0.25	0.28	0.36	0.37	0.36	0.35	0.37
1992	Gini	0.37	0.38	0.37	0.37	0.38	0.46	0.46	0.45	0.45	0.45
	Theil	0.24	0.24	0.24	0.24	0.26	0.34	0.35	0.35	0.34	0.35
1993	Gini	0.37	0.36	0.35	0.35	0.37	0.46	0.46	0.45	0.44	0.45
	Theil	0.23	0.23	0.22	0.22	0.24	0.35	0.34	0.33	0.33	0.34
1994	Gini	0.39	0.38	0.36	0.36	0.37	0.47	0.47	0.45	0.44	0.46
	Theil	0.25	0.25	0.23	0.23	0.24	0.36	0.36	0.34	0.33	0.35
1995	Gini	0.40	0.39	0.38	0.37	0.37	0.47	0.47	0.46	0.46	0.46
	Theil	0.26	0.26	0.25	0.25	0.25	0.37	0.37	0.36	0.35	0.35
1996	Gini	0.40	0.40	0.38	0.37	0.38	0.47	0.48	0.47	0.45	0.46
	Theil	0.26	0.27	0.25	0.24	0.25	0.36	0.38	0.37	0.35	0.36

TABLE 5.11 : INEQUALITY WITHIN AND BETWEEN AGE GROUPS

		1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
individuals	Total	0.247	0.257	0.261	0.257	0.267	0.285	0.310	0.320	0.260	0.240	0.225	0.236	0.250	0.255
	Between	0.004	0.008	0.009	0.009	0.009	0.008	0.005	0.002	0.000	0.000	0.000	0.001	0.001	0.001
	Within	0.242	0.250	0.252	0.248	0.258	0.277	0.306	0.318	0.260	0.240	0.225	0.235	0.249	0.254
spells	Total	0.363	0.371	0.374	0.366	0.367	0.381	0.403	0.409	0.358	0.343	0.334	0.346	0.360	0.364
	Between	0.006	0.009	0.011	0.012	0.011	0.011	0.007	0.005	0.002	0.001	0.002	0.002	0.003	0.004
	Within	0.356	0.362	0.363	0.354	0.356	0.370	0.395	0.404	0.356	0.342	0.332	0.344	0.357	0.360

TABLE 6.2 : POLARISATION ACROSS INDIVIDUALS – 1 YEAR PERIOD

	D	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
standard $1x10^{14}$	0.1	1.83	1.89	2.01	2.03	1.62	0.97	0.64	0.73	1.55	2.72	2.96	2.29	1.69	1.25
	0.05	1.36	1.43	1.53	1.53	1.18	0.68	0.44	0.50	1.11	2.08	2.31	1.72	1.26	0.91
	0.02	1.02	1.10	1.17	1.17	0.86	0.47	0.28	0.32	0.79	1.62	1.84	1.32	0.95	0.66
normalised $1x10^{-2}$	0.1	4.41	4.64	4.69	4.54	4.25	3.96	3.90	3.93	4.10	4.61	4.68	4.39	4.39	4.20
	0.05	3.28	3.51	3.57	3.43	3.10	2.77	2.66	2.68	2.94	3.53	3.65	3.31	3.27	3.05
	0.02	2.46	2.69	2.75	2.61	2.26	1.90	1.72	1.72	2.09	2.74	2.90	2.54	2.47	2.22

TABLE 6.3: POLARISATION ACROSS SPELLS – 1 YEAR PERIOD

	D	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
standard $1x10^{14}$	0.1	3.91	3.94	4.14	4.14	3.25	1.96	1.32	1.48	3.09	5.44	6.05	4.85	3.63	2.68
	0.05	2.81	2.87	3.04	3.01	2.30	1.35	0.89	1.00	2.16	3.99	4.50	3.52	2.61	1.88
	0.02	1.93	2.02	2.14	2.11	1.54	0.85	0.54	0.60	1.41	2.87	3.32	2.48	1.80	1.26
normalised $1x10^{-2}$	0.1	4.46	4.65	4.70	4.56	4.27	3.96	3.86	3.83	4.13	4.61	4.71	4.42	4.40	4.21
	0.05	3.20	3.39	3.44	3.31	3.03	2.73	2.62	2.59	2.88	3.38	3.51	3.20	3.16	2.96
	0.02	2.20	2.38	2.43	2.32	2.03	1.73	1.58	1.55	1.89	2.43	2.58	2.26	2.19	1.98

TABLE 6.4 : POLARISATION ACROSS INDIVIDUALS – VARYING THE FUNCTIONAL FORM OF ALIENATION AND IDENTIFICATION– 1 YEAR PERIOD

	form	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
$1x10^{14}$	linear	1.36	1.43	1.53	1.53	1.18	0.68	0.44	0.50	1.11	2.08	2.31	1.72	1.26	0.91
$1x10^{14}$	concave	2.10	2.17	2.30	2.33	1.85	1.11	0.73	0.83	1.77	3.15	3.47	2.65	1.94	1.43
$1x10^{11}$	convex	1.99	2.15	2.31	2.29	1.71	0.94	0.59	0.67	1.57	3.11	3.47	2.53	1.85	1.30
$1x10^{-2}$	linear	3.28	3.51	3.57	3.43	3.10	2.77	2.66	2.68	2.94	3.53	3.65	3.31	3.27	3.05
$1x10^{-2}$	concave	5.07	5.32	5.38	5.21	4.86	4.52	4.44	4.49	4.68	5.33	5.48	5.09	5.03	4.79
$1x10^{-5}$	convex	4.79	5.27	5.40	5.11	4.48	3.84	3.58	3.60	4.14	5.27	5.47	4.86	4.80	4.37

TABLE 6.5 : POLARISATION ACROSS SPELLS – VARYING THE FUNCTIONAL FORM OF ALIENATION AND IDENTIFICATION– 1 YEAR PERIOD

	form	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
$1x10^{14}$	linear	2.81	2.87	3.04	3.01	2.30	1.35	0.89	1.00	2.16	3.99	4.50	3.52	2.61	1.88
$1x10^{14}$	concave	4.49	4.51	4.74	4.74	3.76	2.32	1.60	1.81	3.58	6.21	6.89	5.57	4.17	3.09
$1x10^{11}$	convex	4.10	4.30	4.58	4.48	3.28	1.82	1.15	1.29	3.01	6.00	6.87	5.18	3.81	2.67
$1x10^{-2}$	linear	3.20	3.39	3.44	3.31	3.03	2.73	2.62	2.59	2.88	3.38	3.51	3.20	3.16	2.96
$1x10^{-2}$	concave	5.12	5.33	5.38	5.22	4.95	4.70	4.68	4.68	4.78	5.26	5.36	5.08	5.06	4.86
$1x10^{-5}$	convex	4.68	5.08	5.19	4.93	4.32	3.67	3.38	3.33	4.02	5.09	5.35	4.72	4.62	4.20

TABLE 6.6 : POLARISATION – 4 YEAR PERIOD

		1983/6	1988/1	1993/6
individuals	standard $1x10^{9}$	2.39	16.40	24.60
	normalised $1x10^{-7}$	1.41	12.50	12.30
spells	standard $1x10^{9}$	22.30	47.50	70.70
	normalised $1x10^{-7}$	1.73	4.96	4.63

TABLE 6.7 : POLARISATION BY AGE ACROSS INDIVIDUALS

	Age	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
standard $1x10^{9}$	18	1.38	1.38	1.17	1.07	0.73	0.40	0.32	0.40	0.51	0.64	0.59	0.41	0.29	0.18
	21	1.60	1.89	1.92	1.87	1.29	0.70	0.46	0.52	0.96	1.48	1.68	0.97	0.68	0.45
	25	0.47	0.51	0.58	0.65	0.53	0.32	0.22	0.27	0.68	1.10	1.09	0.84	0.57	0.39
	35	0.19	0.18	0.16	0.17	0.13	0.07	0.04	0.04	0.11	0.21	0.27	0.22	0.16	0.13
	45	0.06	0.08	0.07	0.07	0.05	0.04	0.02	0.02	0.04	0.12	0.17	0.09	0.06	0.04
normalised $1x10^{-2}$	18	1.92	1.87	1.74	1.71	1.67	1.67	1.90	1.92	1.93	2.21	2.33	2.17	1.99	1.88
	21	3.00	2.93	2.83	2.45	2.19	2.07	2.14	2.07	2.44	2.80	2.84	2.41	2.30	2.20
	25	3.85	3.99	3.98	3.77	3.26	2.75	2.50	2.42	2.90	3.58	3.53	3.34	3.15	2.77
	35	4.38	4.95	5.06	5.03	4.56	3.90	3.35	3.01	3.44	3.89	4.02	3.84	3.55	3.60
	45	5.22	5.72	5.87	5.60	5.03	4.58	3.66	3.38	3.25	4.08	4.29	3.89	4.03	3.48

TABLE 6.8 : POLARISATION BY AGE ACROSS SPELLS

	Age	1983	1984	1985	1986	1987	1988	1989	1990	1991	1992	1993	1994	1995	1996
standard $1x10^{9}$	18	31.40	30.60	27.50	24.00	16.10	9.12	7.55	9.37	12.50	15.00	14.50	10.10	7.44	4.74
	21	43.70	47.60	46.60	46.60	28.80	15.50	11.00	12.30	21.50	32.70	38.00	23.40	16.50	11.50
	25	10.70	11.20	12.40	13.50	11.10	6.98	4.63	5.63	14.00	21.80	22.90	18.30	12.30	8.93
	35	3.67	3.44	3.04	3.21	2.34	1.39	0.81	0.82	1.97	3.92	5.29	4.10	3.16	2.55
	45	1.09	1.40	1.16	1.24	0.88	0.60	0.32	0.37	0.72	2.02	3.00	1.77	1.05	0.81
normalised $1x10^{-2}$	18	20.03	19.36	18.21	17.86	17.45	17.54	18.76	18.91	19.95	21.98	23.06	21.61	20.21	19.32
	21	29.48	28.76	27.43	24.49	21.97	20.63	21.15	20.24	24.03	26.75	27.24	23.51	22.62	21.88
	25	36.84	37.74	37.69	36.12	31.37	26.86	24.77	23.78	28.32	33.82	33.51	32.31	30.23	27.20
	35	41.76	46.74	48.65	48.61	43.19	37.57	32.56	28.85	33.32	37.61	38.84	37.26	34.17	34.38
	45	49.66	55.77	57.15	55.29	48.72	44.11	34.55	32.92	32.14	39.10	41.60	37.62	39.25	34.01

CHAPTER 5

DOES THE PAST COME BACK TO HAUNT YOU ? IDENTIFYING LAGGED DURATION DEPENDENCE EFFECTS IN UNEMPLOYMENT AMONG A SAMPLE OF BRITISH MEN

1. INTRODUCTION

In any given year, between two to four million men of prime working age have some experience of unemployment, and over a four year period, something of the order of five million men will make a claim for unemployment benefit, yet their experiences of unemployment are far from uniform. But should we care whether the experience of unemployment is heavily concentrated on relatively few *chronically unemployed* individuals ?

One obvious response is that on welfare grounds alone the incidence of chronic unemployment is a cause for concern; as Machin and Manning (1999) observe prolonged experiences of unemployment and the incidence of poverty are likely to be highly correlated across individuals. However, chronic unemployment may also be economically inefficient; Blanchard (2000) argues that if in the long run, unemployment is chronically concentrated on a small fraction of the population – the '*outsiders*' – then the unemployment rate will have to rise in order to constrain wage setters – or '*insiders*'.

This Chapter focuses on another reason why accumulated exposure to unemployment may be of concern – if in some way previous spells of unemployment *scar* individuals increasing the likelihood of them suffering future spells then they may become trapped in a vicious cycle, repeatedly unemployed and increasingly unemployable. The scar may be either direct, in the sense that exposure to unemployment erodes an individual's stock of human capital, or indirect, in that a history of unemployment will act as a signal, making him appear less attractive to firms than otherwise identical individuals searching for work. In a statistical sense, these scarring effects are assumed to change individuals' transitions probabilities between labour market states with the net result of increasing their exposure to unemployment – either increasing the probability that they will lose their job when they have one, or making them less likely to escape once unemployed. Of course, the precise mechanism through which this scarring takes place is not known, and neither are the particular transitions which are affected – it is conceivable that scarring may increase the probability of becoming unemployed and/or reduce the probability of becoming employed once unemployed. Heckman and Borjas (1980) identify two specific forms of scarring effect: occurrence dependence, where it is the *event* of previous spells of unemployment in an individual's past that effects him, and lagged duration dependence, where it is the *duration* of those previous spells that matter. In keeping with the literature on the causes of long term unemployment, which argues that through true duration dependence, continued exposure to unemployment reduces the conditional probability of exiting unemployment, it is natural to think of scarring working through a similar mechanism, so that past spells of unemployment will scar the individual through their effect on his probability of leaving unemployment, and it is upon this particular form of scarring which we will primarily concentrate.

Of course, there are a number of other explanations why over an extended period of time the same individuals should suffer chronic unemployment. Principal among these is the idea that repeated experience of unemployment is likely to reflect the fact that an individual is *unemployable*, i.e. that the least skilled or motivated members of the labour force will always be relatively unattractive to firms when they choose who to hire. Webster (2000) offers an alternative explanation – that given that job creation appears to be negligible in certain local labour markets (such as the former coal fields or depressed inner city areas) then the fact that migration out of these areas is relatively weak ensures that those individuals who remain will likely suffer chronic unemployment[97].

[97] Although one might still be interested as to *why* job creation or emigration is so weak in these regions.

Alternatively, the persistently unemployed may be caught in 'unemployment traps', where through perverse incentives in the benefit system, work is made unattractive, implying that given the incentives they face, their recurrent unemployment is in some sense voluntary[98].

Our research proceeds as follows, we implement a survival analysis approach pioneered by (among others) Lancaster (1979) to test for the presence of *'lagged duration dependence effects'* – whether the length of previous spells of unemployment reduces the conditional probability of escaping a current spell of unemployment. This question of whether spells of unemployment have the potential to scar individuals has already received considerable attention in the literature; however, we argue that the data on which this research is based – the matched JUVOS-NESPD dataset – allows a new opportunity to investigate these scarring effect. We have access to data on all the spells of unemployment suffered by a huge sample of individuals over a number of years, together with a wealth of information collected from their workplace when they were previously employed.

The chapter proceeds as follows. In Section 2 we describe the data on which this analysis is based: the matched JUVOS-NESPD dataset. In Section 3 we review the literature on survival analysis and discuss the problems associated with identifying lagged duration dependence effects. Section 4 details the results, Section 5 investigates whether these scarring effects vary with age and Section 6 concludes.

2. DATA

The matched JUVOS-NESPD dataset draws together information from two separate datasets: a subsample of the JUVOS cohort (which we discussed in Chapter 4) and the New Earnings Survey Panel Dataset (NESPD). The NESPD contains information in panel form on the earnings and employment conditions of an approximate one percent

[98] Of course understanding the role each of these factors plays is generating chronic unemployment is a prime concern for policy markers when designing measures to ameliorate its incidence – for example, either through investments in human capital, encouraging migration of factors of production (to bring the workers to the jobs or the jobs to the workers) or reforms of the tax and benefit system.

sample of the workforce since 1975. The data is collected through an annual survey of employers, who are legally obliged to provide information from their payroll records on pay, hours worked and related workplace data for a specified week in April for all selected workers[99]. Of course, inclusion in the panel in a given year is conditional on an individual being employed at the point in which the survey is carried out. However, selection according to a given National Insurance number ensures that those individuals (and only those individuals) will be included in future years of the panel, subject to their being employed at the same point in time in subsequent years. It should be noted that previous research has revealed that the response rate in the NESPD, as with all datasets, is not perfect – typically, non response occurs either where an individual has recently moved job, where they are employed in a small firm or where their earnings are beneath the threshold for paying National Insurance Contributions[100]. This may have implications for our results to the extent that our data under-samples the very low paid, whom we might expect to have a (significantly) higher unemployment rates than the average member of the workforce.

The matched JUVOS-NESPD dataset contains information on the unemployment and employment histories of a large sample of individuals who are randomly sampled according to their National Insurance numbers[101]. This new dataset thus enables a much richer analysis of the determinants of individual's transitions between labour market states, since we can combine information on the individual, and in particular factors which reflect their employability (how much they work, what they are paid, whether they have more than one job etc.) garnered from the NESPD, together with information on their complete history of unemployment spells since 1983, taken from JUVOS. It is this wealth of information that will allow us to identify the scarring effect of unemployment with greater confidence.

[99] Gregory and Kalwij (2000) p.5
[100] See ONS (2000) pp.1-3, and Stuttard and Jenkins (2001).
[101] One out of every five individuals who are selected into the JUVOS dataset on the basis of their National Insurance number will be randomly selected into the JUVOS-NESPD dataset.

For the purposes of this analysis, we have chosen to exclude certain individuals from the dataset. Given that the claimant count is known to give a misleading representation of the incidence of female unemployment we restrict attention to the persistence of male unemployment. Similarly, we have excluded those who are not of working age. Given the lack of available data we have also excluded those from Northern Ireland. Moreover, we restrict attention only to those individuals who appear in the JUVOS panel for whom we have **a prior observation in employment** (in other words, those for whom we also have an observation in the NESPD). Finally, we select only those individuals for whom we can observe the destination to which they leave the claimant count (information on which is only available from August 1996 onwards); and in order to avoid stock-sampling problems we restrict attention to those individuals who enter the claimant count from this point onwards.

We are left with a sample of over 15,000 working age men, and in excess of 26,000 spells of claimant unemployment. In Table 2.1 below we list simple sample statistics for the key variables[102] which we will use in our analysis (for a comprehensive description of our full set of variables see Appendix 1). As we might expect given our source, our data are fairly representative of the male working age population – the average member of our sample is (just) in his forties, and about forty percent of our sample are married. In terms of their workplace characteristics: overtime pay typically forms a fairly minor fraction of real weekly take-home pay, about a third of the sample have their pay covered by a collective agreement, about one in two hundred work more than one job in a week, and a little over one in ten are classified by their employer as a part-time worker. Finally, using a measure of skill, derived by Elias (1995) from an individual's occupational classification, which ranges from **1** (lowest skilled) to **4** (most skilled), we find that the majority of individuals in our sample fall in the intermediary skill categories. On average, their most recent completed spell of unemployment lasted a little under nine months, though the majority of individuals had not suffered a spell of unemployment in the last year.

[102] For each spell in our data, all variables are measured either at the point in time at which the spell began (e.g. age, number of spells experienced in last year etc.) or at the most recent observation in the NESPD.

TABLE 2.1 : DATA SUMMARY

VARIABLES	MEANS	STANDARD DEVIATIONS
Demographic Characteristics		
Start Age	40.8	11.5
Married [%]	40.7	48.7
Cohabit [%]	4.5	19.7
Workplace Characteristics		
Rbpay	168.3	117.4
Ropay	14.0	30.5
Union [%]	33.4	46.0
Dbj [%]	0.6	7.3
Part [%]	11.4	30.9
Skill1 [%]	11.2	31.2
Skill2 [%]	39.9	48.2
Skill3 [%]	34.4	46.8
Skill4 [%]	14.5	34.7
Previous Experiences of Unemployment		
L1durm	8.7	17.9
Nspy1	0.3	0.6

Finally, before we turn to the analysis proper we offer a simple illustration of the variation in individual's experiences of unemployment through time that we observe in our data. If past experiences of unemployment leave a scar, then we might expect that those individuals who spend a large fraction of a given year unemployed may be likely to suffer a similarly high fraction of the following year unemployed, since if they return to the unemployment pool their probability of escape will have been reduced. Consider the transition matrix below (Table 2.2), where individuals are collected into cells according to the fraction of 1997 and 1998 they spent unemployed, when we aggregate across all their spells[103]. We take at least as circumstantial evidence of possible scarring effects the large number of observations on, and to the right of, the leading diagonal of the transition

[103] So, those individuals collected in the first cell were never unemployed in that year; those in the second spell were unemployed for 10% or less of the year; those in the third cell were unemployed for more than 10, but less than 20% of the year, and so on.

matrix below (Table 2.2) – particularly for those who spent the majority of the first year unemployed (the bottom right hand quadrant of the matrix). So for example, of those men who spent between 70 to 80 percent of 1997 unemployed more than a third were unemployed for at least as high a fraction of 1998 (when we aggregate across all their spells), and more than a fifth spent a considerably higher fraction of the period (90 percent or more) unemployed.

TABLE 2.2 TRANSITIONS BETWEEN 1997 AND 1998 FOR MEN AGED 18-64 IN 1997

[PERCENTAGE OF THE YEAR UNEMPLOYED]

	0	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
0	42.4	15.5	12.7	7.5	5.3	4.4	4.2	2.9	2.2	1.6	1.3
0-10	47.0	12.6	9.7	7.5	4.8	5.2	2.5	2.0	1.6	2.5	4.6
10-20	40.0	11.1	7.3	7.6	8.2	4.1	3.9	5.1	2.7	2.9	7.1
20-30	34.9	10.6	9.6	9.5	6.0	4.5	5.8	3.9	4.6	3.0	7.6
30-40	26.4	10.6	10.4	8.9	7.8	7.5	4.9	4.5	3.7	4.6	10.8
40-50	24.7	9.1	8.9	10.7	6.4	7.2	6.6	5.7	5.3	3.8	11.7
50-60	21.5	7.0	8.0	7.4	8.6	6.4	8.4	9.3	6.8	4.2	12.4
60-70	14.4	7.5	9.2	7.7	10.0	6.4	8.1	7.6	7.3	6.6	15.1
70-80	11.3	8.6	6.2	7.8	8.0	6.3	10.7	5.5	8.0	6.5	21.0
80-90	13.0	6.4	6.3	8.1	9.1	3.9	9.1	7.1	5.6	8.1	23.3
90-100	2.0	5.2	4.2	7.7	6.9	5.9	6.9	6.7	8.6	11.2	34.8

Of course, not all the observations on, and to the right of, the leading diagonal of the transition matrix will reflect scarring. We know that the exit rate from unemployment declines at long durations, so some of these observations will reflect long continuous spells of unemployment that span both years. In the matrix below (Table 2.3) we therefore compare the experiences of unemployment in 1997 and 1999 of only those individuals who were not unemployed throughout 1998. It remains the case that even among these individuals those who spent the majority of 1997 unemployed and claiming benefit also spent the majority of 1999 unemployed. So, for example, of those men who spent between 80 to 90 percent of 1997 unemployed one in five went on to spend at least as high a fraction of the 1999 unemployed, and three quarters of those individuals spent a higher fraction of 1999 unemployed.

Of course, all these transition matrices illustrate is the apparent tendency for individuals who spend a large proportion of a given year unemployed to spend at least as high a proportion of the years that follow unemployed too which are consistent with the scarring hypothesis. What we cannot do with these raw correlations is positively identify the presence of scarring effects from previous experiences of unemployment – for that we require the more formal econometric techniques that follow.

TABLE 2.3 : TRANSITIONS BETWEEN 1997 AND 1999 FOR MEN AGED 18-63 IN 1997 [PERCENTAGE OF THE YEAR UNEMPLOYED]

	0	0-10	10-20	20-30	30-40	40-50	50-60	60-70	70-80	80-90	90-100
0	24.5	15.4	13.9	9.8	7.7	6.4	5.9	4.3	3.6	2.5	6.1
0-10	61.2	8.7	8.2	4.4	4.1	2.7	2.7	1.6	1.7	1.2	3.6
10-20	52.6	8.6	8.7	6.7	5.1	5.8	2.8	1.9	2.0	1.8	4.0
20-30	53.8	5.4	8.3	6.8	6.0	2.8	6.1	2.9	2.3	1.0	4.5
30-40	46.0	7.0	8.6	9.0	2.1	5.0	4.8	3.9	3.3	2.5	7.7
40-50	49.1	5.5	6.6	7.8	6.9	6.1	2.6	2.4	3.1	3.4	6.6
50-60	38.9	6.9	6.8	8.2	7.2	5.9	8.3	3.6	4.2	2.6	7.4
60-70	43.8	3.5	6.4	4.8	7.6	5.4	4.0	7.0	2.3	6.4	8.9
70-80	38.9	5.7	8.0	3.5	5.4	5.3	6.6	7.2	6.8	3.8	8.9
80-90	39.1	2.0	7.9	4.3	4.3	7.9	3.4	7.1	4.0	6.9	13.0
90-100	33.1	6.3	4.5	5.7	4.5	6.1	3.3	3.5	9.6	8.1	15.3

3. TESTING FOR THE SCARRING EFFECT OF UNEMPLOYMENT

The scarring effect of unemployment is an example of the concept that current outcomes in the labour market reflect past experiences – in other words, *you are what life made you*. Those who believe in the scarring effect argue that past experiences of unemployment actually increase the likelihood that you will be unemployed today. Of course, because of the inevitable heterogeneity between individuals in terms of their motivation and productivity, some individuals will be more likely than others to experience unemployment in the past, present and future, but this is not scarring (although erroneous econometrics might make it appear so). Scarring occurs where previous experiences of labour market states still have a causal effect on the individual today – or, in other words – where past experiences affect, rather than simply reflect, these differences between individuals.

This concept of scarring remains however very abstract – in order to understand how this process occurs we need to know when and how an individual is materially affected by an experience of unemployment. Despite a renewed interest in this topic, which has spawned a growing literature, these questions remain to some extent unanswered. Economic theory and commonsense have suggested *possible* explanations for the mechanism through which scarring may occur. Experiences of long term unemployment have long been thought to damage an individual's stock of human capital, his mental well-being and his level of motivation – all of which may contribute to the reduced exit rates from unemployment which plague those with long durations of unemployment. If any of these effects persist beyond exit from the spell (i.e. any damage to human capital, mental health or motivation is not instantly wiped clean) then if an individual returns to unemployment his exit rate might be lower than we would otherwise expect, given his observable characteristics: his level of educational attainment, gender, age and so on. Furthermore, if it is the case that firms use an individual's current duration of unemployment as a signal of their quality when considering whom they want to interview when trying to fill vacancies[104], then the long term unemployed may have low exit rates from unemployment because they are unable to match with many (or most) of the vacancies that exist in the labour market. It is therefore plausible that past experiences of unemployment may continue to affect you today if firms also view a past history of considerable unemployment as a signal of your potential quality. Finally, if firms have any degree of flexibility over whom they lay-off when hit by an adverse demand shock

[104] See, Phelps (1972) and Blanchard and Diamond (1994).

they may well choose to fire the least productive members of their workforce[105], so that any erosion of productivity in a past spell of unemployment may also increase the current probability of becoming unemployed. Therefore, it is plausible to assume scarring could effect individuals not only when they are unemployed, but also when they are employed. Certainly, there is considerable evidence[106] that past experiences of unemployment have an effect on individual when they are employed – in that individuals who re-enter employment after a spell of unemployment appear to suffer a wage penalty.

Furthermore, it is not exactly clear *when* this scarring takes place. Heckman and Borjas (1980) provide a framework to help analyse this question by articulating two separate forms of scarring effect from unemployment: occurrence dependence, where the event of a past spell of unemployment has an effect on the individual, and lagged duration dependence, where it is the accumulated duration of unemployment which affects the individual. Of course in many ways our inability to identify how and when scarring takes place reflects an underlying data problem. In order to test conclusively for the presence of scarring we would like to be able to first measure those variables – such as motivation – which are affected by the spell, and then demonstrate how an experience of unemployment causes a fall in, say, motivation which is not reversed upon exit from the spell.

The empirical evidence on the scarring effect of unemployment originated largely in North America. In their seminal contribution, Heckman and Borjas (1980) investigated whether there was any evidence that past experiences of unemployment had any causal impact on the future outcomes of a sample of U.S. high school graduates. They found that once unobserved differences between graduates in their propensity to be unemployed were controlled for there was no evidence that either the event, or the duration, of previous spells had any significant affect on the members of their panel. Ellwood (1982) finds that past experience in the labour market does have a scarring effect on the performance of young men in the U.S.; however, his estimate of the scarring effect is

[105] In a study of firms, Oswald and Turnbull (1985) report that almost a half of all establishments cited 'competence or the level of skills' of employees as a criteria for selecting whom to lay-off.

relatively small. In a study of the durations of claims for Canadian unemployment insurance, Corak (1993) reports evidence of occurrence dependence – *ceteris paribus*, successive spells were found to increase in length. In the U.K., there has been somewhat of a resurgence in interest in identifying the scarring effect of past experiences of unemployment in recent years. Arulampalam *et. al.* (2000) find "strong evidence of state dependence consistent with the 'scarring' theory of unemployment" in a panel of British men. In a study concentrating on the consequences in later life of early experiences of unemployment, Gregg (2001) finds that scarring predominantly affects males and that an extra two months of unemployment before the age of 23 appears to cause an extra month of unemployment for men between the ages of 24 and 33.

Finally over and above establishing the existence of lagged duration, and occurrence, dependence effects in unemployment, there is one further area we will focus on in the research – and that is the extent to which a given experience of unemployment may scar different individuals to different degrees. In particular, we examine whether the scarring effect of unemployment predominantly affects older members of the workforce. To date the existing literature has focused to a great extent on the scarring effects from individual's first experiences in the labour market (i.e. among youths). Arulampalam *et. al.* (2000) find evidence the scarring effect, measured in terms of the proportion of the observed persistence in experiences that can be explained by state dependence, is found to be almost twice as great for those aged 25 and above compared to those aged 24 or less. Furthermore, Gregory and Jukes (2001) show that the scarring effect of unemployment on wages is far more pronounced for older workers. Economic theory offers a partial explanation of these findings; unemployment rates are always higher among youths than adults, and therefore firms may place less faith in past experiences as a signal of youth's quality than adults. Furthermore, it is often argued[107] that particularly for youths, unemployment is a necessary part of a job shopping process through which they can find a secure, stable "lifetime" job by a process of trial and error. If frequent experiences of unemployment now are likely to lead to a well paid stable job – and

[106] See, for example, Gregory and Jukes (2001).

therefore little chance of unemployment – in the future, we would not expect to find evidence of a negative scar from unemployment.

3.1 Estimating the Scarring Effect of Unemployment

In order to identify the scarring effect of unemployment we adopt the survival analysis methodology, which essentially uses information from the length of time agents remain within a given labour market state (or the duration of their spell) in order to gain an understanding of how a defined set of explanatory variables affect the likelihood of an individual flowing out of that state. Typically, the functional form which describes the relationship between the duration of spells of unemployment and the set of explanatory variables will prove to be highly non-linear. Estimation then proceeds via maximum likelihood estimation which, given our data, selects the values of the coefficients in our model which would be most likely to reproduce the pattern of spell durations we observe. Before we can implement our estimation strategy there are four methodological issues we must first address: how do we specify the functional form of the hazard (the conditional probability of escape); how do we control for unobservable differences between individuals which affect their probability of escaping unemployment; how do we specify the underlying dependence of the hazard on the duration of the current spell; and, how do we allow for the fact that individuals leave the claimant count for a number of different labour market states, and that the determinants of each of these flows may vary accordingly. We shall discuss each of these issues below.

3.2 Specifying the Functional Form of the Hazard

The fundamental choice that confronts any analysis of this kind is to select a particular functional form for the hazard function which specifies the potentially highly non-linear relationships between the conditional probability of escape from unemployment and both a set of explanatory variables and the duration of the spell itself. There is a burgeoning

[107] See Jovanovic (1979) for an exposition of this theory and Topel and Ward (1992) for empirical evidence to support it.

literature (see, among many others, Kiefer (1988) and Van den Berg (2001)) which offers a large number of possible specifications of the hazard and the potential pitfalls each involves[108]. We adopt the most common specification of the hazard – the proportional hazard model – which is based on the assumption that the proportional effect of an explanatory variable on the hazard does not depend on the duration of the spell. The continuous time hazard function can then be written

$$\lambda(t) = exp(x\beta).\lambda_0(t) \qquad [5.1]$$

where λ_0 defines the 'baseline hazard' – the underlying shape of the hazard function for all individuals, save only for a vertical shift due to individual heterogeneity, so that for any two individuals, their hazards are proportional at all durations (Lancaster (1979)). If survival times are continuous, but we observe only the interval in which the spell ends, then the discrete time representation of the hazard can be written:

$$\lambda_t = 1 - exp(-exp(x\beta + \gamma_t)) \qquad [5.2]$$

where γ_t represents the log of the integrated baseline hazard over the interval (Jenkins (2003)). Given a specification of the hazard we now need to address two further issues: first, how do we control for possible omitted variable bias in $\phi(\cdot)$, and second what functional form should we choose for λ_0. We now turn to discuss each of these issues in turn.

3.3 SPECIFYING THE DISTRIBUTION OF UNOBSERVED HETEROGENEITY

In reality, it is seldom (if ever) likely to be the case that all the factors which have an effect upon an individual's exit rate out of unemployment are known and observable to

[108] In reality, any choice of functional form for the hazard will at best only approximate the true data generating process. The issue then is how good is the approximation, or alternatively, how bad is the mis-specification bias.

the econometrician[109]. Of course, we hope that through inclusion of both demographic information taken from the JUVOS dataset, and workplace based information taken from the NESPD we can control for much of the differences between individuals in our sample. Nevertheless, failure to allow for unobserved heterogeneity can have serious implications for our results, yielding erroneous parameter estimates (Van den Berg (2000)). The standard approach[110] to controlling for unobserved heterogeneity is to assume that a single random variable: υ can act as a proxy for all the explanatory variables omitted from the systematic component of the hazard and furthermore that this random variable is independent of the included covariates x and the duration of the spell: t (Narendranathan *et. al.* (1985)). Since we will include the duration of past spells of unemployment suffered by the individual among our covariates this unobserved component must be independently distributed across the different spells an individual suffers – i.e., it proxies all unobservable factors which affect the individual's hazard out of unemployment in a specific spell, rather than those which affect his hazard out of *all* spells[111]. So in our discrete time proportional hazards representation we have (Jenkins (2003)):

$$\lambda_t = 1 - exp(-exp(x\beta + ln(v) + \gamma_i)) \qquad [5.3]$$

Broadly speaking there are two approaches to modelling this unobserved component in the literature. The parametric approach has typically assumed that υ is drawn from the Gamma distribution since this produces a closed form for our likelihood function and is thus computationally convenient. Given that under mild regularity conditions, if υ is instead modelled non-parametrically – assumed to be a random variable whose distribution has zero as the lower bound for its support but is otherwise unknown – then that distribution nonetheless approximates the Gamma distribution at high durations[112]

[109] Factors such as the intensity of an individual's job search which will prove crucial in determining their probability of escaping unemployment are almost impossible to measure accurately.
[110] See Lancaster (1979).
[111] If this component is common across all spells, it necessarily follows that υ will be correlated with these lagged durations – those who always have difficulty escaping unemployment will tend to have long past spells of unemployment ! - yielding inconsistent estimators.
[112] Van den Berg (2000).

this particular parametric choice appears to have a sound practical foundation. Moreover, in practice, efforts to identify more than a couple of mass points in the distribution of unobserved heterogeneity have typically proved fruitless (Van den Berg (2000)). Finally, since the consensus in the literature is that given a flexible specification of the baseline hazard, parameter estimates are not particularly sensitive to assumptions on the distribution of unobserved heterogeneity (Ridder (1986), Van den Berg (2000)) we assume that this unobserved component is drawn from the Gamma distribution[113].

3.4 SPECIFYING THE BASELINE HAZARD

A survey of the survival analysis literature reveals that a large number of parametric families have been employed to specify the baseline hazard, some of which impose monotonicity in the rate of change of the baseline hazard with duration, some of which do not. However, it is now understood that the restrictions that such parametric assumptions impose on the model can have serious implication for our estimates – Ridder (1986) demonstrates that misspecification of the baseline hazard results in inconsistent estimators of the impact of the explanatory variables on the hazard. We therefore pursue a semi-parametric approach to estimating the scarring effect of unemployment pioneered by Prentice and Gloecker (1978) and Meyer (1990) where a fully flexible baseline hazard is estimated.

3.5 CONTROLLING FOR THE DESTINATION FOR WHICH THE INDIVIDUAL LEAVES THE CLAIMANT COUNT: A COMPETING RISKS ANALYSIS

As was discussed in Section 2, the JUVOS dataset delineates between those periods of unemployment and either inactivity or employment in an individual's working lifetime. It is inevitable then that the exits out of unemployment we record in our data will mark transitions both into employment and inactivity. However, we might expect the economic variables we have included in our estimation to have quite different effects on the

[113] It might be interesting to examine how sensitive our results are to an alternative specification of the distribution function of spell-specific unobserved heterogeneity; unfortunate this was not possible within

probability of exiting into inactivity or alternatively into employment. For example, a past history of chronic unemployment might decrease the conditional probability of escape from unemployment into employment, but increase the conditional probability of escape into inactivity, at all durations. Treating all exits as identical – i.e. ignoring the state into which the unemployed flow – could therefore potentially bias our results. The inclusion in our data of information which indicates whether individuals exited into employment or inactivity from August 1996 onwards offers a solution to the problem. Following Narendranathan and Stewart (1993) we treat all those spells where exit occurs into states other than the one of interest (employment) as censored at the point of exit, which is essentially a simplified competing risks analysis.

In fact in our dataset, only thirty per cent of our sample are observed to exit into employment, which means that we treat seventy percent of the spells in our sample as censored upon the point of exit. Of those who did not enter employment, the largest group of exits were those did not state a reason for terminating their claim, or simply failed to sign off, who account for almost a third of all exits, with the remainder of those who left the claimant count leaving for a state other than employment. Although the JUVOS dataset provides an excellent source of information on the time at which individuals start and finish their spells, this deficiency in our data might lead us to conclude that other data sources – for example, household surveys (such as the BHPS or LFS) – may in fact give a more reliable estimate of the baseline hazard function out of unemployment into particular states. Certainly, our failure to identify the nature of the exit from unemployment for a third of those who leave the claimant count in our sample is problematic, and ultimately, our results should be judged in this context.

3.6 THE LIKELIHOOD FUNCTIONS

Following Meyer (1990) the likelihood function for a non-parametric specification of the baseline hazard function, where the unobserved heterogeneity component: υ is assumed to be drawn from a Gamma distribution is as follows:

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the routine used to derive our results.

$$\log L\left(\beta,\gamma,\sigma^2\right)=\sum_{i=1}^{N}\log\left(\left(1+\sigma^2\times\sum_{t=1}^{z_i-1}\exp\{x_i(t)'\beta+\gamma(t)\}\right)^{-\frac{1}{\sigma^2}}-\right.$$

$$\left.\delta_i\left(1+\sigma^2\times\sum_{i=1}^{z_i}\exp\{x_i(z_i)'\beta+\gamma(z_i)\}\right)^{-\frac{1}{\sigma^2}}\right) \qquad [5.4]$$

4. RESULTS

Our basic estimation strategy is as follows: we include the length of previous spells of unemployment suffered by the individual (and their square) in the set of explanatory variables in the systematic component of the hazard[114], and if after having controlled for observed and unobserved heterogeneity in the data, the coefficient on these lagged durations is still significant – and negative – then we argue that there is evidence of scarring effects from unemployment. All the results presented below have been generated using Stephen Jenkins' ***pgmhaz*** STATA routine.

In Table 4.1 overleaf we present the results from our baseline model. In column I we present the estimated coefficients, standard errors and corresponding p – values for our full set of explanatory variables when we do not allow for the presence of unobserved heterogeneity; in column II we do likewise under the assumption of gamma distributed unobserved heterogeneity. Finally, in the last row of the table we report the likelihood ratio test statistic of whether the gamma distributed unobserved heterogeneity term is equal to zero, and the corresponding p – value of the test.

[114] The explanatory variables used in the estimation are described in Appendix 1.

TABLE 4.1 : REGRESSION RESULTS

	Model I			Model II		
	Coef.	Std Error	p value	Coef.	Std Error	p value
uratem	-0.068	0.006	0.000	-0.092	0.010	0.000
inac	-0.119	0.005	0.000	-0.189	0.010	0.000
tight	-0.899	0.159	0.000	-1.003	0.213	0.000
l1durm	-0.048	0.002	0.000	-0.066	0.004	0.000
l1durm2	0.000	0.000	0.000	0.000	0.000	0.000
yl1durm	-0.024	0.005	0.000	-0.040	0.007	0.000
yl1durm2	0.000	0.000	0.000	0.001	0.000	0.000
nspy1	0.150	0.015	0.000	0.273	0.027	0.000
ynspy1	-0.105	0.026	0.000	-0.199	0.044	0.000
start_age	-0.103	0.007	0.000	-0.171	0.013	0.000
start_age2	0.001	0.000	0.000	0.002	0.000	0.000
skill	0.071	0.015	0.000	0.100	0.025	0.000
married	0.356	0.028	0.000	0.619	0.051	0.000
cohabit	0.169	0.059	0.004	0.274	0.097	0.005
ropay	0.000	0.000	0.542	0.000	0.001	0.631
rbpay	0.000	0.000	0.179	0.000	0.000	0.245
union	-0.034	0.026	0.192	-0.053	0.042	0.211
dbj	0.267	0.131	0.042	0.575	0.232	0.013
part	0.013	0.037	0.719	0.018	0.061	0.764
qtr_in1	0.112	0.071	0.114	0.133	0.113	0.238
qtr_in2	0.134	0.072	0.062	0.273	0.115	0.018
qtr_in3	0.194	0.070	0.006	0.279	0.114	0.014
qtr_in4	0.297	0.070	0.000	0.427	0.113	0.000
qtr_in5	0.265	0.071	0.000	0.399	0.114	0.000
qtr_in6	0.175	0.072	0.015	0.388	0.118	0.001
qtr_in7	0.119	0.072	0.099	0.228	0.117	0.051
qtr_in8	0.118	0.071	0.097	0.230	0.115	0.046
qtr_in9	0.203	0.070	0.004	0.340	0.114	0.003
qtr_in10	0.149	0.071	0.036	0.252	0.115	0.028
qtr_in11	-0.108	0.074	0.148	-0.104	0.117	0.374
qtr_in12	-0.008	0.074	0.916	0.021	0.117	0.858
qtr_in13	-0.161	0.084	0.056	-0.107	0.133	0.424

TABLE 4.1 : REGRESSION RESULTS (CONTD.)

	Model I			Model II		
	Coef.	Std Error	p value	Coef.	Std Error	p value
NE	0.425	0.062	0.000	0.724	0.102	0.000
NW	-0.002	0.054	0.972	0.034	0.086	0.693
Mersey	-0.222	0.092	0.016	-0.196	0.137	0.153
YorksH	-0.171	0.053	0.001	-0.242	0.084	0.004
EM	-0.131	0.054	0.015	-0.203	0.089	0.022
WM	-0.229	0.055	0.000	-0.315	0.089	0.000
EA	-0.455	0.056	0.000	-0.728	0.095	0.000
London	-0.571	0.055	0.000	-0.794	0.086	0.000
SE	-0.613	0.054	0.000	-0.965	0.093	0.000
SW	-0.411	0.058	0.000	-0.607	0.095	0.000
Wales	0.296	0.063	0.000	0.528	0.103	0.000
pad1	2.174	0.160	0.000	4.842	0.356	0.000
pad2	1.954	0.160	0.000	4.933	0.375	0.000
pad3	1.794	0.161	0.000	4.961	0.388	0.000
pad4	1.615	0.164	0.000	4.954	0.400	0.000
pad5	1.559	0.166	0.000	5.041	0.410	0.000
pad6	1.530	0.168	0.000	5.099	0.417	0.000
pad7	1.418	0.171	0.000	5.101	0.424	0.000
pad8	1.485	0.173	0.000	5.261	0.432	0.000
pad9	1.284	0.180	0.000	5.105	0.438	0.000
pad10	1.324	0.184	0.000	5.263	0.447	0.000
pad11	0.923	0.200	0.000	4.884	0.456	0.000
pad12	0.956	0.205	0.000	4.968	0.462	0.000
pad13	0.876	0.218	0.000	4.913	0.469	0.000
pad14	0.943	0.218	0.000	5.022	0.473	0.000
pad15	0.892	0.248	0.000	4.968	0.489	0.000
pad16	0.393	0.332	0.236	4.521	0.544	0.000
pad17	-0.062	0.476	0.897	3.945	0.639	0.000
pad18	-0.017	0.526	0.975	3.952	0.693	0.000
pad19	0.728	0.600	0.225	4.607	0.746	0.000
Likelihood Ratio Statistic for Model I versus Model II				225.445		
p value				0.000		

4.1 UNOBSERVED HETEROGENEITY

We find strong evidence to reject the null hypothesis that the gamma distributed unobserved heterogeneity term has zero variance – the p – value of the test is less than 0.0005 ! The variance of this unobserved heterogeneity term is in fact estimated to be 3.283 (with a standard error of 0.323). Our results therefore suggest that there is indeed statistically significant unobserved heterogeneity across the separate spells of our sample, and we shall therefore focus our attention on the results from model II.

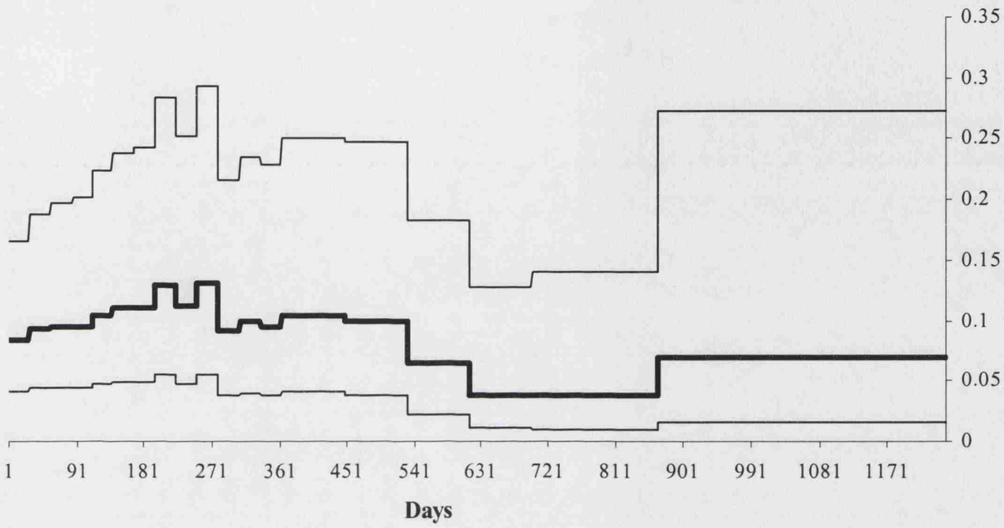
4.2 DURATION DEPENDENCE – THE SHAPE OF THE BASELINE HAZARD

The baseline hazard is assumed to be piecewise constant, with the segments of the baseline captured by a series of dummy variables[115]. In Figure 4.1 below we graph the baseline hazard function implied by our results with its corresponding 95% confidence interval.

The baseline hazard function implied by our results is highly non-monotone, but the confidence interval around this baseline hazard is daunting in size ! In particular the hazard rate out of unemployment into employment is found to increase for the first six months, with the standard downward sloping baseline hazard only (semi-) evident for those spells at least a year, and probably a year and a half in duration. Of course, this may be a function of the fact that for a third of all those who exit unemployment we do not know the labour market state for which they leave, so we are forced to treat all these observations as censored.

[115] Specifically, we use thirteen intervals of twenty eight days in length, followed by four further intervals of eighty four days in length, one interval of one hundred and sixty eight days in length, and finally the last interval of three hundred and eight days.

Figure 4.1 : The Implied Baseline Hazard Function



4.3 DEMOGRAPHIC CONTROLS

Unfortunately we have only a limited set of demographic controls, which in part reflects our underlying data, but also the fact that we have excluded some groups from the analysis. We do not have any information on the ethnicity of the individuals in our panel, nor do we have any women in our panel whatsoever. However, we do have data on whether the man was the only adult living in his household at the time he became unemployed, and we also know his age.

We find that both those men who are married or who are co-habiting have a higher hazard rate out of unemployment into employment than other otherwise equivalent men (with the magnitude of the effect stronger for the former than for the latter). Of course, this does not necessarily imply that becoming married will increase a given man's exit rate out of unemployment, although those men who are either married or cohabit are more likely to have young dependents in the household and may therefore be more motivated to find work. Nonetheless, it is plausible that that there is a selection issue here: those men who have a range of characteristics which enable them to successfully match with employers (and leave the claimant count) also have those characteristics which enable them to match successfully with partners.

Our results also suggest that as a man ages, ceteris paribus his probability of escaping unemployment falls[116], and given the results presented in Chapter 4, this should come as no surprise. However, if we include the square of the individual's age when he starts his spell, we find this quadratic term is significant and enters with a positive sign so that this effect on the hazard (and therefore the average duration of the spell) declines with age.

4.4 WORKPLACE RELATED INDIVIDUAL CHARACTERISTICS

Data from the New Earnings Survey does provide a rich source of information to control for differences in individual characteristics. Since for each individual we have an observation in the NESPD for every year that they were in employment at the time of the survey we choose to take data from the most recent observation prior to a given spell of unemployment, since this should give the most accurate reflection of the individual at that moment in time. Our controls can be divided into two groups: those which refer directly to an individual's level of pay, and those which refer more generally to his characteristics.

The NES allows us to collect accurate information on the gross weekly earnings of all individuals in our panels, including information both on the real gross overtime and basic pay. Theoretically speaking, the effect of the real wage on the expected duration of unemployment is somewhat ambiguous. On the one hand real wages will be heavily correlated with productivity and presumably desirability to potential employers, and therefore we would expect the highly paid to be able to re-enter employment with relative

[116] There might be some concern that this age differential simply reflects the fact that active labour market policies designed to help the unemployed were primarily focused on the young over much of the period – most notably, the New Deal for Young People (NDYP). This scheme will have certainly led to a reduction in the average length of youth spells of claimant unemployment, since all those who failed to find work of their own accord in the Gateway period of that programme would no longer be eligible for benefits. However, this should not have had a material affect on our results since all those individuals who had not found work by the end of the Gateway, including those who would go on to enter employment through a subsidy as part of the scheme, would have been treated as censored at that point.

ease. On the other hand, high wages in the past are likely to raise a workers reservation wage (i.e. the minimum wage offer he is willing to accept) and therefore prolong his spell. In practice, these two effects appear to cancel out – the level of basic and overtime pay appear to have an insignificant effect on the hazard (however, these results should be viewed alongside those regarding the skill measure – see below).

The NES also provides information on a number of characteristics of the job in which the individual was employed. We can observe whether the individual was working full- or part-time, whether his pay was covered by a collective agreement, and whether at the point in which he was last surveyed he was working more than one job. In general our workplace controls do not appear to have a significant impact on the hazard. The one exception is the double job marker [**dbj**] where we find that those individuals who were working more than one job when last observed in the NES appear to have a higher probability of escaping unemployment for employment.

Finally, following Elias (1995) and Elias and Bynner (1997) we can construct a measure of an individual's level of skill based upon his occupation, where an individual is ranked in one of four groups in ascending order of skill[117]. In an interesting corollary to the insignificance of wages in our regression, being in a higher skill group **does** appear to significantly increase the hazard.

4.5 LOCAL LABOUR MARKET CONDITIONS

In order to control for the state of the individual's local labour market we exploit two kinds of controls[118]. The first group are varying measures of labour market tightness in that locality: the male claimant count rate, the male inactivity rate and the ratio of vacancies to unemployed individuals. The second group of controls are a series of

[117] Clearly, information on the educational attainment of the individual would be a welcome addition to this occupation based measure of skill, but no such data is provided in the either the JUVOS or NESPD dataset.
[118] Of course, all those individuals in the same locality will share the same value for the various tightness measures and the final dummy variable. This clustering of observations implies that care should be taken in interpreting the apparent significance of the corresponding coefficients since we were not able to correct the standard errors on these coefficients.

dummy variables to capture both the variation in the state of the local labour market which are not captured by the tightness measures and a set of dummies to soak up the variation in the state of the aggregate labour market at the point in time in which the individual entered unemployment.

The coefficients on our time-varying local labour market controls are largely as expected. An increase in the male claimant count and inactivity rate in your region both significantly reduce your conditional probability of escaping unemployment. The final measure: the ratio of the stock of vacancies to unemployed in the region is significant but enters with the wrong sign which may say more about the quality of our vacancy data, rather than the dependence of the hazard on the tightness of the local labour market. Our set of regional controls suggest that even controlling for the degree of tightness in a local labour market (and the characteristics of the unemployed men therein) there remains a significant variation in the hazard across regions. Our results would therefore appear to lend at least some tentative support to Webster's (2000) argument that unemployment continues to be heavily concentrated in small pockets around the country, such as the former coal fields or depressed inner cities, although we have been unable to shed light on why this may be.

4.6 SCARRING EFFECTS

In order to test the scarring hypothesis we included the duration of the last spell the individual suffered (measured in months) which proved highly significant and entered with the right sign: those individuals with longer spells of unemployment in the past have a lower probability of escaping unemployment spells today. Once again we also tested for the presence of non-linearities in this scarring effect by including the square of the lagged duration in our regressions. This quadratic term was found to be positive and significant – as the length of a past spell increases, the smaller the differential impact of another extra month of unemployment in the past – although the magnitude of this non-linearity effect is small. Furthermore, in order to test for the presence of occurrence dependence effects we include the number of spells the individual had suffered in the year before the start of the current spell. Our results suggest that in fact frequent experiences of unemployment in the past actually **increase** your conditional probability of escaping unemployment.

Taken together then our results suggest that even when we control for observable and unobservable differences between individuals, and the state of the local labour markets in which they search, past experiences can still explain current behaviour. While the length of past spells appear to significantly depress the conditional probability of escaping a current spell, the number of spells suffered is found to have the opposite effect.

To quantify the magnitude of this scarring effect, consider the impact of an increase in the duration of the last spell of unemployment from six to twelve months on the probability that the individual will escape unemployment in, say, the first month. For a man aged forty when he entered unemployment who otherwise has the mean characteristics of his sample, the hazard rate falls from 7.3% to 5.1%; or put another way, the probability that he will exit from unemployment for employment within 12 months falls from 69.6% to 56.3%. The scarring effect of past experiences of unemployment certainly seems far from trivial !

Finally, we also focus on the issue of whether these scarring effects differ with age. In order to address this question we test for the significance of interaction terms on the hazard, which take the value of the corresponding "scarring variable": the length of the previous spell, its square and the number of spells suffered in the last year for those aged under 35 when they entered the spell, and zero otherwise. In fact, all these interaction terms are found to have a significant impact on the hazard.

Somewhat surprisingly, our results suggest that the scarring effect is greater for younger men, although this effect is partially offset by the fact that the rate of increase in the magnitude of the scar is lower for youths. In the case of the occurrence dependence effects, we also find that this positive effect on the hazard is stronger for older men (those over the age of 35).

5. Variation in Scarring Effects by Age

In order to examine the variation in scarring effects by age in greater depth we repeat our analysis, splitting the sample in two – into those aged 35 years of age and under, and those above the age of 35. In this way we relax the implicit restriction in our previous analysis that the impact of each of our covariates on the hazard was common across all age groups in the panel. As we shall go on to discuss, splitting the sample in this way does indeed reveal some interesting effects that are obscured by estimation over the whole sample. We present the results from our analysis on each of our sub-samples in Tables 4.2 and 4.3 overleaf. Again following the convention laid out above, we present the estimated coefficients, standard errors and corresponding p – values for both our models – where we do not allow for the presence of unobserved heterogeneity (Model I) and where we do (Model II). We were only able to obtain results on both sub-samples using a sub-set of our covariates (specifically, we dropped the double job identifier and the quadratic term in the individual's age when he started the spell, we created a composite variable which takes the value one if an individual is either married *or* cohabiting) and where we merged the final three intervals in the baseline hazard.

5.1 Unobserved Heterogeneity

In each of the separate sub-samples we reject the null hypothesis that the gamma distributed unobserved heterogeneity term has zero variance – the p – values of the test are in both cases again less than 0.0005, with the variance of these unobserved heterogeneity terms estimated to be 2.260 and 3.569 for the younger and older sub-samples respectively (with corresponding standard errors of 0.439 and 0.430). Once again we therefore focus our attention on the results from model II in each case.

TABLE 5.1 : REGRESSION RESULTS – MEN AGED 35 AND UNDER

	Model I			Model II		
	Coef.	Std Error	p value	Coef.	Std Error	p value
uratem	-0.058	0.011	0.000	-0.069	0.015	0.000
inac	-0.127	0.008	0.000	-0.183	0.015	0.000
tight	-0.192	0.247	0.438	-0.058	0.337	0.864
l1durm	-0.060	0.005	0.000	-0.085	0.008	0.000
l1durm2	0.000	0.000	0.000	0.001	0.000	0.000
nspy1	0.092	0.024	0.000	0.123	0.037	0.001
start_age	-0.069	0.004	0.000	-0.099	0.008	0.000
skill	0.036	0.027	0.179	0.044	0.040	0.270
married_or_cohabit	0.201	0.054	0.000	0.351	0.085	0.000
ropay	0.001	0.001	0.503	0.000	0.001	0.660
rbpay	-0.001	0.000	0.005	-0.001	0.000	0.009
union	-0.023	0.046	0.614	-0.043	0.067	0.522
part	0.138	0.055	0.013	0.201	0.086	0.020
qtr_in1	0.044	0.114	0.697	-0.002	0.166	0.988
qtr_in2	0.023	0.115	0.840	0.148	0.172	0.389
qtr_in3	0.068	0.113	0.548	-0.016	0.166	0.925
qtr_in4	0.175	0.110	0.113	0.256	0.165	0.121
qtr_in5	0.210	0.115	0.067	0.272	0.169	0.108
qtr_in6	0.076	0.117	0.515	0.232	0.178	0.192
qtr_in7	-0.061	0.119	0.611	-0.063	0.177	0.722
qtr_in8	0.094	0.114	0.408	0.126	0.169	0.456
qtr_in9	0.112	0.117	0.341	0.200	0.174	0.251
qtr_in10	-0.027	0.119	0.820	-0.041	0.176	0.818
qtr_in11	-0.158	0.118	0.180	-0.167	0.173	0.333
qtr_in12	-0.190	0.118	0.107	-0.250	0.171	0.144
qtr_in13	-0.212	0.134	0.112	-0.189	0.195	0.333

TABLE 5.1 : REGRESSION RESULTS (CONTD.)

	Model I			Model II		
	Coef.	Std Error	p value	Coef.	Std Error	p value
NE	0.435	0.104	0.000	0.713	0.166	0.000
NW	-0.048	0.087	0.582	-0.019	0.131	0.884
Mersey	-0.185	0.152	0.224	-0.206	0.216	0.339
YorksH	-0.306	0.090	0.001	-0.375	0.134	0.005
EM	-0.302	0.091	0.001	-0.437	0.141	0.002
WM	-0.300	0.090	0.001	-0.363	0.137	0.008
EA	-0.514	0.094	0.000	-0.739	0.152	0.000
London	-0.595	0.089	0.000	-0.775	0.133	0.000
SE	-0.717	0.091	0.000	-1.079	0.154	0.000
SW	-0.558	0.096	0.000	-0.769	0.149	0.000
Wales	0.030	0.113	0.791	0.101	0.168	0.546
pad1	2.174	0.178	0.000	4.069	0.427	0.000
pad2	2.068	0.179	0.000	4.224	0.464	0.000
pad3	1.815	0.183	0.000	4.136	0.490	0.000
pad4	1.684	0.188	0.000	4.133	0.512	0.000
pad5	1.548	0.196	0.000	4.118	0.531	0.000
pad6	1.657	0.199	0.000	4.286	0.543	0.000
pad7	1.522	0.208	0.000	4.275	0.560	0.000
pad8	1.534	0.215	0.000	4.318	0.569	0.000
pad9	1.458	0.222	0.000	4.275	0.580	0.000
pad10	1.519	0.230	0.000	4.452	0.598	0.000
pad11	1.149	0.269	0.000	4.166	0.628	0.000
pad12	0.817	0.311	0.009	3.807	0.647	0.000
pad13	0.487	0.377	0.196	3.470	0.677	0.000
pad14	0.851	0.338	0.012	3.894	0.668	0.000
pad15	1.442	0.338	0.000	4.539	0.678	0.000
pad16	0.705	0.532	0.185	3.749	0.796	0.000
pad17	1.074	0.608	0.077	4.081	0.856	0.000
Likelihood Ratio Statistic for Model I versus Model II				57876.725		
p value				0		

TABLE 5.2 : REGRESSION RESULTS – MEN AGED OVER 35 YEARS

	Model I			Model II		
	Coef.	Std Error	p value	Coef.	Std Error	p value
uratem	-0.074	0.008	0.000	-0.106	0.012	0.000
inac	-0.116	0.006	0.000	-0.188	0.012	0.000
tight	-1.324	0.201	0.000	-1.509	0.273	0.000
l1durm	-0.048	0.003	0.000	-0.066	0.004	0.000
l1durm2	0.000	0.000	0.000	0.000	0.000	0.000
nspy1	0.144	0.015	0.000	0.269	0.029	0.000
start_age	-0.003	0.002	0.223	-0.004	0.004	0.267
skill	0.091	0.019	0.000	0.129	0.032	0.000
married_or_cohabit	0.370	0.032	0.000	0.633	0.059	0.000
ropay	0.000	0.000	0.701	0.000	0.001	0.733
rbpay	0.001	0.000	0.000	0.001	0.000	0.001
union	-0.042	0.032	0.186	-0.057	0.053	0.280
part	-0.160	0.052	0.002	-0.223	0.082	0.006
qtr_in1	0.141	0.091	0.122	0.199	0.147	0.177
qtr_in2	0.194	0.093	0.037	0.303	0.150	0.043
qtr_in3	0.253	0.090	0.005	0.433	0.150	0.004
qtr_in4	0.343	0.090	0.000	0.457	0.148	0.002
qtr_in5	0.305	0.090	0.001	0.460	0.148	0.002
qtr_in6	0.221	0.092	0.016	0.436	0.151	0.004
qtr_in7	0.198	0.091	0.031	0.339	0.150	0.024
qtr_in8	0.113	0.092	0.218	0.245	0.150	0.103
qtr_in9	0.249	0.088	0.005	0.412	0.146	0.005
qtr_in10	0.219	0.090	0.015	0.375	0.147	0.011
qtr_in11	-0.102	0.096	0.289	-0.104	0.153	0.497
qtr_in12	0.085	0.096	0.373	0.134	0.155	0.387
qtr_in13	-0.174	0.109	0.111	-0.127	0.174	0.467

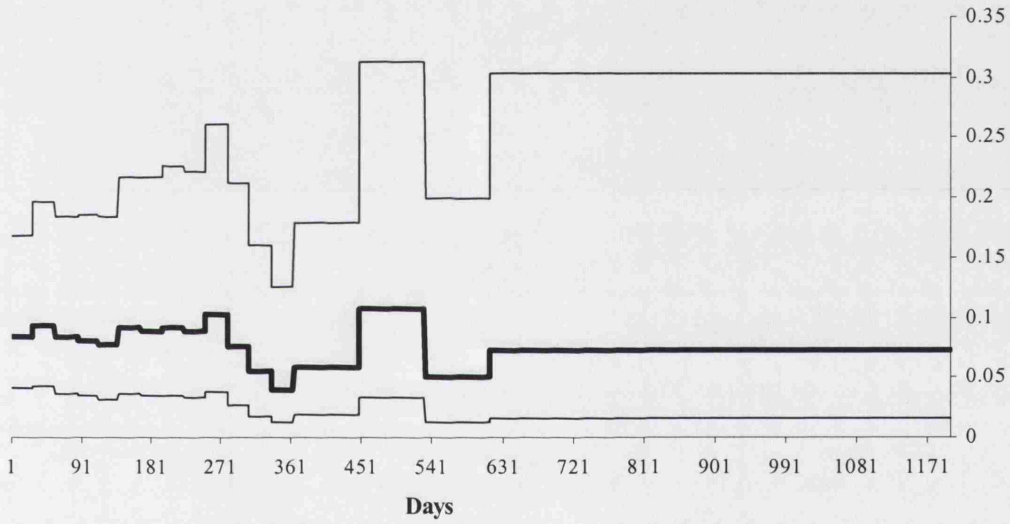
TABLE 5.2 : REGRESSION RESULTS (CONTD.)

	Model I			Model II		
	Coef.	Std Error	p value	Coef.	Std Error	p value
NE	0.391	0.077	0.000	0.766	0.133	0.000
NW	-0.025	0.069	0.720	0.020	0.113	0.863
Mersey	-0.216	0.114	0.058	-0.121	0.176	0.493
YorksH	-0.103	0.066	0.118	-0.165	0.107	0.125
EM	-0.058	0.067	0.386	-0.087	0.115	0.447
WM	-0.199	0.069	0.004	-0.315	0.115	0.006
EA	-0.475	0.070	0.000	-0.811	0.124	0.000
London	-0.595	0.070	0.000	-0.888	0.114	0.000
SE	-0.574	0.067	0.000	-0.962	0.122	0.000
SW	-0.319	0.073	0.000	-0.487	0.124	0.000
Wales	0.408	0.076	0.000	0.756	0.133	0.000
pad1	-0.270	0.149	0.069	0.913	0.292	0.002
pad2	-0.558	0.149	0.000	0.943	0.310	0.002
pad3	-0.662	0.150	0.000	1.029	0.325	0.002
pad4	-0.863	0.154	0.000	1.006	0.340	0.003
pad5	-0.877	0.156	0.000	1.138	0.351	0.001
pad6	-0.977	0.160	0.000	1.134	0.361	0.002
pad7	-1.075	0.165	0.000	1.138	0.370	0.002
pad8	-0.980	0.166	0.000	1.355	0.380	0.000
pad9	-1.243	0.179	0.000	1.135	0.390	0.004
pad10	-1.207	0.185	0.000	1.276	0.401	0.001
pad11	-1.621	0.209	0.000	0.832	0.411	0.043
pad12	-1.433	0.207	0.000	1.118	0.419	0.008
pad13	-1.424	0.218	0.000	1.157	0.426	0.007
pad14	-1.452	0.225	0.000	1.169	0.435	0.007
pad15	-1.800	0.288	0.000	0.759	0.471	0.107
pad16	-2.151	0.384	0.000	0.528	0.546	0.334
pad17	-3.247	0.721	0.000	-0.771	0.815	0.344
Likelihood Ratio Statistic for Model I versus Model II				157.304		
p value				0.000		

5.2 DURATION DEPENDENCE – THE SHAPE OF THE BASELINE HAZARD

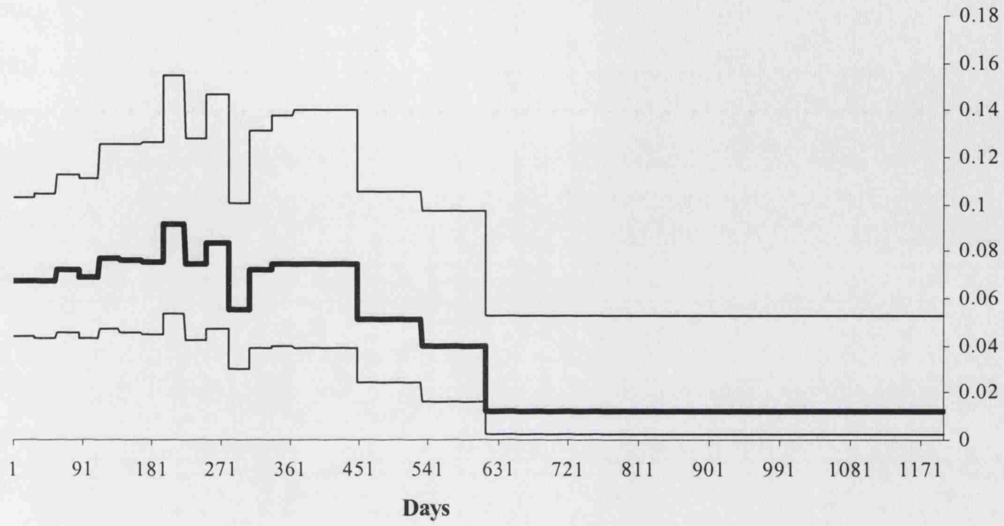
In the Figures 5.1-5.2 we graph the baseline hazards and their corresponding confidence intervals for each of our sub-samples. In basic form both of these baselines are similar to that estimated using the full sample (see Figure 4.1). Once again the confidence intervals around these estimates of the shape of the baseline hazard are wide, and particularly so in the case of the younger sub-sample.

Figure 5.1 : The Implied Baseline Hazard Function : Men aged 35 and under



There are of course differences in the particular shape of the two baseline hazard functions – most strikingly the level of the baseline hazard is lower for the older sample, and particularly at long durations – although these should be put in the context of the width of the surrounding confidence intervals. Imposing a common baseline hazard over both sample may therefore have had serious implications for our results. Before turning to our variables of interest which are intended to cover the scarring effects of unemployment, we shall first review our the estimated effects of our controls in each sub sample, focusing in particular on points where our results differ significantly either between our two sub-samples of from those estimated over the whole sample (presented earlier in Table 4.1)

Figure 5.2 : The Implied Baseline Hazard Function : Men aged over 35



5.3 DEMOGRAPHIC CONTROLS

For both samples, we recover the result that those men who are either married or cohabiting have a significantly higher hazard rate out of unemployment into employment than otherwise identical men. However, we find that only in the younger sample of men (below the age of 36) does age have a significant effect on the hazard. This result might explain the non-linearity we observed in the impact of age on the hazard rate in our earlier regression.

5.4 WORKPLACE RELATED INDIVIDUAL CHARACTERISTICS

For the younger sample, our results are somewhat surprising, when compared to those presented in Table 4.1. First, we find that an individual's level of skill does not appear to have a significant impact on their hazard rate out of unemployment into employment. This may be because the occupational measure of skill we have employed does not perform so well for younger workers, perhaps because youths are more likely to be involved in the process of job shopping where their previous occupation may be a poor indicator either of their level of skill or of the type of job they are currently searching for. We also find that the higher their level of basic pay in the week in which they were last observed in employment the lower their hazard rate out of employment in their current spell (this effect is significant yet small in magnitude). This would tend to suggest that for younger workers, the reservation wage effect dominates the productivity signal effect – those who were on higher pay before might search longer for a better paid job now. Finally, those previously in part-time employment are significantly more likely to escape unemployment than full-time workers.

For older members of the workforce, we find that their level of skill is now important – more skilled workers are significantly more likely to escape unemployment. Moreover, the basic pay effect now goes in the opposite direction (although again this effect is small in magnitude). Now it appears that base pay may be a good indicator of worker's productivity, and hence employability, and the higher their level of base pay when last observed in employment, the higher their chance of escape. It may in fact be that these two effects cancel out when we estimate over the whole sample. We also find a similar effect with the part-time dummy, which is now negative in sign (and on the borders of significance) suggesting older part-time workers are less likely to escape unemployment than their previously full-time peers.

5.5 LOCAL LABOUR MARKET CONDITIONS

We find that the local labour market variables give a fairly consistent impression of the impact of the locality upon the individual's chances of escaping unemployment across both sub-samples. In both samples we found that the inactivity rate and unemployment rate in the locality were significant and entered with the right sign; however, the vacancy-based measure of labour market tightness was (utterly) insignificant in the case of the younger workers. We also found that the many of regional dummies were significant and of the same sign in both regressions – controlling for the level of the labour market tightness in the locality, those in the North East were more likely to escape than the base group (Scotland), those in East Anglia, London and the South East were less likely to do so.

5.6 SCARRING EFFECTS

Finally we turn to our variables of interest: the duration of the previous spell (and its square) and the number of spells suffered in the last year. In our initial results we found the surprising result that the scarring effect of a given unemployment spell decreased with age, and this result remains when we split the sample by age. We find that the magnitude of that scarring effect (-.085) is greater for the younger members of the workforce, and this coefficient lies outside the confidence interval around the effect (-.074,-0.058) estimated over the older sample. It is true that the offsetting quadratic term (which again implies that the marginal impact of an extra month of unemployment diminishes as the length of the spell increases) is more positive in the case of the younger sample, however this coefficient does indeed lie within the confidence interval around the corresponding coefficient estimated from the older sample; and in any case these effects are small. Simply put, on the basis of both our results in this and the previous section of this Chapter, we find no evidence that the scarring effect is indeed more serious for older workers; in fact if anything we find the contrary to be true.

Moreover, we also find the perverse occurrence dependence effects results we obtained for the whole sample – the more spells you had in the last year, the easier you find it to escape unemployment (into employment) is once again weaker for youths, and again outside the confidence interval for the coefficient on the same variable in the older sample. Of course, having been unemployed a lot in the last year, also means by definition that you have escaped unemployment a lot too. Given that youths appear to escape unemployment with greater ease than adults, a track record of being able to escape unemployment might be a particularly valuable thing for adults who become unemployed.

6. CONCLUSIONS

If the experience of unemployment has a detrimental effect on an individual, such that the longer he remains unemployed the harder it becomes to escape, it is possible that some of the damage caused by unemployment is not undone upon escape; unemployment might leave a scar. In this Chapter we investigate whether those individuals whose last experience of unemployment was long appear to have a lower probability of escaping unemployment than an otherwise identical individual. We find that experiences of unemployment do indeed appear to leave a scar.

Our analysis is based on the claimant history of a random sample of working-age men, where we are able to control for the impact of both the labour markets in which these men search, and observable and unobservable differences between them, on their probability of escaping unemployment. We find that the longer the duration of his last spell the lower his hazard rate out of unemployment. In the parlance of survival analysis we can identify significant lagged duration dependence effects in unemployment. Conversely, we find the more spells of unemployment an individual has suffered in the year prior to his becoming unemployed, the easier he finds it to escape unemployment, other things equal.

This research has focused on the rather narrow question of the scarring effect from experiences of unemployment in the recent past: the length of the most recent spell, the number of spells suffered in the last year. It might prove interesting to investigate whether the length of spells in the more distant past appear to have an impact on current outcomes in the labour market[119].

Finally, we can find no robust evidence to suggest that experiences of unemployment leave a greater scar on older members of the workforce, and if anything our results suggest the opposite may be the case – youths seem to be more affected by their

[119] Using the pgmhaz routine from which the results in this Chapter were generated it did not prove possible to achieve convergence upon inclusion of the durations of additional spells.

experiences of unemployment in the past, than an otherwise identical adult. Of course this result must be put in the context that our results also indicate that youths have a higher exit rate out of unemployment for a given duration of unemployment spell.

It may well be that first experiences in the labour market count. Older workers, who in their past have been in regular employment, may not be unduly affected by an experience of unemployment. For a youth, a significant experience of unemployment may be more serious. Moreover, if we believe that part of the explanation for the scarring effect of unemployment is that a past history of unemployment acts as a negative signal to potential employers, we know from the results in Chapter 4 that even though proportionately more youths enter unemployment, a lower proportion of those that do become long-term unemployed, so for those unfortunate youths that do become long-term unemployed, this might act as a strong signal to firms of their unemployability.

APPENDIX 1: DATA DESCRIPTION

The following section describes the explanatory variables used in the survival analysis

[I] INDIVIDUAL DATA: DEMOGRAPHIC CONTROLS

STARTAGE The individual's age in years when he started the current spell of claimant unemployment.

MARRIED Takes the value one if the man is reported as married in the JUVOS dataset, and zero otherwise.

COHABIT Takes the value one if the man is reported as cohabiting (but not married) in the JUVOS dataset, and zero otherwise.

MARRIED_OR_COHABIT Takes the value one if the man is either cohabiting or married, and zero otherwise

[II] INDIVIDUAL DATA: COLLECTED FROM THE WORKPLACE

SKILL Following Elias (1995) and Elias and Bynner (1997), this measure of the individual's level of skill is constructed from his two digit Standard Occupational Classification (S.O.C.)[120] – data on which is contained within the NESPD. The variable takes values between 1 and 4 in increasing order of skill. It could be argued that a measure of skill based on academic attainment might be preferable, but we do not have access to this data.

[120] I am very grateful to Glenda Quintini for providing me with the programme files which convert the SOC codes in the NESPD into Elias' skill classification.

PART Takes the value one if the individual was working on a part-time basis at the point in time he was included in the given wave of the NESPD, and zero otherwise.

DBJ Takes the value one if the individual held more than one job at the point in time he was included in the given wave of the NESPD, and zero otherwise

UNION Takes the value one if the individual was covered by a collective agreement at the time he was included in the given wave of the NESPD, and zero otherwise.

ROPAY Real overtime weekly earnings at the time the individual was included in the given wave of the NESPD.

RBPAY Real overtime weekly earnings at the time the individual was included in the given wave of the NESPD.

PAYYR`T' This dummy variable takes the value one if the observation on the individual's level of pay is drawn from the t^{th} year of the N.E.S.. This variable is intended to control for productivity growth at the aggregate level.

[III] LOCAL LABOUR MARKET DATA

URATEM Claimant Count Unemployment Rate for Men in the individual's local travel to work area.

INAC Male Inactivity Rate in the individual's standard statistical region.

TIGHT Vacancy Rate in the individual's local travel to work area.

**DGOR`K'** A dummy variable taking the value one if the individual lives in a given Government Operating Region:`k'.

QTR_IN`Q' A dummy variable taking the value one if the spell begins at some point during a particular quarter; this captures an aggregate labour market effect.

[IV] INDIVIDUAL DATA ON PREVIOUS EXPERIENCES OF UNEMPLOYMENT

LDURM The duration of the last spell of claimant unemployment measured in months suffered by the individual (prior to the current spell) as reported in the JUVOS dataset.

LDURM2 The square of duration of the last spell of claimant unemployment measured in months suffered by the individual (prior to the current spell) as reported in the JUVOS dataset.

YLDURM The duration of the last spell of claimant unemployment measured in months suffered by the individual (prior to the current spell) as reported in the JUVOS dataset for those below 35 years of age, and zero otherwise.

YLDURM2 The square of duration of the last spell of claimant unemployment measured in months suffered by the individual (prior to the current spell) as reported in the JUVOS dataset for those below 35 years of age, and zero otherwise.

NSPY1 The number of spells of claimant unemployment suffered by the individual in the year before the start of current spell as reported in the JUVOS dataset.

YNSPY1 The number of spells of claimant unemployment suffered by those below 35 years of age in the year before the start of current spell as reported in the JUVOS dataset, and zero otherwise.

CHAPTER 6
CONCLUSION

This thesis has investigated the hypothesis that an appreciation of the age structure of the population can improve our understanding of the labour market, and in particular the incidence of unemployment. Our conclusions are twofold: that experiences of unemployment do indeed differ significantly by age and that shifts in the age composition of the population can have an impact on the incidence of unemployment in the economy.

In the first half of this thesis we focus on the macroeconomic implications of demographic change. In no way do we suggest that demographics can explain all (or indeed most) of the time series variation in the unemployment rate. Indeed, there is an extensive (and impressive) literature which has identified the role played by numerous factors in determining the unemployment rate (see Bean (1994) for an excellent survey). Our intention is simply to examine (or perhaps more humbly re-examine) the part played by demographic pressures in addition to, rather than instead of, these other factors.

In the first of two chapters we employ a shift share methodology as an accounting framework to identify the role played by shifts in the composition of the labour force in determining the behaviour of the unemployment rate. Simply put, if youths always suffer higher unemployment rates than adults then a decline in the youth share of the labour force implies that the aggregate unemployment rate may fall.

Our results indicate that the shifts in the age composition of the working-age population which followed from the collapse in the birth rate during the 'baby bust' were large enough to have a small, yet significant impact on the aggregate unemployment rate. Of course demographic shocks of this magnitude are by their very nature rare – so one might reasonably ask whether our analysis serves any other purpose than a simple historical accounting exercise. However, as with most historical analysis, there are potential lessons for the future – there will continue to be episodes in the future in which the age composition of the working-age population undergoes periods of profound change. Consider for example the long term implications of the recent high rates of emigration among young British men, which have been identified through the process of carrying out the latest census of the population of the United Kingdom. If this trend continues, then the share of the population accounted for by middle aged men will fall significantly as successive cohorts of young men leave for foreign shores.

Of course what matters for monetary policy is not the unemployment rate itself, but the unemployment gap – the difference between the unemployment rate and the natural rate which brings consistency with price- and wage-setters. Although we do not explicitly model it in Chapter 2, the entry of the Baby Bust cohort will also have reduced the natural rate of unemployment in the economy. For an individual, it is the presence of sufficient numbers of individuals in the unemployment pool who are capable of filling their job which restrains their demands for higher wages. To be a plausible candidate to replace the worker, these unemployed individuals will most probably have similar levels of experience and qualifications as the employee. In practice that means they are likely to be of a similar age, especially for those jobs filled by younger members of the workforce. The age-specific employment or unemployment rates should then act as a good proxy for the tightness of the labour market in which the individual operates. Our analysis thus cautions against focusing on the weighted average of these age-specific employment or unemployment rates as a measure of labour market tightness; monetary policy makers should focus on these age-specific rates, and particularly so in periods of significant demographic change. The aggregate unemployment rate can fall without any shift in the group specific rates given a favourable shift in demographic composition, and we would not expect any corresponding increase in wage pressure as a result. This is indeed the interpretation we offer for (part of) the apparent fall in the natural rate over the 1990s.

Demographic change is thus a plausible candidate explanation for why the natural rate fell over the period – and given the meagre estimates of the role played by other more celebrated determinants of the shift in the natural rate[121] – it is one worthy of comment. What makes demographic change interesting in this regard is that its impact is transient, and may indeed reverse. Unlike other factors, such as the structural reforms in the labour market – which are (rightly or wrongly) perceived to have been permanent, demographic change may put upward pressure on the natural rate in the future. Despite its inexorable fall in the 1990s, policy makers would be wise to consider factors such as demographic change which could lead to a rise as well as a fall in the natural rate of unemployment.

In the Chapter 3 we reassess the role played by demographic change within an established theoretical framework which links the mismatch between the relative demand and supply of different skilled groups in the workforce to movements in the unemployment rate. Typically this literature has focused on a worker's level of educational attainment to measure his level of skill. However, if individuals accumulate human capital through experience in the labour market, then a shift in the age composition of the population will involve a shift in the relative supply of skilled labour in the economy.

Our analysis indicates that net shifts in the demand for skilled labour can explain a far higher fraction of the time series behaviour of the unemployment rate than previously assumed. Of course, this result is conditional on the values of certain key parameters of our model – notably, the degree of substitution in production between different skill inputs and the nature of wage setting in the economy – and we would certainly argue that further research to pin down these parameters is of great importance. Nonetheless, this result is potentially intriguing. Our results suggest that the magnitude of the unemployment effect resulting from a given skill biased shock to demand will be determined in part by the size (if any) of the offsetting shift in supply. In an environment in which skill biased shocks are common and where high rates of unemployment among the unskilled are economically inefficient (as well as socially divisive) because they

[121] Take for example Nickell and Quintini (2002) who estimate that the incidence of nominal wage rigidities in the UK labour market have a minor role in determining the equilibrium unemployment rate, so that an increase in the inflation rate from 2.5% to 5.5% would lead to only a 0.13 pp decline in the equilibrium unemployment rate.

produce no downward pressure on wages elsewhere in the economy, our analysis shows that Government interventions to raise the level of skill in the population – through encouraging participation in post compulsory education among youths, and promoting training at the workplace for adults – with which it can mitigate the effects of these shocks take on an added importance. The former of these policies (promoting participation in post-compulsory education) will both reduce the share of youths with little or no qualifications (who we find to be the least skilled members of the workforce) and at the same time increase the share of graduates (who go on to become the most skilled). The latter policy (encouraging training at the workplace) thought it may not deliver an increase in the average level of educational attainment in the workforce – except perhaps through lifetime learning policies such as the Open University scheme – will still raise average levels of productivity.

Of course, access to the workplace might be thought of as the most basic form of training scheme and so in a sense the Government has a final lever on the skill distribution. Through active labour market policies such as the New Deal, or financial incentives created by the National Minimum Wage or tax credits, the Government can encourage those currently in inactivity or unemployment to find work. In this way the worst ravages on the human capital of the socially excluded may be avoided by returning these individuals to the workplace, and thereby indirectly the average level of skill of the workforce is raised.

While the unemployment rate defines the fraction of the labour force who are out of work and claiming benefit or seeking employment (depending on one's definition) it can tell us nothing about how the experience of unemployment is distributed across the labour force over time – and the extent to which that experience is concentrated on a relatively small number of chronically unemployed individuals. In the second half of this thesis we focus on this variation in the experience of unemployment over the long run, and in particular the variation across different age groups in the population.

Over the last couple of decades, and in particular since the election of the Labour Government in 1997, policy interventions in the labour market have increasingly focused on the long-term unemployed. Our results – that in the long run the experience of unemployment is highly concentrated on a relatively small fraction of the workforce – certainly do not challenge the expenditure of resources to alleviate the incidence of long term unemployment – we can clearly identify large numbers of individuals in the JUVOS panel who are continuously unemployed for years at a time. The focus of Chapter 4 is beyond the variation in duration of the claimant spells that are 'live' at a given point in time; we ask, once we aggregate across all the spells they suffer in a given period, how concentrated is the distribution of unemployment across all those who suffer some experience of unemployment ? In fact, something of the order of a quarter of those who have some experience of unemployment over a four year period can account for about three fifths of all the days lost to unemployment over that period. Nor is that to say that the long-term unemployed do not contribute to our understanding of this long-run concentration of unemployment. Over the space of a year, three quarters of those who spend more than six months on benefit, will have done so on account of one spell. But over a four year period, this fraction is more like a third.

Of course, our analysis focuses on a random sample of working age British men, so an element of caution is required in generalising our results to the workforce at large. Nevertheless, our results do suggest that in the long run the experience of unemployment is highly concentrated on a relatively small fraction of people who over the course of a number of spells account for a large fraction of the total number of days lost to unemployment; the frictionally unemployed come and go, the recurrent unemployed remain.

The key observation to draw from these results is that if the aim of policy-makers is to shift people permanently out of welfare and into work, then they should not view the long-term unemployed as the only cause for concern in the unemployment pool. At any moment in time there may be a large number of individuals on the unemployment rolls with a long history of unemployment for whom the discounted stream of benefit claims will be large, even though the length of their current claim might be relatively short.

This observation has potential implications for the design of policy. Within the framework of the New Deal, the unemployment are processed through the Gateway and into the various schemes according to the duration of their current spell – the argument presumably being that since the hazard is assumed to fall with duration, so individuals can be ranked according to the length of their current spell in terms of their relative probability of escape, and so assistance can efficiently allocated on the basis of the observed duration of claimants. However, the Government also has access to the past history of benefit claims of each individual, and our results raise the possibility that individuals with a long history of benefit claims should be fast-tracked into the New Deal. Essentially this is an argument about the importance of deadweight losses. One of the key criticisms levelled at active labour market policies such as the New Deal is that they are inefficient because they subsidize flows into employment which would have happened in the absence of policy – in other words they incur a deadweight loss. Our analysis suggests that for the chronically unemployed, entry into employment is more often than not rapidly followed by job loss and a flow back into unemployment. This is not to say that the deadweight loss does not exist, rather that they should be weighed against the potential benefit savings to the Exchequer (let alone the benefits to the individual) that could be achieved if schemes such as the New Deal can make a permanent impression on the individual's prospects in the labour market. Of course this argument rests upon the notion that policy interventions of the kind involved in the various schemes of the New Deal actually can have a significant and enduring impact on individual's employability. We would therefore argue that research should be focused on identifying which of the various New Deal schemes: entry into paid employment, full-time education or work for a charitable organisation or environment task force have the greatest impact on future outcomes. In practice of course, this may turn out to be an argument for investing more resources, not less, on schemes such as the New Deal.

Finally, there is another motivation for such interventions to reduce the incidence of recurrent unemployment in the labour force. The more heavily concentrated the experience of unemployment is on relatively few individuals, then the more the aggregate unemployment rate will exaggerate insiders risk of being unemployed. As a result unemployment is less likely to restrain wage pressure, since insiders will realise there are few individuals capable of replacing them in the unemployment pool. Consequently, policies which are focused on helping this rump of chronically unemployed individuals back into work may also achieve a reduction in the natural rate of unemployment. The fact then that the distribution of unemployment has become less concentrated over time may perhaps explain the surprising lack of wage growth at current low levels of unemployment.

Blanchard (2000) has advanced the hypothesis that it is the concentration of unemployment on the young in particular that enables (older) insiders to push for higher wages even in the face of a high unemployment rate. This argument suggests that policy should be targeted at unemployed youths - if this group offer little or no restraint on wages, then therefore their removal from the unemployment pool should not trigger higher wage growth. However, although it is certainly the case that youths flow into unemployment in larger numbers than older members of the workforce, we do not find that youths account for an overwhelming fraction of days of unemployment in the JUVOS panel. Our data do not therefore support Blanchard's hypothesis, and we would not argue for targeting of resources on youth unemployment (at the expense of others) on the basis that it will achieve a significant reduction in the natural rate.

In the Chapter 5 of the thesis we focus on a possible cause of the concentration of unemployment on certain individuals that we observe. If, as many believe, prolonged exposure to unemployment damages an individual by stigmatising them in the eyes of potential employers, or eroding their human capital or psychological well-being then it may be that when an individual escapes unemployment the slate is not wiped clean. Our results lend credence to this hypothesis; we find evidence of significant scarring effects in unemployment, so that those individuals who suffered longer spells of unemployment in the past tend to have lower hazard rates out of unemployment than otherwise identical individuals operating in identical labour markets.

The existence of these significant scarring effects in unemployment provide further justification for the type of active labour market policies discussed above, which aim to subsidise the long-term unemployed back into work. The premise that underlines schemes like the New Deal is that prolonged exposure to unemployment wreaks damage on an individual and that without intervention many of the long-term unemployed will remain out-of-work indefinitely. Our analysis suggests that once this damage has been done, the scar remains, and individuals will continue to be affected by the experience into the future. Intervening before erosion to human capital or psychological well-being begins therefore takes on added importance in the presence of these scarring effects.

Of course, the Government cannot intervene to subsidise all the unemployed back into jobs – the deadweight losses involved in subsidising the short-term unemployed back into work would be catastrophically large. However, it is unlikely that for the majority of those who enter unemployment that they are materially affected by the experience of unemployment for some time after their spell begins. Our estimates of the baseline hazard seem to suggest that the conditional probability of exiting unemployment each month does not fall for at least the first year of unemployment, which could be taken as circumstantial evidence that the damage inflicted upon the individual is not significant over this period. However, we would argue that identifying precisely the period over which unemployed individuals become at risk remains a priority for Government, so as to better target its policies.

Governments commit considerable resources to improve the employment prospects of those on the very margins of the labour market. At present active labour market policies such as the New Deal have tended to focus oftentimes on the young. Our results suggest that other things equal youths have a higher exit rate out of unemployment than older members of the workforce. However, we also find that the experience of unemployment leaves a greater scar on youths than older members of the workforce. It may be indeed be that early experiences in the labour market are crucial in determining future outcomes. Our results are therefore broadly supportive of the discrimination in policy towards the young. Resources spent in fighting the worst excesses of youth unemployment may indeed yield large benefit savings over the rest of these individual's lifetimes when the scarring effects of unemployment are severe.

Taken in the round then our conclusions are as follows. At the macro level demographic change plays a small yet significant role in explaining the fall in the unemployment rate, and implicitly the natural rate. Shifts in the age composition of the population drive the size of the skill shifts in labour supply, which in turn have affected the degree of wage inequality and the level of the aggregate unemployment rate. At the micro level, there are indeed significant differences in the distribution of unemployment across age-groups in the population: a larger fraction of the youth population will have some experience of unemployment, but their spells are typically shorter in duration, and by no means do they account for the majority of days lost to unemployment. However, for those youths who do have long experiences of unemployment, the scars those experiences leave behind may be more serious than for older members of the population.

CHAPTER 7

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