Wage Dynamics and Minimum Wages in Britain

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Abstract

After a long period of relative stability, wage differentials in the UK have risen sharply since the late 1970s. Wage inequality is now greater than it was 100 years ago. This increase in cross sectional inequality has been widely documented. The aim of the first part of thesis is to establish the degree to which earnings differences are permanent or transitory and to study the level of mobility of individuals within the earnings distribution. Using data from the New Earnings Survey (1975-1994) and the British Household Panel Survey (1991-1994), I provide an analysis of the dynamics of the earnings process and investigate whether this has changed over time.

An examination of the covariance structure of male earnings points to the existence of a permanent component, that increases with age, and a highly persistent transitory component. Both of these components rise over time, each explaining about half of the rise in wage inequality from 1975 to 1994. The investigation into wage mobility suggests considerable persistence in the wage distribution. There is some evidence that mobility has fallen over this time period.

The second part of this thesis studies the economic effects of minimum wages in Britain. Using a panel of Wages Council industries I report evidence showing that increases in the minimum wage compress the wage distribution, but there is no evidence of any adverse employment effects. Meyer and Wise (1983a, 1983b) propose a technique for estimating the employment effects of the minimum wage from data on a single cross section of earnings. I show that, at least for Britain, their approach is highly sensitive to key assumptions about the functional form for wages and the impact of the minimum on the wage distribution. Their technique although appealing on an intuitive level does not provide robust results in practice.

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DECLARATION

1. No part of this thesis has been presented to any University for any degree.

2. Two Chapters of this thesis were undertaken as joint work with my supervisor, Professor Stephen Machin, and with Dr Alan Manning of the London School of Economics. For the first of these, (chapter 5) "The Effects of Minimum Wages on Employment: Theory and Evidence from Britain", I contributed 33% of the work. For the second, (chapter 6) "Estimating the Effect of Minimum Wages on Employment from the Distribution of Wages: A Critical View", I contributed 50% of the work. A statement from my co-authors confirming this is given below.

I confirm the above declaration referring to joint work carried out with Richard Dickens.

S. Machin

Stephen Machin

I confirm the above declaration referring to joint work carried out with Richard Dickens.

Alan Manning

Alan Manning

To my Mum and Dad

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Chapter 1 - Introduction

One of the most alarming changes in the UK labour market over the last couple of decades has been the sharp rise in wage inequality since the late 1970s. After a long period of relative stability, differentials have risen so that wage inequality is now greater than it was 100 years ago (Machin, 1996a). Differences between individuals have risen at all points in the wage distribution, so that the relative position of workers at the bottom of the distribution has deteriorated markedly. The UK has not been alone in this experience. A number of other OECD countries have also experienced increases in wage dispersion, but the UK and the US stand out for the sheer scale of their increases (OECD, 1993, 1996).

This rise in cross sectional wage inequality has been extensively documented and researched by labour economists. However, little attention has been paid to the important issue concerning the degree of mobility that individuals face within the wage distribution from year to year. Cross section data provide only a snapshot of the earnings distribution at a point in time. The observed wage differences between individuals in a given year may be reflective of long run permanent differences or short run transitory differences. The relative size of these components has potentially important welfare implications concerning the increase in cross sectional inequality. For example, if wage differences are largely transitory, and there is a high level of movement of workers within the wage distribution each period, then inequality is in some sense being averaged out amongst individuals. However, if wage differences are largely permanent, and there is little movement within the wage distribution, then cross section differences are largely reflective of lifetime differences and the welfare implications of the rise in cross sectional wage inequality are likely to be much more serious.

In chapter 2, I provide a review of the literature concerning these important issues. The first section (2.1), summarises the evidence about the rise in cross sectional wage inequality in the UK, setting this in an international context. The evidence shows that the UK and US stand out as the two countries that have experienced massive increases in inequality. Wage differentials have risen both between and within groups of individuals with certain characteristics (i.e. education, age, occupation) with the more highly skilled doing better both in terms of the wage they receive and the employment opportunities open to them. Possible explanations for this phenomena are skill biased technological change or increasing competition due to the growth in world trade. However, there is also evidence that the declining impact of institutions, such as unions and minimum wages, has contributed to the rise in inequality. There are a number of reasons why the rise in wage dispersion is important. Firstly, earnings are a major component of household income. Changes in the distribution of earnings have serious implications for the distribution of income and the incidence of poverty. Secondly, some economists have argued that high levels of inequality are bad for economic efficiency and growth.

The next section (2.2) reviews the evidence on the dynamics of individual earnings. Most of the work in this area has come from the US, however there is a growing literature from the UK as panel data become more widely available. The evidence from the US suggests that a significant proportion of earnings differences are permanent. Furthermore, about half of the rise in wage inequality, since the late 1960s, is explained by a rise in permanent inequality, with mobility rates within the distribution remaining constant or falling. Evidence from the UK is also indicative of the existence of significant permanent differences between individuals. A picture emerges of relatively high persistence, with the bottom of the distribution characterised by individuals cycling between low paid jobs and non-employment. Unfortunately the existing evidence from the UK has not looked at the question of whether earnings dynamics have changed over time. This is a question I address in chapters 3 and 4 of this thesis.

Chapter 3 studies the dynamic structure of individuals' (males) wages in Great Britain between 1975 and 1994. The aim of this chapter is to decompose earnings differences into permanent and transitory components, and to study how these have changed over time. For this analysis I use the New Earnings Survey panel dataset (NES). I split the data into year of birth cohorts and study the auto-covariance structure of hourly earnings for each cohort. This provides the basis for an examination of whether the covariance structure has changed over time, after controlling for life cycle effects. I find that the variances and covariances of earnings increase both over the life cycle and over time. I then go on to fit error component models to the auto-covariances of earnings. The earnings process is adequately fit by a permanent component, modelled as a random walk in age, and a highly persistent transitory component, an ARMA(1,1) process. Time variation is introduced with weights on these components that vary from year to year. I find that nearly half of the rise in wage inequality can be explained by an increase in the permanent component, with the rest explained by an increase in the highly persistent transitory component. A result not dissimilar to that found in the US.

In chapter 4, I go on to study earnings mobility in the NES from 1975-94 for males and females. I have access to the Joint Unemployment and Vacancy Operating Statistics (JUVOS) data, which can be matched into the NES in order to look at individuals' movement into and out of unemployment. This enables an analysis of both mobility within the wage distribution and transitions into and out of employment from different points in the distribution. I append this analysis with an investigation of earnings transitions in the British Household Panel Survey (BHPS) from 1991-1994, and labour market transitions in the Labour Force Survey (LFS) between 1975 and 1994.

The results from looking at decile (and absolute earnings band) transition matrices indicate quite low levels of mobility over the space of one year. Mobility rates are higher when measured over a longer period, but there is still evidence of persistence. Furthermore, mobility rates appeared to have fallen over the time period of my analysis. A potential problem with decile transition matrices is that they only pick up movements across deciles of the wage distribution, but not mobility within the deciles. This problem may be confounded by the rise in inequality, which means the deciles cover a larger range of earnings now than at the beginning of the sample. Consequently, I also present a mobility measure based on each individual's actual percentile ranking in the distribution. There is some evidence that this measure may also have fallen over time, a result that has potentially important welfare consequences.

The second part of this thesis is concerned with the economic effects of minimum wages in the UK. Interest in the impact of minimum wages on earnings and employment has intensified with the publication of a number of recent studies (Card, 1992a, 1992b; Katz and Krueger, 1992; Card and Krueger, 1993; Machin and Manning, 1994; Card and Krueger, 1994) and a much debated book (Card and Krueger, 1995) that have found zero or positive effects of minimum wages on employment. This result is contrary to the conventional view, that arises out of the standard competitive model of the labour market, that minimum wages unambiguously destroy jobs. Prior to the publication of these studies a consensus appeared to have been reached that increases in the minimum wage had small negative effects on employment (Brown, Gilroy and Cohen, 1982). The controversial new results have re-opened the debate about the economic effects of minimum wages.

Interest in the use of a minimum wage as a policy tool to fight low pay and poverty has increased with the huge rise in wage inequality in the US and the UK. Indeed, after years of neglect in the early 1980s the US senate increased the Federal minimum wage in the early 1990s. In addition, there has been a further increase recently and another rise is scheduled for September 1997. Conversely in the UK, the present Conservative government removed the only minimum wage fixing machinery in operation, with the abolition of the Wages Councils in August 1993 (the exception being the Agricultural Wages Boards). However, both the main opposition parties are committed to the introduction of a National minimum wage if they gain power at the next election. As a consequence, the question of the economic effects of the minimum wage has recently received great attention from both economists and policy makers.

In the third section of the next chapter (2.3), I provide an overview of the recent evidence on the economic effects of minimum wages in the US and UK. The evidence from the US confirms that increases in the minimum wage have a positive effect on wages. With the publication of a survey by Brown at al (1982) a consensus seemed to have been arrived at that increases in the minimum had small negative effects on employment. The increases in the Federal and certain States' minimum wages in the early 1990s provided a "natural experiment" for studying the impact of the minimum. Most of the studies conducted in the early 1990s found zero, or even positive, effects on employment. The early evidence in the UK also found conventional negative effects, but some studies did find positive effects. However, more recent analysis has found the unconventional positive effect. The jury is still out on this issue.

In chapter 5, I present an analysis of the economic effects of minimum wages in the UK. As a theoretical background, I present a model of the labour market in which firms potentially have some degree of monopsony power. I then proceed to investigate the effects of the UK Wages Councils using panel data from 1975-1992. I find that minimum wages increase wages at the bottom of the wage distribution. This has the effect of compressing the distribution of wages within the Wages Council industries. However, I can find no evidence that increases in the minimum over this time period had any negative impact on employment. In fact, the results point towards a weak positive effect.

Most of the analyses of the effects of minimum wages on employment use data with some variation in the minimum wage, either over time or regions, to identify the employment effect. However, in an ingenious piece of work, Meyer and Wise (1983a, 1983b) estimate the impact of the minimum on employment using data from a single cross section. Their basic premise is that in the absence of a minimum wage the distribution can be modelled with a certain functional form. When the minimum wage is introduced a number of individuals will lose their jobs, causing a truncation in the wage distribution at the bottom, and a number will have their wages raised to the minimum, causing a spike at the minimum. They present a methodology for estimating this truncated distribution and inferring the employment effect by comparing the predicted size of the truncation with the actual number of individuals at the minimum. Their results suggest that in 1978 the US minimum wage reduced employment for 16-24 year olds by at least 7%.

In chapter 6 of this thesis, I present a critique of the Meyer-Wise study, providing an application of their methodology to British data between 1987 and 1990. I show that their estimation technique is sensitive to a number of key assumptions. In particular, the assumed functional form for the distribution of wages in the absence of minimum wages, and the assumption about how the minimum affects the wage distribution. My conclusions are that, for British data at least, the estimates are not robust and the Meyer-Wise approach can not be applied safely.

In chapter 7, I provide a brief overview of this thesis, with a summary of each chapter. The implications of my results on earnings dynamics and minimum wages are discussed. Possible directions for future work are also considered.

Chapter 2 - A Review of the Literature

The aim of this chapter is to provide a summary of the existing literature that is important to this thesis. In Section 2.1, I review the work that has analysed the rise in cross sectional wage dispersion in the UK, drawing on some international comparisons. Section 2.2 provides a summary of the earnings dynamics literature and section 2.3 looks at the recent evidence on the economic effects of minimum wages.

2.1 Cross Sectional Wage Dispersion in the UK

Most of the empirical work on cross sectional wage and income inequality has originated from the US where dispersion has increased rapidly since the late 1960s. However, the experience of a sharp rise in inequality in the UK over the last couple of decades has led to a burgeoning literature documenting this rise. In this section, I provide a review of the principal papers that have been written on the UK experience and pull out the key points that have emerged from this literature.

2.1.1 The UK Experience in an International Context

Table 2.1, adapting a table from Machin (1996a) and OECD (1996), provides an international comparison of wage inequality between 1973 and 1995.[1] Data on the ratio

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[1] The data for this table are derived from OECD (1993,1996). See Machin (1996a) or OECD (1993,1996) for an international comparison of the changing patterns of wage inequality and low pay.

of the 90th to the 10th percentile of the wage distribution are presented for males and females for eleven OECD countries. We can see that in the 1970s the wage distribution remained stable in most countries with the exception of the US, where inequality has been rising since the late 1960s. The 1980s saw an increase in inequality in a number of countries but by far the greatest increases occurred in the US and the UK. Indeed, the rise in UK wage dispersion in the 1980s was even faster than that in the US. Despite this, the level of inequality in the US remains much higher than in the UK. In many countries inequality was unchanged and in some (notably Germany, France and Italy) it actually fell. The first half of the 1990s has seen a continuation of this trend, with the UK standing out from the other countries, experiencing a continued increase in wage dispersion (See OECD, 1996). Of particular interest is the fact that hourly wage inequality (as measured by the 90/10 ratio) has stopped rising in the US in the early 1990s. However, if one looks at weekly earnings data there is still a rise in inequality over this period.

Although the US and UK have both experienced rapid increases in wage inequality over the last couple of decades, their experiences in terms of real wage growth differ. In the US real wages have fallen sharply at the bottom of the distribution, with real wages for the 10th percentile male falling by 10% between 1985 and 1995 (OECD, 1996). Indeed, wages have fallen for the bottom 80% of males between 1989 and 1995 (Baker and Mishel, 1995). This is in contrast to the experience in the UK where real wages have risen at the bottom of the distribution, albeit at a slower rate than at the middle and the top. Actually, there is some contention over what has happened to the wages of the low paid in the UK. The New Earnings Survey provides evidence that real wages for males at the 10th percentile rose by about 10% over the 1980s. However, Gosling, Machin and Meghir (1996a, 1996b) provide evidence from the Family Expenditure Survey (the only other available survey with a consistent hourly earnings series through the 1980s) that real wages have remained static for the 10th percentile male. The difference may arise due to the undersampling of low paid workers in the NES. Nevertheless, it is clear that wages haven't fallen sharply at the bottom as they have in the US.

Unsurprisingly, the countries with the highest level of inequality also have a high incidence of low pay (as measured by the proportion earning below 50% or 66% of the median). The US has some 25% of full time employees earning below 66% of the median wage, compared to 20% for the UK (OECD, 1996). However, the UK has one of the highest incidences of low pay in Europe (Gregory and Sandoval, 1994).

2.1.2 The UK Experience in More Detail

The experience in the UK of sharply rising wage inequality is perhaps even more striking when one looks at this from a historical perspective. Table 2.2 (also taken from Machin, 1996a) presents time series data on wage dispersion for male manual workers in the UK from 1886 to 1990. This is the only consistent data series available back to the last century. It is evident that throughout most of this century their has been a striking level of stability in the level of wage dispersion as measured by the ratios of the 10th percentile to the median and the 90th percentile to the median. However, since the late 1970s wage dispersion has increased rapidly so that it is now higher than at any other time this century.

A number of papers have decomposed the rise in wage inequality into differences arising between and within groups of individuals with certain characteristics, such as education, occupation, age, etc. The OECD (1993) study presents education differentials for different countries from the late 1960s to the early 1990s. In many countries, including the UK, the education premium fell during the 1970s. However, in the 1980s the premium rose sharply in the UK and US, the two countries with the fastest growth in inequality.

Schmitt (1995) uses the UK General Household Survey between 1974 and 1988 to look at returns to different human capital variables. He estimates Mincer type wage equations for each yearly cross section and looks at the changing returns on different characteristics. This methodology allows him to study changing returns on one variable while controlling for other characteristics. Returns to education fell between the early 1970s and the late 1970s. However, by the late 1980s they had increased again, albeit not up to the level of the early 1970s. This rise in education returns occurred despite an increase in the relative supply of more highly educated workers. Similarly, the wage returns to potential labour market experience fell in the 1970s but rose strongly in the 1980s, surpassing their early 1970s level.

Berman and Machin (1995) study wage differentials by occupation groups for the US and UK. They find that the non-manual/manual wage differential displayed a similar pattern to the education differential, falling in the 1970s but rising quite sharply in the 1980s. Once again, this is despite an increase in the relative employment of non-manual labour throughout the 1970s and 1980s (See Machin, 1996b).

Wage differentials between age groups have also changed over the 1970s and 1980s. Davis (1992) reports an increasing wage premium for older workers over younger workers in both the US and UK. Gosling, Machin and Meghir (1996a, 1996b) also report increasing relative wages for older workers. The early rise in the wage premium could be explained in terms of the "baby boom", where more young workers were entering the labour market. However, since the mid-1980s the increased supply of younger workers stopped but the wage premium for older workers continued to rise.

The evidence for the UK tells us that wage differentials have risen between individuals with different levels of education, skill (as measured by occupation) and experience or age. This has occurred despite an increasing supply of more highly educated and skilled workers. It seems likely that there has been an increase in the relative demand for such workers that has not been sufficiently matched by supply, resulting in higher wage premiums. More highly educated and skilled workers have done relatively better both in terms of the wages they receive and the employment opportunities open to them.

In addition to these clear rises in between group wage differentials there has also been an equally, if not more, important increase in within group dispersion. Machin (1996a), using Family Expenditure Survey data, reports increasing within group standard deviations in the 1980s by education, occupation, public/private sector and age groups. The increase is particularly large for the lower education group. He also reports an increasing dispersion of the residuals from yearly cross section regressions on age and schooling, indicating that a large degree of the rise in dispersion has occurred within these groups. In fact, Schmitt (1995) finds that in addition to the changes in labour market returns between education and experience groups, about 60% of the rise in wage inequality has occurred within these groups between 1974 and 1988.

2.1.3 Possible Explanations for the Rise in Inequality

Perhaps the most common explanation for the large rise in within group wage dispersion is that it is reflective of an increase in demand for unobserved skill or ability. We have seen that there has been an increase in the return to being more highly educated, skilled and experienced, driven by an increase in demand for these qualities. It seems plausible that there would also be a rise in demand for the unmeasured part of an individuals ability. This is not an unreasonable proposition since it is likely that an individuals measured skill attributes are correlated with their unmeasured skill attributes. Given that ability differs within groups of individuals, say amongst university graduates, then we would see a rise in dispersion within these groups.

Another possible explanation put forward by Gosling et al (1996a, 1996b) is that the distribution of pre-labour market skills of new cohorts entering the labour market is becoming wider. In an earlier paper, Gosling, Machin and Meghir (1994), they argue that although the age profile of wages has risen, that this is attributable to cohort differences rather than any increases in the return to experience. In fact they only find experience effects on wages for more educated workers. They also show that the distribution of earnings is larger for younger cohorts entering the labour market. Possible reasons given for this are the successive education reforms that have been introduced in the UK and changes in the quality and distribution of education. One depressing conclusion from their work is that despite the existence of a cross sectional correlation between wages and experience, there is nothing to suggest that the wages of poorly educated young cohorts will rise as they become older and gain experience.

There are two main explanations put forward for the rise in relative demand for more highly skilled workers. These are increased competition in low skill industries due to the growth in world trade and increasing technological change biased towards more highly skilled individuals. Most of the evidence tends to support the technological change hypothesis rather than the trade argument. Berman, Bound and Grilliches (1994) and Machin (1996b) study the skill composition of employment in US and UK manufacturing respectively. If the trade argument were dominant we would expect to see falls in employment in the low skilled industries most affected by foreign competition. However, most of the change in the composition of employment has occurred within industries rather than between industries. In addition, they find that larger changes in the skill composition have occurred in the industries with higher levels of Research & Development, suggesting a link between technology changes and the demand for more skilled workers. This result is backed up by Machin, Ryan and Van Reenen (1996) looking at a panel of manufacturing industries in the UK, the US, Denmark and Sweden between 1973 and 1989.

The changing role of labour market institutions has also been considered as a potential cause of the rise in wage inequality. Gosling and Machin (1995) study the role of falling unionisation on the distribution of wages in the UK. They estimate that around 20% of the rise in inequality can be attributed to the declining importance of unions. Similarly, Bell and Pitt (1996) find that 20% of the rise in the variance of log earnings can be explained by declining union density. Machin and Manning (1994) consider the impact of the declining value of the minimum wage on the wage structure in the Wages Council industries. Their estimates suggest that the erosion of the minimum has increased inequality in these low paying industries by somewhere between 9% and 20%.

2.1.4 Is the Rise in Wage Inequality Important

There are a number of reasons why the rise in cross sectional wage inequality is important. Firstly, labour earnings are the major component of household income and, as such, changes in the distribution of earnings have serious implications for the distribution of income and poverty. Gregg and Machin (1994) consider the common presumption that everybody in society gains from economic growth. They find that the relationship between inequality (and poverty) and aggregate variables such as gross domestic product and unemployment breaks down in the mid-1980s. They interpret this as evidence that the trickle down process stopped in the 1980s with the huge growth in inequality.

Some theorists have also argued that higher inequality may lead to a loss of efficiency and lower economic growth. Persson and Tabellini (1994) develop a theoretical model whereby investment is stifled by higher levels of inequality, leading to lower growth. Murphy, Schleifer and Vishny (1989) have also argued that higher inequality suppresses demand and is therefore bad for economic growth. Indeed, aggregate cross country regressions do display a negative correlation between growth and inequality. One should note that the direction of causation in these correlations is not clear and so should be viewed with some caution.

The importance of the rise in cross sectional wage inequality will also depend on whether it is reflective of a rise in permanent or transitory differences between individuals. If there is a large degree of movement within the wage distribution each year and the rise in inequality is due to a rise in transitory differences then this may be considered less serious. The fact that differences between individuals with relatively permanent characteristics, such as education, have risen suggests that the rise is at least partly reflective of permanent differences. However, we also saw that most of the rise in inequality was occurring within groups of individuals with similar attributes. This could be reflecting increasing transitory differences. In the next section I provide an overview of the existing earnings dynamics literature.

2.2 The Dynamics of Individual Earnings

2.2.1 Evidence from the US

The existing literature on the dynamics of individual wages is predominantly from US data (See Atkinson, Bourgingon and Morrisson (1992) for a survey of the literature on earnings dynamics). Early work concentrated on fitting statistical models to the earnings process. Lillard and Willis (1978) fit an error components model to male earnings from the Panel Study of Income Dynamics (PSID) and find a substantial permanent element, predicting a low degree of mobility. Similarly, Lillard and Weiss (1979) estimate error components models for American scientists for 1960-70, incorporating some time variation with a random growth rate term.

MaCurdy (1982) estimates models of weekly and hourly earnings growth for prime age males from 1967 to 1976, also using the PSID. He finds that a stationary MA(2) process adequately describes the path of wage growth. This is consistent with the presence of a permanent effect in wage levels, since differencing will eliminate any fixed effect or random walk component. Abowd and Card (1989) fit models of the covariance structure of earnings and hours changes for three different US datasets; the PSID from 1969 to 1979, the National Longitudinal Survey of men aged 45-59 from 1966 to 1975 and data from the Seattle and Denver Income Maintenance Experiment between 1971 and 1972. They find that earnings growth is adequately described by a non-stationary bivariate MA(2) process that is compatible with the presence of a permanent effect, possibly a random walk, in earnings levels. Both these studies are consistent with the presence of an permanent individual component of earnings and a serially correlated transitory effect. However, neither of them estimate the relative importance of these components and, perhaps more significantly, neither model the changing structure of these over time.

More recently, Gottshalk and Moffitt (1994,1995) have produced two pieces of work studying permanent and transitory components of annual earnings using the PSID. In the first, Gottschalk and Moffitt (1994), they take white male household heads aged 20 to 59 from 1970 to 1987. They split their sample into two nine year periods, 1970-78 and 1979-87, and for each individual compute average earnings in each of these periods. This they take as their measure of permanent earnings for each period. (They actually use residuals from a regression of log earnings on a quartic in age to remove the effects of systematic life cycle growth on earnings). Transitory earnings are then computed as yearly deviations from the period specific permanent earnings. They then compute the variance of these components and see how they have changed over the period of analysis. The variance of permanent earnings in the first period constitutes two thirds of the total variance in annual earnings. In addition, both the permanent and transitory components have risen by around 42% between the periods, indicating that two thirds of the rise in earnings dispersion is permanent. They also find that earnings are much more transitory for the poorly educated, the young and those at the bottom of the earnings distribution. The rise in the transitory variance has also been more marked for these individuals.

In a later piece of work, Gottschalk and Moffitt (1995) again use the PSID to estimate permanent and transitory components of earnings for white male household heads aged 22 to 59 and study how these have changed over time. Splitting their data into ten year birth cohorts they model the permanent component of earnings as an individual effect (a random walk in age) and the transitory component as a low order serially correlated effect (an ARMA(1,1)). They split their data into cohorts in an attempt to separate out the changes in permanent earnings that arise from life cycle effects from those that arise due to calendar time effects. Hence, they also allow the parameters of their error components model to vary over time. The random walk in age implies that permanent differences between individuals of the same age cohort increase as the cohort grows older. They find that the parameters do increase over time so that the permanent component of earnings explains about 40% of the rise in inequality between 1967 and 1987, the rest being explained by a rise in transitory inequality.

Gottschalk and Moffitt (1995) also look at mobility rates using quintile transition matrices of the earnings distribution. They find that long run mobility fell in the 1970s, as a result of the rise in the permanent variance of earnings, and short run mobility fell in the 1980s, due to the rise in the serially correlated transitory component of earnings. The mobility declines appear to occur in the bottom and top quintiles of the earnings distribution.

In both papers they argue that the literature on earnings inequality has overlooked an important aspect, namely the rise in the instability of earnings. They question the hypothesis that rising inequality is being driven by a rise in the return to unobserved ability. If one thinks of unobserved ability as being a relatively permanent attribute then one would expect this to be reflected in a rise in permanent earnings. The fact that they also find significant increases in transitory dispersion leads them to question this hypothesis. Possible explanations they put forward for the increase in transitory differences are a rise in job shopping and part time work or the decline in union power.

Gittleman and Joyce (1994) use matched cross sections from the Current Population Survey from 1967-91 to estimate patterns of earnings mobility in the US.[2] They find differences across demographic groups in terms of mobility. In particular, the less educated and blacks appear to have less stable earnings. Looking at changes over time, they find little evidence of a changing short run mobility structure.

Buchinsky and Hunt (1996) analyse wage mobility using the National Longitudinal Survey of Youth from 1979 to 1991. This data follows a sample of individuals aged between 14 and 24 in 1979. They use summary inequality measures and study how these change when individuals earnings are averaged over time periods of more than one year. Their results suggest that when dispersion is computed for four year averages of earnings, inequality is reduced by 12-26% in comparison to the one year cross section figure. This is due to the mobility of individuals in the wage distribution each year. Nevertheless, they also report falling mobility over the sample period, as measured by decile transition matrices. This implies that the rise in dispersion of permanent earnings is greater than that of transitory earnings. Consequently, lifetime inequality is actually rising faster than cross sectional inequality.

The evidence from the US suggests a strong permanent component to earnings that increases with age. In addition, the rise in earnings inequality appears to be driven by substantial increases in both permanent and transitory differences in earnings. As a consequence, mobility rates within the distribution are fairly stable or may be falling. This

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[2] The CPS only contains a panel element for one year, since each quarter a fifth of the sample is replaced. As such, Gittleman and Joyce (1994) can only look at one year mobility rates.

is very worrying from a welfare point of view. The increasing cross sectional differences between individuals appear to be reflective of largely permanent differences.

2.2.2 The UK Evidence

The quantity of work on earnings dynamics in the UK has been rather sparse to date. However, with the availability of new panel datasets, research in this area is growing. The early work that was carried out on UK data established a high degree of correlation between individuals' earnings in different time periods (See Creedy and Hart, 1979; Hart, 1976; Department of Employment, 1977; Atkinson et al (1992) provide a summary of this work). This correlation declines at longer lags but is still indicative of a strong permanent component of earnings. For example, the Department of Employment study reports a correlation coefficient of 0.65 between weekly earnings of manual males in 1970 and 1971. This declines to 0.52 when comparing 1970 with 1974.

More recently, Gregory and Elias (1994) use the New Earnings Survey Panel to study transition rates out of the bottom earnings quintile. They find that young males in the bottom quintile in 1976 face a low probability of remaining there by 1984 and 1991. For example, only 8% of males under the age of 25 in the bottom decile in 1976 remain there in 1991. However, exit rates are much lower for older males. Some 35% of low paid males over the age of 35 in 1976 remain low paid in 1991. For females, exit from low pay is much more difficult for all age groups; 30% of low paid females under 25 in 1976 remain low paid in 1991. This rises to 34% for females over the age of 35 in 1976. Gregory and Elias conclude that the experience of low pay is closely linked to life cycle patterns of pay, but that for some individuals low pay is a persistent phenomena. One should note that when looking at transitions Gregory and Elias only look at individuals in the panel in both periods, since their data cannot measure transitions into and out of employment. This is a potential problem if transitions rates into and out of employment are different for individuals at different points in the wage distribution.

Stewart and Swaffield (1996, 1997) use the British Household Panel Survey (BHPS) to study transitions into and out of various low pay thresholds. They report a high degree of persistence of low pay for certain individuals. For example, they find that 44% of low paid males in 1991 remain low paid in 1992. However, of those low paid in both 1991 and 1992, 75% remain low paid in 1993. (Low pay is here defined as one half the median hourly wage.) They also emphasise that the low paid are more likely to move into non-employment than those further up the distribution. As a consequence, restricting attention to those in employment will overstate the probability of moving up the distribution. Those entering employment are more likely to do so into low paid jobs and those who had previously been low paid are more likely to be low paid again when they move back into employment. This, they say, is evidence of a cycle for some individuals of non-employment and low paid jobs.

Sloane and Theodossiou (1996) also use the British Household Panel Survey to study transitions out of low pay between 1991 and 1993. Defining the low paid as those in the bottom third of the earnings distribution, they find that 56% of the low paid in 1991 remain low paid in 1993. Some 15% of the low paid have progressed into higher paying jobs, while 29% have moved into other labour market states. Unsurprisingly, they find that women are more likely to be low paid and also find it harder to escape low pay. They also find important life cycle effects in the progression out of low pay.

A recent study by Ball and Marland (1996) (See also Nicholls, Ball and Marland,

1997) uses National Insurance Contributions data to look at long run earnings mobility between 1978/79 and 1993/94, taking a cohort of males aged between 25 and 44 in January 1978. They have information on annual earnings and employment/benefit status in 1978/79 and 1993/94. Their results paint a picture of a high degree of persistence in terms of earnings and dependency on benefits. Taking those aged 25 to 34 in 1978, of those in the bottom decile in 1978/79 only 13% are in the bottom decile in 1993/94. However, 28% have moved onto either a full or partial years benefit and 8% have moved into self employment. Of those that do move up the distribution, only about 35% get beyond the median. It seems likely that much of this progression is related to the normal life cycle increase in earnings. When they look at the 35 to 44 year olds they find more persistence with 19% remaining in the bottom decile and 41% moving onto benefits. Of these older males that have moved up the distribution, only 22% have moved above the median. Also striking in their analysis is the numbers of individuals who remain on benefits. Some 64% of the 25 to 34 year olds on benefit in 1978/79 are on benefit in 1993/94. This rises to a startling 78% for the older males. Their analysis seems to confirm the pattern of individuals caught in a trap of low paid jobs and non-employment.

A drawback with much of the UK analysis is that it has not addressed the question of whether there have been changes in the dynamics of the earnings process. However, in an ingenious piece of work, Blundell and Preston (1995a, 1995b) develop an intertemporal model of consumption expenditure. They show that permanent and transitory income inequality can be identified from individual level cross section data on consumption and income. The results of their analysis of Family Expenditure Survey Data from 1970-92 suggest a steady increase in permanent inequality over this period coupled with a sharp rise in transitory inequality in the later part of the 1980s.

Jarvis and Jenkins (1996) also study household income mobility using the BHPS from 1991 to 1994. They find evidence of considerable income mobility over the space of a year, but that very few households experience long range mobility. So, although only 40% of households remain in the same decile from one year to the next, over 70% remain in the same or neighbouring decile. Interestingly, they find more income mobility than earnings mobility, a result at odds with the view that the benefit system dampens transitory changes in income. Looking at transitions out of low income (defined as half average income in 1991) they find considerable movement out of this state from one year to the next, with 50% moving up the income distribution. However, 30% of those that do escape experience low income again within another year. They also find that a small group of households are persistently in a state of low income in all years.

2.2.3 Recent Evidence from other Countries

There are also a number of studies of earnings dynamics from other countries. The OECD (1996) provide an analysis of earnings mobility between 1986 and 1991 in eight OECD countries; the US, the UK, Germany, France, Italy, Denmark, Finland and Sweden. Table 2.3 presents some of the summary measures of mobility from this study. It appears that there are similar levels of mobility in these countries both in terms of the number of individuals moving quintiles between 1986 and 1991 and the correlation between earnings in the two periods. This suggests that the differences in cross sectional earnings mobility across these countries is probably reflective of the differences in lifetime earnings inequality.

They also study the movement of workers out of low paying jobs and find that the share of workers who are low paid (in the bottom quintile) in 1986 who remain low paid in 1991 varied from 27% in Germany to 44% in Italy. A considerable proportion of the low paid in 1986 have left full time employment by 1991. There is clearly a potential problem with these cross country comparisons arising from the fact that the range of the quintiles will differ widely across these countries since the distribution of earnings is so different. They attempt to remedy this by looking at absolute threshold points for earnings. For example, when they define low pay as 65% of the median, they find transitions out of low pay vary much more widely; from 6% in Denmark to 34% in the UK and US. They also report some evidence that those countries with higher levels of cross sectional earnings inequality have lower levels of upward mobility of low paid workers.

Bingley, Bjorn and Westegard-Nielsen (1995) study wage mobility in Denmark from 1980 to 1990, a period when the wage distribution was very stable. They report that some 44% of males in the bottom decile in 1985 remain there one year later, with 40% moving up the distribution and the rest leaving employment for other states. 71% of males in the top decile in 1985 retain their position and of those that do move down the wage distribution, 62% fall only to the next decile. Mobility is longer over four years with just over 20% of males in the bottom decile in 1980 remaining there in 1984. However, a further 20% of these have left the sample or gone into non-employment. They estimate an econometric model of the determinants of wage mobility. Their results suggest that mobility is associated with the normal life cycle growth in earnings. Spells of unemployment reduce upward wage mobility as do changes in industry and occupation, although there is clearly a potential for endogeneity bias here.

Bigard, Guillotin, Lucifora and Rappelli (1996) (See also Lucifora, 1997) compare mobility in France and Italy using longitudinal data from Administrative Social Security

Records. They employ a decile transition approach to study mobility between 1974 and 1988. They report a higher level of mobility in France than Italy and find more immobility at higher points in the wage distribution. They also find that mobility is related to the normal life cycle progression of individuals in the wage distribution and that mobility is reduced in periods of lower unemployment.

2.3 The Economic Effects of Minimum Wages

Minimum wages were introduced in the UK in 1909 with the formation of the Wages Councils, which set minimum rates of pay in a number of low paying industries. Wages Councils were initially set up in small manufacturing industries but coverage increased to a peak in the mid 1960s, encompassing the growing service sector. However, with the growth of collective bargaining the influence of the Wages Councils diminished and they were abolished in 1993 by a Conservative Government opposed to any form of wage fixing. The UK has never had a National Minimum wage but both the Labour and Liberal Parties are committed to introducing one if they win the next election. In the US, minimum wages were introduced in Massachusetts in 1912 to protect the pay of women and minors in a number of industries. A number of other states followed suit but these were challenged and declared unconstitutional. However, this ruling was overturned and under the Fair Labor Standards Act of 1938 a Federal minimum wage was introduced.

Ever since the advent of minimum wages economists have debated their relative merits and drawbacks. Minimum wages are designed to protect the low paid by providing a subsistence level of pay, however many economists argue that they destroy jobs and do more harm than good to the people they are supposed to be helping. This question has motivated many studies into the impact of minimum pay rates on wages and employment. Much of this work has come from the US and has taken the form of time series studies on employment and unemployment.

2.3.1 The Effects of Minimum Wages in the US

Brown, Gilroy and Cohen (1982) provide a comprehensive survey of the theoretical and empirical literature on the impact of minimum wages in the US. The standard competitive model of the labour market predicts that minimum wages reduce employment by pricing workers out of jobs. This viewpoint seems to be borne out by the work reviewed by Brown et al (1982). Most of the studies looked at the effect of variations in the minimum over time on teenage (16-19 years) employment rates. Some of the studies have looked at the impact on young adults (20-24 years) and a number have looked at all adults. They find that minimum wages raise the wage of covered workers up to the minimum and has some knock on effects further up the distribution of wages. They conclude that the weight of evidence points to a fairly small negative impact on teenage employment; a 10% increase in the minimum wage reducing employment by 1-3%. For young adults the effects are still negative but smaller in absolute terms, while for all adults the impact is uncertain, although this conclusion is based on a smaller number of studies.

Brown et al (1982) also review the cross section studies of the impact of minimum wages. These generally take the form of cross state studies that attempt to identify the employment effect from the different level of minimum and average wages across states. Because most of the variation comes from differences in average wages across states there is an issue with these studies about whether they are correctly identifying minimum wage effects rather than average wage effects.

However, Meyer and Wise (1983a, 1983b) propose an ingenious methodology for inferring employment effects of the minimum from data on a single cross section of wages. Using individual data they estimate a parametric distribution for wages from the top part of the wage distribution, that is from those individuals unaffected by the minimum. They then predict how many individuals should be in the bottom part of the distribution and compare this to the actual number present. This gives them their measured employment effect. They find that in 1978 the minimum reduced employment of 16-24 year olds by at least 7%. Although this seems an ingenious idea there are a number of serious flaws in their study. Dickens, Machin and Manning (1994) (and Chapter 6 of this thesis) criticises their study by showing how the estimated employment effects are highly sensitive to certain key assumptions.

With the publication of Brown et al (1982) a consensus seemed to have been reached that minimum wages in the US had small negative effects on employment at the levels they had conventionally been set at. However, beginning in the late 1980s, after a couple of decades of neglect, there were a number of sharp increases in minimum wages at both a State and Federal level. In 1988, the Californian State minimum was raised from \$3.35/hour to \$4.25/hour, a 27% increase in the minimum. In April 1990 the Federal minimum, which had been fixed at \$3.35/hour since January 1981, was increased to \$3.80/hour. In April 1991, it was increased further to \$4.25/hour. A year later the New Jersey minimum was increased from \$4.25/hour to \$5.05/hour. These relatively large increases provided an opportunity for economists to study the employment effects in what was probably as close as one will find to a natural experiment in economics. Most of this work was carried out by David Card, Larry Katz and Alan Krueger and is collected in the book by Card and Krueger (1995). The results of these studies cast doubt on the conventional view that minimum wages destroy jobs and have re-opened the arguments about the economic effects of minimum wages which are still raging today.

The first of these studies Card (1992a), (See also Card and Krueger, 1995) analysed the impact of the July 1988 increase in the Californian minimum wage. He estimates that the increase in the minimum raised the average wages of teenagers in California by 10% and the average wage in the Retail sector by 5%. Comparing employment levels in California with the rest of the US, he finds no adverse employment effects. Surprisingly, he finds a small positive effect on teenage employment and a similar trend in Retail employment as in comparable neighbouring States.

Card (1992b) and Card and Krueger (1995) provide a comparison of the impact of the 1990 and 1991 increases in the Federal minimum on cross State changes in wages and employment. They take advantage of the fact that wage rates vary a great deal across States and consequently the importance of a Federal minimum varies from State to State. In low wage States the proportion of workers effected by the increase in the minimum will be far higher than in high wage States. One would expect to see more severe employment consequences from the increase in the minimum in these low wage States. Their results indicate that teenage wages rose more in States with a higher proportion of effected workers. However, they found no evidence that teenage employment rates were lowered more in the highly affected States. They also use data from the retail sector and again find no adverse employment effects across States. In fact, they report that retail sector employment increased more rapidly in States where the Federal increase in the minimum raised wages the most.

Katz and Krueger (1992) analyse the effect of the April 1991 Federal minimum wage increase on the fast food industry in Texas. They carried out a telephone survey of Burger King, Wendy's and Kentucky Fried Chicken restaurants in both December 1990 and July-August 1991 collecting information on starting wages and employment by establishment. They found that those firms that had to raise wages the most to comply with the new minimum were more likely to increase employment. Defining a variable called the wage gap as the proportional increase in the starting wage required to comply with the minimum they find this is positively correlated with changes in employment. A finding that is at odds with the predictions from the standard competitive model of the labour market.

Perhaps the most important and controversial piece of new work on the effects of minimum wages is that by Card and Krueger (1994, 1995) looking at the impact of the State increase in the New Jersey minimum in April 1992. They carried out a telephone survey of fast food restaurants in New Jersey in February-March 1992 and then 10 months later in November-December 1992. They also surveyed restaurants in Pennsylvania, where the minimum was unchanged, to act as a control group. Their results show that employment actually increased in New Jersey as compared to Pennsylvania between the two surveys. In addition, employment in those New Jersey establishments that had to raise their wages the most to comply with the new law rose relative to those unaffected by the minimum. This result is similar to that found in the Texas study and is contrary to the conventional thinking about the economic effects of minimum wages.

Card and Krueger (1995) also carry out a re-evaluation of the time series studies of the impact of the minimum wage on teenage employment. Most of the time series studies were carried out on data up to the late 1970s. They supplement the earlier data and re-estimate the relationship for the years 1954 to 1993. Their results for this period suggest an insignificant negative effect of the minimum wage on teenage employment. This could be partially explained by the fact that they are now including a time period when the value of the minimum wage was falling and had perhaps become less important in determining employment.

There is one piece of recent work that does find the conventional negative employment effect. Neumark and Wascher (1992) use data on employment and minimum wages from a panel of States from 1973-1989. They find results similar to those from the time series studies reviewed in Brown et al (1982), that a 10% increase in the minimum reduces teenage (16-19 years) employment by 1-2% and reduces the employment of young adults (16-24 years) by 1.5-2%. They also find that States that utilise the youth subminimum wage have higher levels of employment. However, this study has been criticised by Card, Katz and Krueger (1994) who point out that there are problems with the treatment of teenagers enrolled in school, the construction of the minimum wage variable and the level of utilisation of the youth subminimum. When the equation is re-specified they find that Neumark and Wascher's data show no significant effect of minimum wages on employment. However, Neumark and Wascher (1994) have defended their work and claim that it stands up to the criticisms of Card, Katz and Krueger.

This collection of recent studies that find zero or positive effects of minimum wages on employment has cast some doubt on the conventional view that minimum wages destroy jobs. Card and Krueger's book has provoked a strong reaction from many economists and commentators who find the results difficult to reconcile with their theoretical priors. The following quote from the Wall Street Journal perhaps provides a flavour of these criticisms:

"No self respecting economist would claim that increases in the minimum wage increase employment. Such a claim, if seriously advanced, becomes equivalent to a denial that there is even minimum scientific content in economics and that, in consequence, economists can do nothing but write as advocates for ideological interests. Fortunately, only a handful of economists are willing to throw over the teaching of two centuries; we have not yet become a bevy of camp-following whores"

- James Buchanan, The Wall Street Journal

A number of leading labour economists have also criticised the work in a review symposium edited by Ehrenberg (1995). Arguments against the book have ranged from questions about the ability of the impact studies to pick up long run effects of the minimum wage increase (Hamermesh, 1995) to those questioning the survey methodology (Welch, 1995).

Perhaps the most robust criticism came from Neumark and Wascher (1995a) who used payroll data on restaurants in New Jersey and Pennsylvania supplied by the Employment Policies Institute, an employers' organisation representing the retail and restaurant trade. They argued that this data is more reliable than the survey data collected by Card and Krueger. An analysis of this data found negative effects of the minimum wage hike on employment, but these were not quite significant at conventional statistical levels. Further analysis by Neumark and Wascher (1995b, 1995c, 1996), using their own sample of restaurants in New Jersey and Pennsylvania found a zero impact on employment. See Schmitt (1996) for a review of these studies. He questions the validity of the Employment Policies Institute data and also their impartiality, which even Neumark and Wascher question. This is where the debate in the US has reached at this stage, with the bulk of the recent evidence suggesting no employment effects of the recent minimum wage increases. However, the arguments are set to continue as the US Senate increase the Federal minimum to \$4.75/hour on 1st October 1996 and has legislated for a further increase to \$5.15/hour on 1st September 1997.

2.3.2 The Evidence from the UK Wages Councils

The debate in the UK about the economic effects of a minimum wage has been nearly as fervent as that in the US. Table 2.4, adapted from Fernie and Metcalf (1996), summarises the evidence on effects of minimum wages on employment from the UK Wages Councils. Lund, Morris, Temple, and Watson (1982) study the impact of minimum wages in agriculture between 1960 and 1980. Estimating a simultaneous model of labour supply and demand, they find that increases in the minimum wage had a small positive effect on employment. Morgan, Patterson and Barrie (1985) study the impact of minimum wages in the clothing industry. Looking at data from 1950-1981 they find that a 10% increase in the product wage reduces employment in the industry by 2.7%. This study has been criticised by Canning and Tarling (1985), who find effects ranging from slightly negative to slightly positive depending on the specification estimated.

Kaufman (1989) provides a study of the impact of minimum wages set by the Wages Councils on employment using data from the 1960s and 1970s. He finds that a 10% increase in the minimum wage reduces employment by 0.6%. However, this study has been criticised by Dickens, Machin and Manning (1993, and Chapter 5 of this thesis). They point out that he has concentrated on small manufacturing industries and ignored several of the large service sector Wages Councils which constitute the bulk of Wages Council employment. He also included two Wages Councils that had been abolished by the time of his study. His methodology is also arguably flawed in that he constrains the effect of the minimum wage to act through the average wage, something which is only true in the competitive model of the labour market.

An analysis of the impact of the Wages Councils in the 1980s was carried out by Machin and Manning (1994). They found that increases in the minimum compressed the wage distribution from below, reducing the dispersion of wages within these sectors. However, they could find no evidence that increases in minimum pay rates were bad for employment and actually found a weakly positive association between increases in the minimum wage and employment. Further work on the Wages Councils was carried out by Dickens, Machin and Manning (1993, and Chapter 5 of this thesis). They found that between 1978 and 1992, increases in the minimum compressed the distribution of wages by increasing wages at the lower deciles of the distribution. They also could find no adverse employment effects. If anything the impact seemed to be positive.

Dickens, Machin, Manning, Metcalf, Wadsworth and Woodland (1995) study the impact of the Agricultural Wages Board from the mid-1950s to the early 1990s. They find that increases in the minimum over this period reduced the dispersion of wages in this sector. On employment, they could find no evidence that increases in the minimum had adverse effects. This seems to hold when the analysis is disaggregated by sex and skill groups.

Dickens and Manning (1995) study the impact of the abolition of the Wages Councils in August 1993 on wages and employment in those sectors covered. They find evidence of a spike in the wage distribution at the minimum wage before abolition, providing evidence that the Wages Councils exerted an effect on wages. This spike is still evident after abolition and is only slightly smaller. However, when one looks at new jobs there is a noticeable decrease in the proportion paid at or near the minimum rate. In addition, pay rates in the covered sectors seem to be rising more slowly than in the rest of the economy after abolition. Turning to employment, they find no evidence that the share of Wages Council sector employment has increased since abolition.

Dolado, Kramarz, Machin, Manning, Margolis and Teulings (1996) study the economic effects of minimum wages in four European countries; France, The Netherlands, Spain and the UK. They find some evidence that minimum wages have reduced employment for young workers. But, they also find evidence that (total) employment is increased by increases in the minimum. They conclude that there is no strong evidence that minimum wages have had an adverse effect on employment. Any effects found, positive or negative, are fairly small.

Taken overall the evidence suggests that the minimum wage does have a impact on wages; raising wages of individuals up to the minimum and having a knock on effect on wages higher than the minimum. Contrary to the predictions of the standard competitive model of the labour market, the bulk of recent evidence can find no significantly negative impact of the minimum on employment. It seems that, at the sort of level the minimum has recently been set, there are no adverse effects on employment opportunities.

Table 2.1

90 - 10 Wage Ratios for selected OECD Countries: 1973-1995

	1973	1980	1990	1995	Definition
Males					
Australia	2.00 (1976)	2.01	2.23	2.38	Gross weekly earnings (FT, non-managerial)
Austria	-	2.19	2.38	2.40 (1994)	Gross daily earnings, 80-10 ratio
Belgium	-	1.90 (1983)	1.92 (1988)	-	Gross average FT income per day, 80-10 ratio
Canada	3.21	3.48 (1981)	3.98	3.77 (1994)	Gross annual earnings (FT all year)
France	3.23	3.25	3.21	-	Gross annual earnings (FT)
Germany	-	2.40 (1983)	2.32	2.24 (1993)	Gross monthly earnings
Italy	-	2.12	2.08 (1987)	-	Net annual earnings (FT all year)
Japan	-	2.59 (1979)	2.84	2.77 (1994)	Monthly scheduled earnings of regular workers
Sweden	2.07	2.15	2.15 (1991)	-	Gross hourly earnings
UK	2.50	2.53	3.21	3.61	Gross hourly earnings
US	4.71 (1975)	4.76	5.63 (1989)	5.56 (1992)	Gross hourly earnings (FT all year)
Females					
Australia	1.78 (1976)	1.83	1.96	2.05	Gross weekly earnings (FT, non-managerial)
Austria	-	3.35	3.51	3.69 (1994)	Gross daily earnings
Belgium	-	1.79 (1983)	1.75 (1989)	-	Gross average FT income per day, 80-10 ratio
Canada	3.09	3.74 (1981)	3.98	4.01 (1994)	Gross annual earnings (FT all year)
France	2.65	2.66	2.51	-	Gross annual earnings (FT)
Germany	-	2.64 (1983)	2.39	2.26 (1993)	Gross monthly earnings
Italy	-	2.22	2.02 (1987)	-	Net annual earnings (FT all year)
Japan	-	2.20 (1979)	2.33	2.24 (1994)	Monthly scheduled earnings of regular workers
Sweden	1.87	1.69	1.82	-	Gross hourly earnings
UK	2.57	2.40	3.02	3.33	Gross hourly earnings
US	4.19 (1975)	3.92	4.89 (1989)	4.86 (1992)	Gross hourly earnings (FT all year)

Notes: 1. Ratios of 90th to the 10th percentile of the relevant wage distribution (defined in final column).
2. Source: Table 1 Machin (1996a) and OECD (1996). Adapted from OECD (1993) and OECD (1996). See OECD (1993,1996) for more detailed definition and data source for each country.

Table 2.2

Wage Inequality in the UK: 1886-1990

Year	10th percentile/median	90th percentile/median
1886	0.69	1.43
1906	0.67	1.57
1938	0.68	1.40
1970	0.67	1.48
1976	0.70	1.45
1979	0.68	1.49
1982	0.68	1.53
1988	0.64	1.57
1990	0.64	1.59

Notes: 1. Male manual full time weekly earnings.
2. Source: Machin (1996a) taken from New Earnings Survey, British Labour Statistics.

Table 2.3
Five Year Earnings Mobility in Selected OECD Countries for Full Time Wage and Salary Workers: 1986-1991

	Correlation in Earnings	Quintile Transitions (1986-91)			Transitions out of low pay (Status in 1991 of those in bottom quintile in 1986)			
	Pearson Correlation Coefficient	Stayed in same quintile (%)	Moved one quintile (%)	Moved two or more quintiles (%)	No longer employed full time (%)	Still in bottom quintile (%)	Moved to second quintile (%)	Moved to quintiles 3-5 (%)
Denmark	0.649	47.6	35.6	16.8	26.7	32.1	20.5	20.7
Finland[a]	0.363	44.1	34.4	21.5	26.3	28.8	20.1	24.8
France[b]	0.760	56.8	32.0	11.2	22.5	35.7	23.8	18.0
Germany	0.793	53.0	35.7	11.2	39.3	27.4	16.8	16.6
Italy[b]	0.785	50.6	35.3	14.1	8.3	43.8	25.1	22.8
Sweden	0.711	52.7	33.8	13.5	27.6	35.5	18.4	18.4
UK[b]	0.705	48.1	36.8	15.1	12.9	35.8	27.8	23.6
US	0.680	48.8	35.5	15.7	41.4	30.6	16.7	11.3

Notes: a) Calculated for 1985-90.
b) Calculations exclude those leaving wage and salary employment altogether.
Source: OECD (1996) Tables 3.5 and 3.9.

Table 2.4
The Effects of the UK Wages Councils on Employment

Author	Sample	Definition of Statutory Minimum Wage (SMW)	Controls	Elasticity of Employment with respect to pay	Remarks
All Wages Council Sectors					
Kaufman (1989)	Small manufacturing & agricultural Wages Councils 1963, 1968, 1971-1979. (Dept of Employment & NES data) n=54-186.	Real statutory minimum wage	See Remarks	-0.06	Cross Section/ Time Series. (I) Estimate Elasticity of Labour Demand wrp average Wage. (ii) Estimate impact of SMW on average wage. (iii) Combine (I) and (ii) for employment elasticity.
Machin and Manning (1994)	10 Main Wages Councils 1979-1990. (NES published data) n=108.	Toughness, Defined as: (SMW/Average Wage)	GDP growth	+0.33. +0.99 Catering +0.60 Retail +0.27 Clothing -0.45 Hairdressing	First Differenced panel estimates of Log(employment) on Log(toughness). Also allow different coefficients on toughness for each sector.
Dickens, Machin and Manning (1993)	12 Main Wages Councils 1978-1992. (NES & Workforce in Employment Survey data) n=162.	Toughness, Defined as: (SMW/Average Wage)	Sales, Time dummies, sectors dummies and lagged effects.	+0.05 to +0.43	First Differenced panel estimates of Log(employment) on Log(toughness). Also study impact on employee hours. Also instrument toughness using lags of minimum wage.

Table 2.4 continued
The Effects of the UK Wages Councils on Employment

Author	Sample	Definition of Statutory Minimum Wage (SMW)	Controls	Elasticity of Employment with respect to pay	Remarks
Sectoral studies of Wages Councils					
Lund et al (1982)	Agriculture 1960-80.	Real statutory minimum wage.	GNP growth Capital stock Land stock Time trend.	+0.03 to +0.45	Simletaneous time series labour supply and demand model.
Morgan et al (1985)	Clothing Industry 1950-81.	Real product statutory minimum wage.	GNP growth Non wage labour costs Capital stock Foreign Competition	Male: -0.15 to -0.30. Female: -0.20. All: -0.27	Simletaneous time series labour supply and demand model.
Canning and Tarling (1985)	Clothing Industry 1950-81.	Real statutory minimum wage.	as Morgan et al (1985).	Overall: -0.05	Criticism of Morgan et al (1985). Different definition of SMW variable.
Dickens et al (1995)	Agriculture 1954-91.	Toughness Defined as: SMW/average wage	as Lund at al (1982)	Males: +0.1 to +0.2. Females: +0.1 to 0.2.	Time series reduced form estimation.

Notes: 1) Adapted from Fernie and Metcalf (1996).

Chapter 3 - The Evolution of Individual Male Earnings in Great Britain: 1975-94

3.1 Introduction

Possibly the most striking phenomenon in the UK labour market over the last couple of decades has been the massive rise in wage inequality. Wage differentials have risen to a degree that pay inequality is now greater than it was in 1886. This increase in cross sectional inequality has been widely documented. (For example see Machin (1996a) or Chapter 2.1 of this thesis for a summary of this literature).[1] Dispersion appears to have risen in almost every measurable dimension. Looking at groups of individuals with different observable characteristics (such as education, experience, age, occupation, etc) one finds an increase in dispersion both between and within these groups.

Despite this comprehensive literature on the cross sectional rise in inequality, little attention has been paid to the evolution of individuals' earnings through time.[2] Observed differences in a cross section of earnings may reflect long run permanent differences or short run transitory differences between individuals. The relative importance of these two

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[1] There is also a large literature on the rise in wage inequality in the US. See Levy and Murnane (1992) for a survey of that literature.

[2] This is largely due to limitations in data availability. However, see Atkinson, Bourguignon and Morrisson (1992) for a cross country survey of the earnings dynamics literature to that date. More recent work on US data which links the changing cross sectional distribution of earnings with changes in dynamics can be found in Gottschalk and Moffitt (1994, 1995), Gittleman and Joyce (1994) and Buchinsky and Hunt (1996). Recent work on UK data includes: Ball and Marland (1996), Gregory and Elias (1994) and Stewart and Swaffield (1996, 1997). See Chapter 2.2 of this thesis for a review of the recent literature.

components has implications for the way in which we view the rise in inequality and may throw some light onto the likely causes of increased inequality. From a welfare point of view, if earnings dispersion is composed of largely transitory shocks to individuals then inequality is in some sense being averaged out amongst individuals. However, if earnings differences are largely permanent then inequality has much more serious implications for individuals' lifetime welfare. From the point of view of explaining the rise in inequality, an analysis of changes in the permanent and transitory components of earnings may shed some light on the various competing hypotheses. For example, a popular view is that inequality is rising due to skill biased technological change resulting in an increase in the demand for skilled relative to unskilled labour. This manifests itself as a rise in return to both the observed and unobserved component of skill. Since it is likely that the core component of skill is a fairly permanent characteristic of an individual, one would expect this to be reflected in a rise in the permanent component of earnings. Of course, skills may be job specific and as such have transitory effects on wages.

In this chapter I study the pattern of individual male wages over time in Great Britain.[3] In order to assess the relative importance of permanent and transitory components of individual wages I require panel data on individuals with a sufficient time dimension. For this I use the New Earnings Survey Panel Dataset (NESPD) which covers some 180,000 males for the period 1975 to 1994. I divide the data into year of birth cohorts and analyse the auto-covariance structure of hourly earnings for each cohort. The covariances display an increasing pattern over the life cycle and also with time. Defining the permanent element of earnings as a non-mean reverting component and the transitory

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[3] In this chapter I concentrate on earnings dynamics. See Jarvis and Jenkins (1996, 1997) for an analysis of household income dynamics.

element as a serially correlated, mean reverting component I estimate error component models decomposing earnings into these two parts and analysing changes in these over time. The earnings process is adequately fit by a permanent component, modelled as a random walk in age and a highly persistent serially correlated transitory component (an ARMA(1,1)), with weights on these components that vary each year. Nearly half of the rise in inequality can be explained in terms of a rise in the permanent component, with the rest being explained by the persistent transitory effect.

In the next section I present reasons why it is important to study the dynamic process of earnings. Section 3.3 describes the data and the construction of the cohorts. Section 3.4 presents evidence on the auto-covariance structure of hourly earnings by cohort. Section 3.5 fits error components models to this covariance structure, decomposing the rise in dispersion into that accounted for by changes in the permanent and transitory components. Section 3.6 offers some conclusions.

3.2 Why are Earnings Dynamics Important?

Recent cross section studies of wage inequality have established a widening of the pay distribution throughout the 1980s in the UK. This is in contrast to the experience of most other developed countries with the exception of the US, which has also experienced a large increase in wage dispersion. In fact, the rise in dispersion in the UK has been even faster than that in the US over 1980s. Despite this, inequality remains much higher in the US. (See OECD, 1996), Katz, Loveman and Blanchflower, 1995, Machin, 1996a, for international comparisons and Juhn, Murphy and Pierce, 1993, Levy and Murnane, 1992 for a more detailed account of the US experience). This increased dispersion has occurred both between and within groups with the same observable characteristics.[4] So wage differentials between different education, experience and skill groups have increased over the last decade as well as wage dispersion within these groups. Whilst this literature has documented the patterns in the structure of earnings and how they have changed, little attention has been paid to the nature of earnings dynamics and how these may have changed over time. This issue has important implications for the welfare consequences of cross section inequality and may shed some light on the possible causes of the rise in inequality.

Atkinson, Bourguingon and Morrisson (1992) provide an excellent survey of the earnings mobility literature and highlight the limitations of cross sectional analysis of inequality. Repeated snapshots of the distribution of earnings tell us little about the extent of movement up and down the distribution each period. If we are interested in lifetime inequality and welfare then it is important to look at the degree of mobility within the distribution. Cross section snapshots of the distribution may appear the same, but they may be concealing a high level of mobility within each period. It is important from a welfare point of view to understand if people are persistently low paid or whether this is just a transitory state.

The degree of earnings mobility in the labour market may also have important policy implications. For example, the desirability or otherwise of a minimum wage may depend on the persistence of low pay. Many have argued that a minimum wage is an ineffective tool for tackling inequality since most people it affects are in a transitory state of low pay. In the same way, the success of policies that offer employment subsidies to

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[4] This is partly because a single index model of skill does not provide a sufficient characterisation of the rise in wage inequality, Card and Lemieux (1996).

get the unemployed back to work will depend on their degree of progression up the wage distribution. For example, Bingly, Bjorn and Westegard-Nielsen (1995) study mobility in Denmark and find a high level of progression out of low wage jobs. They conclude that policy should be designed to get the unemployed into jobs, albeit low paid ones from where they can progress. One should note that this is in the context of an economy with a stable wage distribution over the period under study.

Atkinson et al (1992) point out that we may be concerned about mobility as a means to some objective, such as equity, or just in its own right. Many people would agree that equality of opportunity is a desirable feature for a society and a more mobile labour market, where jobs and earnings are more evenly shared may be favoured on these grounds. However, as pointed out by Gittleman and Joyce (1994), a high level of mobility may also be seen as creating more instability and a difficulty in retaining one's position in the earnings distribution, thus making mobility less desirable. One person's rise in the distribution is another's fall. So the question of whether more or less mobility is preferred is a normative one with no clear answer.

So far I have been discussing intra-generational mobility, and this is what I concentrate on in this chapter. However, the related question of inter-generational earnings mobility is also very important. When considering the degree of inter-generational mobility, most people are likely to favour higher mobility on the grounds of equality of opportunity. Somehow, the idea that you will inherit the position that your father had in the earnings distribution seems less deserving than that of you retaining the position you have had in the past. Recent work on the degree of inter-generational mobility of earnings has found a high correlation between the earnings and education of children and their fathers, suggesting quite low levels of inter-generational mobility (See

Dearden, Machin and Reed, 1997 or Machin, 1997).[5]

The degree of earnings mobility takes on even more importance in the light of the huge rise in cross sectional earnings dispersion. Given that dispersion in the cross section has risen we may expect there to have been changes in the dynamic structure of earnings. How permanent and transitory components of earnings have changed over time has potentially serious implications for the welfare consequences of the rise in inequality. If the rise in earnings inequality is due to a rise in permanent inequality and mobility has decreased then this can have important implications for individuals' welfare. However, if the rise in earnings inequality is due to an increased dispersion of the transitory component of earnings and mobility has increased then it is not necessarily true that the dispersion of lifetime earnings has increased. Nethertheless, the welfare consequences in this case may be serious if individuals find it difficult to transfer income between periods and smooth short run fluctuations in earnings, due to, for example, imperfect capital markets. A decomposition of the rise in inequality into that due to permanent and transitory components of earnings is essential for gauging the significance of the rise in inequality in welfare terms. Of course, if one believes the permanent income model of consumption then a study of the pattern of consumption inequality should provide some answers to this question.[6]

An analysis of the dynamics of the earnings structure may also shed some light on the possible causes of rising inequality. Juhn, Murphy and Pierce (1993) break down the

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[5] Work from the US has also found that the correlation between consecutive generations' income (Solon, 1992) and earnings (Zimmerman, 1992) is higher than previously thought.

[6] See Cutler and Katz (1992) for this type of analysis on US data and Blundell and Preston (1995a, 1995b) for the UK.

rise in US wage inequality from 1963-89 into within and between group components. Although they do not present an explicit model for wages, their hypothesis can be represented within the following framework. Wages for individual *i* in time period *t* are defined as:

$$W_{it} = b_t X_{it} + U_{it} \tag{3.1}$$

The rise in wage inequality is decomposed into that due to changes in the observable characteristics of the workforce X_{it}, that due to changes in the returns to these observable characteristics b_t, and that due to changes in the unobservable component of earnings U_{it}. They find that about two thirds of the rise in inequality is due to a rise in the unobserved component of earnings. (Schmitt (1995) carries out a similar analysis for Britain and finds that about 60% of the rise in earnings inequality between 1974 and 1988 occurred within education and experience groups).

Juhn et al (1993) interpret their results as being indicative of a rise in the return to unobserved skill brought about by an increase in the demand for skilled relative to unskilled labour. This hypothesis is best presented by further decomposing the unobserved component of wages into unobserved ability, V_{it} and the price of unobserved ability, d_t to give a wage equation of the form:

$$W_{it} = b_t X_{it} + d_t V_{it} \tag{3.2}$$

They assume that the distribution of unobserved ability, V_{it} is unchanged over the sample period. If their hypothesis is correct then the rise in the unobserved component is driven by a rise in d_t, the price of unobserved skill. Given that unobserved skill is generally a permanent asset, one would expect the rise in inequality to be largely composed of a rise in permanent inequality. In order to test their hypothesis, one needs to be able to control for the individual effect in this equation and identify the relative importance of changes in the permanent and transitory components of earnings.

Of course, even when it is possible to decompose the rise in earnings inequality into permanent and transitory components, it is not always clear what interpretation should be given to these. Typically the permanent component is associated with relatively stable individual characteristics such as unobserved education and skill effects. On the other hand the transitory component is identified with what we may believe to be rather more unstable determinants of the rise in earnings dispersion, such as the decline in union power, increased job turnover or the falling value of the minimum wage. However, it is not obvious that this distinction is correct. For example, it is entirely possible that a rise in demand for skilled labour may result in an increase in both the permanent and transitory variances. If skill biased technical change leads to significant changes in the workplace then more workers may behave like workers in new jobs, resulting in greater transitory fluctuations in earnings. (This idea was put forward by Larry Katz in his discussion of Gottschalk and Moffitt (1994)). So although it is interesting to analyse the changes in these two components of earnings, the results of such an exercise may throw up many questions of interpretation regarding possible causes of the rise in inequality.

The purpose of this chapter is to extend the UK work on the dynamics of the earnings process. Before going on to look at these issues I will first provide an outline of the data that I will use for this analysis.

3.3 Data Description

The New Earnings Survey (NES) is an annual survey, conducted in April, of roughly one percent of employees in employment in Great Britain.[7] The sample frame is derived from those with a National Insurance number ending with two particular digits. Employees' workplaces are obtained through the Inland Revenue tax register using current Pay-As-You-Earn (PAYE) tax records and the questionnaire is sent for completion by the employer. About 75% of the responses are collected in this way. The remainder are obtained directly from large public and private organisations who supply details of all employees with the selected National Insurance numbers. This second method of tracing individuals was introduced in 1981 and initially accounted for only a small proportion of individuals in the NES. However, by 1983 this method of collection had been extended so that the proportion obtained directly from their employers had risen to 25%, where it has remained in subsequent years. Employers are required by law to respond to the survey under the Statistics of Trade Act 1947.

Individuals can be matched across years by their National Insurance number to form a panel of employees in employment. The panel is characterised by a constant churning of the sample as new individuals enter the labour market and older ones exit, maintaining the sample size each year. A clear benefit of the NES panel is that if individuals do go missing in a given year they still have the potential of re-entering in later years. I have access to the data for the years 1975 to 1994.

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[7] As such, the sample frame covers about 220,000 individuals. See Gregory and Thompson, 1990, and Office for National Statistics, 1996, for a detailed description of the survey.

Details on individual characteristics are limited,[8] but there is a wealth of detailed information on earnings, hours, industry, occupation, public/private sector and region. Individuals may be missing from the panel for a number of reasons. They may leave the stock of employees for retirement, unemployment, inactivity or self employment. Alternatively, their weekly pay may fall below that required to national insurance contributions, in which case they will not appear on Inland Revenue PAYE records. They may also be untraced if they have left the employer they worked for when the sample frame was collected. Indeed, there is a time lag of about a month between the formation of the sample frame and the questionnaire being sent to the employers.[9]

Because of this, the NES is likely to under sample individuals with weekly earnings which fall below the income tax threshold. This is predominantly a problem for part-time workers, most of whom are women. In the empirical work here I restrict the sample to full time males between the ages of 22 and 59 who are unlikely to be seriously affected by the National Insurance cut off. However, the NES is also likely to under sample employees in small organisations and those who experience high rates of job turnover (See Bell and Ritchie, 1993). This is a potential problem for the sample that I am using here.

In further work, Dickens (1996b) and Chapter 4 of this thesis, I look in more detail at the attrition problems in the NES panel. It is evident that more people go missing

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[8] In particular, the NES does not contain data on individuals' education. However, because my sample is of males aged 22 to 59 their level of education is unlikely to change much once they are in the sample. Therefore, education effects will emerge as a part of the estimated fixed effect in earnings.

[9] In addition, the NES does not cover those in private domestic service, occupational pensioners, non-salaried directors, those working outside Great Britain, people working for spouses or clergymen. As a consequence, anyone moving into these categories will also exit from the panel.

from one year to the next in the NES than in other datasets, such as the Labour Force Survey or the British Household Panel Survey. This seems likely to be a result of the NES undersampling individuals who have changed jobs recently. Perhaps more worrying is the fact that the NES seems to have got better at tracing individuals over time. There is a marked decrease in attrition that corresponds to the introduction of the direct sampling of large organisations. It is likely that the NES has improved in its ability to trace individuals who have changed jobs recently.

Attempting to resolve these attrition problems in the NES is difficult since there is no information on why an individual may have been absent in any given year or any suitable instruments to model this with. Therefore, it is not possible to estimate a structural model of presence or absence in the panel. It is likely that the panel will contain those with more stable employment histories and as a consequence may overstate the permanent element of earnings. However, it is also likely that because the panel now contains more high turnover individuals, any observed rise in the transitory component of earnings may be overstated.[10]

For the empirical analysis, I categorise individuals into age cohorts and follow them through time. This allows an analysis of the covariance structure of individuals' earnings at the same age but at different points in time, forming the basis for an examination of whether the covariance structure has changed over time.[11] The cohorts

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[10] In Dickens (1996b and Chapter 4) I report evidence that those individuals who change jobs from one year to the next are more likely to change their position in the earnings distribution.

[11] The aim is to separate out life cycle effects from time effects and this requires a cohort analysis. Of course, it is impossible to separately identify age, time and cohort effects (See Gosling, Machin and Meghir, 1996a, 1996b) and some assumption has to be made in order to proceed.

are arranged by each year of birth and are tracked over the period 1975 to 1994. So the youngest cohort is aged 22 in 1994 (born in 1972), the next youngest is 22 in 1993 (born in 1971) and so on down to the oldest cohort, aged 59 in 1975 (born in 1916). The cohorts can be present for between 1 and 20 years depending on their date of birth. This gives a total of 57 cohorts.

The earnings measure is the log of real hourly earnings, defined as gross weekly earnings/total weekly hours, deflated by the consumer price index. I exclude individuals whose real hourly earnings are below £0.50/hour or above £100/hour at 1994 prices to reduce the noise in the data. In order to maximise the sample utilised I include every wage observation for each individual over the time period 1975-1994, allowing individuals to re-enter the panel if they exit. This gives an unbalanced panel since many individuals are not present for the full 20 years. The final sample consists of 182,344 men with a total of 1,298,849 individual-year observations.

The structure of the panel is presented in Table 3.1 for selected cohorts and years. The table presents the sample size for a cohort in a given year and the percentage of these that are still in the panel after a given number of years. Taking the cohort born in 1953 as an example; 1679 individuals from this cohort are present in 1975. Some 68 percent of these individuals are still in the panel in 1976, falling to 51 percent in 1994. A large proportion of the attrition appears to occur in the first year. Notice that the percentage present may rise again at longer lags since individuals may re-enter the panel after exit. So although some 56% of this cohort are present after 10 years, this number rises to 57% after 15 years. Also, the size of the cohort may rise over time as new individuals enter the panel. For example, by 1980 there are 1955 individuals in this cohort.

The attrition rate is similar for the other age cohorts. However, when a cohort approaches retirement age the percentage present falls more steeply. For example, for the cohort born in 1933 only 44 percent of those present in 1975 are there 15 years later (i.e. at age 57) compared to 57% and 59% for the cohorts born in 1953 and 1943 respectively. Attrition rates for other starting years exhibit a similar pattern to that described above, but it is evident, as discussed above, that attrition rates have decreased over time. For example, comparing the 1943 cohort in 1980 with the 1953 cohort in 1990 (i.e. at the same age) some 70% are present after one year in 1980, but this has risen to 81% in 1990.

Table 3.2 presents descriptive statistics on the earnings measure for each year for the full sample. Real average hourly earnings have risen by about 31% between 1975 and 1994. However, this wage growth has not been uniform across the distribution of wages. Table 3.2 also includes the 10th, 50th and 90th percentiles of the distribution. We can see that whilst the 10th percentile has risen by some 13% over the period, the median has risen by 31% and the 90th percentile by nearly 50%. It is clear from these figures that there has been a large increase in dispersion since the late 1970s (See Gosling, Machin and Meghir, 1996a, 1996b or Gregg and Machin 1994).[12] However, they tell us nothing about the relative importance of permanent and transitory components of earnings and which is driving the increase in dispersion. I turn to this now.

3.4 The Covariance Structure of Earnings

To begin with, it is informative to have a description of the dynamic nature of

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[12] In fact, Gosling, Machin and Meghir (1996a, 1996b), using the Family Expenditure Survey, find no increase in real hourly earnings for the 10th percentile male over the 1980s. This is at odds with the trends in the NES and is possibly explained by the under-sampling of low wage workers in the NES.

individual earnings. For this purpose, I compute the covariance structure of hourly wages for each cohort described above. Taking each cohort separately I compute the variance and covariances, at differing lag lengths, following the cohort through time. The methodology used to compute these covariances and their corresponding standard errors is similar to that employed by Abowd and Card (1989) and is presented in Appendix 1.

Computing covariance matrices for each cohort gives some 6650 variance and covariance elements, so in order to present the patterns in the data clearly I have taken selected cohorts and auto-covariances. Figure 3.1 presents the variances and covariances of lags 1, 5, 10 and 15 years for selected cohorts born in 1923, 1933, 1943, 1953 and 1963.[13] The first point to notice is that the auto-covariances display different patterns across cohorts. The younger the cohort the faster the rise in the variance and covariances, even over the same time period. In fact, the cohort born in 1923 shows no significant rise in dispersion between 1975 and 1982.

For all cohorts the covariances are positive and quite large in magnitude relative to the variances. They fall quite sharply for the first couple of lags and then appear to asymptote to a long run level at longer lags. This is consistent with the presence of a permanent individual component of earnings and a transitory component that is serially correlated. However, the relative magnitudes of the covariances differ across cohorts. For the older cohorts the ratio of the longer lag covariances to the variances is greater than that for the younger cohorts. While the variances will reflect both permanent and transitory components of earnings, the longer lag covariances will largely reflect the permanent component of earnings. As such, Figure 3.1 indicates that the proportion of

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[13] Information on all cohorts is presented in Figure A3.1 in Appendix 2.

earnings that is accounted for by the permanent component is larger for older cohorts.

It appears that the covariance structure of earnings is changing over the life cycle. There are a number of theoretical reasons that can explain why this may be the case. For example, matching models where information about the individual's ability is revealed on the job imply that wage dispersion within a cohort will rise as the cohort ages and more information is revealed (See Jovanovic, 1979, or Farber and Gibbons, 1996).[14]

To look at these life cycle effects more clearly we need to strip out the time effects that are present in these within cohort covariances. Figure 3.2 presents the auto-covariances by age for the years 1975, 1980, 1985, 1990 and 1994.[15] Each panel of the Figure is takes out time effects, and we are left with life cycle and cohort effects. The variance and covariances of hourly wages rise quite sharply over the life cycle until about age 40, after which they are fairly stable. This is consistent with the presence of a permanent component that rises with age until an individual reaches their forties. Looking across the different panels we can see that the variances and covariances are larger in later years. It is also interesting to note that the life cycle profile appears to be steeper in later years (For example, the variance rises more sharply with age in 1994 than in 1975). This is compatible with increasing returns to the permanent component over time, resulting in a faster rise in dispersion of wages for younger cohorts. It is also apparent that the difference between the variance and longer covariances has increased with time, at a given age. This is an indication that the transitory component of earnings may also have risen

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[14] Of course, there are other models that predict increasing life cycle covariances within a cohort. For example, a model whereby human capital is acquired with age at different rates across individuals will lead to increasing wage dispersion with age.

[15] Information for all years is presented in Figure A3.2 in Appendix 2.

over time.

3.5 Variance Components Models

Having presented some of the trends in the data the aim in this section is to fit a parsimonious model that explains the auto-covariance structure of earnings in all cohorts. We have seen that there is evidence of a strong permanent component of earnings and also a transitory component that may exhibit some degree of serial correlation. Both of these components are likely to have changed in magnitude over the sample period. In addition there appear to be important differences in the covariance structure over the life cycle. The error components model has to be general enough to allow for these patterns in the data. At the same time my interest lies in modelling how the components of earnings have changed over time. The following model of earnings provides a general equation which encompasses many of the features in the data:

$$w_{iat} = \alpha_t \mu_{iat} + \delta_t \nu_{iat} \qquad \textbf{(3.3)}$$

Here w_{iat} are log real hourly earnings for individual i, at age a and time t. The first term, $\alpha_t \mu_{iat}$, is the permanent component of earnings. I will estimate models where the μ_{iat} is a random individual effect, i.e. $\mu_{iat} = \mu_i$ where μ_i is independently distributed across individuals $\mu_i \sim (0,\sigma_\mu^2)$. Alternatively, μ_{iat} may be a random walk term; $\mu_{iat} = \mu_{ia-1t-1} + \pi_{iat}$ where $\pi_{iat} \sim$ iid $(0,\sigma_{\pi a}^2)$ and the variance $\sigma_{\pi a}^2$ may differ with age. α_t is a parameter that allows the permanent effect to vary over time. This may seem a little odd but I use the term permanent here to signify non-mean reverting effects. One could think of the term μ_{iat} as a proxy for ability (or revealed ability) and the term α_t as the return on this ability.

In the same way the transitory effect, $\delta_t v_{iat}$, may exhibit persistence through some serial correlation structure, but this effect is mean reverting. So v_{iat} may be some ARMA process, where the parameters of this process may vary with time. An alternative way of allowing time variation of this effect is to let δ_t vary with time. One may think of measurement error in this model as coming through the transitory component.

The parameters of these models are fit to the covariance structure for all cohorts using minimum distance methods of estimation. For estimation I have dropped those cohorts that are in the sample for less than five periods. This leaves 49 cohorts and a total of 6610 variances and covariances. More details of this estimation procedure are presented in Appendix 1, along with the inference procedures. Essentially, the covariance structure implied by each model is mapped to the observed covariance structure. The sum of the squared distance between these is minimised, weighted by an appropriate weighting matrix. The optimal choice for this weighting matrix is the inverse of the covariance matrix of these covariance elements, i.e. the inverse of the matrix of fourth moments. However, Altonji and Segal (1994) show that this can seriously bias the estimates due to correlation between measurement error in the second and fourth moments. They recommend the use of equally weighted minimum distance, i.e. using an identity matrix as the weighting matrix. I follow their procedure here and weight using an identity matrix.[16]

Before presenting the results I should like to make a point about the expected fit

[16] I also experimented with a weighting matrix that contained in each cell the corresponding number of observations used to compute each autocovariance, as such, giving less weight to covariances of earnings measured at time periods further apart. The results obtained from such an exercise were not qualitatively different from the equally weighted estimates.

of such error components models when such large samples are used to compute the covariance elements. When computing inference statistics of the model's fit with these large samples, any small deviation from the expected distribution will be multiplied up, resulting in rejection of the model at conventional critical values. For this reason, I do not expect to find a model that will not be rejected by standard significance levels. My aim is to find the best fitting among a number of models.

Table 3.3 presents the results of fitting assorted estimates of equation 3 to the 6610 covariance elements, with different restrictions applied to the parameters. Column 1 presents an estimate of the simple canonical permanent-transitory model of earnings, whereby earnings consist of a stationary individual effect and a white noise transitory effect. In terms of equation 3.3 we have:

$$w_{iat} = \mu_i + \epsilon_{it} \tag{3.4}$$

where μ_i is a stationary random effect, $\mu_i \sim (0,\sigma_\mu^2)$ and ϵ_{it} is a white noise error term, $\epsilon_{it} \sim (0,\sigma_\epsilon^2)$. This model implies that the variances and covariances are constant over time and age and that all the covariances are the same at all lags. This simple model is clearly rejected by the large chi-square value in column 1. Nethertheless, the estimated parameters provide some evidence of a permanent individual component of earnings.

Casual observation of the covariances presented in Figures 3.1 and 3.2 suggests three reasons why the simple canonical permanent-transitory model is not a good approximation to the earnings process. Firstly, the covariance elements are not all the same at all lags, secondly the variances and covariances are not stationary through the sample period and thirdly they are not stationary over the life cycle. Column 2 attempts to deal with the first of these problems. I have shown that the covariances appear to diminish as the lag length increases, sharply for the first couple of lags and then more smoothly at longer lags. This is consistent with some serial correlation in the transitory error term. Therefore, column 2 presents a model with an individual random effect plus an ARMA(1,1) transitory effect:

$$w_{iat} = \mu_i + \nu_{it} \tag{3.5}$$

where:

$$\nu_{it} = \rho\nu_{it-1} + \phi_{it} + \theta\phi_{it-1} \tag{3.6}$$

and $\phi_{it} \sim (0,\sigma_\phi^2)$ is a white noise error term. The model fit is somewhat improved with this extension. There is evidence of a strong permanent individual component of earnings as well as a serially correlated transitory component that exhibits a high degree of persistence.

In the next column, I present the model of column 2 but allow the weighting parameters on the permanent and transitory effects to vary each time period in an attempt to fit the non-stationarity in the auto-covariances. (The α's and the δ's are free to vary each year, normalised to one in 1975). Permitting time variation helps to provide a better fit of the data, however the chi-square statistic is still way above conventional critical values.

Column 4 replaces the random effects term with a random walk in age. This implies increasing dispersion over the life cycle as observed in Figure 3.2. The weighting parameters are permitted to vary over time to capture the changing patterns of the permanent and transitory components.

$$w_{iat} = \alpha_t \mu_{iat} + \delta_t \nu_{it} \qquad \textbf{(3.7)}$$

where $\mu_{iat} = \mu_{ia\text{-}1t\text{-}1} + \pi_{iat}$ is the random walk term with initial variance σ^2_μ at age 22 and $\pi_{iat} \sim$ iid $(0,\sigma^2_\pi)$ is the innovation each period. v_{it} is an ARMA(1,1) and the α's and the δ's are allowed to vary freely each year. The random walk in age provides a significant improvement over the random effects model. The variance of the initial shock (σ^2_μ) is estimated to be zero, implying that all the dispersion at age 22 is transitory. As each cohort ages the permanent variance increases by the innovation variance, σ^2_π each year. Notice that the weights of both the permanent and transitory components have risen over the sample period, the transitory weights rising substantially more. Most of the increase in the permanent component occurs in the early 1980s whereas the transitory component increases sharply in the late 1980s. The persistence parameter ρ is very high, implying that over 65% of a shock today will be present in 10 years time.

This random walk model with a constant innovation variance implies that the life cycle profile of the variance of permanent earnings is linear over the whole life cycle. In fact Figure 3.2 displayed a concave profile with the variance rising up until the early 40s after which it remained quite stable. Given this, I experimented with a specification which allowed the innovation variance to be different at each age. The results implied that the variances decreased over the life cycle and after age 41 were zero. Column 5 of the table reports such a specification, also setting the initial variance to zero, as estimated in column 4. The model's fit is greatly improved by this generalisation. (The chi-squared value of 11539 (df = 6550) is more acceptable).

The innovation variance $\sigma^2_{\pi a}$ is largest at the younger ages and declines with age. This pattern indicates that the permanent component of earnings becomes increasingly important over the life cycle, but at a diminishing rate. So the proportion of earnings variation within a cohort accounted for by the permanent component of earnings rises with age up until the early forties, after which it remains at its current level. The model is effectively a random walk in age up to age 41 and after that is a random effects model with the distribution of the effects fixed at that level implied by the random walk. This model is consistent with many matching or human capital models whereby human capital is acquired, or revealed, for the first 20 or so years of labour market experience, after which time differences between individuals stop growing.

The α_t 'price' term on the permanent component also increases over the sample period, indicating a rise in the permanent variance of earnings. Most of this rise occurs in the early 1980s, after which it rises slightly up until 1994. The weights on the transitory component also rise, by a little more than those on the permanent. Notice also that they are quite stable until the mid 1980s, at which point they rise sharply for the rest of the sample period. The persistence parameter remains high in this specification implying 40% of a shock today will remain after 10 years. As such, the transitory component estimated here is behaving very much like a permanent component itself.

The specification estimated here seems to explain the auto-covariance structure of wages within and between cohorts well.[17] However, one may be concerned that the specification should allow for separate cohort effects. It is informative to think about the

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[17] All the analysis presented here is in terms of the autocovariance structure of wage levels. One might believe that constructing the autocovariance structure of first differenced wages would simplify the analysis and provide a clearer split between the permanent and transitory components. However, the levels model I have presented here with changing "price" terms on the permanent and transitory components has some intuitive appeal. First differencing this model would not remove the permanent effect because of the changing "price" term and would actually complicate the model further.

impact cohort effects may have on the patterns in the covariance structures presented above. If one believes that rising dispersion is a result of younger cohorts being more heterogeneous, due to say greater dispersion in the quality of education (Gosling, Machin and Meghir, 1996a, 1996b), then this would serve to flatten the age profiles in Figure 3.2 in any given year, since younger cohorts would enter the labour market with a greater degree of dispersion. In fact the age profiles become steeper over time. This could only happen if the age and time effects were outstripping this rise in cohort dispersion. Alternatively, we might believe that successive cohorts are becoming more homogeneous. This would explain the steepness of the lifecycle profile of the auto-covariances but seems rather unlikely given the large rise in wage dispersion over the sample period.

Figure 3.3 plots the actual and predicted variances from the preferred specification for the cohorts in Figure 3.1. It is clear that this model works pretty well in capturing the age and time profile of the variance structure for these cohorts. The random walk in age gives the rising life cycle dispersion for the first 20 or so years. The increasing weights on this term explain why dispersion within a cohort continues to rise at all ages and also why younger cohorts display a faster rise in dispersion than older ones, over the same age range. Therefore, this estimated specification appears to adequately model the dynamic structure of earnings for these cohorts.

Having estimated a suitable error components models for the earnings process I now want to assess the relative importance of the permanent and transitory components of this process and analyse their contribution to the rise in the total variance over the sample period. To do this I have computed the predicted variances for each year, holding fixed the transitory and permanent weighting parameters in turn to estimate their impact on the total variance. Figure 3.4 presents four different predicted variances for selected cohorts. The first is the predicted variance allowing all the parameters to vary. The second restricts both the permanent (α_t) and transitory weights (δ_t) to their 1975 values, so the only rise in the variance is that which occurs due to the random walk term. The third restricts the permanent weights (α_t) to their 1975 values, giving the transitory effect, and the fourth restricts the transitory weights (δ_t) to their 1975 values, giving the permanent effect.

Looking at the cohort born in 1953 first, one can see that from 1975 to about 1984 all of the rise in the variance is explained by a rise in the permanent variance, after which time its effect is very small. In 1985 the transitory component begins to rise sharply and by 1989 has become slightly more important than the permanent variance. Taking the whole period 1975 to 1994, about 60% of the rise in the variance is explained by a rise in the transitory component, the rest being accounted for by the permanent component. The older cohorts portray a similar pattern, with the rise in the variance from 1975-1994 accounted for by similar increases in the permanent and transitory components. For the youngest cohort (born in 1963), the effect of the transitory component is greater, explaining about 75-80% of the rise in the variance between 1985 and 1994. This is because the proportion of the variance that is permanent is lower for the younger group.

3.6 Summary and Conclusions

In this chapter I have used the New Earnings Survey Panel Dataset to analyse the covariance structure of individual earnings by cohort over the period 1975 to 1994. The results of this analysis of the earnings process imply that an individual's earnings contain a highly permanent element, modelled by a random walk in age. As such, the proportion of earnings variation accounted for by this permanent element increases with age within a cohort. In addition, the rise in earnings inequality since the late 1970s appears to be driven by similar increases in both the permanent and transitory elements of earnings, the transitory component explaining slightly more. It is interesting to note that although the variance of earnings rises smoothly over the 1980s, the components of variance display different trends. The permanent component increases for the most part in the early 1980s, whereas the rise in the transitory element occurs later in the decade. This finding is consistent with the results of Blundell and Preston (1995a, 1995b) who use a different methodology based on cross sectional differences in consumption and income inequality described above.

Trying to draw any implications from these results regarding possible causes of the rise in inequality is difficult. The substantial rise in the permanent component is consistent with increasing returns to skill. Interpretation of the rise in the transitory component is less clear. Because of the persistence this exhibits, it is not obvious what this term is picking up. It could be some combination of rising skill demand, decentralisation of bargaining, the decline in the value of the minimum wage or the end of the social contract.

However, these results do imply that from a welfare point of view one should be worried about both the level of earnings inequality in the UK and the increase in this over the last decade or so. The observed cross sectional dispersion in earnings reflects largely persistent differences between individuals. Against the backdrop of rising inequality these permanent differences have become greater over the last twenty years.

**Table 3.1: Structure of the Panel by Cohort -
Percent of cohort present after given number of years**

Cohort born 1963							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1985	1754	72	64	60	-	-	-
1990	2087	75	68	-	-	-	-

Cohort born 1953							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1679	68	65	61	56	57	51
1980	1955	69	67	61	59	-	-
1985	1761	76	72	67	-	-	-
1990	1827	81	71	-	-	-	-

Cohort born 1943							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1625	71	68	62	57	59	47
1980	1718	70	67	62	61	-	-
1985	1579	78	73	70	-	-	-
1990	1613	79	66	-	-	-	-

Table 3.1 continued: Stucture of the Panel by Cohort - Percent of cohort present after given number of years

Cohort born 1933							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1628	72	68	64	55	44	-
1980	1693	70	65	59	46	-	-
1985	1421	77	67	58	-	-	-
1990	1165	75	-	-	-	-	-

Cohort born 1923							
Year	Sample size	% of these present after 1 year	% of these present after 3 years	% of these present after 5 years	% of these present after 10 years	% of these present after 15 years	% of these present after 19 years
1975	1779	71	68	63	-	-	-
1980	1724	68	-	-	-	-	-

Source: New Earnings Survey Micro Data.

Table 3.2: Descriptive Statistics of Log Real Hourly Earnings each Year

Year	Average Log Real Hourly Wage	10th Percentile Log Real Hourly Wage	50th Percentile Log Real Hourly Wage	90th Percentile Log Real Hourly Wage	Standard Deviation Log Real Hourly Earnings	Sample Size
1975	1.760	1.363	1.716	2.225	0.356	65224
1976	1.787	1.383	1.738	2.272	0.365	69406
1977	1.711	1.321	1.662	2.182	0.355	69475
1978	1.759	1.353	1.711	2.244	0.362	68862
1979	1.787	1.374	1.746	2.268	0.364	68492
1980	1.794	1.370	1.749	2.286	0.372	68474
1981	1.821	1.376	1.769	2.350	0.393	66736
1982	1.827	1.369	1.780	2.364	0.401	66227
1983	1.872	1.407	1.824	2.426	0.408	65060
1984	1.892	1.412	1.847	2.451	0.415	63862
1985	1.890	1.403	1.846	2.449	0.418	61277
1986	1.938	1.443	1.894	2.507	0.427	63059
1987	1.967	1.453	1.920	2.549	0.442	62536
1988	2.006	1.480	1.959	2.604	0.453	64954
1989	2.011	1.477	1.962	2.621	0.463	64837
1990	2.010	1.467	1.959	2.626	0.466	64801
1991	2.040	1.482	1.993	2.667	0.475	64049
1992	2.060	1.495	2.015	2.702	0.480	61375
1993	2.083	1.504	2.040	2.723	0.490	59751
1994	2.073	1.489	2.030	2.723	0.497	60392

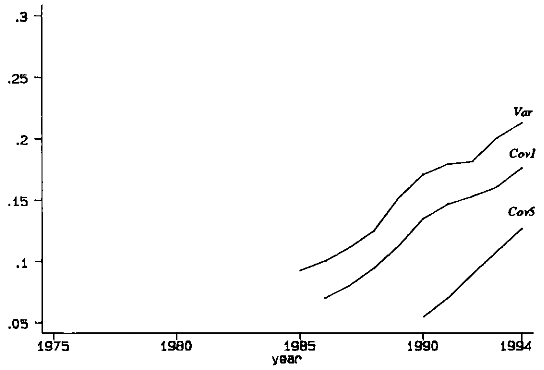
Source: New Earnings Survey Micro Data.

Table 3.3: Error Components Models for Log Real Hourly Earnings

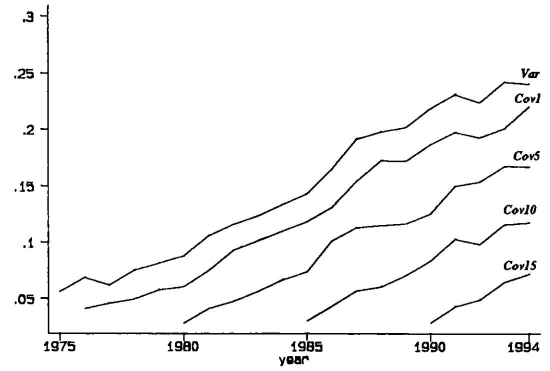
	Random Effect + White Noise	Random Effect + ARMA(1,1)	α_t (Random Effect) + δ_t ARMA(1,1)	α_t (Random Walk) + δ_t ARMA(1,1)	α_t (Random Walk to 41) + δ_t ARMA(1,1)
σ^2_μ	.1295 (.0008)	.0666 (.0056)	.0124 (.0032)	6.6E-10 (.0037)	
$\alpha_{75} = 1$					
α_{76}			1.0987 (.0707)	1.0133 (.0219)	1.0666 (.0248)
α_{77}			1.0796 (.0742)	1.0087 (.0229)	1.0670 (.0269)
α_{78}			0.9281 (.0731)	0.9874 (.0230)	1.0787 (.0279)
α_{79}			0.6862 (.0879)	0.9604 (.0236)	1.0468 (.0291)
α_{80}			0.9052 (.0812)	0.9934 (.0253)	1.1031 (.0320)
α_{81}			1.3060 (.0943)	1.0690 (.0265)	1.2237 (.0342)
α_{82}			1.3429 (.1028)	1.1121 (.0280)	1.2448 (.0357)
α_{83}			1.3313 (.1047)	1.1069 (.0290)	1.2503 (.0377)
α_{84}			1.5323 (.1251)	1.1220 (.0306)	1.2658 (.0384)
α_{85}			1.6139 (.1379)	1.1147 (.0314)	1.2553 (.0393)
α_{86}			1.6369 (.1380)	1.1166 (.0324)	1.2560 (.0398)
α_{87}			1.7531 (.1504)	1.1349 (.0345)	1.2827 (.0412)
α_{88}			1.5157 (.1342)	1.1174 (.0359)	1.2726 (.0415)
α_{89}			1.2688 (.1188)	1.1080 (.0371)	1.2723 (.0417)
α_{90}			1.1851 (.1149)	1.1136 (.0382)	1.2700 (.0420)
α_{91}			1.0742 (.1148)	1.1082 (.0412)	1.2906 (.0436)
α_{92}			1.0138 (.1167)	1.1415 (.0453)	1.3116 (.0453)
α_{93}			0.9664 (.1217)	1.1846 (.0509)	1.3339 (.0483)
α_{94}			0.8495 (.1278)	1.1799 (.0543)	1.3041 (.0497)
ρ		.9441 (.0047)	.9721 (.0012)	.9794 (.0013)	.9567 (.0012)
θ		-.4762 (.0071)	-.5327 (.0057)	-.6367 (.0074)	-.5693 (.0068)
σ^2_ϕ		.0351 (.0003)	.0240 (.0005)	.0199 (.0006)	.0242 (.0011)
σ^2_ϵ	.0429 (.0003)				
$\delta_{75} = 1$					
δ_{76}			1.0283 (.0084)	1.0470 (.0138)	0.9957 (.0194)
δ_{77}			0.9981 (.0089)	0.9979 (.0143)	0.9263 (.0211)
δ_{78}			1.0393 (.0086)	1.0292 (.0151)	0.9446 (.0216)
δ_{79}			1.0552 (.0095)	1.0124 (.0158)	0.9465 (.0239)
δ_{80}			1.0585 (.0098)	1.0403 (.0164)	0.9425 (.0251)
δ_{81}			1.0983 (.0122)	1.1306 (.0171)	0.9813 (.0247)
δ_{82}			1.1125 (.0132)	1.1301 (.0173)	0.9937 (.0257)
δ_{83}			1.1291 (.0135)	1.1534 (.0181)	1.0162 (.0275)
δ_{84}			1.1125 (.0164)	1.1629 (.0185)	1.0240 (.0276)
δ_{85}			1.1061 (.0191)	1.1757 (.0192)	1.0488 (.0288)
δ_{86}			1.1355 (.0201)	1.2197 (.0204)	1.1102 (.0296)
δ_{87}			1.1669 (.0224)	1.2761 (.0221)	1.1702 (.0312)
δ_{88}			1.2307 (.0172)	1.3260 (.0239)	1.2353 (.0322)
δ_{89}			1.3032 (.0144)	1.3839 (.0257)	1.3055 (.0332)
δ_{90}			1.3227 (.0136)	1.3938 (.0263)	1.3244 (.0333)
δ_{91}			1.3756 (.0136)	1.4440 (.0284)	1.3584 (.0348)
δ_{92}			1.4084 (.0139)	1.4551 (.0294)	1.3706 (.0360)
δ_{93}			1.4462 (.0146)	1.4700 (.0310)	1.3963 (.0385)
δ_{94}			1.4787 (.0152)	1.4932 (.0337)	1.4573 (.0405)
σ^2_π				.0025 (.0001)	
$\sigma^2_{\pi 23}$					.0054 (.0005)
$\sigma^2_{\pi 24}$					.0057 (.0006)
$\sigma^2_{\pi 25}$					.0070 (.0006)
$\sigma^2_{\pi 26}$					.0046 (.0006)
$\sigma^2_{\pi 27}$					.0052 (.0006)
$\sigma^2_{\pi 28}$					.0053 (.0006)
$\sigma^2_{\pi 29}$					.0044 (.0006)
$\sigma^2_{\pi 30}$					.0039 (.0006)
$\sigma^2_{\pi 31}$					.0040 (.0006)
$\sigma^2_{\pi 32}$					.0043 (.0007)
$\sigma^2_{\pi 33}$					.0037 (.0007)
$\sigma^2_{\pi 34}$					.0032 (.0007)
$\sigma^2_{\pi 35}$					.0030 (.0008)
$\sigma^2_{\pi 36}$					.0033 (.0008)
$\sigma^2_{\pi 37}$					.0021 (.0008)
$\sigma^2_{\pi 38}$					.0013 (.0008)
$\sigma^2_{\pi 30}$					.0010 (.0008)
$\sigma^2_{\pi 40}$					.0006 (.0008)
$\sigma^2_{\pi 41}$					.0035 (.0012)
$\chi 2$ (DF)	127780 (6608)	84484 (6606)	41959 (6568)	19248 (6567)	11539 (6550)

Figure 3.1: Auto-Covariances for Selected Cohorts: 1975-94

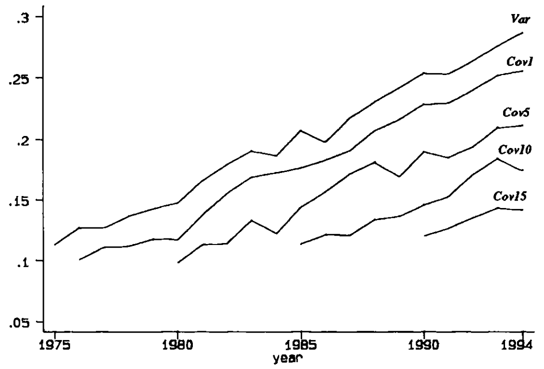
Cohort born 1963



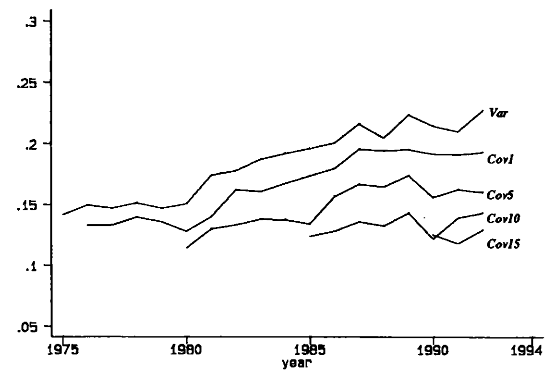
Cohort born 1953



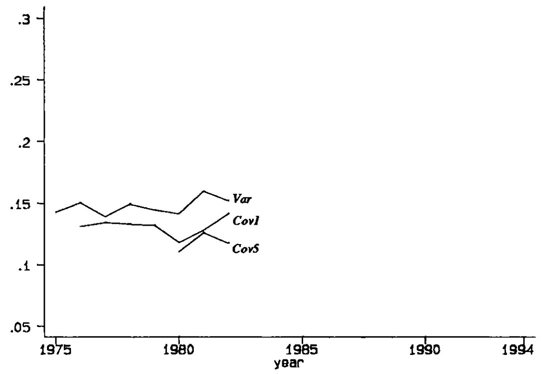
Cohort born 1943



Cohort born 1933

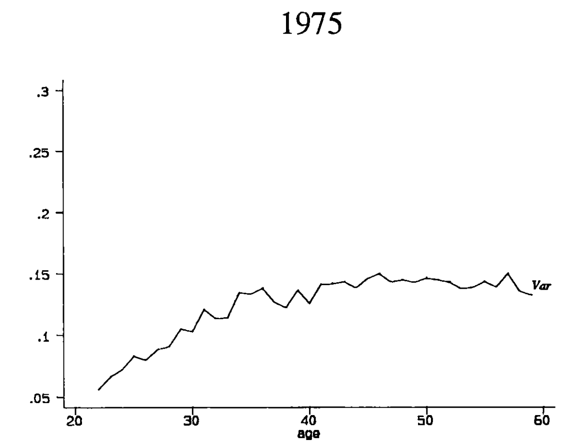


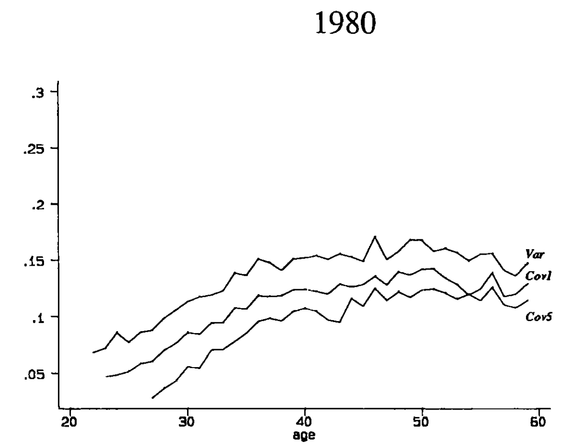
Cohort born 1923

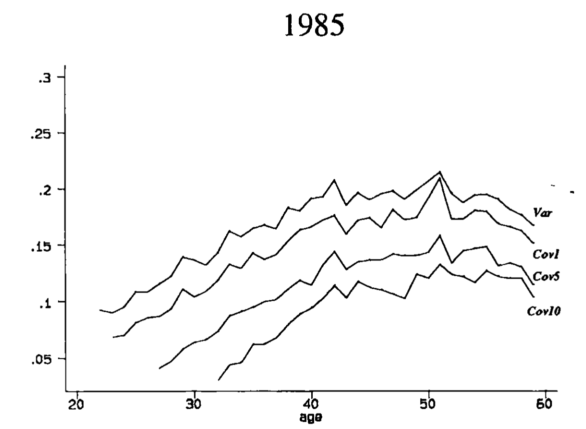


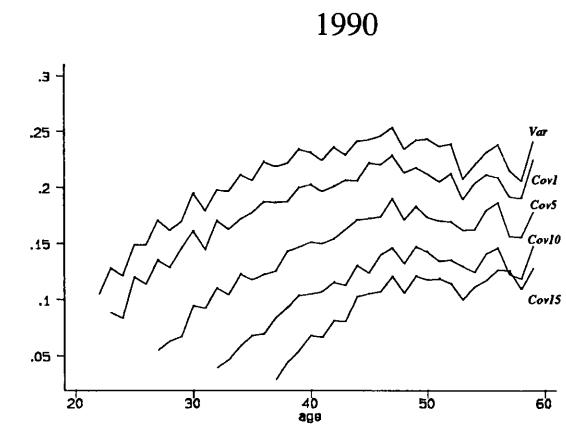
Notes: var - variance(w_t)
cov1 - covariance(w_t,w_{t-1})
cov5 - covariance(w_t,w_{t-5})
cov10 - covariance(w_t,w_{t-10})
cov15 - covariance(w_t,w_{t-15})

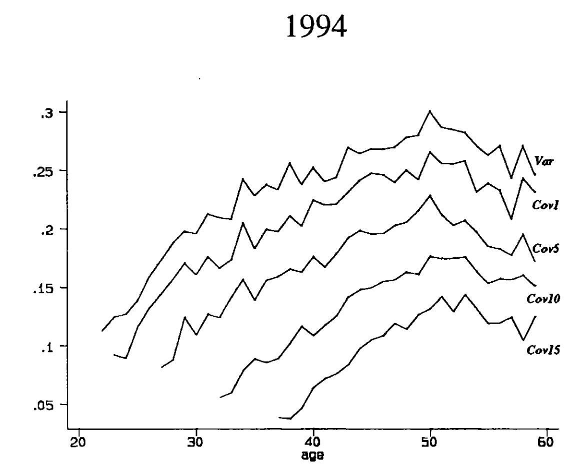
Figure 3.2: The Life Cycle Profile of the Auto-Covariances for Selected Years: Age 22-59











Notes: var - variance(w_t)
cov1 - covariance(w_t,w_{t-1})
cov5 - covariance(w_t,w_{t-5})
cov10 - covariance(w_t,w_{t-10})
cov15 - covariance(w_t,w_{t-15})

Figure 3.3: Actual and Predicted Variances for Selected Cohorts: 1975-94

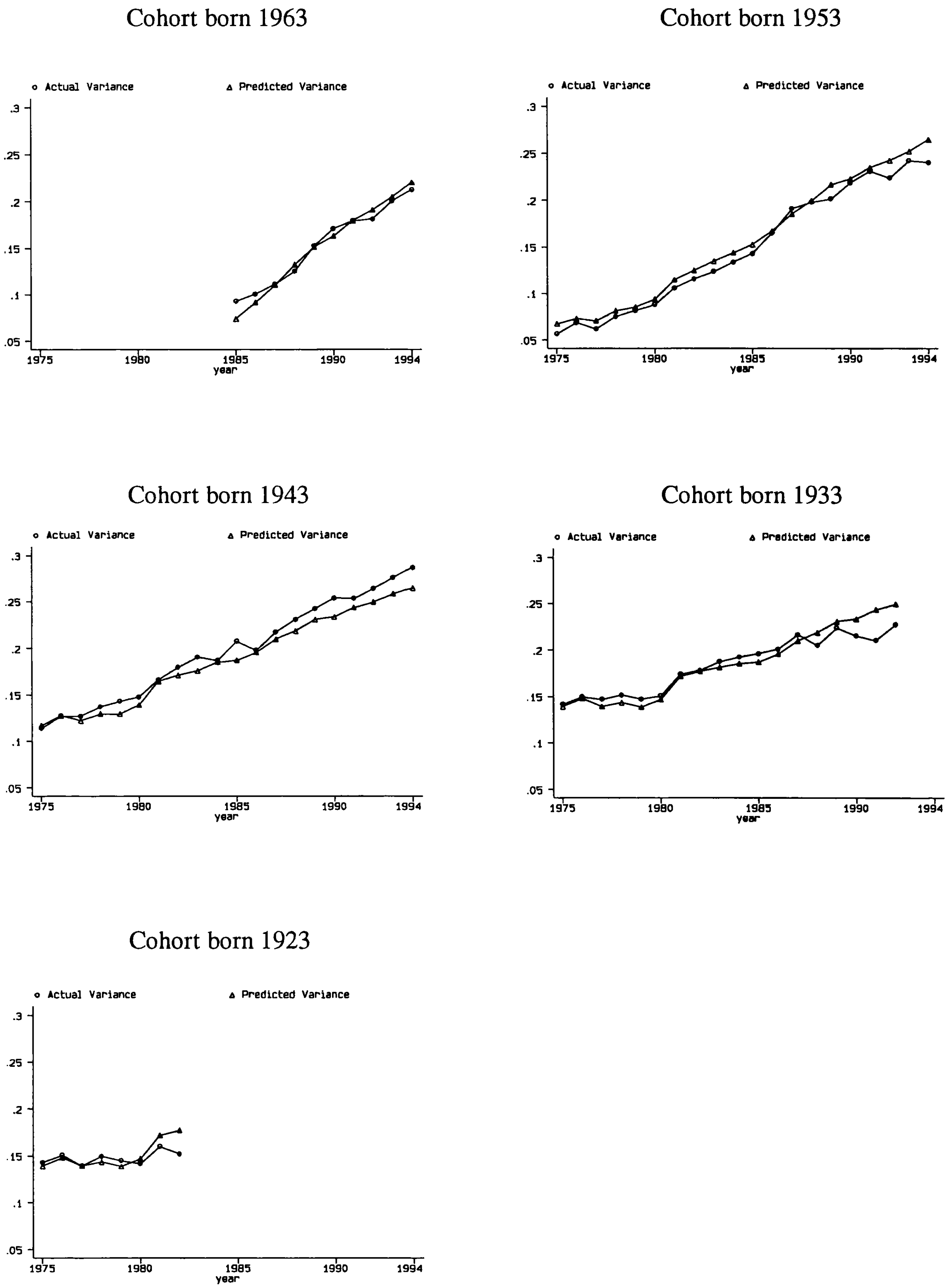
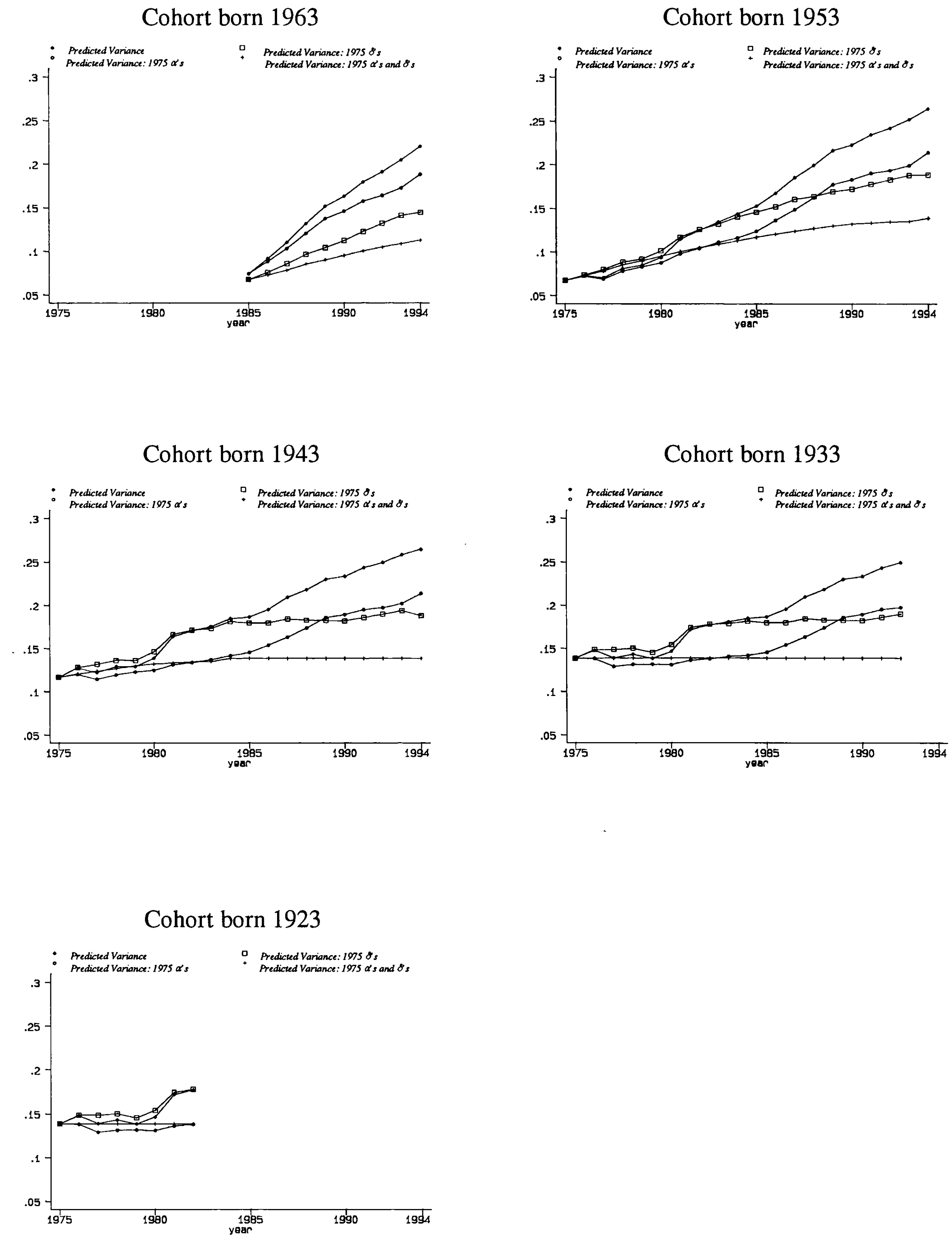


Figure 3.4: Permanent and Transitory Effects on the Predicted Variances for Selected Cohorts: 1975-94



Chapter 4 - Caught in a Trap?

Wage Mobility in Great Britain: 1975-1994

...there is no evidence here that large numbers of people are trapped on low earnings which are falling over time, nor that large numbers of people are trapped permanently in unemployment. The greater inequality seen in snapshot studies has more to do with greater mobility across a range of earnings in and out of work.

Press Release from the Department of Social Security, June 1996

4.1 Introduction

Wage inequality in the UK has risen sharply over the last couple of decades to levels unprecedented this century (See Machin, 1996a or Chapter 2.1 of this thesis for a summary). The relative position of workers at the bottom of the wage distribution has deteriorated markedly. For example, in 1979 the 10th percentile of male earnings was 64% of the median. By 1995 this ratio had fallen to 56% (OECD, 1996). However, despite the widespread acceptance of these facts about pay inequality, there is considerable disagreement over the question of how long individuals remain low paid. The argument heard from some quarters is that there is a large amount of "churning" of individuals within the wage distribution and that very few of those who are low paid today will be low paid in a years time. The quote above comes from a press release that accompanied the Department of Social Security's study of male earnings mobility in the UK by Ball and Marland (1996) (see also Nicholls, Ball and Marland, 1997). The DSS study claims that many of the low paid are in this state temporarily and that many move up the distribution of earnings in later periods. Conversely, the work of Stewart and Swaffield (1996, 1997) finds a high degree of persistence in the earnings distribution, characterised by those at the bottom cycling between low paid jobs and non-employment.

The fact that there is disagreement over the degree of earnings mobility in the UK is perhaps unsurprising given the relative sparsity of work carried out in this area.[1] However, the question of the degree of wage mobility is vitally important from a welfare perspective given the large rise in cross sectional wage inequality that has taken place over the last couple of decades. It is possible, as the DSS purport, that the rise in cross sectional wage inequality has come about from greater transitory fluctuations in earnings with individuals facing more mobility within the earnings distribution. However, it is also possible that the rise in inequality is reflective of increasing permanent differences between individuals, with mobility remaining constant or even falling. The welfare implications in the second case are likely to be much more serious than in the first. If it is the case that individuals face very little prospect of movement within the wage distribution, then the observed increase in cross sectional inequality is reflective of increasing lifetime differences between individuals. (For a more detailed discussion of these issues see Dickens, 1996a, 1997 or Chapter 3.2 of this thesis).

In this chapter I study wage mobility in Great Britain using the New Earnings Survey panel dataset (NES) from 1975 to 1994. The NES is a sample of employees in employment, but I also have access to information on individuals in the NES moving into

[1] See Atkinson, Bourgignon and Morrison (1992) for a survey of the earnings dynamics literature at that date. Since then there has been a considerable surge of interest in this area, largely due to the availability of new panel datasets. See Dickens (1996a, 1997) and Chapter 2.2 of this thesis for a review of the recent work.

and out of claimant unemployment from the Joint Unemployment and Vacancy Operating Statistics dataset (JUVOS). There are some potential problems with the NES in that it undersamples individuals on low weekly earnings and those who have recently changed jobs. Therefore, I also use data from the British Household Panel Survey (BHPS) over the period 1991 to 1994, to provide a comparison. I begin by defining transition matrices in terms of deciles of the wage distribution and looking at how many individuals change decile from one period to the next. I also incorporate information on individuals' labour market status outside of employment. This provides an analysis of the earnings of those who move into or out of unemployment or inactivity. I find a fairly low level of wage mobility over the space of one year with many individuals stuck in the bottom of the wage distribution or moving into unemployment or out of the labour force. One does finds more mobility when looking at time periods of more than one year apart, but there still seems to be significant persistence in earnings and labour market states. Of course, whether one thinks mobility is high or low is a subjective matter. Less subjective is the question of whether mobility has change over time. I find some evidence that mobility rates have fallen over the period of my analysis, with individuals now finding it more difficult to improve their position in the wage distribution.

There is a potential problem measuring mobility in terms of decile transition matrices because they will only pick up mobility between deciles of the wage distribution and not mobility within these deciles. This problem may be confounded by the increase in inequality which means the deciles now cover a wider range of earnings. Given the increase in inequality it may not be surprising that between decile transitions have fallen. Therefore, I also use a mobility measure based on the individuals actual ranking in the distribution in different time periods. I find that this measure has fallen somewhat between

1975 and 1994, with a large fall occurring in the early 1980s.

The structure of this chapter is as follows. In the next section I provide a description of the data used in this analysis. Section 4.3 then provides a mobility analysis based on decile transition matrices, addressing the question of whether mobility rates have changed over time. Section 4.4 then proposes a mobility measure based on individuals actual ranking within the wage distribution. Section 4.5 offers some conclusions.

4.2 Data Description

The New Earnings Survey (NES) is an employer reported survey, conducted in April each year, of employees in employment in Great Britain (See Gregory and Thompson, 1990, and Office for National Statistics, 1996, for a detailed description of the survey). The sample is derived from individuals whose National Insurance number ends in two particular digits. As such, the sample frame covers roughly one percent of all employees, some 220,000 individuals in 1994. Individuals eligible for the survey are traced in two ways. Employees' workplaces are obtained through the Inland Revenue tax register using current Pay-As-You-Earn (PAYE) records and the questionaire is sent for completion by the employer. In 1994, about 75% of the responses were collected this way. The rest are obtained from large organisations who supply details of all employees with the selected National Insurance numbers directly. This second method of tracing employees was first introduced in 1981, when it only accounted for a small proportion of the total responses. However, by 1983 the proportion collected directly had risen to about 25%, where it has remained in subsequent years. Employers are required by law to respond to the survey under the Statistics of Trade Act 1947.

Individuals can be matched across years by their National Insurance number to form a panel of employees in employment. The panel is characterised by a constant churning of the sample as new individuals enter the labour market and older ones exit, maintaining the sample size each year. A clear benefit of the NES panel is that if individuals do go missing in a given year they still have the potential to re-enter in later years. I have access to the data for the years 1975 to 1994.

Details on individual characteristics are limited, but there is a wealth of detailed information on earnings, hours, industry, occupation, sector and region. Individuals may be missing from the panel for a number of reasons. They may leave the stock of employees for retirement, unemployment, inactivity or self employment.[2] Alternatively, their weekly pay may fall below that required to pay national insurance contributions, in which case they will not appear on Inland Revenue records. Another potential source of attrition arises from the time lag between the identification of an individual's employer from tax records and the date the questionaire is sent out for completion by that employer. This is in the region of one month and so a sizable proportion of individuals will have left their employer by the time the questionaire reaches them.

These sampling techniques mean that the NES under samples individuals with weekly earnings below the income tax threshold and also individuals who have a greater propensity to change jobs. The low weekly earnings cut off is predominantly a problem for female part time workers. However, the turnover problem will affect a far broader spectrum of individuals, although it does seem to be more concentrated on younger

[2] In addition, the NES does not cover those in private domestic service, occupational pensioners, non-salaried directors, those working outside Great Britain, people working for spouses or clergymen. As a consequence, anyone moving into these categories will also exit from the panel.

workers (Bell and Ritchie, 1993). The fact that the NES now obtains information directly from large organisations for more individuals suggests that it has got better at tracing these high turnover workers. This is a potential problem for mobility analysis and below I am careful to check the NES against other datasets that do not have these sampling problems.

As a complement to the NES, I also have access to the Joint Unemployment and Vacancy Operating Statistics (JUVOS) data. This data contains information on individuals claiming unemployment related benefit and can be matched to the NES using national insurance numbers. (See Jukes, 1995, for more information on this dataset). The aim is to fill in some of the attrition from the NES and to look at transitions into and out of unemployment. The JUVOS data supplied only contains individuals who also have an NES record. This means that I do not have information on individuals who have never had a spell of employment, a possible problem for younger workers. The JUVOS data is a quarterly dataset, covering the period 1984-94. I take the data from the spring quarter (March-May) which covers the NES sample week in early April to look at year on year transitions.

I also use data from the British Household Panel Survey 1991-94 (BHPS) and the Labour Force Survey 1975-94 (LFS).[3] These are both household datasets and do not suffer from the same sort of sampling problems as the NES. The BHPS is a panel dataset containing labour market and earnings information each year and so can also be used to look at transitions and wage mobility. A problem with the BHPS are its relatively small

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[3] The BHPS data covers Great Britain. See Taylor (1994) for more details on this dataset. The LFS covers Great Britain and Northern Ireland but I have excluded individuals from Northern Ireland to make it consistent with the other data sets.

sample sizes which reduces the precision of the results. In addition, it is possible that the earnings data in the BHPS is less reliable than that in the NES, where the information comes from payroll records and is likely to be more accurate. The LFS is much larger than the BHPS but does not contain panel information on wages. However, it does contain retrospective information on labour market status, and so can be used to study transitions. All the analysis below is carried out separately for males and females. I take individuals between the ages of 22 and 59.

Before looking at the issue of wage mobility I first carried out a comparison of the three datasets in terms of labour market transitions. Table 4.1a presents information for males on transitions into and out of different labour force states between 1993 and 1994 for the NES/JUVOS, the BHPS and the LFS.[4] The Table presents the percentage of those in a given state in 1993 who are in a given state in 1994. From the NES, we can see that about 85% of those in employment in 1993 appear in employment in the NES in 1994. 3.6% move into unemployment and 11% are missing from the NES/JUVOS data altogether. For both the BHPS and the LFS the number remaining in employment is higher, with some 91%-93% of those employed in 1993 still employed in 1994. However, the numbers moving into unemployment are roughly comparable with the NES, 3.0% for the BHPS and 3.7% for the LFS. Note that the numbers entering other states, such as self employment, retirement or inactivity in the BHPS and LFS are too small to account for

[4] There are a number of differences in what each of these datasets measure in these transitions. The NES/JUVOS picks up those individuals claiming unemployment related benefit (the claimant count definition), whereas in the LFS and BHPS the unemployed are those actively seeking work (the ILO definition). Furthermore, the NES/JUVOS and BHPS transitions are based on the given state in each year, but the LFS measure comes from retrospective information on what the individual said they were doing a year ago. We may expect some discrepancies to arise in the transitions due to these differences.

the numbers going missing from the NES. It appears that the individuals moving out of the NES are not actually leaving employment for other states. It is likely that they are remaining in employment but are not traced by the NES due to some of it's sampling problems. It is probable that these missing individuals are those with a propensity to change jobs more often. This is further backed up by looking at the proportion of the unemployed in 1993 who enter employment in 1994 for the different datasets. In the BHPS, 29% enter employment and in the LFS, some 25% enter employment. However, the figure from the NES is considerably lower at 18%, with 27% of the unemployed going missing. Comparing these numbers it seems probable that more of these unemployed in the NES are entering employment but are not being traced in the NES employment figures, due to the undersampling of low paid and high turnover individuals.

Table 4.1b presents these transitions for the three datasets for females. The picture here is the same with a significant number of the NES employees going missing compared to the number leaving employment in the other datasets. If anything, the NES may be slightly worse at tracking females, with only 84% of employees turning up next year compared to 91-93% from the BHPS and LFS. This may be a result of the national insurance threshold effecting females more than males, since many more females are part time workers. Notice also the well established fact that females are more likely to exit employment into inactivity than males, who tend to move into unemployment.

Both Tables 4.1a and 4.1b present a picture of quite high persistence of employment status over a one year period. We have seen the high level of persistence of those in employment. Self employment is also a very persistent state, with about 83-91% of self employed males remaining in that state and about 73-88% of females. Unemployment is also a fairly persistent state, especially so for males, with around 48-

57% of the unemployed remaining so a year later. If one includes the inactive and looks at non-employment then this figure rises substantially for males and females.

For reasons given above, there is some concern that transitions may have changed in the NES/JUVOS over time. Figures 4.1a and 4.1b presents a time series of the proportion of male and female employees respectively moving into unemployment from one year to the next for both the NES and LFS. (Note that the NES/JUVOS data doesn't start until 1984). It is evident that the NES/JUVOS data is pretty good at picking up those male employees that enter unemployment. The numbers from the two datasets conform very well over this time period. However, the tracking of females does not conform so well between the two datasets, particularly over the period 1989-92.

Figures 4.2a and 4.2b present a time series of the proportion of employees who remain in employment one year later for the NES and LFS for males and females respectively. As we saw in Table 4.1 there are quite large discrepancies between the NES and the LFS in this proportion. Perhaps more worrying though is the tendency for this discrepancy to change over this period. In 1976 the discrepancy for males is about 17% but by 1994 this had fallen to around 8%, while for females it has fallen from around 17% to 9%. It appears that changes in the administration system of the NES have made it better at tracking individuals across years. Indeed, one can see the sharp rise in the proportion remaining in employment in the NES in the early 1980s that corresponds to the introduction of direct sampling of large organisations by the NES. This is at a time when we may expect this proportion to fall as the economy goes into recession and in fact the figures from the LFS do fall over this period.[5]

[5] We also see an improvement in the NES/JUVOS through the late 1980s and 1990s. This could be an effect of increased computerisation of tax and personnel

These sampling problems may have some serious implications for the measurement of wage mobility using the NES. It seems likely that individuals who change job more frequently are also likely to be more mobile in the wage distribution. In fact, evidence from the BHPS suggests that this is the case. Computing the immobility ratio for those who have changed jobs and those who haven't, one finds a higher ratio for those who don't change (The immobility ratio is defined here as the average proportion of individuals who remain on the diagonal of a decile transition matrix). Consequently, the NES is likely to understate the degree of mobility in the wage distribution. Perhaps more worrying is the effect that the changes in sampling technique may have on these estimates of mobility patterns over time. However, since the degree of undersampling in the NES has fallen, it is probable that any changes in the estimate of mobility are going to be biased towards finding more mobility, as the NES is likely to be composed of more mobile individuals now than at its inception.

4.3 The Transition Matrix Approach to Mobility

4.3.1 Mobility in the 1990s

Having looked at the transitions into and out of different employment states for the three datasets and gained some insight into the problems of attrition with the NES, I now turn to look at mobility patterns using the NES and BHPS, the two datasets which contain wage information. The earnings measure that I use is hourly earnings including

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records.

overtime pay. For the NES, this is defined as gross weekly pay divided by total weekly hours. For the BHPS the definition is similar except that earnings are converted to a weekly measure from whatever the length of the individuals pay period.

It is well established that earnings rise over the life-cycle and there is an issue of whether we should strip out these effects when looking at mobility (See Dickens ,1996a or Gosling, Machin and Meghir, 1996b, 1996b). The earnings measure that I use for these transition matrices is unadjusted earnings. However, I have also experimented using age adjusted earnings by taking residuals from yearly cross section regressions of earnings on age and computing the transition matrices on these. The results are not substantially effected but, as we may expect, adjusting for age gives lower levels of mobility.

It is informative to look at mobility both within the wage distribution and into and out of the distribution to other employment states. It seems likely that those in the lower part of the wage distribution are likely to be those that exit to unemployment more frequently. To look at this I have computed the deciles of the wage distribution and presented one year transitions both between deciles and to other employment states. Tables 4.2a and 4.2b presents these transition matrices for males between 1993 and 1994 from the NES/JUVOS and the BHPS datasets respectively. Tables 4.2c and 4.2b presents the same information for females.

One of the striking things to come out of these matrices is the degree of immobility both in terms of deciles of the wage distribution and in states outside of employment. The diagonal elements of these matrices are all much higher than the off diagonal elements, signifying a degree of persistence. Notice also that, as expected from the analysis of transitions above, the NES gives a higher degree of persistence than the BHPS. Persistence appears to be higher at the ends of the wage distribution, but this could well be an artifact of computing mobility in terms of decile transition matrices. The range of wages at the bottom and top are much larger than in the middle so for a given wage change it is more difficult to escape these deciles.

For males in the NES, some 48% of the bottom decile remain there one year later. This may sound like there are quite a large number of escapees, however many leave employment altogether. In fact only 20 percent move up the wage distribution and two thirds of these only make it as far as the next decile. One finds greater mobility in the BHPS, with 43% remaining in the bottom decile and 34% moving up the distribution. Once again however, of those that move up, 45% only make it to the next decile. Practically no individuals move beyond the median of the distribution.

Looking at deciles in the middle of the wage distribution one finds greater mobility, with about 40% staying on the diagonal in the NES compared to about 30% in the BHPS. However, there is still evidence of a concentration around the diagonal, indicating that those individuals that do move over the year don't move very far. When one looks at the top of the wage distribution one finds a very high level of persistence. Over 70% of the top decile remain there in the NES and 67% in the BHPS. Very few of those that do leave move any great distance down the distribution.

Another important point to note is that those in the lower deciles are more likely to enter unemployment, in both the NES/JUVOS and BHPS. Somewhere between 6.5% and 9.5% of the bottom decile enter unemployment compared to about 1.8% of the top decile. Similarly, those unemployed that make it into work are more likely to enter into the lower deciles of the wage distribution. Between 4.6% and 6.3% of the unemployed enter the bottom decile, compared to 0.9-2.1% entering the fifth decile and practically nobody entering at the top.

In the NES, it is evident that those in the bottom deciles are also more likely to go missing. This is surely related to the sampling problem associated with low wage individuals. However, this pattern also emerges, to a lesser extent, in the BHPS and so is probably reflective of the low paid being more likely to enter inactivity. The matrices portray a picture of persistence, with little mobility over a one year period. Many of the low paid either remain in the bottom of the wage distribution or move out into unemployment or inactivity. Somewhere between 60% and 70% of the bottom decile either remain there or move out of employment altogether. Many of the unemployed and inactive remain in this state, and those that do move into employment are more likely to enter in the lower deciles of the wage distribution.

The matrices for females from the NES and BHPS look very similar to those just described for males. There is a concentration on the diagonal of a similar order as that for males. However, it does look like females are slightly more likely to move up from the bottom decile than males. Nevertheless, between 55% and 65% either remain in the bottom decile or move into non-employment. Women in the bottom deciles are also more likely to move into unemployment or out of employment than those further up the wage distribution. Those who are non-employed that move into employment, do so into lower wage jobs.

So far I have only presented transition matrices for periods one year apart. It seems likely that mobility will rise the greater the time period over which the transition is measured. Tables 4.3a-4.3d present three year transitions for the two datasets for males and females between 1991 and 1994. What is evident from these matrices is that mobility measured over this longer time horizon is somewhat higher. The concentration along the diagonals is less than when measured over one year. Also, the differences observed between the two datasets for the one year transitions are less apparent over this longer time horizon. Although the numbers leaving the NES are still much higher than those entering the "other" state in the BHPS, the proportion remaining in each of the deciles look more alike than for the one year transitions.

Despite giving a higher degree of mobility, these three year transitions still point to some signs of significant persistence. For example, 26-31% of those males in the bottom decile are still there three years later. A further 25-32% have moved out of employment and around 9-10% have no observable wage. This leaves somewhere between 26% and 40% moving up the distribution in the space of three years. Of these that do move up, only about half make it beyond the second decile and very few are above the median. At the top end of the wage distribution, a striking 56% of the top decile remain after three years. Most of those moving down only drop by one decile.

Movement into unemployment has a higher incidence in the lower deciles of the distribution, with 10-11% of the bottom decile becoming unemployed compared to 6% of the fifth decile and 1-3% of the top. More of the unemployed move into employment over the three year period than the one year period. However, the entrants are concentrated in the bottom few deciles.

The transition matrices for females show a similar pattern (Tables 4.3c and 4.3d). Once again the females display a higher degree of mobility, with a lower concentration on the diagonals, at least at the extremes of the distribution. However, the number that leave for the "other" category which largely covers the inactive is much higher than for men, particularly so for the lower deciles. Although only 24-27% of the bottom decile remain there, between 32% and 34% have left employment. Between 26% and 42% have moved up the distribution and somewhere between 55% and 65% of these have got beyond the second decile, indicating slightly more mobility than for males. The bottom deciles display a higher propensity to enter unemployment and inactivity, and individuals entering employment from these states are more likely to enter in the lower deciles. Again there is a high level of persistence at the top of the wage distribution, with 49-52% of the top decile remaining there three years later.

Tables 4.4a and 4.4b present five year transitions between 1989 and 1994, for males and females from the NES/JUVOS. Again, mobility is higher over this longer time period for males and females. Nevertheless, although only somewhere between 20% and 22% stay in the bottom decile, many have moved out of the NES and only about 29-31% have moved up the distribution. Of those in the top decile, around 44-48% hold their position at the top five years later.

4.3.2 Have Mobility Patterns Changed Over Time?

The documentation of transition matrices over different time horizons carried out above is of interest in it's own right. However, the question of whether mobility is high or low is largely a subjective one. Perhaps more interesting is the question of whether mobility rates have changed over time. Given that there have been large changes in the shape of the cross section distribution of wages, it is not unreasonable to expect that there may have been some changes in the level of mobility within the wage distribution.

Tables 4.5a-4.5d present one year transition matrices for males and females in 1977/78 and 1988/89. Looking first at the male transitions, it is apparent that fewer individuals are concentrated on and around the diagonal of the matrix in 1977/78 than in 1988/89, particularly in the middle deciles of the wage distribution. For example, the number of individuals remaining in the bottom decile is 40% in 1977/78 compared to 42% in 1988/89. The respective figures for the fifth and top deciles increase from 22% to 31% and from 61% to 66%. This looks like pretty strong evidence that mobility has fallen over this period, particularly in the middle deciles of the wage distribution.

However, one has to be careful and remember that there have been changes in attrition from the NES/JUVOS over this period, as discussed above. The number of individuals going missing from the panel in 1977/78 is higher than in 1988/89 and part of this change is a result of changes in the sampling procedure in the NES. Nevertheless, it is unlikely that these sampling changes in the NES can account for such large changes in the transition matrices. Figure 4.2a shows us that the gap between the LFS and NES/JUVOS in terms of the number of individuals remaining in employment over the space of a year fell from 17% in 1977 to 11% in 1989. The NES/JUVOS has become more successful at following individuals from one year to the next.

Dealing with this problem is rather difficult since I don't have any direct information on who the extra individuals are. As discussed above, it is likely that these individuals are being traced now because of the introduction of direct sampling of large organisations. Some of these individuals were probably not traced before because their earnings fell below the National Insurance threshold. However, because they are in larger firms, it is more likely that they are individuals who have changed jobs in the month before the survey and were previously untraced because their tax records had not been updated.

One can carry out an experiment to see what the transition matrix would look like in 1988/89 if the extra individuals were not traced. One way of doing this is to reconstruct the transition matrix by removing the extra individuals in 1988/89 and comparing this matrix with that from 1977/78. There is a question over where these extra individuals are in the transition matrix. It is quite possible that they are individuals who are more likely to be in the bottom of the wage distribution. Therefore, I have computed the change in the numbers remaining in employment between 1977/78 and 1988/89 for each decile.[6] I then reconstruct the transition matrix for 1988/89 in a way that maximises mobility by assuming that the extra individuals are ones that stay in the same decile. This exercise is likely to overstate the level of mobility in 1988/89 since those extra individuals in the NES/JUVOS are likely to be those that change jobs more frequently and consequently those that are more likely to move deciles. However, even taking this "worst case" scenario, one still finds a fall in mobility over this period with a greater concentration on the diagonal of the adjusted 1988/89 transition matrix. Most notable are the increasing numbers staying in the middle deciles of the wage distribution. For example, the adjusted figures give 40.6% remaining in the bottom decile in 1988/89 compared to 40.2% in 1977/78. However, the figure for the fifth decile is 26.1% in 1988/89 compared to 21.6% in 1977/78, while the corresponding figures for the top decile are 61.8% in 1988/89 and 61.1% in 1977/78.

Comparing the one year transitions for females in 1988/89 with those in 1977/78 (Tables 4.5c and 4.5d) tell a slightly different story. The proportion on and around the diagonals has increased between 1977/78 and 1988/89, but by less than those for males.

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6 The change in the proportions remaining in employment between 1977/78 and 1988/89 for decile 1 to decile 10 respectively are: 1.15, 5.71, 6.37, 5.57, 5.32, 7.61, 6.34, 5.19, 5.28 and 4.54. The extra individuals appear to be quite evenly distributed across the deciles. Surprisingly there are far fewer extra individuals in the bottom decile of the wage distribution. However, these figures may be misleading in two respects. Firstly, they take no account of the way in which the decile thresholds themselves may change if they were computed across all individuals in both years. Secondly, we saw in Figure 2a that the aggregate proportion staying in employment from one year to the next has fallen in the LFS data.

The largest increases seem to be occurring in the middle deciles of the distribution. The percentage staying in the bottom decile increases minimally from 37.7% in 1977/78 to 38.2% in 1988/89. However, the proportion in the fifth decile rises from 27.1% to 32.3% over these years and the proportion in the top increases from 57.3% to 60.4%.

However, these results should be viewed with caution because of the changes in attrition rates in the NES. If one carries out a similar experiment to that above to try to adjust for the lower attrition in the NES in later years, it is apparent that the proportion remaining on the diagonal of the transition matrix has fallen slightly. This suggests that mobility for females may have risen between 1977/78 and 1988/89. However, it is important to remember that assuming all the extra individuals in the NES are immobile is likely to overstate the degree of mobility in 1988/89.

It is of interest to see if the longer run transitions have also changed over time. Tables 4.6a to 4.6d present five year transition matrices for males and females for 1975/80 and 1984/89. These should be compared with the matrices in Tables 4.4a and 4.4b for 1989/94. Taking males first, we can see that the transition matrices have changed little between 1984/89 and 1989/94, suggesting that long run mobility has been stable over this period. However, when we look back to 1975/80 we find a lower concentration on the diagonal for the middle deciles but the top and bottom deciles appear not to have changed much over time. One may consider how the change in NES attrition may effect these results. The numbers leaving the NES/JUVOS after five years appears not to have changed very much over this time period, at least for males. As such, it could be that this longer term attrition has not changed significantly and is less of a problem for these comparisons.

The figures for females show increases in the numbers remaining on the diagonal between 1975/80 and 1984/89 and again up to 1989/94. In contrast to the males, this increase has not just occurred in the middle deciles with the proportion staying in the bottom decile rising from 15% to 20% between 1975/80 and 1989/94. However, the proportion staying in the top decile has remained quite stable. Nevertheless, it does appear that the attrition rate has changed for these individuals. In contrast to the males, the numbers going missing over a five year period has fallen substantially. If we carry out the same experiment as above then it could be that five year mobility has remained constant or even risen.

All of the analysis so far has been in terms of relative earnings classes (deciles for each year). However, it is also of interest to look at transitions across absolute earnings classes to see if any different patterns emerge. Tables 4.7a - 4.7d present transition matrices for males and females in 1977/78 and 1988/89 where the thresholds are defined as multiples of mean real earnings in 1975 (0.5, 0.75, 1, 1.25 and 1.5 times mean earnings). Transitions out of these earnings bands can now occur not just as individuals do better relative to others, but there can be a general shift upwards as real earnings growth effects the whole distribution. The earnings mobility one gets here is both relative and absolute. One can see that the distribution across these earnings classes is rather uneven with most individuals in the ranges 0.75-1.25 times real earnings. Notice also that the effects of real wage growth between 1977/78 and 1988/89 are apparent, with the distribution of individuals shifting upwards.

Taking males first (Tables 4.7a and 4.7b), it is evident that there is a concentration on the diagonals, particularly in the middle earnings bands. As may be expected, there is an asymmetry with more individuals moving up the distribution than down, at least in the bottom half of the distribution. The numbers remaining in the bottom band (<0.5 times mean 1975 real earnings) has fallen slightly from 16.9% to 16.0% between 1977/78 and 1988/89. However, this is a very small group and the proportion leaving employment is very high and has actually risen for this group. In fact, the proportion moving up the distribution from this group has fallen from 29% to 23%. This is quite surprising considering we are comparing the same real earnings band over ten years apart. The proportions remaining in the higher earnings bands have risen slightly, particularly so in the top band. However, one should remember that the numbers leaving the NES have fallen over this period and this has potential implications for comparisons across these years.

For females we see a greater shift up the distribution due to real wage growth between 1977/78 and 1988/89 than for males. Although the number of individuals actually in the bottom two earnings classes has fallen significantly, those that are there don't seem to find it any easier to escape in 1988/89 than they did in 1977/78. However, those that do escape seem to move further up the distribution. The proportions remaining in the next three bands have stayed about the same, but there is some evidence of more movement up the distribution from the higher earnings bands. The numbers staying in the top band have risen but again this may be confounded by changes in attrition.

The analysis of the decile (and absolute) transition matrices has shown that there are quite high levels of persistence in individuals wages, with limited movement within the distribution from year to year. Looking at transitions over longer time horizons, I find higher levels of mobility, as may be expected. Comparing transition matrices from earlier time periods it appears that the degree of mobility within the distribution has fallen, with less individuals moving decile now than before. However, there is a potential problem with this analysis. Categorising individuals into deciles is an arbitrary method of ranking.

In doing this I am throwing away information about the movement of individuals within these deciles. In addition, when making comparisons over time one has to be careful to check the validity of comparing deciles in one time period with deciles in a later time period. A potential problem with the analysis above is that, with the widening of the cross section distribution of wages, the decile widths have grown over the period of analysis. That I find more people staying in each decile is perhaps unsurprising since to move from one decile to another an individual needs a proportionately larger wage change in later periods.[7] In the next section I turn to look at other methods of analysing wage mobility and study whether it has changed over time.

4.4 Other Approaches to Mobility

One needs to be clear about what is meant by wage mobility before trying to find a satisfactory measure for it. There are two basic characteristics of a changing distribution of wages. Firstly there is the question of how far apart individuals are from each other in terms of their wage. Secondly, there is the issue of how much the ranking of individuals changes from one period to the next. Some analysis of mobility has been concerned with both of these components, particularly in the literature on the convergence of countries incomes (See Quah, 1996). The literature on the growth in wage inequality has well documented the changes in the first characteristic of the wage distribution. Here I will concentrate on the changing rankings of individuals within the distribution. I think of this as a pure mobility measure.

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[7] This is not a problem when looking at the transitions across the absolute real earnings bands.

An alternative to the decile transition matrices above is to compute the actual ranking of individuals in the wage distribution for each year and examine the amount of movement. In effect, this is the same as computing a transition matrix with the number of earnings classes set equal to the number of individuals. A problem with this approach concerns the question of what to do with those individuals that join and leave employment, and those that have missing wage data in any of the periods. Here I will look at a balanced sample for each mobility comparison, taking only those individuals who have wage data in both periods. There are potential biases that may arise from this. As mentioned before, the NES is likely to undersample high turnover individuals and so underestimate the extent of wage mobility. However, since it is likely that the proportion of high turnover individuals has risen over time in the NES, it is possible that these results will be biased towards finding an increase in mobility.

Firstly, take one year mobility from the NES. As discussed above, there are important life-cycle effects on wages and it is informative to study mobility with these effects removed. Therefore I adjust the earnings variable to take out the effects of age. The wage variable that I use is the residual from fully saturated regressions of the log hourly wage on age dummies for each year. This allows the return on age to vary over time. Taking a balanced sample for the two years I am studying, I then compute the percentile at which each individual is placed in the wage distribution in each year. The degree of movement in percentile ranking from one year to the next is then a good measure of mobility.

Figures 4.3a and 4.3b present plots of the percentile rankings of male earnings in simletaneous years for 1977/78 and 1988/89 respectively. These plots give an indication of the level of mobility. If there were no mobility and everyone stayed at the same percentile then one would expect a 45 degree line starting at the origin. If earnings in one year were independent of those in the next year then one would expect a random scattering of individuals in each direction, with no association between the percentiles. Another possibility is that there is a perfect negative correlation between earnings in each year. This would manifest itself in a downward sloping 45 degree line starting from the upper left point on the graph. Although this case gives a higher measure of mobility, since individuals on average move further in the distribution, the independent earnings case is usually thought of as the benchmark case.

Notice that for 1977/78 in Figure 4.3a there is a dispersion of individuals around the 45 degree line. Most individuals are concentrated in a band around this line. The concentration appears to be higher at the two extremes of the distribution, suggesting lower mobility at the top and bottom of the wage distribution. Individuals who start off in the middle of the distribution tend to move further in terms of percentile ranking. Of course there are some individuals that move a great distance from one year to the next. Some individuals start at the bottom and finish at the top, and vice versa. This is undoubtedly related to the problem of measurement error in earnings and I attempt to address this below.

Looking at the figure for 1988/89 there is a slightly greater concentration around the 45 degree line, indicating less movement of individuals within the wage distribution compared to 1977/78. The greater concentration largely arises in the middle part of the distribution. These figures indicate that one year mobility has fallen for males over this period. A large amount of the fall in mobility appears to have occurred in the middle of the wage distribution, a conclusion that was also found from the decile transition matrices above.

Figures 4.4a and 4.4b present the same one year plots for females for the years 1977/78 and 1988/89. These figures look similar to those for the males. In 1977/78 there is a dispersion of individuals around the 45 degree line. At the two extremes of the distribution there appears to be a higher degree of concentration, with individuals moving less. In 1988/89 there are signs of more concentration around the 45 degree line than in 1977/78. The increase in concentration is perhaps less striking than for males. However, mobility appears to have fallen for females as well as for males.

These plots give us an indication of the changing level of mobility in the wage distribution. However, they don't give us any concrete numbers with which to measure this change. Nevertheless, we can use the percentile rankings in each year to compute a measure of mobility based on the degree of change in ranking from one year to the next. Define this mobility measure between year t and year s as follows:

$$M = \frac{2 \sum_{i=1}^{N} \mid F(w_{it}) - F(w_{is}) \mid}{N} \tag{4.1}$$

Where $F(w_{it})$ and $F(w_{is})$ are the cumulative distribution functions for earnings in year t and s respectively and N is the number of individuals. This mobility measure is twice the average absolute change in percentile ranking between year t and s. It takes a minimum value of zero when there is no mobility ($F(w_{it})$- $F(w_{is})$ will be zero for all individuals since they all remain at the same percentile). It takes a maximum value of one when earnings in the two years are perfectly negatively correlated. If earnings are independent in the two years then it returns a value of 2/3.

Figure 4.5 presents a time series of this one year mobility measure for males and females respectively between 1976 and 1994. The first point to note from this is that the value of this mobility index for males and females is far below the value one would expect to get if earnings were independent in both years. Unsurprisingly, this tells us that there is considerable immobility over the space of one year. The second point is that these indices have fallen over this time period for males and females. The index in 1975/76 is 0.19 for males and 0.18 for females. It rises to a peak of 0.20 in 1979/80 for both males and females and then falls sharply in the early 1980s. It recovers somewhat in the later part of this decade but begins to fall again in the 1990s and by 1993/94 it has fallen to 0.12. This constitutes a 41% fall in the mobility index for both males and females since 1979/80.

However, one needs to be cautious in interpreting these results. The 1970s were a time of very high inflation. In contrast to this, inflation was much lower in the mid 1980s and early 1990s. It is quite possible that these changes in mobility are largely being driven by changes in the inflation rate. The data that I am using here records earnings over a relatively short period (one week to one month). Given this, the timing of wage settlements may be crucial in any comparison across individuals since I effectively have wages at a point in time. When inflation is high and wage settlements are larger, the timing of settlements will become more important. As such, I would expect to find more mobility in the wage distribution in periods of high inflation.

In Figure 4.5, I have also plotted the inflation rate (on the right hand scale). One can see a high degree of correlation between the inflation rate and the mobility index. In particular, the large fall in mobility in the early 1980s coincides with a sharp fall in inflation. It is apparent that when looking at changes in mobility over time one needs to be careful to control for the effects of inflation. A comparison can be made of mobility rates at two points in time with similar levels of inflation.

In 1978 inflation was about 7.6% and in 1989 it was 8.2%. As such, these are probably reasonable years to make a comparison across. In fact, it was for this reason that I used these years to compare the decile transition matrices in Section 4.2.2 above. The mobility index for males is 0.181 in 1977/78 and has fallen to 0.145 by 1988/89, a 20% fall in mobility. This provides evidence of a fall in wage mobility regardless of the effects of inflation between these years. In addition, I estimated a simple OLS regression of the mobility index on the inflation rate and a time trend. The estimated coefficients are presented the first row of Table 4.8. There is a positive and significant coefficient on the inflation rate and the coefficient on the time trend is -0.0023 with a t-statistic of 3.49. This suggests that despite the fact that falling inflation explains a large proportion of the fall in mobility there is still a significant fall in the index of 0.0414 (18*-0.0023) between 1976 and 1994. This constitutes a 22% fall in mobility over this period.

I have also checked the robustness of this result using other measures of mobility. Figure 4.6 plots my ranking measure of mobility with three other measures that are customarily used in the literature; a measure of the proportion of individuals changing decile from one year to the next in a decile transition matrix, the inverse of the Pearson correlation coefficient of earnings between simultaneous years, and one minus the ratio of the variance of earnings averaged over two years to the average of the single year variances as proposed by Shorrocks (1978).[8] The Shorrocks index measures the proportional reduction in inequality due to increasing the period over which earnings are measured. The indices are all computed over the same sample and have been rescaled to fit on the same graph for comparative purposes. It is evident that there is a high degree

[8] 1- Var $((w_t + w_{t-1})/2)$ / $(\eta_t \mathrm{Var}(w_t) + \eta_{t-1} \mathrm{Var}(w_{t-1}))$, where the weights (η) are the ratio of single period earnings to two period earnings.

of correlation between these measures of mobility. I have also estimated simple OLS regressions for these other measures of mobility on inflation and a time trend the coefficients for which are also presented in the top panel of Table 4.8. Unsurprisingly, inflation is also significantly correlated with these measures of mobility. Nevertheless, there is some evidence, from the ranking measure and the decile transition matrix measure at least, that there is a downward trend in mobility.

Comparing female mobility between 1977/78 and 1988/89 one finds a smaller fall than for males, with the ranking index falling from 0.162 to 0.153. When I estimate the same regression as above for females I obtain a coefficient on inflation of 0.2630 (t-statistic 4.08) and on the time trend of -0.0011 with a t-statistic of 1.81 which is significant at the 10% level. So, after stripping out the effects of inflation, the mobility index for females falls by 0.0198 (18*-0.0011) between 1976 and 1994, an 11% fall in mobility. I have also computed the alternative mobility measures for females. Figure 4.7 again plots the four measures for females and the bottom panel of Table 4.8 presents the time series regressions on inflation and a time trend for females. It appears that mobility for females has fallen by less than that for males, a result obtained above from the decile transition matrices.

In an attempt to overcome the problem that this mobility index will also be picking up a degree of measurement error in earnings I have computed the index over consecutive two year averages of earnings. This is presented in Figure 4.8 with the two year averaged inflation rate. Unsurprisingly, the index is lower than when computed over one year. In addition, the decrease in the index is less severe, falling by 32% for males and 34% for females between 1978/81 and 1991/94. This index is also highly correlated with inflation. Again, I can estimate a regression of the index on inflation and a time trend to see if there is any downward trend once inflation is controlled for. The coefficient on inflation is positive and significant for both males and females. The coefficients on the time trends are -0.0010 (t-ratio of 1.73) for males, which is significant at the 10% level, and -0.0001 (t-ratio of 0.37) for females. So there is some weak evidence that this measure of mobility has fallen for males over this time period.

One can also use this ranking method to study longer term mobility. Figures 4.9a-4.9c plots the percentile rankings of male earnings five years apart for the years 1975/80, 1984/89 and 1989/94. Notice that these plots display a greater scattering of individuals than the one year plots presented above, indicating a higher degree of mobility over this longer time horizon. As with the one year measures, the scattering becomes more concentrated in later years around the 45 degree line. There appears to be a greater concentration in 1984/89 than in 1975/80, but it is difficult to see any significant change between 1984/89 and 1989/94 from these figures. However, one needs to be careful to acknowledge the effects of inflation on the degree of mobility. Ideally one would like to compare time periods where five year inflation is at a similar level. As such, comparing 1984/89 with 1989/94 may be reasonable, but a comparison with 1975/80 is probably not valid since the five year inflation rate was much higher over this period. Figures 4.10a-4.10c presents the same information for females. The story here is very similar with some signs of a greater concentration of individuals in 1989/94.

I have also computed the mobility measure used above for the five year percentile rankings for males and females. This is presented for males and females in Figure 4.10 along with the five year inflation rate. Notice that the mobility measure is higher than when measured over one year. The pattern over time is similar, with a sharp fall in the early 1980s. However, it is clear that five year mobility is highly correlated with inflation.

In order to see if there is any trend fall in mobility once inflation is controlled for I have run simple regressions of five year mobility on five year inflation and a time trend. The coefficients are reported for males and females in the first rows of the top and bottom panels of Table 4.9. The coefficient on inflation is positive and significant for both males and females. The coefficient on the time trend is -0.001 (t-ratio: 1.38, significant at the 20% level) for males and 0.000 (t-ratio: 0.31) for females. This suggests some weak evidence that longer term mobility may have fallen for males but has remained static for females.

Once again, I have compared this measure of mobility with the alternative measures used above, computed for earnings five years apart. Figures 4.12 and 4.13 present the four measures for males and females respectively, rescaled for comparative purposes. It is evident that the correlation between the measures is lower over five years. The ranking measure and the decile measure appear to be the most highly correlated. Table 4.9 presents the regressions of these measures on five year inflation and a time trend for males and females. Five year inflation is significantly correlated with these measures of mobility, less so for the inverse of the correlation coefficient and the Shorrocks measure for females. There is very weak evidence that the decile measure has fallen for males (coeff -0.0014, t-ratio 1.20). However, there is also some evidence that the Shorrocks measure has risen for both males and females.

These patterns in the one year and five year mobility indices fit reasonably well with the results obtained in Dickens (1996a) where I study the changing nature of permanent and transitory components of male earnings using this same data. In that paper I found evidence of a significant permanent component of earnings and a serially correlated transitory component. The variance of these components both rose over time, each explaining about half of the rise in wage dispersion. The following equation describes the error components model that I estimated:

$$w_{it} = \beta_t \mu_{iat} + \delta_t v_{it} \tag{4.2}$$

where the permanent component μ_{iat} is a random walk in age: $\mu_{iat} = \mu_{iat-1} + \pi_{iat}$ and the transitory component v_{it} is an ARMA(1,1):

$$v_{it} = \rho v_{it-1} + \phi_{it} + \Theta\phi_{it-1} \tag{4.3}$$

The parameters β_t and δ_t vary freely each year and capture the increasing variances of the permanent and transitory components of earnings. These may be thought of as "price" terms that capture the increasing return to skill. Both of these parameters increase over the sample period, with the permanent parameter rising in the early 1980s and the transitory parameter increasing sharply in the late 1980s and early 1990s.

These results accord well with the patterns observed here in the mobility index. An increase in either of these "price" parameters will lead to a fall in mobility since the correlation in earnings between two points in time will be higher. The presence of the serially correlated ARMA explains why the mobility index is higher when measured over a longer period. The correlation in the ARMA at two points in time falls as the distance between the two points increases, so mobility will be higher over five years than over one year.

As I have presented it so far, this mobility index provides a measure of average mobility across the whole distribution of wages. However, it is interesting to see if mobility is higher or lower at different parts of the distribution. In the plots of the percentile rankings presented above it certainly looked as though there was less mobility at the extremes of the distribution. To look at this more closely I have computed the index by individuals starting decile.

Table 4.10 presents this mobility index computed over one year for males and females by origin decile for 1977/78 and 1988/89, years of comparable inflation levels. Notice that the index takes on similar values between decile 3 and decile 7. However, mobility is lower the closer one moves towards the extremes of the wage distribution. In particular, the mobility index is much lower in the top decile. This may be expected since the dispersion of wages is higher at these points of the distribution, particularly in the top decile. Hence, a given wage change for an individual will lead to less movement within the distribution if they are closer to the top. Notice also that mobility has fallen by much less at the top of the distribution than elsewhere. Although the index has fallen by 20% for males between 1977/78 and 1988/89 it has only fallen by 3% in the top decile. For females, the index has fallen by 5.5% overall but has risen by 27% in the top decile of the wage distribution. So, despite the fact that there is much less movement at the top of the distribution it is evident that the changes in mobility at the top for males and females are counter to those experienced in the other deciles.

I also present five year mobility decomposed by starting decile in Table 4.11 for the years 1975/80, 1984/89 and 1989/94. Longer term mobility is significantly lower at the top of the distribution than elsewhere. Comparing similar inflation periods 1984/89 to 1989/94, there is very little change in this mobility measure at any point in the distribution.

4.5 Conclusion

In this chapter I have studied wage mobility for males and females in Great Britain between 1975 and 1994 using the New Earnings Survey Panel Dataset and the British Household Panel Survey. Starting with a decile transition matrix analysis, I found considerable levels of immobility within the wage distribution in the 1990s, with many individuals staying in the same decile from one year to the next. In addition, those individuals lower down the wage distribution are more likely to enter unemployment or other non-employment states. Mobility is found to be higher when measured over a longer time period, with less individuals stuck in the same decile after three years than after one year. I then go on to compare the mobility levels that prevailed in late 1980s with those in the late 1970s. I find some evidence that wage mobility has fallen over this time period so that the opportunity to move up the distribution of wages has fallen.

The use of decile transition matrices to look at mobility has it s drawbacks, particularly when looking at changes in mobility over time. With a widening distribution of wages the size of the deciles has increased so it is perhaps unsurprising that movement across deciles has fallen. However, it could be the case that there is now more movement within deciles of the wage distribution. To address this question I compute a measure of mobility based on the actual percentile rankings of workers within the wage distribution. The proposed mobility index has fallen considerably over this time period with most of the fall occurring in the early 1980s. However, I find that mobility is highly correlated with the inflation rate. This is probably the result of the different timing of wage settlements impacting on the earnings data, which is a point in time measure. Nevertheless, when I take out the effects of inflation I still find a fall in mobility over this time period, at least for males. Mobility is found to be lower in the top and bottom deciles of the distribution and, although it has fallen by a similar degree in most deciles, it has remained unchanged in the top decile.

So what has caused these declines in mobility rates? Falling mobility in the wage distribution is reflective of increasing permanent wage differences between individuals. This is consistent with the common hypothesis that increasing wage inequality is a result of increasing returns to education or ability. However, there are many other hypotheses about the causes of increased wage inequality that are consistent with increases in permanent differences between individuals but it is not possible to discriminate between them here.

Perhaps more important are the welfare implications of these results. It appears that individuals find it harder now to better their position in the wage distribution than they did twenty years ago. This has occurred against the backdrop of a huge rise in cross sectional wage dispersion. Not only are differences in wages between individuals in a given year larger than they were, but the possibility of moving up the distribution over the next year has now become more remote. So the low paid are worse off both in terms of the relative wage they receive and in terms of their opportunity to progress out of the low pay trap.

Table 4.1a: Labour Force Transitions 1993/94 - Males

New Earnings Survey

NES		State in 1994					
State in 1993	Cell Size	Employed	Self Emp	Unemployed	Retired	Inactive	Missing
Employed	71194	85.25	-	3.56	-	-	11.19
Self Emp		-	-	-	-	-	-
Unemployed	13187	18.03	-	54.80	-	-	27.17
Retired		-	-	-	-	-	-
Inactive		-	-	-	-	-	-

British Household Panel Survey

BHPS		State in 1994					
State in 1993	Cell Size	Employed	Self Emp	Unemployed	Retired	Inactive	Missing
Employed	1868	91.49	2.14	3.00	0.37	1.12	1.87
Self Emp	449	8.46	83.07	4.23	0.22	1.56	2.45
Unemployed	237	29.11	6.75	47.68	1.27	13.50	1.69
Retired	26	3.85	3.85	7.69	69.23	15.38	0.00
Inactive	166	7.83	1.81	10.24	3.01	75.90	1.20

Labour Force Survey

LFS		State in 1994					
State in 1993	Cell Size	Employed	Self Emp	Unemployed	Retired	Inactive	Missing
Employed	24995	93.16	1.34	3.66	0.13	1.70	-
Self Emp	5243	4.39	91.25	3.09	0.06	1.22	-
Unemployed	3742	25.23	6.47	57.14	0.16	11.01	-
Retired	184	4.35	1.63	1.63	60.33	32.07	-
Inactive	3070	12.80	2.67	7.43	0.52	76.58	-

Notes: 1) NES is conducted in April. The unemployed are those claiming unemployment related benefit. The missing includes the self employed, retired, inactive and those not captured by the survey.
2) The BHPS is largely conducted in September/October. The unemployed are those seeking work.
3) The LFS is conducted March-May. The unemployed are those seeking work. Information on transitions is from retrospective questions on what the individual was doing one year ago.

Table 4.1b: Labour Force Transitions 1993/94 - Females

New Earnings Survey

NES		State in 1994					
State in 1993	Cell Size	Employed	Self Emp	Unemployed	Retired	Inactive	Missing
Employed	62139	83.53	-	1.89	-	-	14.59
Self Emp		-	-	-	-	-	-
Unemployed	3952	29.05	-	36.08	-	-	34.87
Retired		-	-	-	-	-	-
Inactive		-	-	-	-	-	-

British Household Panel Survey

BHPS		State in 1994					
State in 1993	Cell Size	Employed	Self Emp	Unemployed	Retired	Inactive	Missing
Employed	1942	90.53	1.39	1.75	0.41	5.25	0.67
Self Emp	146	13.70	72.60	3.42	0.00	9.59	0.68
Unemployed	111	35.14	3.60	29.73	0.90	27.03	3.60
Retired	55	1.82	1.82	5.45	58.18	30.91	1.82
Inactive	762	13.91	1.97	2.49	1.71	79.13	0.79

Labour Force Survey

LFS		State in 1994					
State in 1993	Cell Size	Employed	Self Emp	Unemployed	Retired	Inactive	Missing
Employed	24213	92.62	0.61	2.14	0.31	4.32	-
Self Emp	1797	5.56	88.48	1.61	0.00	4.34	-
Unemployed	1887	35.24	2.44	37.10	0.26	24.96	-
Retired	275	2.55	0.36	0.73	65.82	30.55	-
Inactive	11566	12.22	1.23	5.04	1.02	80.49	-

Notes: See Table 4.1a.

Table 4.2a: Male One Year Transition Rates (NES) 1993/94
Percent of Given State in 1993 in Given State in 1994

	State in 1994												
State in 1993	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	54.80	27.17	4.35	4.62	2.45	1.76	1.35	0.90	0.85	0.57	0.39	0.39	0.40
Missing Wage	5.27	17.49	36.70	5.16	4.83	4.34	4.39	4.12	3.78	3.30	3.02	3.42	4.18
1st Decile	6.44	14.38	11.12	48.23	13.22	3.14	1.34	0.67	0.55	0.30	0.18	0.23	0.18
2nd Decile	4.01	10.28	9.49	6.57	43.65	17.45	5.30	1.56	0.97	0.39	0.17	0.10	0.07
3rd Decile	3.71	9.16	8.04	1.91	8.81	40.49	19.69	5.12	1.89	0.67	0.30	0.10	0.12
4th Decile	3.24	9.36	8.00	0.87	2.55	9.55	38.42	19.20	5.98	1.87	0.63	0.28	0.05
5th Decile	2.82	9.57	7.32	0.53	1.05	2.96	9.34	40.52	18.42	5.16	1.55	0.50	0.25
6th Decile	3.02	8.73	7.19	0.48	0.50	0.96	2.77	9.75	42.34	18.85	3.94	1.05	0.42
7th Decile	2.94	9.36	6.32	0.37	0.45	0.53	0.98	3.29	10.14	45.83	15.92	2.82	1.06
8th Decile	2.47	8.99	5.84	0.28	0.17	0.18	0.43	1.04	2.47	9.25	53.68	13.47	1.72
9th Decile	1.97	9.61	6.44	0.15	0.18	0.15	0.25	0.55	0.96	1.67	8.15	59.58	10.34
10th Decile	1.84	10.75	7.49	0.35	0.12	0.08	0.15	0.18	0.28	0.42	1.13	6.88	70.32

Notes: See Table 4.1a.

Table 4.2b: Male One Year Transition Rates (BHPS) 1993/94
Percent of Given State in 1993 in Given State in 1994

State in 1993	Unemployed	Other	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	49.68	23.21	5.06	6.33	5.49	1.69	3.38	2.11	2.53	0.84	0.84	0.42	0.42
Missing Wage	4.81	17.12	40.64	6.42	2.14	2.14	3.74	1.07	2.14	4.28	4.81	2.67	8.02
1st Decile	9.64	6.02	4.22	42.77	16.87	11.45	5.42	1.81	0.60	0.00	0.00	0.60	0.60
2nd Decile	3.53	5.88	5.29	12.35	31.76	20.59	10.00	6.47	2.35	1.18	0.00	0.00	0.59
3rd Decile	1.23	4.90	2.45	7.98	18.40	30.60	16.56	12.27	2.45	2.45	0.61	0.00	0.61
4th Decile	2.40	4.19	5.99	1.80	10.78	13.77	27.54	18.56	5.39	4.79	2.40	1.80	0.60
5th Decile	1.18	2.96	3.55	2.96	3.55	7.10	14.20	26.04	20.12	11.83	3.55	1.78	1.18
6th Decile	2.94	2.94	5.29	0.00	0.59	1.18	8.24	15.88	32.94	18.82	6.47	4.71	0.00
7th Decile	1.80	6.59	7.19	1.20	0.00	1.80	4.19	9.58	15.57	25.15	17.37	7.78	1.80
8th Decile	1.74	3.49	2.33	1.74	0.00	0.58	1.16	2.33	8.72	18.02	40.70	16.28	2.91
9th Decile	1.75	1.75	2.92	0.00	0.58	0.58	0.00	0.58	2.92	6.43	15.79	48.54	18.13
10th Decile	1.81	3.61	4.22	0.60	0.00	0.00	1.20	0.60	0.60	0.60	4.82	15.06	66.87

Notes: See Table 4.1a.
The "Other" category corresponds to "missing" in the NES.

Table 4.2c: Female One Year Transition Rates (NES) 1993/94
Percent of Given State in 1993 in Given State in 1994

	State in 1994												
State in 1993	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	34.87	36.08	7.11	4.05	3.97	3.24	2.73	2.13	1.42	1.44	1.57	0.94	0.46
Missing Wage	2.70	22.07	36.62	5.96	4.85	4.78	3.89	3.33	2.70	3.10	2.58	3.14	4.27
1st Decile	2.56	19.16	13.79	43.65	11.45	4.16	1.76	1.16	1.00	0.58	0.28	0.26	0.20
2nd Decile	2.25	15.73	12.13	8.59	41.31	12.63	3.94	1.55	0.76	0.66	0.30	0.10	0.06
3rd Decile	2.15	13.36	10.37	2.57	7.94	39.67	15.61	4.58	1.71	1.02	0.64	0.30	0.10
4th Decile	1.67	11.68	9.65	1.47	2.65	7.98	40.90	16.37	4.32	1.63	0.94	0.62	0.14
5th Decile	1.59	10.80	8.28	0.85	1.23	2.70	7.37	43.06	17.52	4.28	1.43	0.67	0.22
6th Decile	1.37	11.08	7.46	0.76	0.62	1.23	2.84	7.48	46.15	15.95	3.68	1.07	0.32
7th Decile	1.68	11.19	7.90	0.51	0.41	0.51	1.26	2.70	7.51	46.61	16.26	2.96	0.49
8th Decile	1.66	11.51	7.44	0.22	0.30	0.47	0.71	0.91	1.99	7.70	50.30	15.23	1.56
9th Decile	1.30	11.44	8.52	0.28	0.10	0.18	0.26	0.34	0.53	1.66	7.16	55.97	12.27
10th Decile	0.81	12.59	13.36	0.16	0.14	0.12	0.20	0.18	0.26	0.45	1.16	4.95	65.62

Notes: See Table 4.1a.

Table 4.2d: Female One Year Transition Rates (BHPS) 1993/94
Percent of Given State in 1993 in Given State in 1994

	State in 1994												
State in 1993	Unemployed	Other	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	29.73	35.13	7.21	8.11	1.80	3.60	1.80	1.80	1.80	3.60	3.60	0.90	0.90
Missing Wage	2.17	22.47	25.36	6.52	4.35	7.25	3.62	0.00	5.07	2.17	3.62	7.97	9.42
1st Decile	3.26	16.84	1.63	35.33	19.02	7.61	5.98	3.26	2.72	1.63	1.09	1.09	0.54
2nd Decile	3.26	12.50	0.54	17.93	30.43	19.02	4.89	3.26	2.72	2.72	2.17	0.54	0.00
3rd Decile	1.09	4.37	2.73	10.93	15.85	27.32	21.86	8.74	3.28	1.64	2.19	0.00	0.00
4th Decile	0.56	6.12	3.89	2.78	8.33	16.67	29.44	22.78	6.11	2.22	0.56	0.56	0.00
5th Decile	0.56	6.74	3.93	3.37	3.37	5.62	10.11	33.71	18.54	10.67	1.69	1.69	0.00
6th Decile	2.75	3.85	3.30	1.65	1.10	2.75	8.24	14.29	31.87	15.93	9.89	2.20	2.20
7th Decile	1.13	3.95	2.82	1.13	1.69	0.56	2.26	3.39	18.64	39.55	14.69	7.91	2.26
8th Decile	1.65	3.85	2.75	0.00	1.10	0.55	3.30	2.20	6.04	12.64	41.76	21.43	2.75
9th Decile	1.14	2.27	6.82	0.57	0.00	0.57	0.57	2.27	1.70	3.41	17.05	41.48	22.16
10th Decile	1.69	5.06	5.06	1.12	0.00	0.56	1.12	1.69	0.56	1.12	2.81	16.85	62.36

Notes: See Table 4.1a.
The "Other" category corresponds to "missing" in the NES.

Table 4.3a: Male Three Year Transition Rates (NES) 1991/94
Percent of Given State in 1991 in Given State in 1994

	State in 1994												
State in 1991	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	41.53	33.53	5.33	5.88	3.74	2.51	1.89	1.50	1.18	0.98	0.84	0.63	0.46
Missing Wage	7.49	26.33	24.63	4.42	4.38	4.38	4.24	3.89	3.81	3.78	3.57	4.12	4.94
1st Decile	10.90	21.57	10.04	31.09	14.20	5.75	2.55	1.62	0.76	0.55	0.35	0.30	0.33
2nd Decile	7.68	17.46	9.31	6.71	26.69	17.84	7.50	3.42	1.83	0.81	0.41	0.18	0.17
3rd Decile	7.05	16.42	8.41	2.84	8.48	24.94	17.68	7.66	3.87	1.53	0.64	0.25	0.25
4th Decile	6.01	17.22	8.93	1.45	3.28	8.77	22.56	17.73	8.31	3.51	1.47	0.56	0.21
5th Decile	5.64	15.26	7.53	1.28	1.65	2.97	9.76	23.94	19.14	8.79	3.04	0.70	0.29
6th Decile	5.48	15.54	6.70	1.01	1.09	1.27	3.56	10.39	25.15	20.11	6.76	2.11	0.83
7th Decile	4.85	15.49	7.31	0.66	0.61	0.79	1.75	3.89	10.58	27.67	19.93	5.17	1.32
8th Decile	4.34	16.16	5.79	0.62	0.48	0.67	0.70	1.42	2.64	10.27	35.91	17.95	3.04
9th Decile	4.27	16.91	7.55	0.38	0.37	0.34	0.40	0.54	0.91	2.10	8.70	43.42	14.10
10th Decile	3.20	20.78	8.09	0.50	0.37	0.18	0.19	0.26	0.42	0.75	1.69	7.55	56.04

Notes: See Table 4.1a.

Table 4.3b: Male Three Year Transition Rates (BHPS) 1991/94
Percent of Given State in 1991 in Given State in 1994

	State in 1994												
State in 1991	Unemployed	Other	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	30.27	30.27	4.86	11.35	3.78	5.41	2.16	2.16	4.86	0.54	2.16	2.16	0.00
Missing Wage	5.63	14.72	9.96	4.33	6.06	7.36	7.79	6.93	4.76	5.19	8.23	9.96	9.09
1st Decile	10.07	14.77	9.40	25.50	16.78	8.72	9.40	2.01	0.67	1.34	0.00	0.67	0.67
2nd Decile	3.79	11.36	6.06	12.12	25.00	20.45	10.61	6.06	4.55	0.00	0.00	0.00	0.00
3rd Decile	7.75	11.27	7.75	4.93	9.86	16.90	14.79	9.86	6.34	7.04	0.70	1.41	1.41
4th Decile	3.42	14.38	4.79	4.79	5.48	10.27	19.86	19.86	5.48	7.53	2.74	0.68	0.68
5th Decile	5.52	6.90	4.14	0.69	3.45	6.90	12.41	17.93	21.38	9.66	6.90	4.14	0.00
6th Decile	5.07	11.59	3.62	1.45	4.35	3.62	9.42	10.87	18.84	15.22	9.42	3.62	2.90
7th Decile	4.94	12.35	5.56	0.62	3.09	1.23	3.70	6.79	13.58	21.60	16.67	7.41	2.47
8th Decile	2.55	10.83	3.18	0.64	1.27	3.18	0.64	2.55	5.73	12.74	31.21	21.66	3.82
9th Decile	2.55	10.83	5.73	0.64	1.27	0.00	1.27	1.91	4.46	7.01	15.92	32.48	15.92
10th Decile	1.27	12.66	5.70	1.27	1.27	0.00	0.63	2.53	0.00	0.63	3.16	13.92	56.96

Notes: See Table 4.1a.
The "Other" category corresponds to "missing" in the NES.

Table 4.3c: Female Three Year Transition Rates (NES) 1991/94
Percent of Given State in 1991 in Given State in 1994

	State in 1994												
State in 1991	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	19.05	44.12	7.90	4.26	4.16	4.32	3.15	2.83	2.31	2.47	2.31	1.92	1.20
Missing Wage	3.05	32.08	24.67	4.87	4.92	4.44	3.90	3.64	3.09	3.09	3.30	3.54	5.41
1st Decile	3.51	30.78	12.63	27.32	11.85	6.04	3.39	1.65	1.02	0.82	0.43	0.35	0.22
2nd Decile	3.08	25.37	10.94	9.76	26.55	12.03	5.78	3.06	1.49	0.94	0.59	0.29	0.13
3rd Decile	3.10	24.26	11.48	3.43	8.17	23.39	14.11	5.69	3.20	1.40	1.05	0.53	0.18
4th Decile	3.02	21.75	9.12	2.41	3.47	9.46	22.54	15.63	6.79	3.21	1.41	0.84	0.35
5th Decile	3.04	19.59	8.83	1.31	1.53	3.37	9.73	24.22	18.45	6.24	2.45	0.84	0.41
6th Decile	3.10	19.25	7.87	0.91	1.36	1.72	3.85	9.61	27.02	16.80	6.25	1.74	0.53
7th Decile	2.63	20.23	8.26	0.58	0.54	1.13	1.81	3.32	8.33	29.20	17.74	4.99	1.25
8th Decile	2.14	19.56	8.14	0.30	0.38	0.58	0.86	0.92	2.28	9.06	32.48	20.34	2.96
9th Decile	2.13	19.61	8.18	0.30	0.34	0.36	0.44	0.74	0.90	1.65	8.80	39.10	17.46
10th Decile	1.68	21.81	14.07	0.14	0.06	0.32	0.28	0.46	0.20	0.64	1.18	6.82	52.34

Notes: See Table 4.1a.

Table 4.3d: Female Three Year Transition Rates (BHPS) 1991/94
Percent of Given State in 1991 in Given State in 1994

	State in 1994												
State in 1991	Unemployed	Other	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	20.00	45.00	1.25	2.50	10.00	5.00	3.75	2.50	3.75	1.25	3.75	0.00	1.25
Missing Wage	4.00	18.40	7.60	4.80	7.60	8.40	6.80	5.60	7.20	6.40	7.20	5.60	10.40
1st Decile	4.08	27.89	2.04	23.81	14.97	10.20	3.40	5.44	2.04	3.40	1.36	0.68	0.68
2nd Decile	2.50	19.37	1.25	15.00	25.62	11.25	11.88	5.62	3.75	1.88	1.25	0.00	0.62
3rd Decile	1.32	14.57	1.99	9.93	13.25	27.15	12.58	9.27	2.65	3.97	1.99	1.32	0.00
4th Decile	2.01	9.40	7.38	4.03	7.38	16.11	19.46	15.44	12.75	3.36	2.01	0.67	0.00
5th Decile	1.96	11.76	5.88	5.23	5.88	7.19	15.69	20.26	13.73	7.84	3.27	1.31	0.00
6th Decile	4.27	10.37	1.83	2.44	2.44	1.83	7.32	11.59	23.17	20.12	8.54	3.66	2.44
7th Decile	1.24	8.69	3.73	1.24	0.62	0.62	5.59	6.21	16.77	24.84	20.50	8.70	1.24
8th Decile	1.31	13.73	4.58	1.31	0.65	0.65	2.61	3.27	5.23	14.38	26.80	21.57	3.92
9th Decile	0.63	13.30	5.70	0.63	0.63	0.00	0.63	0.63	3.16	3.80	12.03	35.44	23.42
10th Decile	0.00	14.90	5.59	0.00	0.00	1.24	1.24	1.86	1.24	3.73	4.35	16.77	49.07

Notes: See Table 4.1a.
The "Other" category corresponds to "missing" in the NES.

Table 4.4a: Male Five Year Transition Rates (NES) 1989/94
Percent of Given State in 1989 in Given State in 1994

	State in 1994												
State in 1989	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	38.34	36.53	5.31	5.98	3.55	2.47	2.23	1.79	1.19	1.00	0.60	0.67	0.33
Missing	6.80	70.32	4.63	2.33	1.98	1.85	1.72	1.63	1.70	1.73	1.65	1.68	1.98
Missing Wage	8.34	30.23	20.09	4.09	4.20	4.14	4.47	4.03	4.03	3.61	3.70	4.29	4.77
1st Decile	11.54	26.49	8.82	22.25	13.45	7.53	3.76	2.11	1.59	1.10	0.68	0.31	0.38
2nd Decile	9.62	23.18	8.32	6.86	18.76	14.25	8.38	4.96	2.52	1.57	0.88	0.50	0.21
3rd Decile	7.84	21.57	8.72	3.56	8.50	17.99	13.29	8.66	5.20	2.69	1.18	0.51	0.29
4th Decile	7.04	20.81	8.49	2.33	4.11	8.64	16.53	14.47	8.98	4.88	2.35	0.85	0.53
5th Decile	6.67	20.04	7.75	1.77	2.56	4.03	9.79	16.47	14.64	9.70	4.43	1.67	0.49
6th Decile	5.77	19.81	6.84	1.39	1.74	1.96	4.28	9.53	18.37	16.15	9.76	3.20	1.19
7th Decile	5.79	19.23	7.05	1.10	1.13	1.21	2.10	5.01	10.18	19.43	18.35	7.49	1.95
8th Decile	4.85	19.84	6.53	0.83	0.64	0.82	1.29	1.97	3.21	10.31	25.69	19.41	4.62
9th Decile	4.61	20.69	8.19	0.53	0.51	0.53	0.61	0.87	1.53	2.78	8.84	33.15	17.16
10th Decile	3.93	25.51	8.68	0.54	0.29	0.20	0.34	0.45	0.61	0.87	2.15	8.54	47.89

Notes: See Table 4.1a.

Table 4.4b: Female Five Year Transition Rates (NES) 1989/94
Percent of Given State in 1989 in Given State in 1994

	State in 1994												
State in 1989	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	13.49	49.07	8.35	4.86	4.44	4.26	3.49	2.92	2.25	2.08	1.69	1.59	1.51
Missing	1.90	67.32	7.65	3.77	3.30	2.73	2.37	2.10	1.85	1.73	1.62	1.68	1.99
Missing Wage	2.76	37.08	20.19	4.30	4.24	4.38	4.14	3.82	3.25	3.19	3.40	3.47	5.78
1st Decile	3.32	35.63	11.31	20.11	10.86	6.62	4.65	2.94	1.73	1.23	0.81	0.50	0.28
2nd Decile	2.71	31.84	10.51	9.44	19.76	10.39	6.56	3.73	2.19	1.24	0.93	0.43	0.26
3rd Decile	2.94	29.88	10.28	4.34	8.32	16.53	11.14	6.04	4.69	2.84	1.86	0.91	0.23
4th Decile	2.94	27.68	9.72	2.62	4.16	9.60	14.62	11.96	8.50	4.27	2.55	1.05	0.33
5th Decile	3.24	26.24	8.25	1.60	2.17	4.21	9.99	16.21	12.95	8.88	3.70	2.01	0.55
6th Decile	2.84	25.82	7.53	1.48	1.48	2.43	3.94	9.44	19.81	13.13	7.92	3.28	0.91
7th Decile	3.00	25.72	7.75	0.84	0.95	1.48	2.39	4.04	9.41	20.27	15.31	6.79	2.05
8th Decile	3.06	25.59	8.79	0.49	0.76	0.96	1.23	1.58	2.50	9.13	23.20	17.67	5.04
9th Decile	2.43	24.50	9.54	0.44	0.44	0.48	0.44	0.94	1.07	2.37	9.52	29.21	18.62
10th Decile	1.75	27.64	12.71	0.18	0.11	0.20	0.31	0.43	0.72	0.74	1.54	9.29	44.38

Notes: See Table 4.1a.

Table 4.5a: Male One Year Transition Rates (NES) 1977/78
Percent of Given State in 1977 in Given State in 1978

	State in 1978											
State in 1977	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Missing	67.52	6.58	3.68	2.92	2.66	2.52	2.50	2.49	2.27	2.30	2.18	2.38
Missing Wage	26.46	31.94	4.12	3.96	3.99	4.45	4.30	4.63	4.46	4.12	3.54	4.04
1st Decile	27.82	10.38	40.19	11.43	4.34	1.99	1.25	1.06	0.49	0.57	0.24	0.25
2nd Decile	22.86	10.48	11.27	28.56	14.47	5.88	2.84	1.57	0.95	0.65	0.34	0.15
3rd decile	21.70	9.91	3.48	16.04	23.26	12.95	5.98	3.26	1.83	0.89	0.48	0.22
4th Decile	19.72	10.22	1.57	5.38	15.25	22.56	13.30	6.30	3.11	1.73	0.65	0.20
5th Decile	18.68	10.74	0.83	2.12	6.35	16.05	21.64	13.04	6.59	2.54	1.14	0.29
6th Decile	19.58	10.32	0.77	1.23	2.89	5.98	16.30	21.65	13.44	5.82	1.76	0.28
7th Decile	18.14	9.58	0.47	0.89	1.34	2.66	5.71	16.53	25.00	14.45	4.46	0.77
8th Decile	17.66	9.26	0.32	0.39	0.62	1.13	2.01	4.88	18.15	30.87	12.83	1.87
9th Decile	17.98	7.44	0.28	0.22	0.28	0.44	0.74	1.39	2.37	15.21	44.75	8.92
10th Decile	18.54	8.12	0.16	0.32	0.15	0.17	0.17	0.26	0.52	0.96	9.49	61.14

Notes: See Table 4.1a.
Missing also includes the unemployed.

Table 4.5b: Male One Year Transition Rates (NES) 1988/89
Percent of Given State in 1988 in Given State in 1989

	State in 1989												
State in 1988	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	43.65	33.71	5.28	6.29	3.38	2.18	1.61	1.31	0.83	0.57	0.48	0.48	0.23
Missing	2.55	82.03	3.09	1.72	1.43	1.24	1.31	1.13	1.14	1.06	1.12	1.02	1.17
Missing Wage	3.35	19.73	33.45	5.48	5.10	4.95	4.40	4.11	3.84	3.71	3.60	3.82	4.46
1st Decile	8.28	18.39	10.06	41.73	12.88	4.04	1.73	1.24	0.63	0.56	0.14	0.20	0.11
2nd Decile	3.15	14.00	10.04	11.94	35.97	14.76	5.45	2.47	1.04	0.73	0.23	0.15	0.06
3rd Decile	1.96	13.37	9.22	2.41	14.27	33.04	15.44	5.68	2.67	1.13	0.42	0.35	0.06
4th Decile	1.54	12.61	8.86	1.39	3.72	14.94	31.20	15.75	5.72	2.52	1.14	0.42	0.20
5th Decile	1.40	11.96	8.17	0.62	1.40	3.83	15.61	31.39	16.21	6.57	1.88	0.79	0.17
6th Decile	1.12	10.85	7.37	0.48	0.57	1.62	3.88	15.86	34.81	16.72	5.50	1.02	0.22
7th Decile	1.06	10.74	7.14	0.31	0.43	0.84	1.51	4.33	14.16	37.99	16.99	3.58	0.92
8th Decile	0.84	11.63	7.23	0.40	0.31	0.34	0.57	1.15	3.30	12.65	44.05	15.35	2.19
9th Decile	0.98	11.72	6.92	0.37	0.20	0.14	0.37	0.57	1.09	2.59	11.46	52.48	11.12
10th Decile	0.93	13.07	7.66	0.23	0.15	0.08	0.15	0.35	0.28	0.40	1.26	9.13	66.30

Notes: See Table 4.1a.

Table 4.5c: Female One Year Transition Rates (NES) 1977/78
Percent of Given State in 1977 in Given State in 1978

	State in 1978											
State in 1977	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Other	78.19	4.78	2.47	2.15	1.89	1.86	1.68	1.49	1.48	1.42	1.27	1.31
Missing Wage	29.52	29.86	4.71	4.26	4.16	4.30	4.14	3.55	3.20	3.51	3.20	5.59
1st Decile	32.35	10.44	37.66	9.54	2.94	2.36	1.41	1.00	0.83	0.75	0.51	0.22
2nd Decile	27.47	9.92	11.07	32.44	9.14	4.36	2.32	1.44	0.76	0.41	0.37	0.32
3rd Decile	26.21	8.80	1.98	10.47	34.72	8.97	4.12	2.10	1.28	0.70	0.41	0.24
4th Decile	24.75	10.05	1.96	3.66	11.43	26.85	11.16	4.77	3.00	1.21	0.87	0.29
5th Decile	24.01	10.38	1.14	1.91	3.03	12.71	27.11	11.79	4.91	1.89	0.92	0.19
6th Decile	22.47	9.84	0.51	0.92	1.84	3.99	12.91	27.86	13.35	4.57	1.43	0.31
7th Decile	22.00	9.08	0.63	0.65	0.73	1.69	3.99	15.63	27.42	13.19	3.85	1.14
8th Decile	21.25	8.20	0.29	0.41	0.48	0.90	1.55	3.03	15.37	33.95	13.43	1.14
9th Decile	20.38	7.60	0.34	0.41	0.36	0.63	0.72	0.70	2.99	13.34	43.70	8.83
10th Decile	19.16	12.26	0.14	0.22	0.14	0.27	0.24	0.46	0.36	0.77	8.71	57.27

Notes: See Table 4.1a.
Missing also includes the unemployed.

Table 4.5d: Female One Year Transition Rates (NES) 1988/89
Percent of Given State in 1988 in Given State in 1989

	State in 1989												
State in 1988	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	27.03	48.21	6.45	4.08	2.90	2.87	2.44	1.52	1.33	0.94	1.16	0.65	0.41
Missing	1.24	82.72	4.27	1.97	1.61	1.39	1.17	1.05	0.98	1.00	0.98	0.91	0.72
Missing Wage	2.97	25.29	31.21	4.94	3.91	4.96	4.11	3.72	3.13	3.33	3.17	3.81	5.45
1st Decile	1.97	24.40	13.78	38.18	10.38	5.09	2.42	1.62	0.83	0.59	0.37	0.17	0.20
2nd Decile	1.61	20.36	11.88	10.70	36.93	10.29	3.89	2.00	0.85	0.56	0.56	0.24	0.13
3rd Decile	2.18	16.96	10.62	3.74	12.78	30.78	13.19	4.92	2.18	1.31	0.72	0.39	0.24
4th Decile	1.68	16.24	10.40	2.02	2.85	13.95	30.69	12.91	5.05	2.33	1.00	0.57	0.33
5th Decile	1.58	14.83	8.95	1.36	1.49	2.72	14.92	32.27	14.35	4.71	1.77	0.73	0.30
6th Decile	1.52	13.56	8.17	0.67	1.17	1.80	3.26	14.95	34.84	14.17	4.19	1.15	0.52
7th Decile	1.19	14.56	8.52	0.67	0.48	0.91	1.95	2.77	14.30	35.17	14.28	4.40	0.80
8th Decile	1.19	14.31	7.43	0.50	0.45	0.69	0.86	1.51	2.33	14.87	39.38	14.46	2.01
9th Decile	1.19	12.94	8.15	0.22	0.22	0.11	0.37	0.47	0.91	1.88	13.52	45.83	14.21
10th Decile	0.65	14.09	10.99	0.28	0.06	0.17	0.13	0.19	0.45	0.62	0.88	11.06	60.41

Notes: See Table 4.1a.

Table 4.6a: Male Five Year Transition Rates (NES) 1984/89
Percent of Given State in 1984 in Given State in 1989

	State in 1989												
State in 1984	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	25.09	41.59	6.48	7.08	4.81	3.55	3.35	1.94	2.05	1.64	1.22	0.82	0.38
Missing	2.71	72.35	4.90	2.16	1.97	1.89	1.87	1.94	1.78	1.91	1.81	2.12	2.58
Missing Wage	4.56	31.36	19.97	4.17	4.45	4.55	4.79	4.55	4.09	4.29	4.01	4.53	4.67
1st Decile	6.44	29.60	8.58	22.89	12.96	6.75	4.24	2.94	2.14	1.46	1.03	0.57	0.41
2nd Decile	3.50	24.69	8.81	9.27	20.74	13.03	8.08	4.63	2.94	2.05	1.24	0.74	0.28
3rd Decile	3.52	24.29	8.64	4.00	10.81	17.64	11.63	7.79	4.87	3.54	1.92	0.89	0.46
4th Decile	2.89	23.55	9.41	1.88	4.75	11.79	16.14	11.95	7.55	5.12	2.86	1.40	0.70
5th Decile	2.53	22.03	8.35	1.69	2.28	5.28	12.11	16.16	13.05	8.33	4.78	2.46	0.96
6th Decile	1.89	21.65	7.73	1.00	1.36	2.07	5.32	13.17	18.20	13.45	8.58	4.15	1.43
7th Decile	2.04	21.36	7.68	1.15	1.08	1.36	2.42	5.97	12.68	18.64	15.32	7.89	2.42
8th Decile	1.74	20.35	7.82	0.58	0.63	0.93	1.03	1.98	4.49	13.63	25.53	16.01	5.28
9th Decile	1.74	21.06	7.40	0.88	0.52	0.49	0.69	1.03	1.47	2.81	13.32	32.50	16.07
10th Decile	1.68	22.97	8.93	0.57	0.21	0.21	0.35	0.66	0.74	0.68	1.68	11.46	49.87

Notes: See Table 4.1a.

Table 4.6b: Male Five Year Transition Rates (NES) 1975/80
Percent of Given State in 1975 in Given State in 1980

	State in 1980											
State in 1975	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Missing	56.14	8.58	4.24	3.63	3.64	3.37	3.37	3.35	3.17	3.36	3.53	3.62
Missing Wage	35.37	22.85	3.82	3.93	4.31	4.42	4.44	4.25	4.60	4.13	3.51	4.39
1st Decile	36.20	9.70	22.04	12.19	6.29	4.16	2.73	2.22	2.01	1.26	0.69	0.51
2nd Decile	31.18	9.05	11.33	15.08	11.13	7.40	5.47	3.41	2.81	2.04	0.82	0.27
3rd Decile	28.46	10.27	6.33	11.57	12.39	9.87	7.65	5.22	3.83	2.73	1.19	0.49
4th Decile	26.76	10.34	3.36	6.91	10.19	11.95	10.72	8.38	5.31	3.29	2.07	0.71
5th Decile	26.15	9.89	2.14	4.04	7.29	11.67	11.26	10.60	8.16	5.36	2.61	0.83
6th Decile	24.66	10.17	1.39	2.52	4.23	7.82	9.80	12.73	11.80	8.44	5.06	1.39
7th Decile	25.47	9.65	1.02	1.69	2.78	4.79	7.35	10.99	13.68	12.14	8.14	2.30
8th Decile	24.47	9.58	1.05	0.86	1.48	2.36	3.86	6.71	12.12	17.30	15.92	4.28
9th Decile	24.83	10.61	0.77	0.55	0.74	0.90	1.54	2.01	4.53	12.65	25.11	15.77
10th Decile	27.10	10.45	0.29	0.34	0.34	0.29	0.36	0.43	0.97	2.25	9.99	47.20

Notes: See Table 4.1a.
Missing also includes the unemployed.

Table 4.6c: Female Five Year Transition Rates (NES) 1984/89
Percent of Given State in 1984 in Given State in 1989

	State in 1989												
State in 1984	Unemployed	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Unemployed	9.42	54.86	8.83	4.12	3.13	3.31	3.20	2.77	2.28	2.21	2.15	2.21	1.50
Missing	1.46	69.91	7.15	3.55	3.13	2.73	2.36	2.07	1.66	1.50	1.42	1.52	1.54
Missing Wage	2.18	38.76	18.78	4.45	4.23	4.33	3.99	3.65	2.96	2.85	2.82	3.44	7.56
1st Decile	2.32	39.74	10.78	16.33	12.76	6.35	4.22	2.56	2.22	1.04	0.88	0.40	0.40
2nd Decile	2.21	37.36	9.44	10.66	16.83	8.88	5.29	3.51	2.66	1.60	0.90	0.48	0.19
3rd Decile	2.65	34.85	9.66	4.82	9.79	14.64	9.64	5.88	3.45	2.04	1.62	0.72	0.23
4th Decile	3.10	31.97	9.79	2.84	4.32	9.66	14.53	9.87	6.09	3.93	2.06	1.38	0.47
5th Decile	2.56	31.75	8.01	1.71	1.94	4.16	12.05	15.15	10.21	6.75	3.46	1.63	0.62
6th Decile	1.96	30.99	7.70	1.45	1.53	2.37	4.62	11.79	14.44	11.91	6.22	3.88	1.12
7th Decile	1.55	29.74	7.26	0.86	0.94	1.60	2.01	4.06	14.91	15.98	11.96	7.04	2.08
8th Decile	2.07	28.57	7.85	0.91	0.83	0.81	1.49	1.77	4.82	14.49	18.63	13.00	4.77
9th Decile	1.68	28.72	7.18	0.47	0.44	0.64	0.79	0.84	0.99	3.21	13.10	24.70	17.25
10th Decile	1.45	29.66	12.42	0.27	0.32	0.45	0.37	0.52	0.62	0.92	1.40	9.43	42.16

Notes: See Table 4.1a.

Table 4.6d: Female Five Year Transition Rates (NES) 1975/80
Percent of Given State in 1975 in Given State in 1980

	State in 1980											
State in 1975	Missing	Missing Wage	1st Decile	2nd Decile	3rd Decile	4th Decile	5th Decile	6th Decile	7th Decile	8th Decile	9th Decile	10th Decile
Other	62.32	7.95	4.12	4.04	3.52	3.31	2.92	2.61	2.52	2.24	2.07	2.39
Missing Wage	43.03	18.88	3.96	3.45	4.21	4.53	4.07	3.94	3.08	3.65	2.52	4.68
1st Decile	48.21	8.40	15.03	9.01	6.18	4.25	3.32	2.19	1.77	0.58	0.61	0.45
2nd Decile	42.77	7.87	9.34	9.37	10.90	7.06	4.65	3.09	2.09	1.31	0.94	0.62
3rd Decile	39.92	8.51	4.89	12.23	8.45	7.93	6.64	4.55	2.95	2.52	1.08	0.34
4th Decile	37.91	9.31	2.61	6.26	10.44	9.75	6.98	6.10	5.53	2.86	1.79	0.47
5th Decile	37.34	8.65	2.15	2.73	5.25	8.07	10.19	9.30	7.89	5.09	2.64	0.71
6th Decile	37.41	8.63	1.47	1.69	2.55	6.17	7.83	10.75	10.47	7.52	4.45	1.04
7th Decile	37.61	7.53	1.09	1.12	1.54	3.19	5.76	9.92	10.82	11.81	7.14	2.47
8th Decile	36.98	7.15	1.31	0.73	1.04	1.95	3.45	4.92	9.34	14.93	14.08	4.12
9th Decile	36.20	7.13	0.86	0.68	0.71	1.23	1.17	1.75	4.06	10.66	21.79	13.77
10th Decile	32.03	15.85	0.39	0.15	0.18	0.27	0.39	0.30	0.72	1.23	5.80	42.68

Notes: See Table 4.1a.
Missing also includes the unemployed.

Table 4.7a: Male one Year Transition Rates (NES) 1977/78 by Absolute Earnings Bands
Percent of Given State in 1977 in Given State in 1978

	State in 1978								
State in 1977	Missing	Missing Wage	< 0.5	0.5 - 0.75	0.75 - 1	1 - 1.25	1.25 - 1.5	> 1.5	Column Percent of Earnings Dist
Missing	67.52	6.58	0.15	2.94	12.64	7.39	2.23	0.54	-
Missing Wage	26.46	31.94	0.17	3.16	20.33	13.39	3.54	1.01	-
< 0.5	38.44	15.64	16.94	17.92	8.47	2.28	0.33	0.00	0.40
0.5 - 0.75	27.29	10.16	0.35	34.01	26.39	1.53	0.20	0.08	9.55
0.75 - 1	20.43	10.29	0.05	2.07	54.06	12.77	0.31	0.03	51.73
1 - 1.25	17.83	8.71	0.02	0.24	8.04	57.91	7.04	0.22	28.68
1.25 - 1.5	18.34	7.93	0.00	0.17	0.96	7.06	60.02	5.53	7.89
> 1.5	20.41	9.01	0.00	0.09	0.68	1.36	8.08	60.37	1.71
Row Percent of Earnings Dist	-	-	0.29	7.51	47.49	32.85	9.65	2.21	100.00

Notes: See Table 4.1a.
Missing also includes the unemployed.
Earnings bands defined using fixed real earnings cutoffs of 0.5, 0.75, 1, 1.25, 1.5 time mean earnings in 1975.

Table 4.7b: Male one Year Transition Rates (NES) 1988/89 by Absolute Earnings Bands
Percent of Given State in 1988 in Given State in 1989

	State in 1989									
State in 1988	Unemployed	Missing	Missing Wage	< 0.5	0.5 - 0.75	0.75 - 1	1 - 1.25	1.25 - 1.5	> 1.5	Column Percent of Earnings Dist
Unemployed	43.65	33.71	5.28	0.24	3.15	8.80	3.96	1.01	0.20	-
Missing	2.55	82.03	3.09	0.08	0.81	3.72	4.37	2.24	1.11	-
Missing Wage	3.35	19.73	33.45	0.25	2.10	13.87	15.27	7.66	4.33	-
< 0.5	8.00	33.60	19.20	16.00	11.20	7.20	4.00	0.80	0.00	0.19
0.5 - 0.75	10.89	20.58	10.89	0.70	30.84	22.58	2.98	0.46	0.11	4.40
0.75 - 1	3.21	13.99	9.47	0.11	2.26	55.89	14.42	0.59	0.06	27.35
1 - 1.25	1.25	11.53	7.83	0.04	0.26	7.30	62.80	8.65	0.36	38.14
1.25 - 1.5	0.90	11.74	7.12	0.07	0.20	0.70	9.77	62.24	7.26	20.92
> 1.5	0.96	13.10	7.59	0.05	0.10	0.36	1.08	8.93	67.82	9.00
Row Percent of Earnings Dist		-	-	0.28	3.76	26.84	38.12	21.23	9.77	100.00

Notes: See Table 4.1a.
Earnings bands defined using fixed real earnings cutoffs of 0.5, 0.75, 1, 1.25, 1.5 time mean earnings in 1975.

Table 4.7c: Female one Year Transition Rates (NES) 1977/78 by Absolute Earnings Bands
Percent of Given State in 1977 in Given State in 1978

	State in 1978								
State in 1977	Missing	Missing Wage	< 0.5	0.5 - 0.75	0.75 - 1	1 - 1.25	1.25 - 1.5	> 1.5	Column Percent of Earnings Dist
Missing	78.19	4.78	0.23	2.41	8.00	4.43	1.21	0.74	-
Missing Wage	29.52	29.86	0.49	4.55	17.72	10.75	3.04	4.06	-
< 0.5	32.34	13.99	14.68	22.02	13.76	2.52	0.23	0.46	1.00
0.5 - 0.75	31.03	10.23	0.67	34.86	20.64	2.24	0.27	0.06	12.56
0.75 - 1	24.90	9.79	0.18	2.14	50.95	11.47	0.48	0.11	43.65
1 - 1.25	21.31	8.37	0.07	0.45	7.45	55.79	6.31	0.25	28.80
1.25 - 1.5	20.35	8.80	0.00	0.44	1.67	9.87	51.89	6.97	8.82
> 1.5	18.74	14.91	0.00	0.09	0.66	0.95	4.40	60.25	5.11
Row Percent of Earnings Dist	-	-	0.77	10.17	42.75	31.17	9.33	5.81	100.00

Notes: See Table 4.1a.
Missing also includes the unemployed.
Earnings bands defined using fixed real earnings cutoffs of 0.5, 0.75, 1, 1.25, 1.5 time mean earnings in 1975.

Table 4.7d: Female one Year Transition Rates (NES) 1988/89 by Absolute Earnings Bands
Percent of Given State in 1988 in Given State in 1989

	State in 1989									
State in 1988	Unemployed	Missing	Missing Wage	< 0.5	0.5 - 0.75	0.75 - 1	1 - 1.25	1.25 - 1.5	> 1.5	Column Percent of Earnings Dist
Unemployed	27.03	48.21	6.45	0.19	1.28	7.78	5.80	2.22	1.04	-
Missing	1.24	82.72	4.27	0.14	0.54	3.97	3.44	2.07	1.61	-
Missing Wage	2.97	25.29	31.21	0.40	1.43	10.91	11.84	6.77	9.18	-
< 0.5	0.58	33.33	13.37	9.94	4.09	21.05	9.36	2.92	2.34	0.37
0.5 - 0.75	1.98	26.26	16.73	1.44	22.93	24.37	4.32	1.62	0.36	2.41
0.75 - 1	1.93	19.95	11.65	0.45	2.03	49.35	12.81	1.39	0.44	26.34
1 - 1.25	1.60	15.01	9.17	0.21	0.34	6.67	54.61	11.18	1.20	32.11
1.25 - 1.5	1.16	14.26	7.81	0.13	0.11	1.27	8.20	52.59	14.47	21.42
> 1.5	0.87	13.42	9.99	0.04	0.06	0.30	1.04	4.55	69.73	17.35
Row Percent of Earnings Dist		-	-	0.59	2.44	24.85	31.10	20.75	20.27	100.00

Notes: See Table 4.1a.
Earnings bands defined using fixed real earnings cutoffs of 0.5, 0.75, 1, 1.25, 1.5 time mean earnings in 1975.

Table 4.8
The Effects of Inflation on One Year Mobility Measures: 1976-94

Mobility Measure	Inflation Rate	Time Trend
Males		
Ranking Measure[1]	0.2096 (3.037)	-0.0023 (3.489)
Proportion Changing Decile[2]	0.4521 (2.680)	-0.0054 (3.267)
Inverse of Correlation Coefficient[3]	0.2863 (3.087)	-0.0007 (0.771)
Shorrocks Index[4]	0.1526 (3.386)	0.0002 (0.366)
Females		
Ranking Measure[1]	0.2630 (4.080)	-0.0011 (1.813)
Proportion Changing Decile[2]	0.7191 (4.398)	-0.0022 (1.360)
Inverse of Correlation Coefficient[3]	0.2568 (1.925)	0.0001 (0.080)
Shorrocks Index[4]	0.1391 (1.863)	0.0007 (0.907)

Notes: 1) Ranking measure as defined in text.
2) Proportion changing decile of balanced sample one year decile transition matrix.
3) Inverse of pearson correlation coefficient of earnings in year t and year t-1.
4) Shorrocks Index: 1- Var $((w_t + w_{t-1})/2) / (\eta_t Var(w_t) + \eta_{t-1} Var(w_{t-1}))$. Where the weights ($\eta$) are the ratio of single period earnings to two period earnings.
5) T-Ratios in brackets.

Table 4.9
The Effects of Inflation on Five Year Mobility Measures: 1980-94

Mobility Measure	Five Year Inflation Rate	Time Trend
Males		
Ranking Measure[1]	0.0506 (2.896)	-0.0013 (1.377)
Proportion Changing Decile[2]	0.0593 (2.875)	-0.0014 (1.204)
Inverse of Correlation Coefficient[3]	0.0494 (1.204)	-0.0014 (0.597)
Shorrocks Index[4]	0.0693 (2.677)	0.0037 (2.540)
Females		
Ranking Measure[1]	0.0777 (5.285)	0.0003 (0.311)
Proportion Changing Decile[2]	0.1111 (4.281)	0.0012 (0.811)
Inverse of Correlation Coefficient[3]	0.0538 (0.806)	0.0019 (0.519)
Shorrocks Index[4]	0.0458 (1.187)	0.0041 (1.891)

Notes 1) Ranking measure as defined in text.
2) Proportion changing decile of balanced sample five year decile transition matrix.
3) Inverse of pearson correlation coefficient of earnings in year t and year t-5.
4) Shorrocks Index: $1 - Var((w_t + w_{t-5})/2) / (\eta_t Var(w_t) + \eta_{t-5} Var(w_{t-5}))$. Where the weights ($\eta$) are the ratio of single period earnings to two period earnings.
5) T Ratios in brackets.

Table 4.10
One Year Mobility Index by Decile of Origin: Males and Females

	Males		Females	
Origin Decile	1977/78	1988/89	1977/78	1988/89
All	0.181	0.145	0.162	0.153
Decile 1	0.152	0.114	0.169	0.152
Decile 2	0.186	0.149	0.166	0.151
Decile 3	0.213	0.168	0.162	0.177
Decile 4	0.225	0.179	0.193	0.176
Decile 5	0.225	0.177	0.197	0.179
Decile 6	0.227	0.175	0.195	0.178
Decile 7	0.208	0.160	0.190	0.173
Decile 8	0.175	0.141	0.160	0.155
Decile 9	0.130	0.072	0.130	0.115
Decile 10	0.067	0.065	0.060	0.076

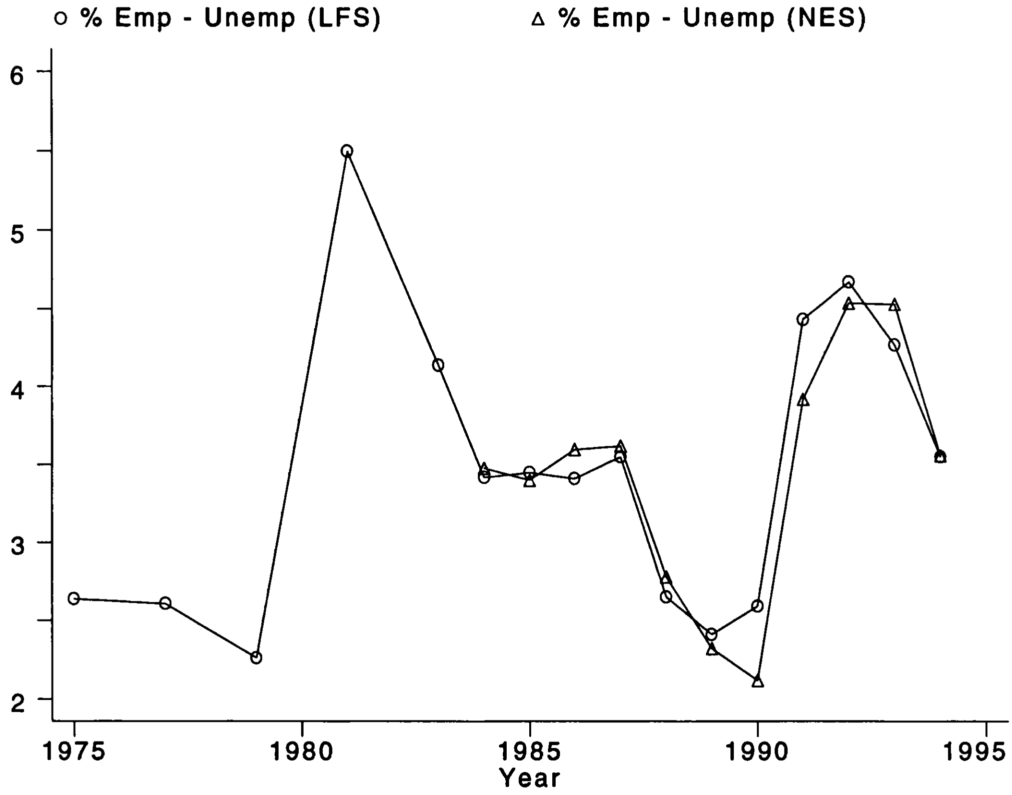
Notes: 1) New Earnings Survey Data.
2) Mobility Index Defined in Text.

Table 4.11
Five Year Mobility Index by Decile of Origin: Males and Females

	Males			Females		
Origin Decile	1975/80	1984/89	1989/94	1975/80	1984/89	1989/94
All	0.284	0.241	0.230	0.300	0.254	0.239
Decile 1	0.273	0.220	0.206	0.335	0.292	0.266
Decile 2	0.298	0.241	0.222	0.348	0.242	0.236
Decile 3	0.321	0.265	0.247	0.329	0.274	0.264
Decile 4	0.313	0.276	0.264	0.329	0.277	0.268
Decile 5	0.319	0.273	0.265	0.332	0.278	0.263
Decile 6	0.326	0.279	0.270	0.329	0.291	0.276
Decile 7	0.314	0.261	0.251	0.323	0.276	0.261
Decile 8	0.303	0.242	0.236	0.307	0.257	0.231
Decile 9	0.233	0.211	0.201	0.254	0.210	0.192
Decile 10	0.139	0.145	0.142	0.115	0.143	0.133

Notes: 1) New Earnings Survey Data.
2) Mobility Index Defined in Text.

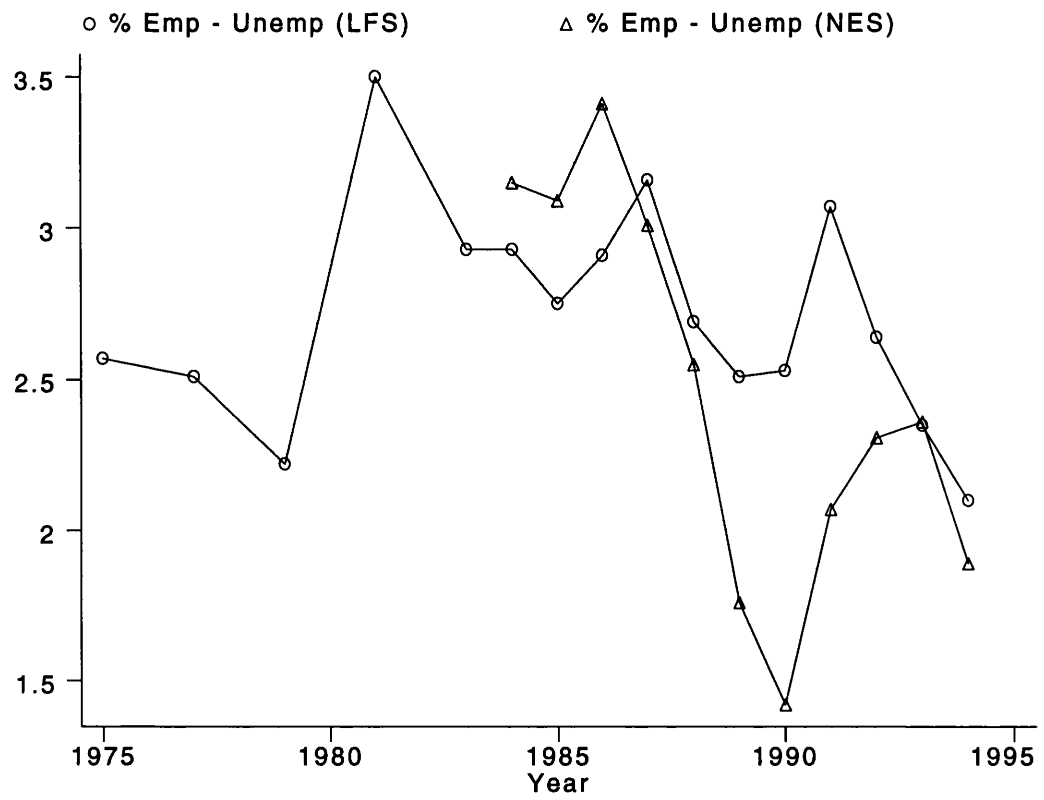
Figure 4.1a
Proportion of Employees Entering Unemployment: Males 1975-94



Notes:

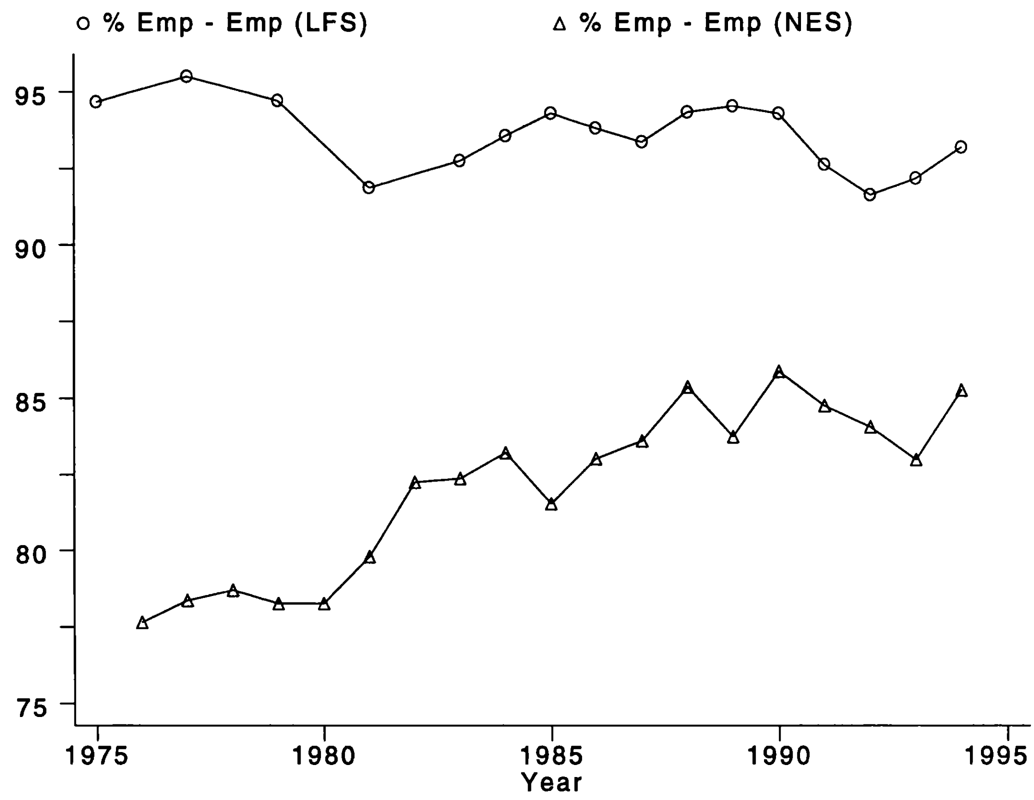
1) The proportions presented are the percent of employees in year t-1 who are in unemployment in year t.
2) The data from the NES records individuals present in the NES in year t-1 who are present in the JUVOS data in year t.
3) The LFS data comes from a retrospective question, in year t, about labour force status in year t-1.

Figure 4.1b
Proportion of Employees Entering Unemployment: Females 1975-94



Notes as Figure 4.1a.

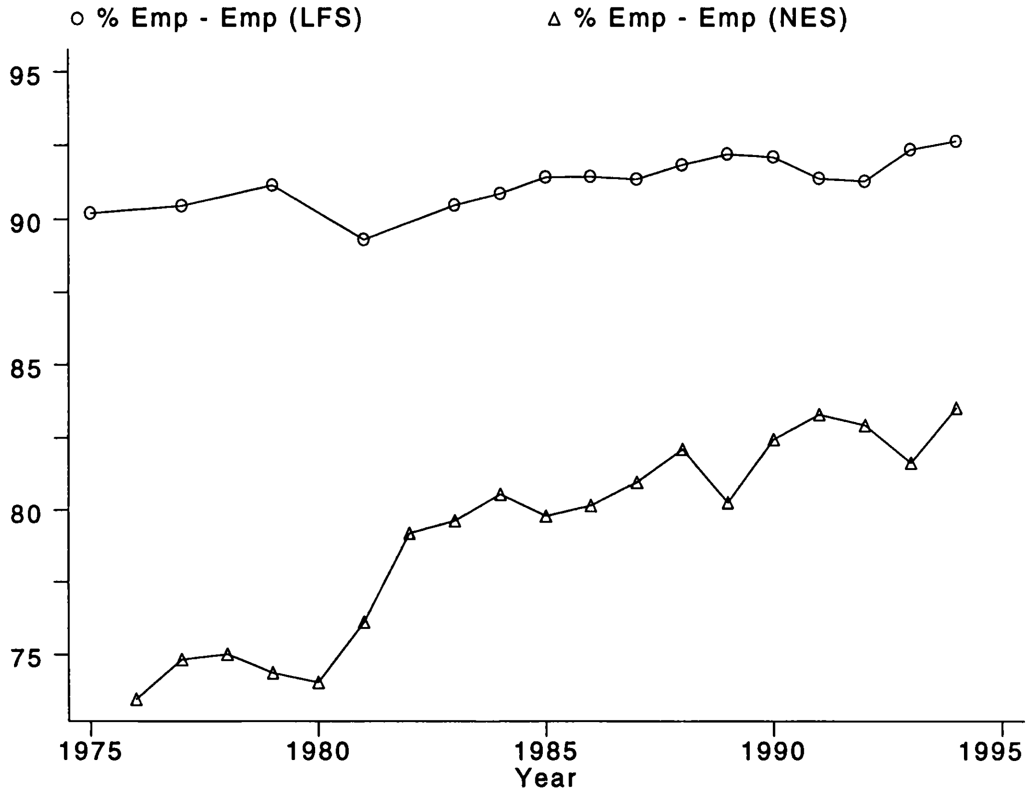
Figure 4.2a
Proportion of Employees Remaining in Employment: Males 1975-94



Notes:

1) The proportions presented are the percent of employees in year t-1 who are in employment in year t.
2) The data from the NES records individuals present in the NES in year t-1 who are present in the NES in year t.
3) The LFS data comes from a retrospective question, in year t, about labour force status in year t-1.

Figure 4.2b
Proportion of Employees Remaining in Employment: Females 1975-94



Notes as Figure 4.2a.

Figure 4.3a
Earnings Ranking in 1977 and 1978: Males

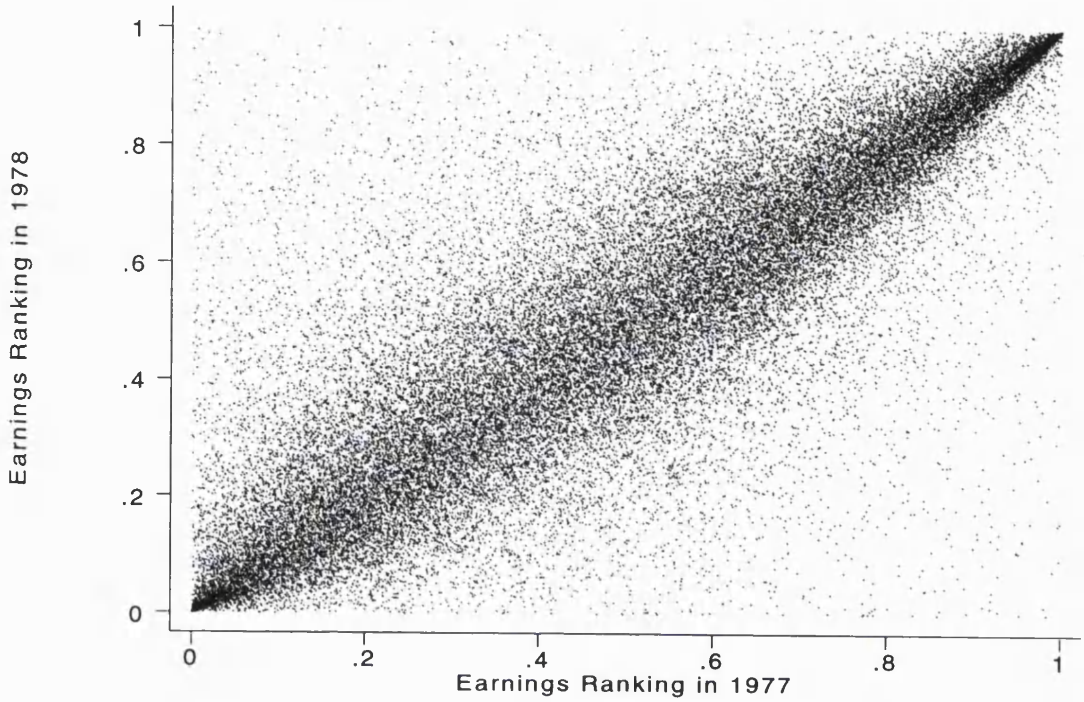


Figure 4.3b
Earnings Ranking in 1988 and 1989: Males

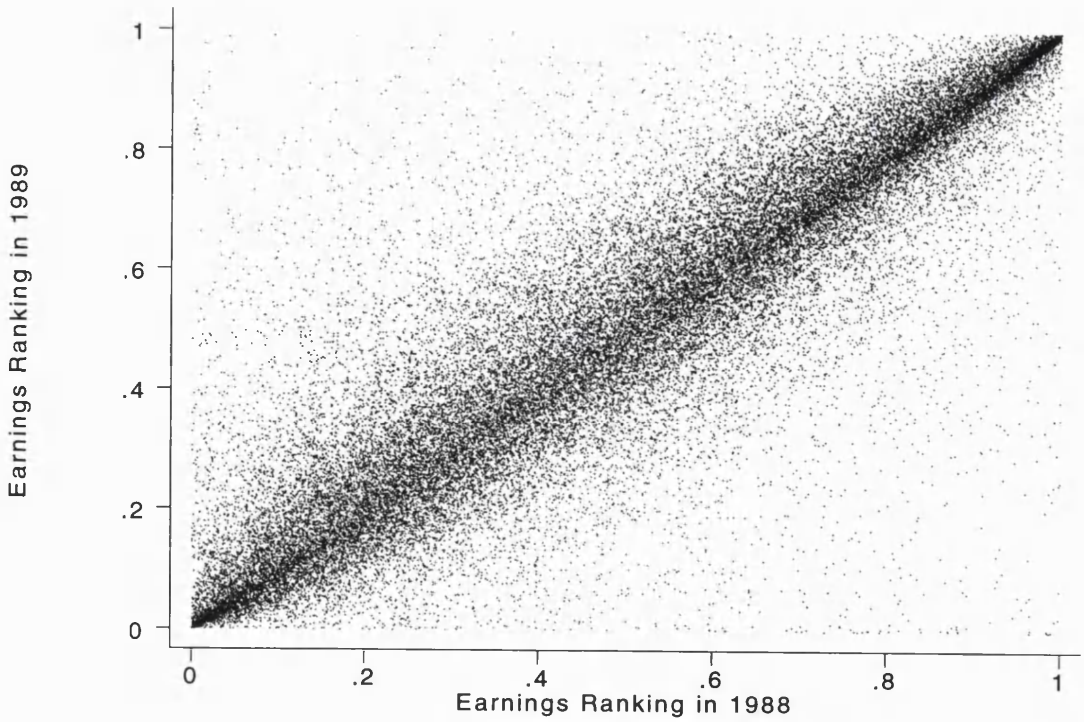


Figure 4.4a
Earnings Ranking in 1977 and 1978: Females

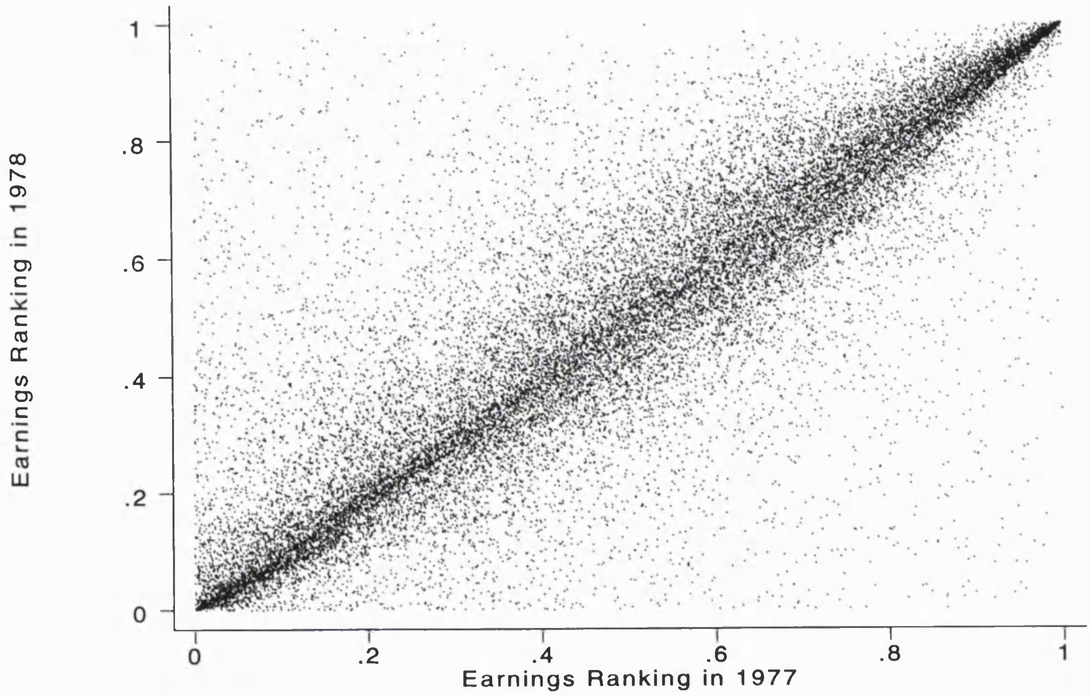


Figure 4.4b
Earnings Ranking in 1988 and 1989: Females

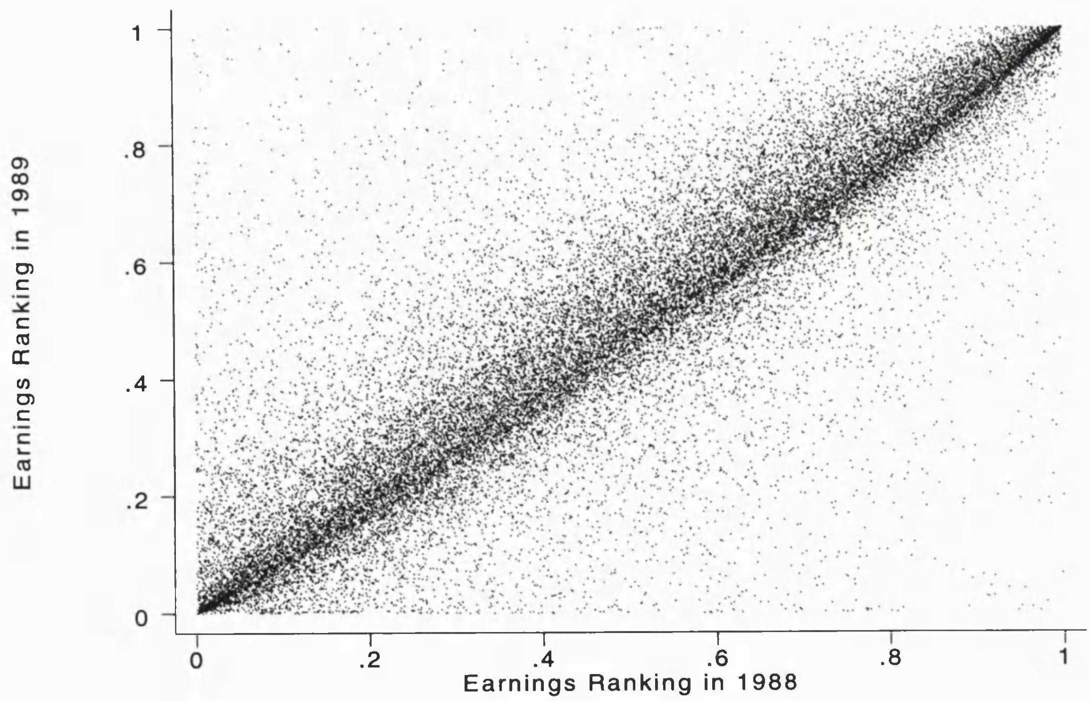
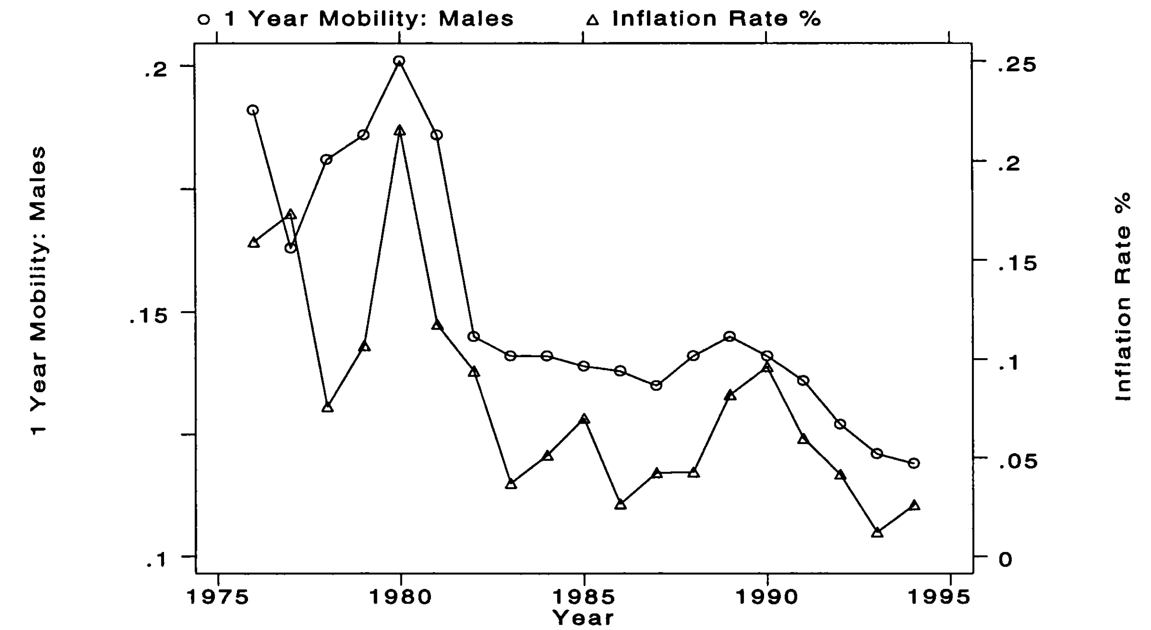
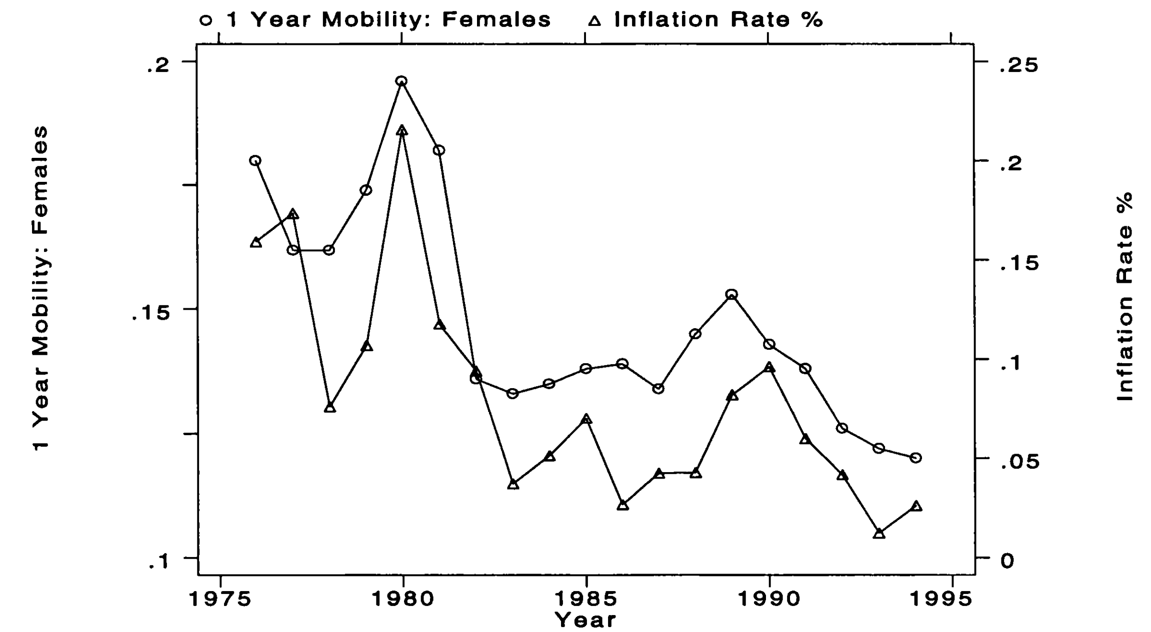


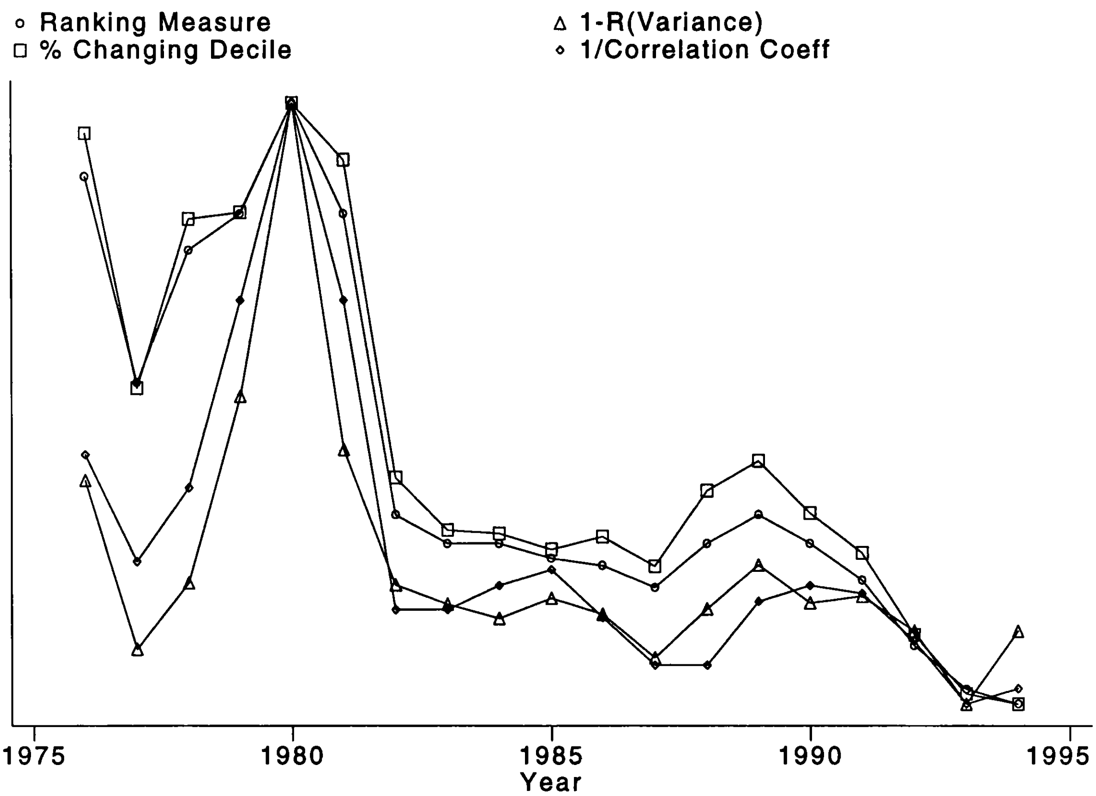
Figure 4.5
One Year Mobility Index and Inflation: Males and Females 1976-94





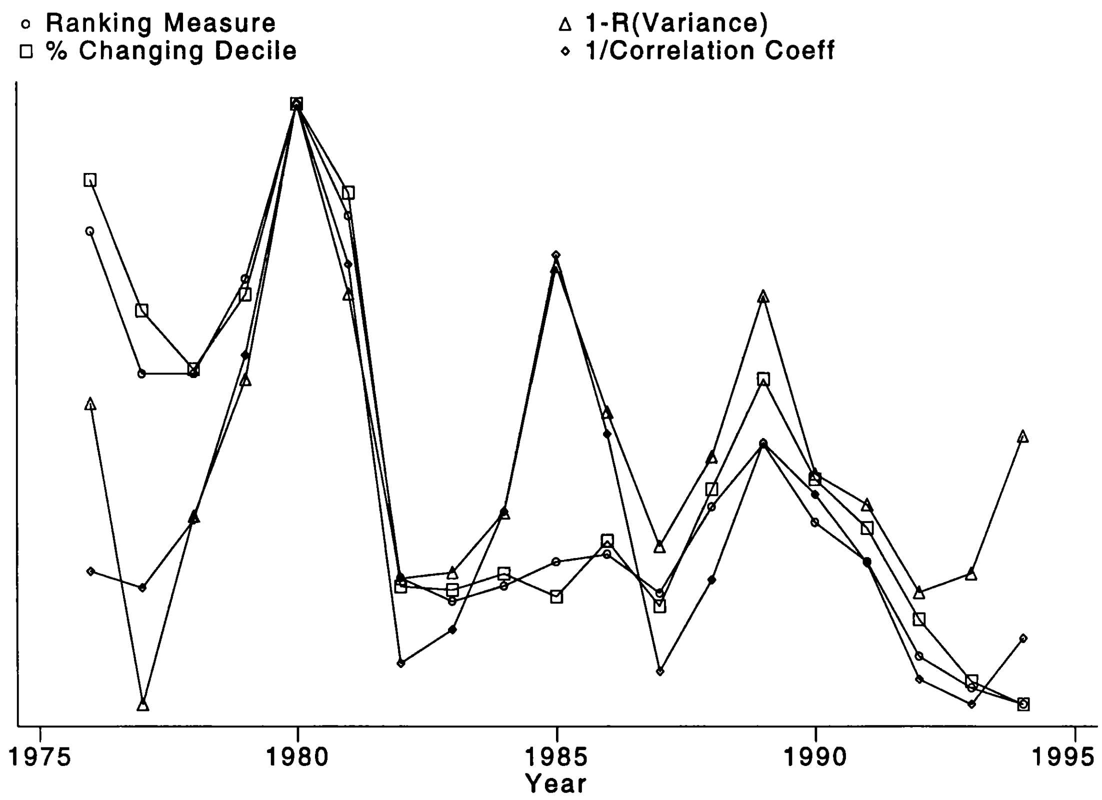
Notes: 1) New Earnings Survey Data.
2) Mobility Index Defined in Text. The index for year t is computed from earnings in year t and earnings in years t-1.

Figure 4.6
Alternative One Year Measures of Mobility - Males: 1976-94



Notes: 1) Ranking measure as defined in text.
2) Proportion changing decile of balanced sample one year decile transition matrix.
3) Inverse of pearson correlation coefficient of earnings in year t and year t-1.
4) 1-R(Variance) (Shorrocks): 1- (Var $(w_t + w_{t-1})/2)$ / $(\eta_t \mathrm{Var}(w_t) + \eta_{t-1}\mathrm{Var}(w_{t-1}))$. Where the weights ($\eta$) are the ratio of single period earnings to two period earnings.

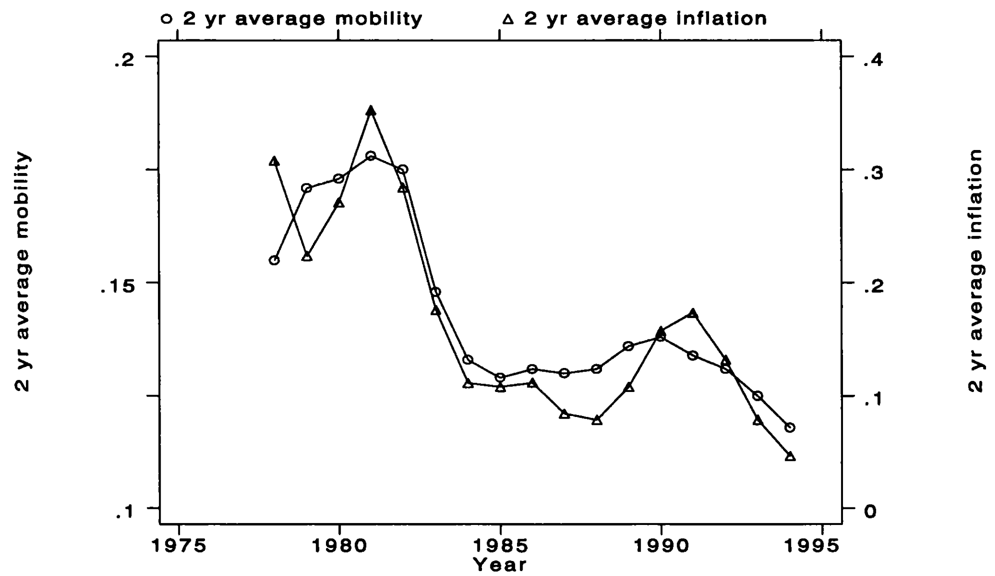
Figure 4.7
Alternative One Year Measures of Mobility - Females: 1976-94



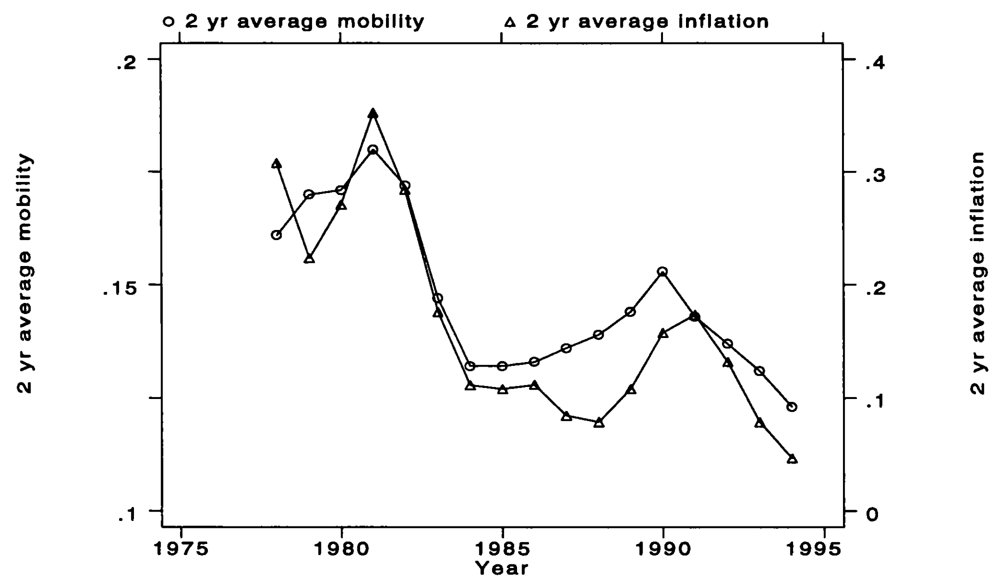
Notes: 1) Ranking measure as defined in text.
2) Proportion changing decile of balanced sample one year decile transition matrix.
3) Inverse of pearson correlation coefficient of earnings in year t and year t-1.
4) 1-R(Variance) (Shorrocks): 1- (Var $(w_t + w_{t-1})/2)$ / $(\eta_t \mathrm{Var}(w_t) + \eta_{t-1}\mathrm{Var}(w_{t-1}))$. Where the weights ($\eta$) are the ratio of single period earnings to two period earnings.

Figure 4.8
Two Year Averaged Mobility Index: Males and Females 1978-94

Males



Females



Notes: 1) New Earnings Survey Data.
2) Mobility Index Defined in Text. The index for year t is computed from average earnings in years t and t-1 and average earnings in years t-2 and t-3.

Figure 4.9a
Earnings Ranking in 1975 and 1980: Males

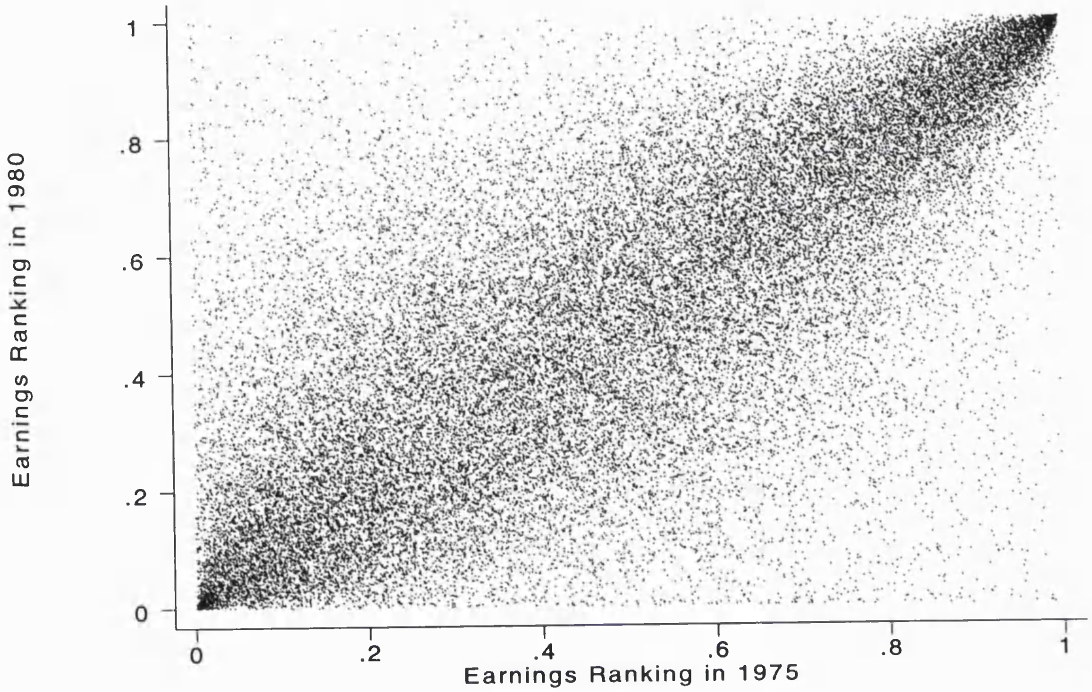


Figure 4.9b
Earnings Ranking in 1984 and 1989: Males

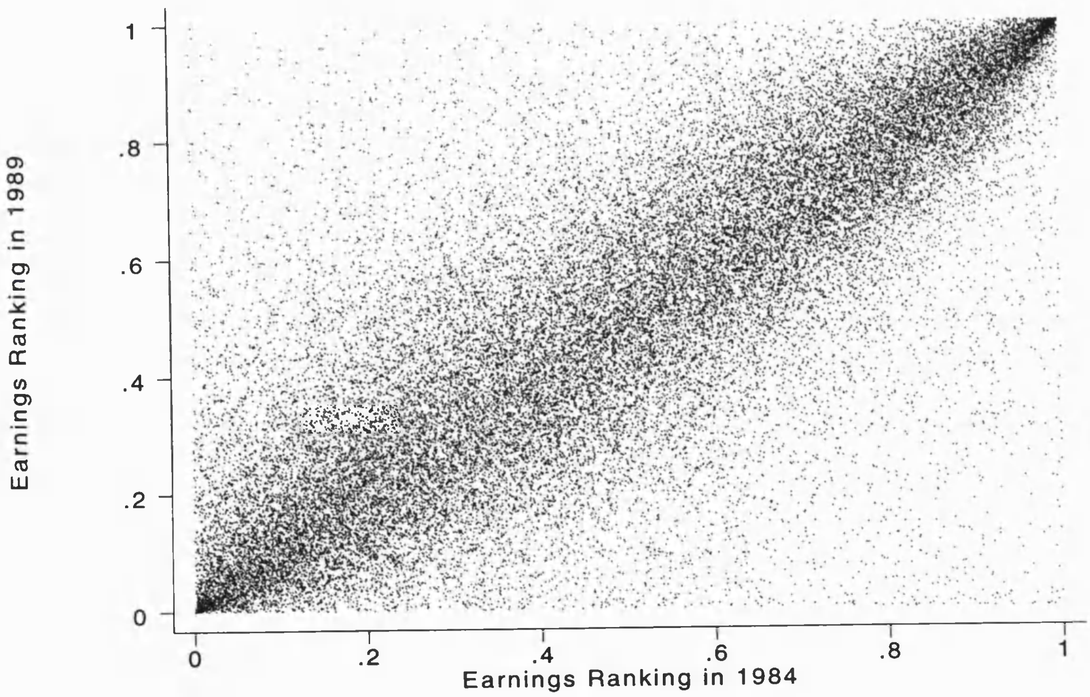


Figure 4.9c
Earnings Ranking in 1989 and 1994: Males

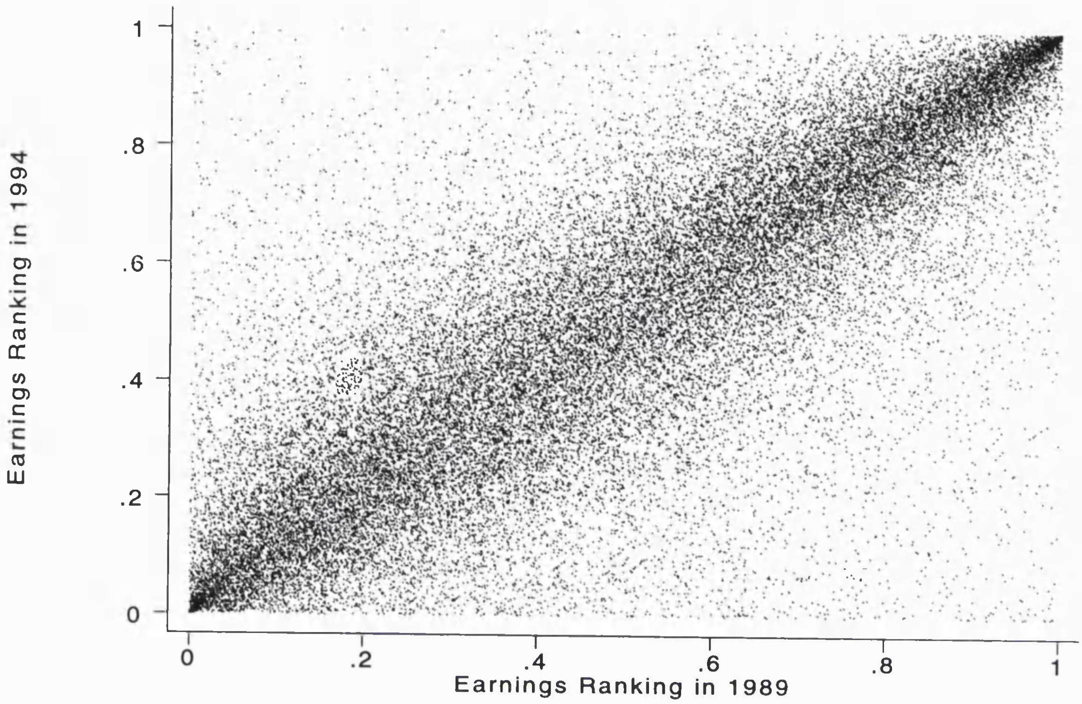


Figure 4.10a
Earnings Ranking in 1975 and 1980: Females

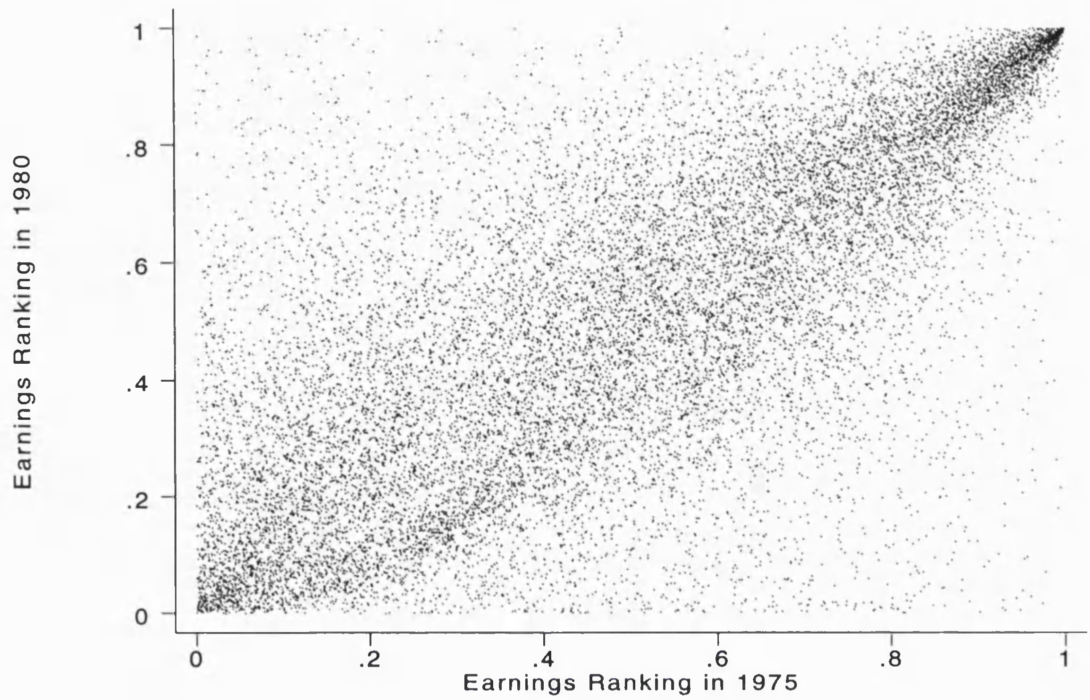


Figure 4.10b
Earnings Ranking in 1984 and 1989: Females

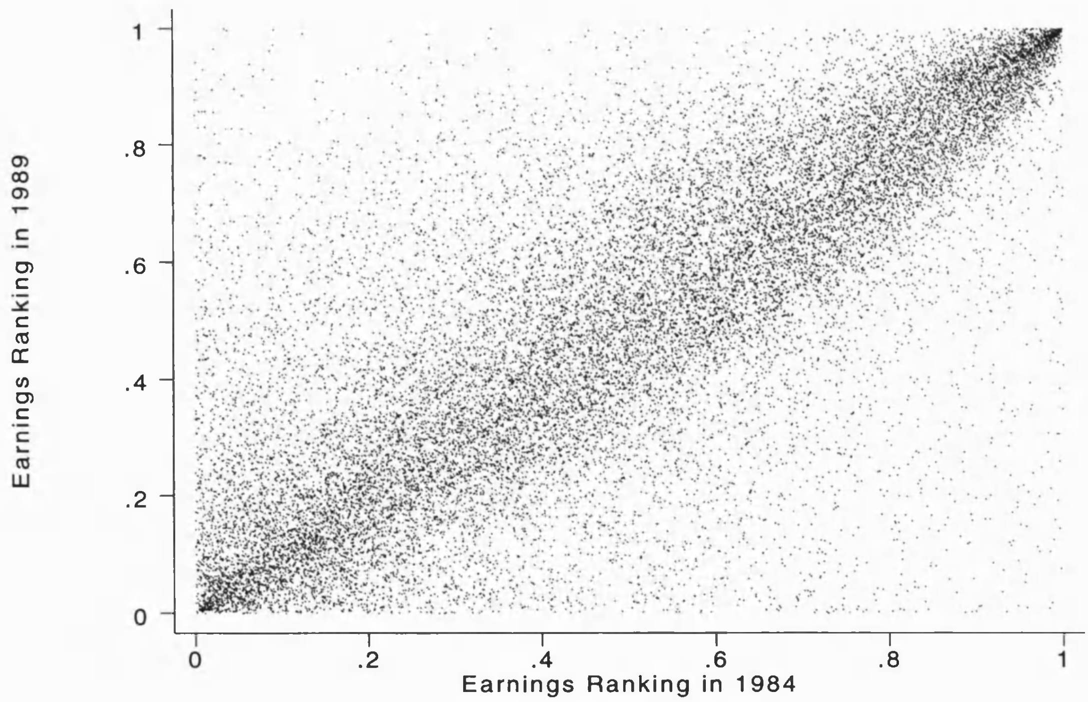


Figure 4.10c
Earnings Ranking in 1989 and 1994: Females

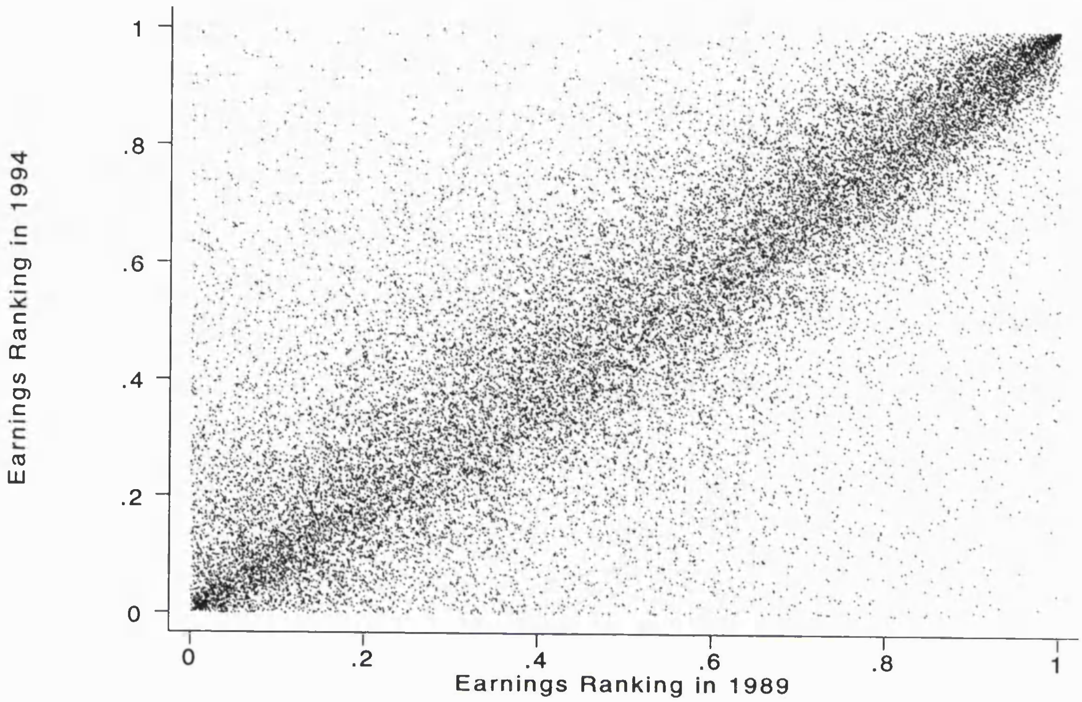
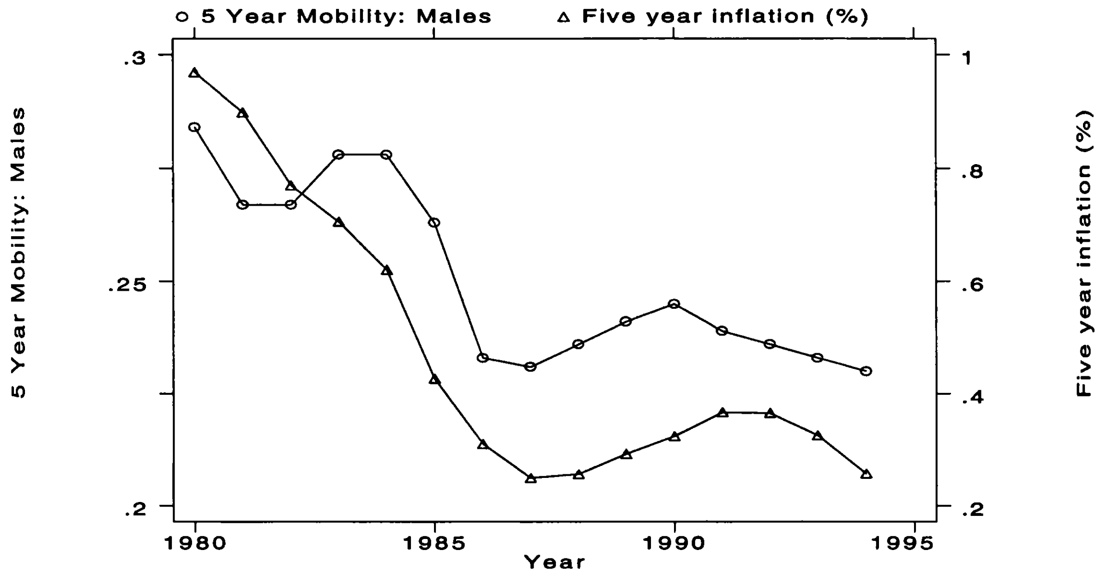
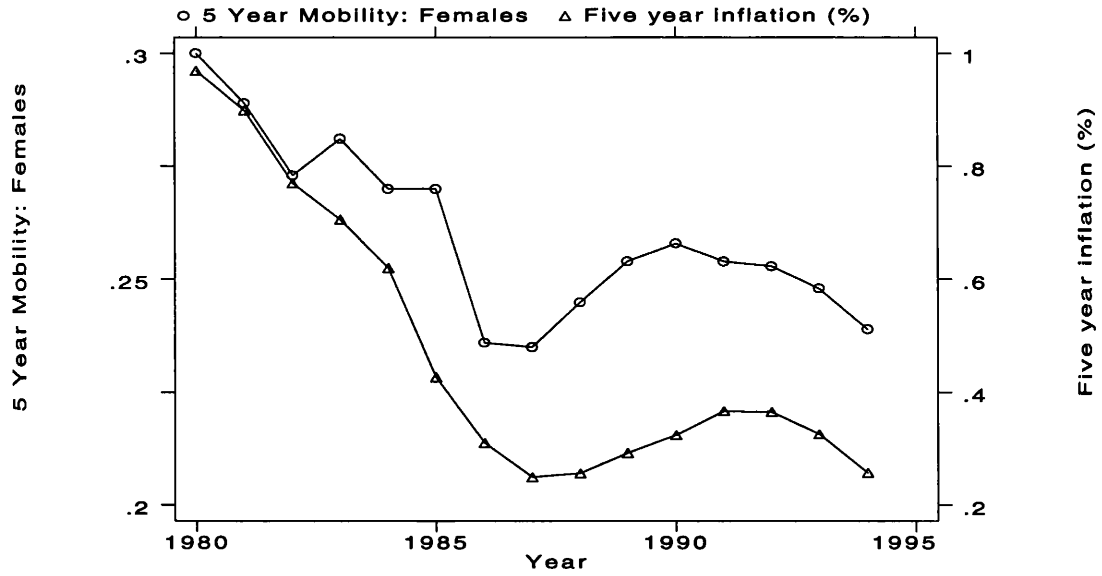


Figure 4.11
Five Year Mobility Index and the Inflation Rate: Males and Females 1980-94

Males

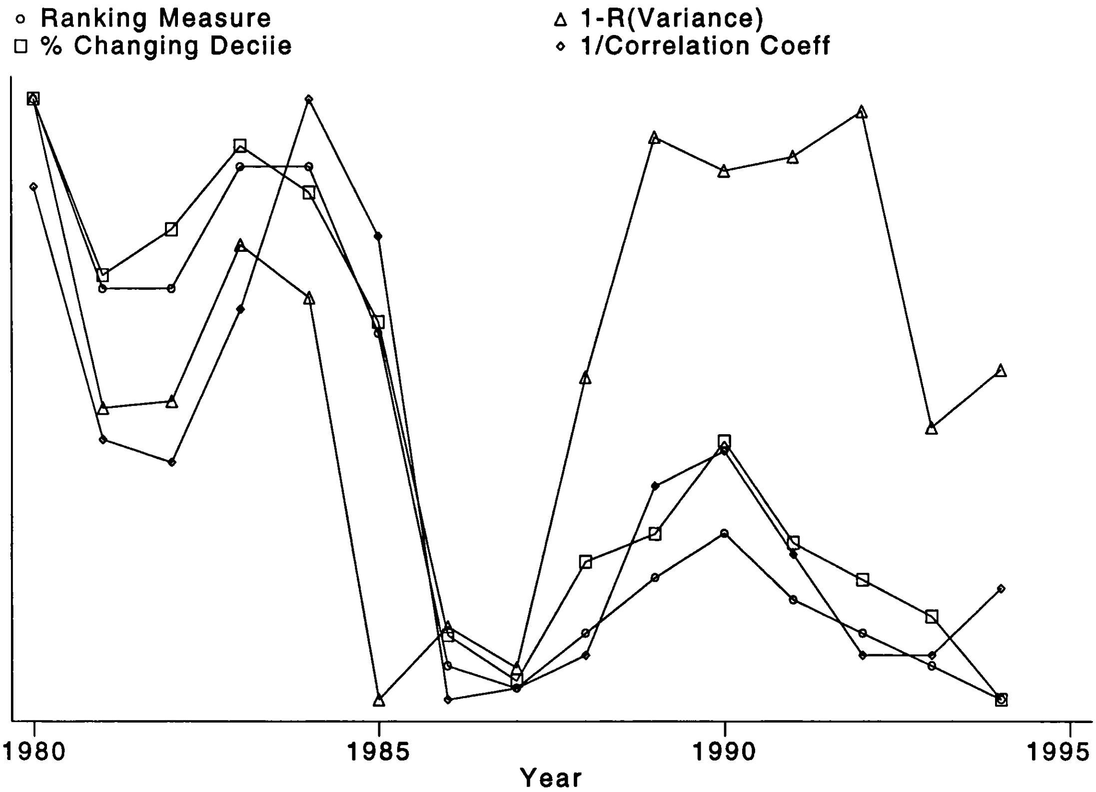


Females



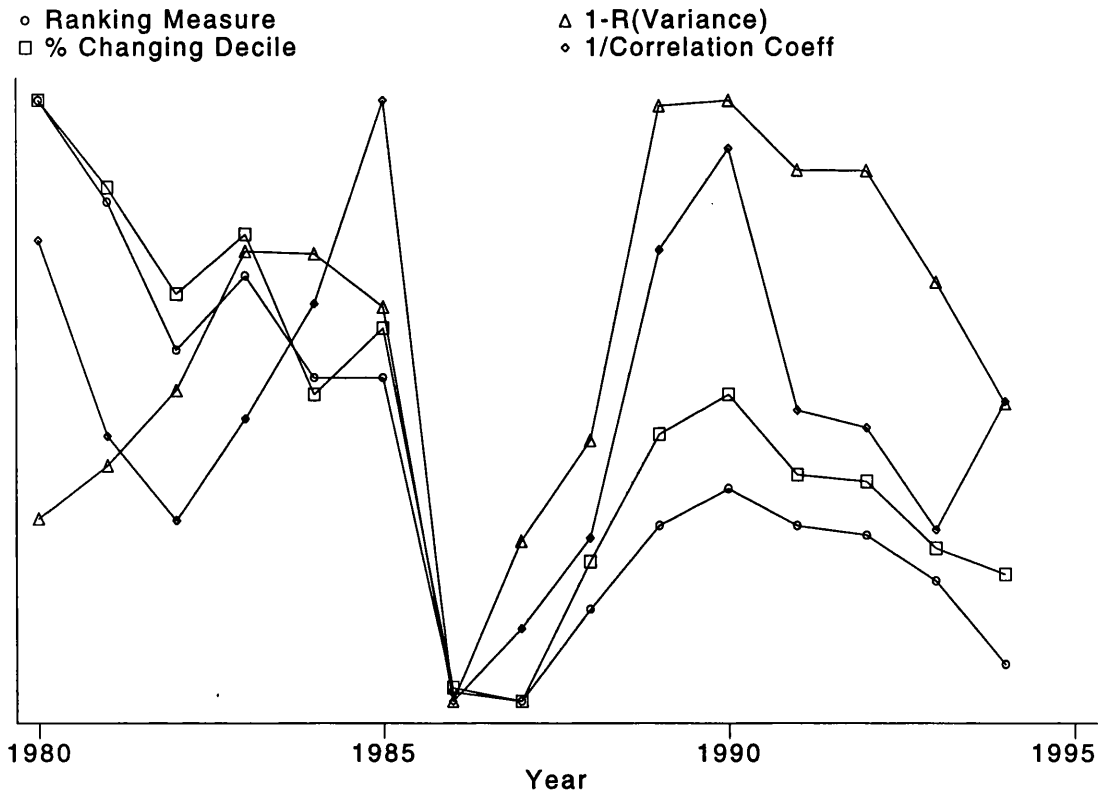
Notes: 1) New Earnings Survey Data.
2) Mobility Index Defined in Text. The index for year t is computed from earnings in year t earnings in year t-5.

Figure 4.12
Alternative Five Year Measures of Mobility - Males: 1980-94



Notes: 1) Ranking measure as defined in text.
2) Proportion changing decile of balanced sample one year decile transition matrix.
3) Inverse of pearson correlation coefficient of earnings in year t and year t-1.
4) 1-R(Variance) (Shorrocks): 1- (Var $(w_t + w_{t-5})/2) / (\eta_t Var(w_t) + \eta_{t-5} Var(w_{t-5}))$. Where the weights ($\eta$) are the ratio of single period earnings to two period earnings.

Figure 4.13
Alternative Five Year Measures of Mobility - Females: 1980-94



Notes: 1) Ranking measure as defined in text.
2) Proportion changing decile of balanced sample one year decile transition matrix.
3) Inverse of pearson correlation coefficient of earnings in year t and year t-1.
4) 1-R(Variance) (Shorrocks): 1- (Var $(w_t + w_{t-5})/2$) / (η_tVar(w_t) + η_{t-5}Var(w_{t-5})). Where the weights (η) are the ratio of single period earnings to two period earnings.

Chapter 5 - The Effects of Minimum Wages on Employment: Theory and Evidence from Britain

5.1 Introduction

There has been a considerable resurgence of interest in the economics of the minimum wage following the recent publication of a number of papers (Card, 1992a, 1992b; Katz and Krueger, 1992; Card, Katz and Krueger, 1993; Machin and Manning, 1994; Card and Krueger, 1994) and a much discussed book (Card and Krueger, 1995) which, contrary to the accepted wisdom of the standard competitive model of the labour market, have found zero or even positive effects of minimum wages on employment.[1] Prior to the publication of these studies a consensus appeared to have been reached that increases in the minimum wage had small negative effects on employment (Brown, Gilroy and Cohen, 1982). The controversial results from these recent studies have re-opened the debate about the economic effects of minimum wages. At present, explaining these results is something of a puzzle.

The main economic model which could potentially explain these results is the monopsony model. But, monopsony is currently not a popular model of the labour market. For example, it has been claimed that "there is little evidence that it is important in modern-day low-wage labour markets" (Brown, Gilroy and Kohen, 1982, page 489).[2] This viewpoint is based on the company-town example of monopsony which is cited in

[1] See Chapter 2.3 of this thesis for a review of this work.

[2] Exceptions are sometimes noted, with probably the most commonly cited exception being the US market for nurses (see Sullivan, 1989).

many labour economics textbooks. However, I would argue that monopsony derived from models of labour market frictions may be far more common than this. For example, in most labour markets employers that cut wages do not instantaneously lose all their workers. Hence the supply of labour to a firm is not perfectly elastic so that firms possess some degree of monopsony power. These ideas can be given more formal expression: search models of the labour market (like Burdett and Mortensen, 1989) provide some support for the view that it is not difficult to construct reasonable theoretical models of the labour market where employers have some monopsony power in both the short and the long-run.[3]

In this chapter I present a simple model of the labour market in which all firms potentially have some monopsony power. This model is a good starting-point for thinking about the effect of minimum wages for a number of reasons. First, the effect of minimum wages on employment is not determined *a priori* as it is when competitive models are used. Secondly, it can explain the existence of a spike in the empirical wage distribution at the legal minimum.[4] Thirdly, it can be used to evaluate different empirical approaches to estimating the employment effects of minimum wages.

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[3] Rebitzer and Taylor (1993) present an efficiency wage model which can create monopsony-like behaviour by firms. As such, increases in the minimum wage can increase employment. Bhaskar and To (1996) present a model of monopsonistic competition in which increases in the minimum wage may increase or reduce employment.

[4] One should also recognise that there are other competitive explanations of this phenomenon, notably that firms adjust non-wage compensation or that the labour markets studied are made up of many different sub-markets, a fraction of which have wages equal to the minimum (Teulings, 1991). In this chapter, I do not address whether the spike is better explained by these theories although it should be noted that Holzer, Katz and Krueger (1991) claim that minimum wage jobs do not offer the same level of utility as "surrounding" jobs, and Katz and Krueger (1992) and Card and Krueger (1994) found that few fast food restaurants reduced non-wage benefits when confronted with an increase in the minimum wage.

In the next section of this chapter I outline a theoretical model of the labour market and use it to discuss empirical approaches to investigating the employment effects of minimum wages. Section 5.3 looks in some detail at the employment effects of the minimum rates of pay set by the British Wages Councils using panel data from the 1970s through to the 1990s. Section 5.4 then offers some concluding remarks.

5.2 The Model

In this section I present a simple model of a monopsonistically competitive labour market which provides a useful framework for thinking about the effect of minimum wages.[5] One might wonder what this analysis adds to the textbook model of a single monopsonistic firm. I think its contribution is twofold. First, it brings out the important distinction between the elasticity of labour supply to an individual firm (which determines their monopsony power) and the elasticity of labour supply to the market as a whole (which is more important in determining employment effects of the minimum wage). Secondly, it allows an analysis of the way in which different firms in the same market are differentially affected by the minimum wage. This is useful when one wants to consider how appropriate various empirical strategies are for investigating the employment effects of minimum wages.

Assume firm i in the market has a marginal revenue product of labour curve (*MLRP*) given by:

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[5] An explicit version of this model with log-linear demand and supply curves and log-normally distributed shocks is presented in Dickens, Machin and Manning (1993).

$$MRPL_i = M(L_i, A_i) \tag{5.1}$$

where L_i is employment and A_i is a shock to the $MRPL$ reflecting demand or productivity shocks. Assume that M is a decreasing function of L_i and an increasing function of A_i.

On the supply side I assume that the wage paid by firm i, W_i, depends on the average wage, W, a supply shock, B_i, and, potentially, on employment, L_i:

$$W_i = W^s(W, B_i, L_i) \tag{5.2}$$

Equation (5.2) can be thought of as analogous to the Dixit and Stiglitz (1977) specification of the demand curve facing an individual firm in models of monopolistic competition. If the labour market is perfectly competitive then W^s will not depend on L_i but it will do if the market is, to some extent, monopsonistic. As emphasized in the introduction I think of the source of the monopsony power of employers as being labour market frictions.[6] B_i is a firm specific labour supply shock which could represent differences in the non-pecuniary attractiveness of work in different firms. I assume that an increase in B_i raises the wage that a firm must pay. It is the existence of this shock that ensures that the model generates a distribution of wages even if the labour market is perfectly competitive. Finally, consider the likely effect of the average wage paid on the wage that firm i must pay. As firm i is competing for labour with other firms, one would

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[6] Some arguments along these lines are presented in more detail in Machin and Manning (1994) and Machin, Manning and Woodland (1993). Search related frictions may also be used to underpin the notion of an upward sloping firm labour supply schedule. It is also evident that one can debate whether this monopsony power exists only in the short-run. This model, which is static for analytical convenience, cannot address this issue, but because workers are continually leaving and entering the labour market it is not unreasonable to believe that some firms do have some monopsony power in the long-run.

expect a rise in the average wage to increase W_i for a given level of L_i but it is conceivable that this is not the case. For example, suppose that workers must make a conscious decision to enter a particular industry (perhaps because it requires some investment in industry-specific skills): total labour supply to the industry may then be positively related to the average wage. As total labour supply rises one would expect that firm i can obtain a given level of employment more cheaply which will tend to make an increase in W reduce W^s. The effect of W on W^s is also important in determining the likely employment effect of the minimum wage. If it is possible to write:

$$W^s(W, B_i, L_i) = W.W^s(B_i, L_i) \tag{5.3}$$

then, although an individual firm can raise its labour supply by raising its wage, the total labour supply to the industry is fixed. In this case, each individual firm can be a monopsonist paying workers a wage below the value of their marginal product but aggregate employment cannot be raised by raising the minimum wage.

Now, consider the equilibrium when there are no minimum wages. Suppose that firms choose wages (or equivalently employment) to maximise profits.[7] Then each firm chooses a level of employment where the *MRPL* equals the marginal cost of labour so that:

$$M(L_i, A_i) = W_i + L_i.\frac{\delta W_i}{\delta L_i} = (1+\theta).W_i \tag{5.4}$$

[7] An alternative approach could be to set up the model as a bilateral monopoly problem where the providers of labour services also have some monopoly power (e.g. as in MacLeod and Malcolmson, 1993). I do not pursue this here but similar results would be obtained if worker bargaining power is small.

where θ is the elasticity of the wage with respect to employment as given by equation (5.2). In general, θ will depend on (W, B_i, L_i). Equating equations (5.4) and (5.2) gives employment in firm i as:

$$M(L_i, A_i) = (1+\theta).W^s(W, B_i, L_i) \qquad \textbf{(5.5)}$$

Write employment as $L(A_i, B_i, W)$. Given employment, the wage can be found from equation (5.2):

$$W_i = W^s(W, B_i, L(A_i, B_i, W)) \qquad \textbf{(5.6)}$$

One can then close the model by taking expectations of equation (5.6) to solve for the average wage, W. Equations (5.5) and (5.6) are straightforward to understand. Revenue shocks, A, have a positive effect on employment while supply shocks, B, will generally have a negative effect (a sufficient condition for which is that θ is constant). In contrast, both A and B are positively related to wages although, as one would expect, A only has an effect to the extent that the labour market is not perfectly competitive.[8] The joint distribution of wages and employment depends on the joint distribution of (A_i, B_i) across firms. Because of the existence of the employer-size wage effect (see Brown and Medoff, 1989) there are strong reasons to believe that this distribution is such as to induce a positive correlation between wages and employment and I will proceed on this basis, although nothing of particular importance depends on it. For what follows it is helpful to make the assumption that changes in the average wage do not affect the ranking of firms

8 There is a lot of empirical evidence that wages do depend on variables related to firm and industry productivity, even in the non-union sector (e.g. Nickell and Wadhwani, 1990; Dickens and Katz, 1987) which is consistent with the monopsony model.

in terms of wages (a sufficient, but not necessary, condition for this is that all functions are iso-elastic).

Denote the wage chosen by firm i in the absence of a minimum wage by W_{0i}. I will refer to this as the initial wage. Now consider what happens if a minimum wage of W^* is introduced. A firm can now be in one of three qualitatively distinct regimes. In the first, which I will call the Unconstrained Regime, the firm pays a wage above the minimum and the employment and wage rates of equations (5.5) and (5.6) continue to be relevant. Note that if W^s depends on W, the change in the average wage caused by the minimum wage will mean that the set of firms initially paying above W^* will not be the same as the ones now paying above W^* and that although the unconstrained firms pay above the minimum they are still affected by it. Which firms will be in this regime? Given my assumptions, it must be the case that it is the firms with the highest initial wages, W_{0i}, that are in this regime. So firms with $W_{0i} \geq W^+$ for some W^+ will be in this regime. One has something like the situation depicted in Figure 5.1 where $MRPL_1$ represents a firm in this regime.

For firms with W_{0i} slightly below W^+, say with $MRPL_2$ in Figure 5.1, it is optimal to pay W^* and accept all workers forthcoming at this wage. I refer to these as Supply-Constrained firms. Their employment can be found by substituting $W_i = W^*$ in equation (5.2). As they are on their labour supply curves, employment in these firms will, given W, be higher with the minimum wage than without.

But if the initial wage is sufficiently low (i.e. W_{0i} is less than some W^-) then the firm will be in a situation where it is not profitable for the firm to employ all the workers forthcoming at W^*. I will refer to these firms as Demand-Constrained. These firms choose employment so that $MRPL_i = W^*$ which is depicted by $MRPL_3$ in Figure 5.1 i.e. employment will be on the labour demand curve. The employment level of firms in this regime will rise with the introduction of the minimum wage if W_{0i} is close to W^{*} but will fall if W_{0i} is very low.

One can summarise the employment effects of a minimum wage by considering Figure 5.2. Assume, for simplicity that the average wage does not affect W^{s}. The line *LL* gives the average relationship between employment and W_{0i} before the introduction of a minimum wage. Suppose a minimum wage is introduced that induces a cut-off point W^{+} between the unconstrained and supply-constrained regimes. Only employment in firms with W_{0i} below W^{+} are affected; denote the new level of employment in these firms by the dotted line. It should be obvious from Figure 5.2 that one cannot tell, *a priori*, the effect on total employment unless $\theta = 0$ and the labour market is perfectly competitive when the supply-constrained regime disappears and all demand-constrained firms suffer employment losses. The picture of Figure 5.2 needs modification if the average wage affects employment in each firm since *LL* then depends on the minimum wage, but the basic ideas remain the same. In general, aggregate employment will first increase in the minimum wage but will eventually fall and the empirical question of interest is the point at which this occurs.[9]

Figure 5.2 also has certain implications for the empirical investigation of the effect of minimum wages. For example, it is sometimes argued that looking at the effect on employment in the lowest-wage parts of the market gives a good estimate of the impact of the minimum wage. But Figure 5.2 suggests there is a bias in doing this as one would

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[9] In this kind of model where firms that would otherwise pay below the minimum wage come up to the minimum wage once it is imposed there is an issue regarding non-compliance, especially for firms that would like to pay very low wages (see Ashenfelter and Smith, 1979). The extent of non-compliance seems limited in the British data that I consider below as there are not many individuals paid below the minimum wage, even in the early 1990s when the minimum wage system was weaker than before.

expect the employment effect of minimum wages to be most negative in these parts of the market but this tells us little about the overall employment effect.

Some studies also argue that one can get an estimate of the effect of the minimum wage on employment by looking at the differential impact of the minimum wage on firms within a market (what are sometimes called impact studies). It is argued that if there is a negative correlation between the change in the wage and the change in employment when a minimum wage is introduced, then this is evidence that minimum wages reduce employment. There is a problem with this procedure since it will estimate the slope of the gap between the solid and dotted lines in Figure 5.2 while to compute the employment effect of minimum wages on employment one needs to integrate the area between the two lines (weighting by the distribution of W_{0i}). There is no necessary connection between the two measures. For example, suppose all firms are to the left of the point where the gap between the dotted and solid lines is maximised. Then there will be a negative correlation between employment change and wage change but it is quite possible that employment has actually risen. This problem is likely to be less severe if one finds a positive correlation between employment change and wage change as this can only be possible if the dotted line is above the solid line. The solution to this problem is to obtain some estimate of what would have happened if the minimum wage had not been introduced. So, impact studies must, to be convincing, have a control group to provide an estimate of what would have happened without the minimum wage. This is done for example in Card and Krueger's (1994) comparison of New Jersey and Pennsylvania but not in most other studies of this type.

In this section I have presented a simple framework for thinking about the employment effects of the minimum wage. I have emphasized the importance of looking at the affected market as a whole when trying to evaluate the employment effects of minimum wages. It is this principle that guides my empirical approach below.

5.3 The Effect of Minimum Wages on Employment in Britain: The Wages Councils

5.3.1 The Data

The Wages Councils were established by Winston Churchill in 1909 to protect the pay of workers in the so-called 'sweated' trades. They set minimum wage rates in a number of different industries. Over the years, the number of industries covered first increased (to a peak of about 60 covered sectors in the early 1960s), then decreased and by the early 1990s the 26 remaining Wages Councils set minimum wages for approximately 2.5 million workers in low paid sectors (mostly in hotels and catering, retail, clothing manufacture and hairdressing but also in a number of very small manufacturing industries). Each Wages Council consisted of an equal number of employer and worker representatives, plus a maximum of three independent members (nominated by the government of the day) who had the casting vote if an agreement was not reached. Until the 1986 Wages Act, the Councils generally set a myriad of minimum wages differentiated by age, occupation and region but since 1986 set only a single rate. The 1993 Trade Union Reform and Employment Rights Bill abolished the remaining 26 Councils so that from September 1993 there are no minimum wages in operation (except in agriculture: see Dickens et al., 1995). One of the Government's arguments for abolition was based on the claim that the minimum rates of pay set by the Councils were bad for employment (see Dickens et al., 1993).

The best source of information on workers covered by the Wages Councils is the annual New Earnings Survey (NES). This is an employer-reported survey conducted in April based on a 1% (approximately) sample of all employees who are members of a Pay-As-You-Earn (PAYE) income tax scheme. I have access to the data for the years 1975 to 1992 and perform the empirical analysis on a panel of Wages Council industries over time.

There are two ways of identifying workers in Wages Council industries from the NES. First, employers are asked whether workers are covered by a Wages Council agreement. Secondly, I can use the detailed industrial and occupational information to work out who should be covered. Typically, the numbers obtained using the first method are less than the numbers obtained by the second method and there seems to be a number of misclassifications. For this reason, I prefer the numbers obtained from the second method.[10] Only the relatively large Wages Councils have enough workers in the NES for the data to be considered reliable; the ones used in this study are reported in Table 5.1. A potential problem is that the 1986 Wages Act removed people under the age of 21 from the coverage of the Wages Councils. However, it seems that after 1986 the adult minimum rates still exerted an effect on youth wages (which is reminiscent of the US finding of Katz and Krueger, 1992, that the youth sub-minimum is rarely used), so I use total employment in the Wages Council industries in the empirical analysis.

A further concern is that the NES undersamples part-time workers as workers only contribute to the PAYE scheme if they earn more than a certain amount (£66.50 per week in 1994). So I also used employment figures from the Workforce in Employment survey

[10] Despite this, Machin and Manning (1994) used the former numbers and reached very similar conclusions to those reported below.

published by the Department of Employment in the Employment Gazette (EG). These have the advantage that they include part-time workers but the disadvantage that the map between the industry classification and the Wages Councils is not perfect. Table 5.1 summarizes the employment data. I present average employment based on both NES and EG figures and the correlation between the two. As can be seen, the correlation is low in some cases (though this only seems to be a problem for the Councils I do not follow through the entire 1975-92 period) so it is important to check the strength of the results using both measures; I am careful to do this below.

For the wage variable I use the basic hourly wage. I use the ratio of the minimum to the average wage as a measure of the impact of the minimum wage: this is what I call toughness. After 1986 the computation of toughness is straightforward as a single rate was set. Prior to that date, I use the lowest adult minimum rate in force.[11] The average level of toughness for each Wages Council is reported in Table 5.1 and mean toughness in each year is plotted in Figure 5.2. As can be seen, the toughness of the minimum wage increased in the 1970s but decreased in the 1980s with the arrival in 1979 of a Government hostile to the idea of minimum wages.

5.3.2 The Effect of the Wages Councils on the Wage Distribution

In this section I investigate the effect of the minimum rates set by the Wages

[11] I conducted robustness checks using the highest adult minimum rate to construct the toughness variable. The correlation between the two toughness measures is high, giving a correlation coefficient of .91 for log(toughness) and .72 for the change in log(toughness). I also used this alternative measure of toughness in our employment equations and it gave qualitatively similar results.

Councils on the distribution of wages. There are a number of reasons for being interested in this. First, some commentators have expressed doubts about whether the Wages Councils have any effect at all because of lack of enforcement. Secondly, I would like to have some idea of the effect of the minimum wage on wages further up the wage distribution.

I investigated this by estimating first-differenced regressions of the log hourly wage at each decile in the earnings distribution on the log of the hourly minimum wage, together with year dummies (the regressions are weighted by the cell sizes in each industry-year cell). The results are reported in Table 5.2. As would be expected, the effect of the minimum wage on earnings levels is strongest at the lowest deciles of the distribution. Effects are estimated to be insignificantly different from zero for the median and higher deciles in the distribution, indicating the minimum has the effect of compressing the distribution of earnings. As the bottom row of the Table testifies, there is a positive significant impact on the average wage.

5.3.3 The Effect of the Wages Councils on Employment: Panel Data Estimates

In this section I investigate the relationship between employment and minimum wages using my panel on the British Wages Councils between 1975 and 1992. For Wages Council j in year t the reduced form of the employment equation suggested by the theory above is $L_{jt}(A_{jt}, B_{jt}, (W^*_{jt}/ W_{jt}))$, where employment depends on demand and supply shocks in the market as a whole and the minimum wage. I choose to normalise the minimum wage by the Wages Council's average wage (to give what we call toughness, W^*/W) as there is considerable growth in average wages over the sample so that a given minimum might be expected to have very different effects in the early years of the sample. I operationalise the employment equation as:

$$Log(L_{jt}) = f_j + \delta_1 Log(W^*_{jt} / W_{jt}) + \delta_2 TIME_t$$
$$+ \delta_3 Log(SALES_{jt}) + \delta_4 SECTOR_{jt} + u_{jt} \quad \textbf{(5.7)}$$

where f_j is a Council-specific fixed effect, *TIME* is a set of time dummies, *SALES* is real sales, *SECTOR* denotes a set of linear trends for specific sectors and u_{jt} is a random error.

Equation (5.7) forms the basis for the empirical work. I think of most supply shocks as coming from the aggregate labour market, so model these by including time and Wages Council dummies. Modelling demand shocks is more tricky, mainly because most Wages Council workers are employed in service sector industries for which there is limited information on variables that shift the revenue function (e.g. prices). I follow two strategies to try to control for demand shifts. First, I have data on industry sales which will be related to the industry shocks, A, through the revenue function $R=A.L^{\alpha}$ so I include (appropriately instrumented) sales variables in the employment functions. Second, I allow for different employment trends in the Catering, Clothing and Retail sectors to control for sector-specific employment changes.

Figure 5.4 presents a scatterplot of the log of employment changes against changes in the log of toughness. In the raw data there is an upward sloping relationship, suggesting little support for the notion that minimum wages were bad for employment in the Wages Council industries between 1975 and 1992. However, as noted above, it is important to control for demand and supply shocks so I next consider the relationship using econometric models of employment.

In Table 5.3, I present a set of results based on estimating variants of equation

(5.7) in first-differences (to eliminate the fixed effects) using three different measures of employment. I report five specifications for each measure of employment that differ in their estimation method and in their inclusion of controls for supply and demand shocks.

The first five rows present results using the employment measure from the NES as the dependent variable. Row (1) is a simple least squares regression of the change in log(employment) on the change in log(toughness) plus a set of year dummies. The coefficient on the toughness variable is estimated to be positive (and significantly different from zero at the ten percent level) with a t-ratio of 1.74. Hence, the basic correlation between employment changes and changes in the toughness of minimum wages is not in line with the conventional viewpoint.

The functional form of the toughness variable imposes equal and opposite regression coefficients on the minimum and average wage variables in the estimated employment equation. But, if the real minimum and the real average wage are included as separate arguments, their coefficients and standard errors are estimated as .280 (.161) and -.135 (.164) respectively. A formal test of their restriction to the toughness variable has a p-value of 0.465 suggesting that the restriction is not rejected by the data.

The next two rows of Table 5.3 attempt to control for the effects of demand shocks using a number of different variables (sector-specific trends and sales growth). In row (2) I include dummy variables for Clothing and Retail Councils (which allow for different employment trends in these sectors). Their estimated coefficients are negative and significant suggesting slower employment growth over the sample period than in the Catering sector. The coefficient on log(toughness) is reduced slightly by their inclusion but remains positive with a t-ratio of about 1.4.

In row (3), I control for sales growth (deflated by an aggregate price index to convert it to real terms) in the employment growth equation. It is evident that one cannot simply enter the contemporaneously dated sales variable as it is jointly determined with the dependent variable. Thus I instrument current sales growth using the log of real sales dated (t-2) and (t-3) (with the coefficient in the instrumentation equation allowed to vary in each cross-section).[12] Controlling for sales appears to strengthen the effect of the minimum wage variable. Whilst (instrumented) sales is significantly associated with employment, the coefficient on log(toughness) remains positive and gains in significance. There is little comfort here for those who claim that Wages Council minimum pay rates were bad for employment in the 1975-92 time period.

One concern with the results to date is the potential endogeneity of the toughness variable, caused either by endogeneity of the average wage or the minimum itself. I can deal with the former by ensuring employment variations come through the minimum wage changes and not through average wage changes by instrumenting toughness using the minimum wage. In row (4) of the Table I use the log of the real minimum wage dated t, t-1, t-2 and t-3 as instruments for the log of toughness. The coefficient on log(toughness) remains similar to that in row (3), but falls somewhat in significance.[13]

Dealing with the potential endogeneity of the minimum is somewhat more

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[12] I instrument using the log of real sales dated (t-2) and back since the MA(1) error induced by first-differencing the employment equation means that sales dated (t-1) is not independent of the error term. I also tried simply using sales growth dated (t-2) as a regressor and this did not give qualitatively different results.

[13] The results were very similar when I experimented by instrumenting toughness with different lags of the minimum and the average wage. For example, when I instrumented toughness with lags of the real minimum dated (t-1) to (t-3) the estimated coefficient (standard error) on log toughness was .341 (.199). When instrumenting with both lags of the real minimum and real average dated (t-1) to (t-3) the estimated coefficient (standard error) was .445 (.186).

problematic. Ideally, one would like to have an independent variable which exogenously shifts the minimum wage and has no direct effect on employment, but the only available instruments are lags of the minimum wage. However, my discussions with independent members who sat on the Wages Councils suggests that the method of minimum wage fixing was generally rather crude, using only recent pay settlements and inflation figures, and making no attempt to forecast future market conditions.[14] As such, lags would seem to be reasonable instruments. In row (5) of Table 5.3 I therefore instrument toughness only using lags of the minimum wage dated (t-2) and (t-3). The coefficient on the log of toughness is similar to that in both rows (3) and (4), and remains positive and significant at the ten percent level.

Hence, the specifications using the NES employment measure yield evidence that, counter to the conventional economic model, increases in Wages Council minimum rates of pay were not associated with reduced employment. There is no evidence whatsoever for the notion that minimum wage effects on employment were negative, and in statistical terms we can comprehensively reject a null hypothesis of an employment-minimum wage elasticity in the -.1 to -.3 range which was cited as typical of the earlier time-series based evidence by Brown et al. (1982).

I conducted a large number of tests of the robustness of these results. First, I used total employee hours (from the NES) as the dependent variable. Rows (6) to (10) of Table 5.3 report hours specifications analogous to those presented for NES employment. The

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[14] I would like to thank Professor J. J. Hughes for providing me with an insight into the internal workings of the Wages Councils when setting minimum rates. Professor Hughes sat as an independent member on a number of Wages Councils, including the Retail Food and Waste Reclamation Councils. From his experience rate setting was essentially backward looking, using current inflation figures and other pre-dated Wages Council agreements as a basis for rate fixing.

coefficient on the minimum wage variable is estimated to be positive in all specifications although the effects are generally slightly less well determined.

Still concerning possible discrepancies due to hours differences, I also considered whether the results could be explained by the under-sampling of part-time workers in the NES. I did this in two ways. First, I included a variable measuring the minimum number of hours that had to be worked to earn more than the PAYE earnings limit. I constructed two variables of this type; in one I divided the weekly earnings limit by the minimum in the Wages Council concerned while in the other I divided by average earnings. At no time did this variable alter the sign or magnitude of the measured minimum wage effects.

I also considered whether our results hold for alternative measures of employment, and report estimates using employment data from the Employment Gazette in rows (11) to (15) of Table 5.3. Again the results are very similar to those reported earlier. The impact of toughness on employment is positive and significant in row (9), the basic specification. When I control for demand shocks using sector dummies and sales growth, the coefficient on log(toughness) increases in magnitude and significance. This result is unchanged when I instrument toughness using the current value and lags of the real minimum (row (14)) or just lags of the minimum (row (15)).

On the basis of the results in Table 5.3, I conclude that my findings are relatively robust across alternative employment measures and to various specification changes and robustness checks. However, despite the fact that the models reported in Table 5.3 do not appear to suffer from model misspecification via omitted dynamics (see the serial correlation tests), there is an issue of whether these results are contaminated by not considering the potential for dynamic minimum wage effects on employment (see Neumark and Wascher, 1992, who argue that minimum wage effects on employment may persist across time periods). To this end the final set of empirical results are dynamic employment functions that allow for minimum wage effects dated back to (t-2) to affect employment.

I report six dynamic employment functions in Table 5.4. The equations differ in their dependent variable (the two employment variables and the total employee hours variable) and in whether or not toughness is instrumented. Whilst there are some noticeable differences in the nature of the estimated employment functions they still paint an unambiguous pattern. Minimum wage effects are estimated to be positive, and are even above the estimates from static models in some specifications (a possible reason being that it takes some time for the supply of labour to increase). There remains no evidence of any negative impact of minimum wages on the employment patterns of Wages Council workers.

Of course, it should be noted that I have only investigated the effect of the Wages Councils on employment in the affected industries; it is possible that employment in other industries is affected but it seems rather implausible and unlikely to think that these indirect effects could overturn the direct effects. Irrespective of specification and data definition, the effect of minimum wages on employment is always estimated to be non-negative and in many cases to be positive.

These results provide a stark contrast with Kaufman's (1989) study of the employment effects of the Wages Councils so it is probably worth commenting on differences between this study and his. First, there is a difference in the sample period used: most of his results are based on the 1970s. Secondly, the sample of Wages Council industries used are different. Kaufman concentrates on small manufacturing industries and excludes several of the large service-sector industries (notably retail and catering).

Curiously, he also seems to have included two industries in his sample, jute and paper box, in which the Wages Councils were abolished in 1969 yet almost all his observations come from the 1970s. I believe that this sample covers the vast bulk of workers in Wages Council industries and so is likely to present a much more accurate picture of the effect of Wages Councils. Finally, there is a difference in methodology. Kaufman starts from the premise of the competitive model, then estimates a labour demand curve as a relationship between employment and the average wage and then investigates the effect of the minimum on the average. This obviously constrains the minimum wage to have an effect on employment only through its effect on the average wage, something that is true only in the competitive model. This seems to prejudge the issue in a very specific way, probably accounting for the differences between his results and those presented here.

5.4 Conclusion

In this chapter I have presented a model of the labour market which I have argued can be used for thinking about the likely effects of minimum wages on the labour market when one is not sure *a priori* that minimum wages reduce employment. Using this theoretical framework, I have evaluated a number of possible empirical approaches for looking at the effect of minimum wages. Implementing the approaches that I favour to examine the effect of minimum wages in Great Britain, I find strong evidence that they have compressed the distribution of earnings and no evidence that they have reduced employment, the latter being a result that would be regarded as anomalous in a competitive model but one that can easily be explained in this framework.

Of course, the results reported here cast severe doubt on the UK Government's claim that the recent abolition of the Wages Councils, in its 1993 Trade Union Reform and Employment Rights Bill, could be justified on the grounds that they have traditionally hindered employment. According to the results presented here, it seems that the only likely impact of abolition will be increased inequality of earnings, coupled with no gains in employment.

Figure 5.1

The Monopsony Model: Three Regimes

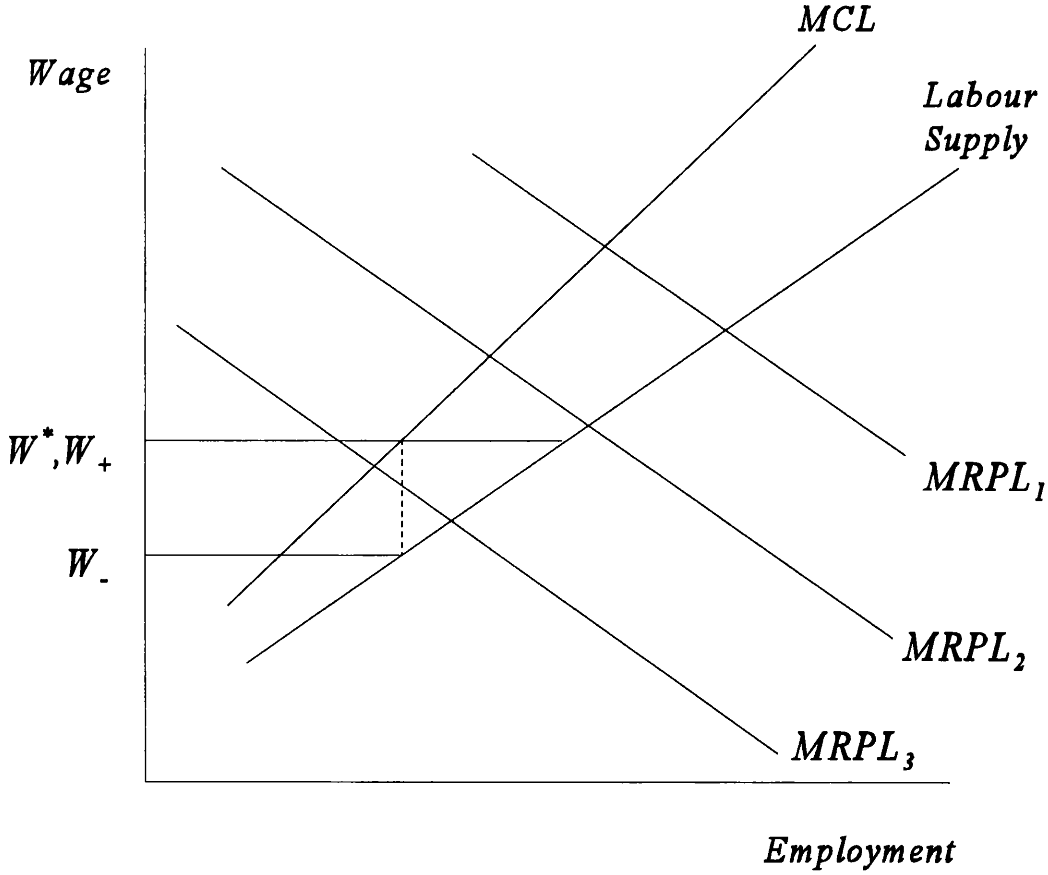


Figure 5.2

The Effect of the Minimum Wage on Employment

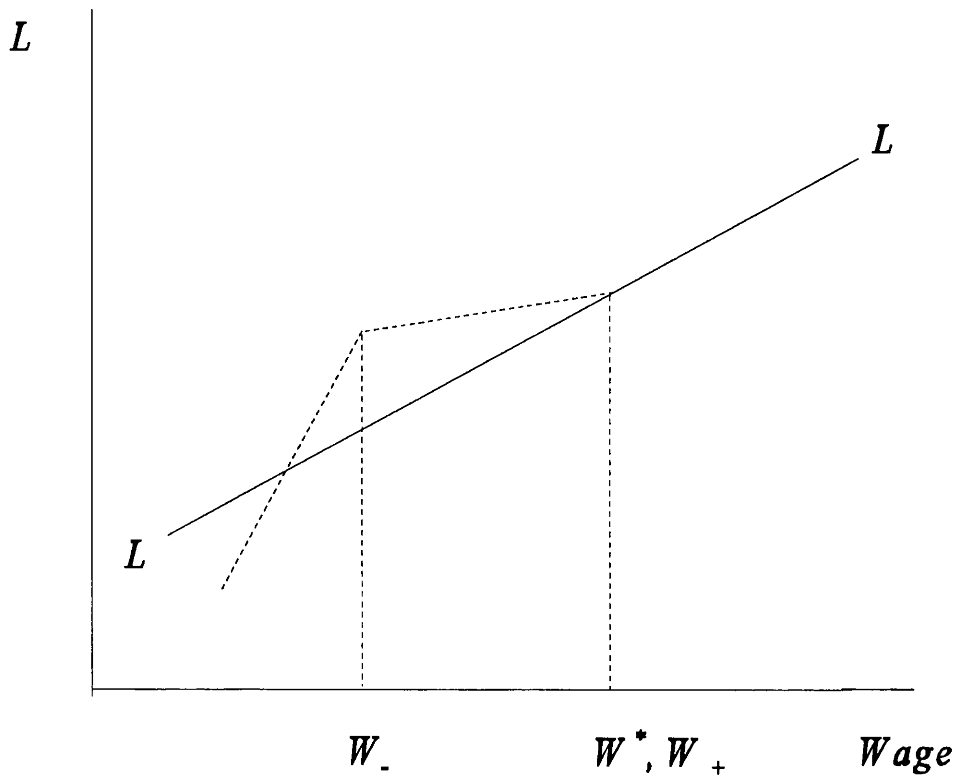
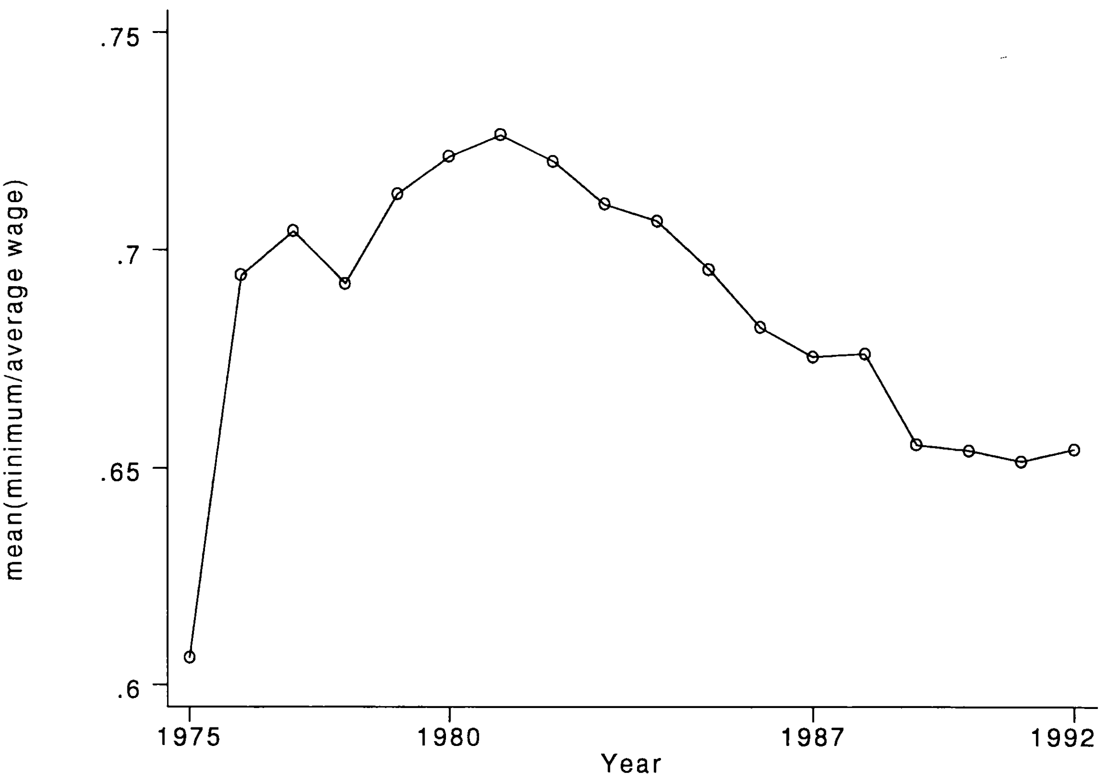


Figure 5.3

The Toughness of the Wages Councils:
Mean of Ratio of Minimum to Average Hourly Earnings 1975-1992

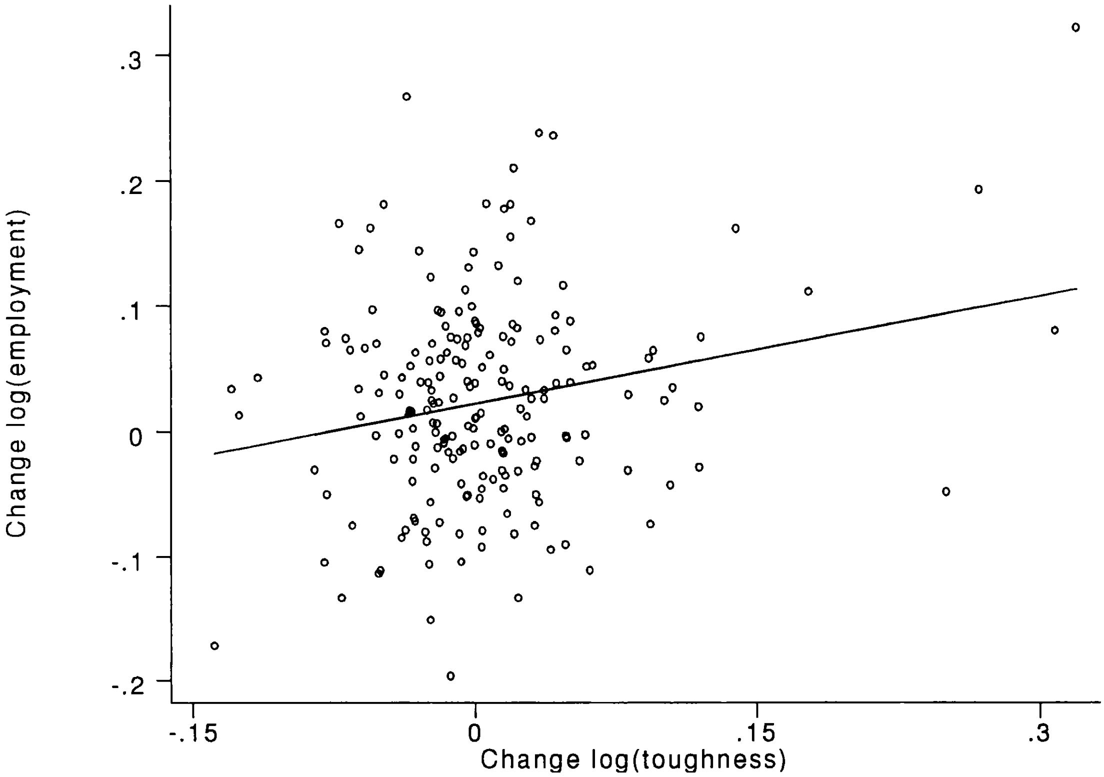


Notes:

1) Source: New Earnings Survey Micro Data

Figure 5.4

Changes in Log(Employment) and Changes in Log(Toughness)



Notes.

1. Based on New Earnings Survey data described in Table 1. The regression line is from a regression of the change in log(employment) on the change in the log(minimum/average) (standard errors in brackets):

   Change in log(employment)= .022 + .286 Change in log(minimum/average)
   (.006) (.125)

2. An analogous regression estimated by robust regression methods to downgrade the importance of potential outliers was:

   Change in log(employment)= .020 + .220 Change in log(minimum/average)
   (.006) (.092)

Table 5.1: Summary of Wages Council data

Wages Council	Average Toughness	Average Employment, NES	Average Employment, EG	Correlation between NES and EG series
Councils in Sample 1975-1992				
Licensed Residential Establishment, Male	0.595	534	106189	0.646
Licensed non-Residential Establishment, Male	0.652	480	129089	0.556
Unlicensed Place of Refreshment, Male	0.591	358	81461	0.970
Licensed Residential Establishment, Female	0.783	679	170744	0.776
Licensed non-Residential Establishment, Female	0.884	796	264417	0.769
Unlicensed Place of Refreshment, Female	0.773	479	136622	0.975
Councils in Sample 1975-1981				
Clothing Manufacture, Male	0.517	326	49586	0.663
Retail Food & Allied Trades, Male	0.548	1373	223186	-0.228
Retail Trades (Non-Food), Male	0.517	2536	406471	-0.174
Clothing Manufacture, Female	0.791	1453	212557	0.930
Retail Food & Allied Trades, Female	0.855	2293	382114	-0.224
Retail Trades (Non-Food), Female	0.809	5378	850657	-0.329
Councils in Sample 1982-1992				
Clothing Manufacture, Male	0.449	244	41045	0.011
Retail Food & Allied Trades, Male	0.602	1897	244754	-0.384
Retail Trades (Non-Food), Male	0.494	2598	360436	0.912
Clothing Manufacture, Female	0.714	1125	158082	0.690
Retail Food & Allied Trades, Female	0.868	3073	472127	0.727
Retail Trades (Non-Food), Female	0.762	5316	758673	0.611

Notes.

1. The 1975-81 and 1982-92 Councils are treated separately as a consequence of the 1980 change in the Standard Industrial Classification (i.e. pre-1980 and post-1980 definitions did not match after the change) which was adopted in the New Earnings Survey data in 1982.
2. NES refers to New Earnings Survey and EG to published Employment Gazette figures.
3. Toughness is defined as the ratio of the minimum hourly wage to the average hourly wage.

Table 5.2: Effects of Minimum Wages on the Wage Distribution

Dependent variable:
Δith percentile / average of log real hourly earnings distribution

Dependent Variable	Coefficient (standard error) on ΔLog(real minimum hourly wage)	Test for Serial Correlation
Δ10th percentile	.193 (.082)	-1.168
Δ20th percentile	.242 (.065)	-1.778
Δ30th percentile	.217 (.068)	-0.707
Δ40th percentile	.126 (.057)	-1.213
Δ50th percentile	.089 (.066)	-1.558
Δ60th percentile	.040 (.069)	-1.803
Δ70th percentile	-.001 (.058)	1.533
Δ80th percentile	.005 (.069)	0.229
Δ90th percentile	.020 (.083)	0.300
Δaverage	.114 (.057)	-1.414

Notes:

1. Sample size: 198; Estimation period: 1976-92. Regressions weighted by employment in industry-year cell.
2. Heteroskedastic consistent standard errors in parentheses.
3. Time dummies included in all specifications.
4. Serial correlation test is an N(0,1) statistic for first-differenced panel data models as described in Arellano and Bond (1991).

Table 5.3
Employment Equations in 18 Wages Council Industries, 1978-92

Employment Variable / Method of Estimation		ΔLog(Toughness)$_{jt}$	Retail Sector	Clothing Sector	ΔLog(Sales)$_{jt}$ (Instrumented)	Serial Correlation
NES Employment, Toughness Not Instrumented	(1)	.178 (.102)				1.269
	(2)	.139 (.100)	-.019 (.007)	-.069 (.007)		0.205
	(3)	.275 (.144)	-.009 (.007)	-.008 (.014)	.876 (.237)	-1.255
NES Employment, Toughness Instrumented	(4)	.282 (.194)	-.010 (.007)	-.013 (.013)	.760 (.223)	-1.100
	(5)	.330 (.196)	-.009 (.006)	-.009 (.013)	.810 (.228)	-1.177
NES Employee Hours, Toughness Not Instrumented	(6)	.240 (.138)				1.111
	(7)	.200 (.143)	-.019 (.007)	-.072 (.011)		0.828
	(8)	.197 (.150)	-.013 (.009)	-.007 (.015)	.941 (.177)	0.246
NES Employee Hours, Toughness Instrumented	(9)	.047 (.189)	-.017 (.009)	-.014 (.013)	.840 (.169)	0.490
	(10)	.108 (.194)	-.015 (.008)	-.012 (.013)	.866 (.179)	0.421
EG Employment, Toughness Not Instrumented	(11)	.100 (.048)				1.495
	(12)	.064 (.075)	-.020 (.003)	-.050 (.003)		0.169
	(13)	.283 (.089)	-.014 (.004)	-.025 (.012)	.405 (.153)	-0.778
EG Employment, Toughness Instrumented	(14)	.395 (.145)	-.014 (.005)	-.027 (.012)	.335 (.143)	-1.170
	(15)	.434 (.166)	-.013 (.006)	-.023 (.012)	.397 (.159)	-1.304

Notes:
1. Sample size: 162.
2. Heteroskedastic consistent standard errors in parentheses.
3. The serial correlation test is an N(0,1) statistic for first-differenced panel data models as described in Arellano and Bond (1991).
4. ΔLog(Toughness) is instrumented using the Log of Real Minimum Wages dated t, t-1, t-2 and t-3 in rows 4, 9 and 14 and using the Log of Real Minimum Wages dated t-2 and t-3 in rows 5, 10 and 15.
5. Year dummies are included in all specifications.

Table 5.4: Dynamic Employment Equations in 18 Wages Council Industries 1978-92

Dependent Variable:
ΔLog(Total Employment, NES)$_{jt}$ (Columns 1 and 2)
ΔLog(Total Employee Hours, NES)$_{jt}$ (Columns 3 and 4)
ΔLog(Employment, EG)$_{jt}$ (Columns 5 and 6)

	Log of toughness not instrumented	Log of toughness instrumented	Log of toughness not instrumented	Log of toughness instrumented	Log of toughness not instrumented	Log of Toughness instrumented
	(1)	(2)	(3)	(4)	(5)	(6)
ΔLog(Toughness)$_{jt}$	.295 (.091)	.242 (.121)	.271 (.122)	.173 (.121)	.192 (.069)	.246 (.120)
ΔLog(Toughness)$_{j,t-1}$	.204 (.133)	.381 (.137)	.027 (.097)	.201 (.171)	.077 (.069)	.049 (.085)
ΔLog(Toughness)$_{j,t-2}$	.259 (.074)	.294 (.066)	.201 (.081)	.106 (.127)	.143 (.038)	.142 (.061)
Retail sector	-.000 (.008)	-.003 (.008)	-.000 (.006)	-.004 (.007)	-.009 (.003)	-.007 (.004)
Clothing sector	-.006 (.013)	-.012 (.012)	-.005 (.011)	-.010 (.011)	-.013 (.007)	-.013 (.007)
Sales growth$_{jt}$ (Instrumented)	.295 (.221)	.202 (.194)	.193 (.141)	.165 (.152)	.191 (.127)	.158 (.100)
Sales growth$_{jt-1}$ (Instrumented)	.494 (.220)	.467 (.211)	.674 (.187)	.696 (.179)	.026 (.126)	.044 (.122)
Sales growth$_{jt-2}$	.105 (.116)	.125 (.106)	-.058 (.117)	-.085 (.121)	-.107 (.071)	-.080 (.079)
Dependent variable$_{j,t-1}$ (Instrumented)	.170 (.091)	.140 (.087)	.358 (.069)	.315 (.075)	.453 (.113)	.492 (.130)
Dependent variable$_{j,t-2}$	.029 (.065)	.021 (.063)	.068 (.050)	.061 (.052)	.077 (.142)	.063 (.153)
Serial Correlation	-.905	-.884	.891	.899	-.694	-.638

Notes.

1. As for Table 5.3.
2. Due to bias on coefficient on lagged dependent variable dated (t-1) in first-differenced panel data models, it is instrumented using values of itself dated t-2 and t-3 as instruments (with coefficients in the instrumenting equation allowed to differ in each cross-section).

Chapter 6 - Estimating the Effect of Minimum Wages on Employment from the Distribution of Wages: A Critical View

6.1 Introduction

Most of the work that analyses the effects of minimum wages on employment uses data with some variation in the minimum wage to identify these effects. Studies are usually based on time series or panel data.[1] These include the impact studies which look at the effect of changes in the minimum on changes in employment, usually within establishments.[2] However, in an original and ingenious model, Meyer and Wise (1983a,b) presented an alternative way of estimating the effect of minimum wages on employment and the wage distribution using data from a single cross-sectional distribution of wages. This approach has a number of attractions over the others. First, it can provide a better picture of the differing effects of minimum wages on different groups of workers. Secondly, it can be used to evaluate the effect of minimum wages in situations where only cross-sectional information is available.

Given these potential advantages, it is perhaps surprising that their technique has not been extensively applied. Only in the Netherlands does it seem to have been used

1 See Card (1992a), Neumark and Wascher (1992), Kaufman (1989), Machin and Manning (1994) and Dickens, Machin and Manning (1993), for recent studies of this type based on US and British data.

2 Examples are the recent papers by Katz and Krueger (1992), Card (1992b), Card and Krueger (1994) who consider the impact of recent changes in US federal and state minimum wages on changes in employment. See also Card and Krueger (1995) for a collection of their work and Chapter 2.3 of this thesis for a review of recent work.

more widely (Van Soest, 1989, 1993, and Teulings, 1992, for a more theoretical analysis). The reason for the lack of use is probably, as Brown, Gilroy and Kohen (1982, page 512) argue, that "the estimate depends on the assumed functional form relating the wage to the personal characteristics and on the assumed distribution of the error term". However, Meyer and Wise do undertake a number of robustness tests and argue that their conclusions are not very sensitive to the precise assumptions used so the charge that the results are not robust remains unproved. In addition, the OECD Jobs Study (OECD, 1994) devotes as much space in its discussion of the employment effects of minimum wages to the Meyer-Wise technique as to all the other techniques put together.

The aim of this chapter is to apply the Meyer-Wise technique to British data and to investigate more thoroughly how sensitive the estimates are to various assumptions. In particular I focus on two issues: the choice of functional form for the distribution of wages in the absence of minimum wages, and the assumption on how the minimum wage affects the wage distribution. My conclusions are that the estimates are not at all robust and that, at least for British data, the Meyer-Wise approach, while appealing on an intuitive level, can not be safely used in practice.

The plan of this chapter is as follows. In the next section, I slightly reformulate the Meyer-Wise model by generalising it in a way which I believe is more appropriate as it clarifies the way in which the method works. Section 6.3 describes the data and the results are presented in sections 6.4 and 6.5.

6.2 The Meyer-Wise Approach

In their papers, Meyer and Wise present a number of variants of their model. In the presentation here, I discuss only the most rudimentary version which, for my purposes, is probably sufficient. The basic idea is that in the absence of minimum wages there will be some distribution of wages. When the minimum is introduced some fraction, p, of those workers who were originally paid below the minimum have their wage raised to the minimum and remain in employment (they actually also allow some workers to continue to be paid below the minimum). These workers represent the spike in the wage distribution. A fraction, (1-p), lose their jobs and this is a measure of the adverse employment effect of the minimum wage. Meyer and Wise show how p can be estimated from observations on the distribution of wages among those paid above the minimum, inferring how many would be paid below the minimum in the absence of the legislation and comparing this with the size of the spike.

Now consider the following alternative set-up of their model. Suppose that in the absence of a minimum wage, employment is L_0 and the density function of wages is given by $f(W;\theta)$ where θ is a set of parameters to be estimated. Suppose that a minimum wage is introduced, causing employment to be L_1 and the density function of wages to be $f_1(W;\theta)$. $f_1(W;\theta)$ can, of course, be estimated from the observed distribution of wages. But, to infer the effect of the minimum wage on the wage distribution and employment one needs to be able to infer $f(W;\theta)$ and L_0. Without further assumptions it is impossible to do this. But, one can make progress if one is prepared to make the following assumption:

Assumption: There is some wage W_1 such that the number of workers earning above this rate, and the distribution of wages among them, is unaffected by the minimum wage.

Meyer and Wise assume that W_1 is very close to the minimum wage. One of the contributions of this chapter is to show that it is not necessary to do this.[3] Indeed, I will show that failing to specify W_1 correctly can have very serious consequences. Assuming that those earning substantially above the minimum are unaffected by it appears, at first glance, to be a relatively weak (and attractive) assumption. Indeed, it seems surprising that quite so weak an assumption is all that is necessary to estimate the effects of the minimum wage on employment.

Let us now see how this can be done. Suppose I estimate a tobit model for a wage equation with the truncation at W_1. Order the workers so that the first j have wages above W_1 and the others have wages below. The log-likelihood function can be written as:

$$logL = \sum_{i=1}^{j} \log f_1(W_i,\theta) + (L_1 - j).\log F_1(W_1;\theta) \qquad \textbf{(6.1)}$$

Under the assumptions made above, the following must hold:

$$f_1(W;\theta) = \frac{L_0}{L_1}.f(W;\theta) = \phi.f(W;\theta) \quad for \quad W>W_1 \qquad \textbf{(6.2)}$$

and

$$\begin{aligned} L_1.\left(1-F_1(W_1;\theta)\right) &= L_0.\left(1-F(W_1;\theta)\right) \\ i.e. \quad F_1(W_1;\theta) &= 1-\phi.\left(1-F(W_1;\theta)\right) \end{aligned} \qquad \textbf{(6.3)}$$

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[3] In footnote 9 on page 1682 of Meyer and Wise (1983b), they do state that they experimented with having W_1 above the minimum and that it made little difference to the results. But, what remains unclear is the extent of the experimentation. Furthermore, the reported results use a value of W_1 that is only one cent above the minimum wage.

where the ratio of employment before and after the introduction of the minimum wage is defined as $\phi=(L_0/L_1)$, which is a measure of the employment effect of the minimum wage. Equation (6.2) says that the density function for wages with the minimum wage for those earning above W_1 is simply the density function for wages without the minimum scaled by a constant which is the change in employment. According to equation (6.3) the total number of workers earning above W_1 must be the same before and after the introduction of the minimum wage. Substituting equations (6.2) and (6.3) into equation (6.1) yields the likelihood function written in terms of $f(W;\theta)$ and ϕ, the employment effect of a change in the minimum wage:

$$logL = \sum_{i=1}^{j} \log f(W_i;\theta) + j.\log \phi + (L_1-j).\log[1-\phi.(1-F(W_1;\theta))] \quad \textbf{(6.4)}$$

One can estimate (θ,ϕ) by maximisation of equation (6.4). If one maximises equation (6.4) with respect to ϕ, then one obtains, after some rearrangement, the following expression for the maximum likelihood estimator of ϕ:

$$\phi_{MLE} = \frac{j}{L_1.[1-F(W_1;\theta)]} \quad \textbf{(6.5)}$$

This has a very simple interpretation. Whether employment increases or decreases depends on whether the actual fraction of workers with a wage below W_1 is greater or less than would be predicted on the basis of the distribution of wages among those paid more than W_1.[4]

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[4] Note that one can only concentrate the likelihood function in this way if one does not model the wage distribution as varying with individual characteristics. But, if one does introduce personal characteristics into the wage distribution then one should probably also model ϕ as varying with those characteristics. This is not difficult but is less elegant.

By substituting equation (6.5) into equation (6.4), one can write the concentrated likelihood function as:

$$logL = \sum_{i=1}^{j} \log f(W_i;\theta) - j.\log\,[1-F(W_1;\theta)] + constants \qquad \textbf{(6.6)}$$

Equation (6.6) is simply the likelihood function for estimating the distribution of wages from a sample of workers where the wage observations are truncated at W_1. After obtaining an estimate of θ from maximisation of equation (6.6), one can then estimate ϕ from equation (6.5).

This procedure can be represented graphically. Suppose that the distribution of wages in the absence of minimum wages is normal (as drawn in Figure 6.1a). Now suppose that a minimum wage is imposed and the resulting distribution is as drawn in the solid line with the spike at the minimum wage. Assuming that the minimum wage is used as the cut-off W_1, the Meyer-Wise procedure would estimate the distribution truncated at the minimum, then infer how much density should be to the left of the minimum (this obviously requires the assumed distribution to satisfy a recoverability assumption). This area is then compared with the size of the spike at the minimum wage to obtain an estimate of the employment change associated with the minimum wage (Figure 6.1a has been constructed so that the employment effects of the minimum wage is zero). There are several important things to note about this procedure.

First, note that the only problem caused by setting W_1 too high is that one loses observations and hence the estimates are likely to be less precise. In contrast, setting W_1 too low will lead to inconsistent estimates of ϕ, which is obviously more serious. To see this consider the wage distribution as drawn in Figure 6.1b. In contrast to Figure 6.1a, I have now assumed that there are some spillover effects of the minimum wage so that the spike is smaller and the density is higher to the right of the minimum wage. Applying the Meyer-Wise procedure in this case, with the minimum wage as the cut-off, will find that there are fewer workers than expected paid the minimum wage and hence will estimate employment losses. But this is because the underlying assumption is wrong: the number of workers paid above the cut-off has changed. As Meyer and Wise only consider values of W_1 very close to the minimum wage, a procedure which is only valid if there are no spillover effects of the minimum wage on workers paid higher wages at all, their results are likely to be sensitive to this problem and this is likely to lead to an overestimate of the employment losses from the minimum wage. But, as shown above, there is no reason why their general approach cannot be used with a cut-off wage different from the minimum.

Secondly, the specification of the likelihood function used here differs slightly from that used by Meyer and Wise in that they estimate not ϕ, but $p=1+(\phi^{-1}-1).F(W_1;\theta)^{-1}$ which they interpret as the probability of a worker who was originally paid less than the minimum retaining their job after the introduction of the minimum wage. I prefer to estimate ϕ for three reasons:

(i) it is a direct measure of the total employment effect and this is what we are ultimately interested in.

(ii) there is no guarantee that the estimated value of p will be less than 1 in which case it cannot be interpreted as a probability. The case where the introduction of a minimum wage raises employment will be inconsistent with $p<1$. Meyer and Wise, who start from a competitive view of the labour market would not put much weight on this as a likely outcome, but as argued elsewhere (Dickens, Machin and Manning, 1993, or chapter 5 of this thesis, Bhaskar and To, 1996, Rebitzer and Taylor, 1993) it is possible to present a coherent theoretical model in which minimum wages raise employment and that it is very important not to prejudge this issue.

(iii) if one varies the cut-off W_1 (which I do below) the estimate of p will change but, if the model is correct, the estimate of ϕ should be invariant to this change.

To make equation (6.6) operational, one obviously needs to make a specific assumption about the form of $f(W;\theta)$. A serious concern is that incorrect specification of the density function for wages, $f(W;\theta)$, leads to incorrect inference on ϕ. Meyer and Wise are well aware of this potential problem and experiment with a Box-Cox transformation of the wage variable, ending up with the assumption that the distribution of wages is log-normal. Below, I try to deal with this problem by considering a number of choices of f, considering tests of the adequacy of functional form, and also by estimating the model for similar labour markets without minimum wages when one would expect to find $\phi=1$ if f is correctly specified.[5]

6.3 The Wages Councils

The Wages Councils were established by Winston Churchill in 1909. They set minimum wage rates in a number of different industries. Over the years, the number of industries covered first increased (to a peak of about 60 covered sectors in the early 1960s) and then decreased and by 1993 the 26 remaining Wages Councils set minimum wages for approximately 3 million workers in low paid sectors (mostly in hotels and catering, retail, clothing manufacture and hairdressing but also in a number of very small

[5] I am able to do this because, prior to abolition of minimum wages on August 31 1993, the minimum wage system in the Great Britain only covered certain industries.

manufacturing industries). Until the 1986 Wages Act, the Councils generally set a myriad of minimum wages differentiated by age, occupation and region but since 1986 set only a single rate. In addition, people under the age of 21 were removed from coverage. The 1993 Trade Union Reform and Employment Rights Act abolished the remaining 26 Councils so that from September 1993 onwards no form of minimum wages operated in the UK (except in agriculture). One of the Government's arguments for abolition was based on the claim that the minimum rates of pay set by the Councils were bad for employment (see Dickens, Gregg, Machin, Manning and Wadsworth, 1993).

The best source of information on workers covered by the Wages Councils is the New Earnings Survey. This is a 1% sample of all employees who are members of the Pay-As-You-Earn (PAYE) Income Tax Scheme, conducted in April each year. I have access to the data for the years 1975-92. There are two ways of identifying workers in Wages Council industries from the NES. First, employers are asked whether workers are covered by a Wages Council agreement. Secondly, we can use the detailed industrial and occupational information to work out who should be covered. Typically, the numbers obtained using the first method are substantially less than the numbers obtained by the second method and there seem to be a number of misclassifications. For this reason, I prefer the numbers from the second method.[6]

The wage variable is defined as the basic hourly wage (gross weekly pay excluding overtime/weekly hours excluding overtime) for workers aged 21 and over working in the

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[6] This makes no difference to the results e.g. see Machin and Manning (1994) for estimates of employment functions based on the first numbers which yield similar employment effects of minimum wages to those reported using employment numbers from the second method in Dickens, et al (1993) and Chapter 5 of this thesis. My impression is that the coding of Wages Council affiliation is rather erratic which accounts for the discrepancy between the two methods.

industries and occupations covered by the Wages Councils (only a few small occupations in the relevant industries are not covered).

6.4 The Effect of the Minimum Wages on the Wage Distribution

Before using the Meyer-Wise approach I consider the evidence on the effect of minimum wages on the distribution of wages. This is important because, as discussed above, it is necessary to choose as a truncation point a level of the wage which is unaffected by the minimum.

I investigated this by using data from 1975-1992 on a panel of 18 Wages Councils industries (as used in Dickens, et al, 1993, and Chapter 5 of this thesis). Only those Wages Councils large enough to have enough workers in the NES for the data to be reliable were included (the Councils used are listed in Dickens, et al, 1993 and in Table 5.1 in chapter 5 of this thesis). Table 6.1 reports the results of a first differenced regression of the log hourly wage at each decile in the adult earnings distribution on the log of the minimum hourly wage, together with year dummies. First differencing removes any Wages Council fixed effect that may be present. I estimate separate equations for men and women. Before 1986 there were many minimum wages set, differentiated by age, occupation, region, etc. Prior to this date I used the lowest adult rate as the minimum wage variable.[7]

As would be expected, the effect of the minimum wage on earnings levels is strongest at the lowest deciles of the distribution. For male Councils, there is only a

[7] Qualitatively similar results are obtained when the highest adult minimum rate is used as the minimum wage variable prior to 1986.

significant earnings compression effect at the tenth percentile of the distribution. For female Councils, effects are strong up to the fiftieth percentile, after which all effects are estimated to be insignificantly different from zero. Hence, Wages Council minimum pay rates appear to significantly compress the distribution of earnings, and do so more strongly for women covered by minimum wages than for men. This finding of a spillover effect, where minimum wages have an impact on wages higher up the wage distribution, is consistent with the findings of Grossman (1983) for the US and Van Soest (1989) for the Netherlands. It also implies that use of the Meyer-Wise assumption that all workers paid above the minimum are unaffected may be likely to lead to serious biases.

6.5 The Effect of Minimum Wages on Employment

In this section I present Meyer-Wise type estimates of the employment effects of Wages Councils. The way in which I do this is as described above. I choose a truncation point W_1, and a density function $f(W,\theta)$, estimate θ using equation (6.6) as the likelihood function and then estimate the employment effect of the minimum wage, ϕ, using equation (6.5). If ϕ is estimated to be larger than one this implies that there are employment losses from the minimum wage. If it is less than one there are employment gains.

For this exercise, I use data on workers in the two retail Wages Councils for the years 1987-90 inclusive. I chose these two Councils because they provide a reasonably large sample and they had virtually the same minimum wage set in the chosen years (they were within 2 pence/hour of each other). I restrict attention to those years after the 1986 Wages Act since a single minimum wage was in force at that time whereas previously there had been many rates. I also include workers in wholesale distribution as a control group who are not covered by the Wages Councils to see whether the Meyer-Wise approach gives sensible results when applied to an industry without a minimum wage.

Some descriptive statistics on the data are given in Table 6.2. I use information on about 6000 to 7000 retail and wholesale workers for both males and females in each of the years 1987 to 1990 inclusive. The Table shows that about 18-25% of women are paid at or below the retail minimum wage compared to 4-5% of men. Figures 6.2a-6.2d present the distribution of log hourly wages for men and women in the retail and wholesale industries in 1990. The minimum wage is at the noticeable spike in the distribution for women in retail: the other distributions show no very noticeable evidence of a spike.[8] Given that there is no evidence of a spike in the wholesale wage distribution at the retail minimum wage I feel justified in using this industry as a control group.

I experimented with two density functions for the distribution of wages in the absence of minimum wages. I used the log normal (which was Meyer and Wise's preferred model) and also the Singh-Maddala which has been found to provide a better fit to the distribution of income (Singh and Maddala, 1976; McDonald, 1984). The Singh-Maddala is a three parameter distribution with distribution function given by:

$$F(W;\theta) = 1 - [1 + (W/\theta_1)^{\theta_2}]^{-\theta_3} \qquad \textbf{(6.7)}$$

where $(\theta_1, \theta_2, \theta_3)$ are all positive and $W>0$.

Table 6.3 presents the estimates of the employment parameter using the log-normal distribution (the estimates of all the parameters of the model are contained in

[8] As the data on hourly earnings is derived as weekly earnings (excluding overtime) divided by weekly hours (excluding overtime) one would expect the spike to be less pronounced than in data where hourly earnings are reported directly as in Meyer and Wise.

Tables A6.1 and A6.2 in Appendix 3). I present results for men and women separately, for the retail and wholesale industries, for the years 1987-90 and using a cut-off from the 10th to 40th percentile. I do not present the estimates for the 10th and 20th percentiles for women as the wage at this point in the distribution lies below the minimum wage.

The first point to note is that all the estimates of ϕ are significantly above one which, taken at face value, implies employment losses. Most of these estimates are so large as to be simply incredible.[9] This is the case for workers in the uncovered wholesale sector as well as in the covered retail distribution sector which immediately suggests that we should be very suspicious of this as a measure of the employment loss associated with the minimum wage. The reason for this finding is that the log-normal assumption is an extremely poor one for characterising the distribution of wages. As a test of the adequacy of the assumed functional form, I use a Kolmogorov-Smirnov test, the p-values for which are reported in Table 6.4.[10] The distribution of this test statistic is not known when the null hypothesis is an estimated distribution but with these sample sizes this is probably not a serious problem particularly given the size of the p-values.[11] For cut-offs at the lower percentiles one always rejects the hypothesis of correct functional form. The problem is

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9 One should note that Meyer-Wise also estimate a two-equation model with an employment equation in addition to the wage equation. One might expect that this would make the employment loss estimates less ridiculous. I cannot estimate this model with this data which is a sample of workers only, but I would emphasize that one should, if the model is correctly specified, be able to obtain consistent estimates with the single equation and if these estimates are absurd then this is evidence of model misspecification.

10 I have used a non-parametric test rather than some more powerful test for normality because I want to have a test for functional form for other specifications of the density function and because I am interested in testing for the presence of a truncated normal.

11 This dramatic rejection of log-normality occurs also if I use residuals from regressions with explanatory variables such as age, region, etc.

that the wage distributions are skewed with the right tail longer and thicker than the left tail (even allowing for truncation) - one can see this from Figures 6.2a-6.2d. This skewness is also the reason why the procedure ascribes large employment losses to the minimum wage: since the log-normal assumes that the tails of the distribution are symmetric the procedure ascribes the small number of observations in the left-hand tail to the effects of the minimum. As the cut-off increases, one can eventually pass the Kolmogorov-Smirnov test as one is ultimately only estimating the right tail of the distribution and there is no conflict with the left-tail. The estimates of employment losses tend to be larger as the right tail becomes more important in estimating the parameters of the wage distribution, and, as a result, the observed weight in the left-hand tail is even less than expected.

One obvious potential solution is to estimate a three parameter distribution to allow for a distribution with some skewness. Table 6.5 presents results based on the Singh-Maddala distribution (the parameter estimates are presented in Tables A6.3 to A6.5 in Appendix 3). There are a number of pieces of evidence suggesting that this distribution is more satisfactory than the log-normal distribution. First, although the spot estimates of ϕ are all above unity for wholesale distribution, the estimates are generally not significantly different from one. And secondly, most of the Kolmogorov-Smirnov tests of functional form for the wholesale sector reported in Table 6.6 are much improved over the values for the log-normal distribution.

But, once I try to use the results to infer the effects of the minimum wage on employment, problems begin. First, the estimates of ϕ for retail distribution vary wildly. Particularly striking are the results for women. Using the thirtieth percentile as the cut-off these estimates suggest (significant) employment gains from the minimum wage in 1987, but enormous losses in 1988-1990 (although the estimates have enormous standard errors). However, using the fortieth percentile as the cut-off one would conclude that there were large employment losses from the minimum wage in 1987 and much smaller losses in 1990.

It is difficult to have any confidence in these results. The basic problem is that if one chooses a high cut-off it is very difficult, if not impossible, to estimate the degree of skewness from the right-hand tail of the distribution alone. The result is huge imprecision in the estimate of the weight that should be in the left-hand tail. Choosing a low cut-off avoids these problems but, as argued above, is likely to lead to overestimates of employment losses from the minimum wage as it ignores the effect of the minimum wage in raising the wage of those workers paid above the minimum. This is a particular problem with the data on women as one does not have to move very far up the wage distribution before one has only the right-hand tail to work with.

The basic problem with estimating the employment effects of minimum wages in this data is that once one assumes that there are even moderate spillover effects from the minimum wage, one is left with nothing but the right-hand tail of the wage distribution with which to work and it obviously then becomes extremely risky to infer the left-hand tail of the distribution from this information. However, the model analysed here has no covariates and one might reasonably hope that the introduction of covariates would lessen this problem as they allow a better fit of the wage distribution. In addition, for groups with high mean wages one might hope to observe the left-hand tail of their wage distribution which could then be used (albeit with some risk) to estimate the left-hand tail of the distribution for the other individuals as well. The NES data is noticeably light in covariates and contains little except age. Nevertheless, it is of interest to see whether introducing age as a covariate alters the results.

For this data it turns out that introducing age does not improve the credibility of the estimates. Table 6.7 provides estimates of ϕ for the log-normal distribution and Table 6.8 for the Singh-Maddala distribution. In the interests of economy of space I report results for only one year, 1990, but the results for the other years are broadly similar and are presented in Tables A6.6 to A6.11 in Appendix 3. I have divided the sample into four age groups and present estimates for these age groups separately.[12] These results show that introducing covariates does not make the results more credible. In particular, note that the estimates of the disemployment effects are generally smallest for the youngest age groups (although the standard errors are, as usual, often very large), a finding that should make one very suspicious. So I conclude that controlling for age does little to resolve the problems identified above.

6.6 Conclusions

At first glance, the Meyer-Wise approach appears to be an attractive way of estimating the employment consequences of minimum wages using cross-sectional information alone. But, at least for Great Britain, the fact that the minimum wage seems to affect the distribution of wages among workers paid above the minimum, and the fact that the distribution of wages cannot be adequately explained by a two-parameter model conspire to make estimates of the employment effects derived in this way very dubious. Of course, it is possible that in other countries it may be possible to obtain more sensible

[12] An alternative strategy would be to estimate on the whole sample and model the way in which age affects the parameters.

estimates using this modelling approach. This is likely to be true where one can more precisely estimate the wage distribution and where there are likely to be small spillover effects associated with minimum wages. But, what these results suggest is that any researcher using this approach should be extremely careful to present a wide range of experiments with truncation points and wage distributions in order to be convincing.

These conclusions all seem rather negative but one positive line of research that emerges naturally from the Meyer-Wise approach is the issue of the effect of changes in the minimum wage on the distribution of wages as a whole. Meyer and Wise have a very simplistic model of the way in which a change in the minimum wage affects individuals at different points in the wage distribution, a model that is almost certainly at variance with the reality. But this raises the issue of what the effect really is. To provide a convincing answer to this question probably requires large changes in the minimum wage which are not present in this data so I leave this important topic to future research.

Table 6.1
The Effects of Minimum Wages on the Adult Wage Distribution

Dependent variable: Δith percentile or average of log real hourly earnings distribution

Dependent Variable	Coefficient (standard error) on ΔLog(real minimum hourly wage)	
	Male Councils	Female Councils
Δ10th percentile	.217 (.079)	.184 (.060)
Δ20th percentile	-.010 (.091)	.292 (.072)
Δ30th percentile	-.142 (.099)	.208 (.052)
Δ40th percentile	-.084 (.104)	.180 (.049)
Δ50th percentile	-.047 (.116)	.102 (.046)
Δ60th percentile	-.086 (.134)	.081 (.042)
Δ70th percentile	-.048 (.119)	.015 (.051)
Δ80th percentile	-.037 (.127)	.025 (.062)
Δ90th percentile	.011 (.205)	.063 (.077)
Δaverage	.090 (.096)	.129 (.039)

Notes:

1. Sample size: 99 for both males and females; Estimation period: 1976-92.
2. Heteroscedastic consistent standard errors in parentheses.
3. Time dummies included in all specifications.
4. Regressions weighted by employment in each Wages Council/ Year cell.

Table 6.2

Descriptive Statistics

Industry	Retail Distribution		Wholesale Distribution
	Number of individuals	Percent of individuals paid at or below the minimum	Number of individuals
Females			
1987	5933	25.3	1138
1988	5988	19.0	1248
1989	5946	18.6	1297
1990	6424	20.6	1312
Males			
1987	3066	5.3	2764
1988	3089	4.3	3081
1989	3029	4.0	3144
1990	2970	4.9	3197

Notes.
1. Based on New Earnings Survey micro-data.

Table 6.3
Maximum Likelihood Estimates of Employment Parameter ϕ, Assuming Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	_	1.813 (0.189)	_	2.489 (0.503)	$5.5x10^4$ ($1.8x10^4$)	4.949 (2.292)	NC	6.412 (4.296)
1988	_	1.413 (0.094)	_	2.081 (0.366)	407.362 (204.455)	2.152 (0.504)	906.991 (308.928)	2.206 (0.691)
1989	_	1.709 (0.147)	_	2.348 (0.408)	NC	6.045 (2.956)	NC	7.347 (4.857)
1990	_	1.410 (0.094)	_	1.920 (0.301)	662.140 (1062.89)	2.265 (0.556)	315.573 (463.208)	2.727 (1.006)
Males								
1987	1.389 (0.056)	1.531 (0.084)	1.525 (0.107)	1.904 (0.202)	2.383 (0.414)	2.083 (0.321)	3.801 (1.087)	2.235 (0.480)
1988	1.575 (0.088)	1.489 (0.072)	2.159 (0.264)	1.865 (0.180)	3.972 (1.594)	2.219 (0.343)	7.875 (4.385)	2.303 (0.470)
1989	1.447 (0.067)	1.561 (0.085)	1.960 (0.208)	2.112 (0.249)	2.328 (0.396)	2.536 (0.472)	4.805 (1.847)	3.232 (0.958)
1990	1.454 (0.067)	1.675 (0.102)	1.900 (0.190)	2.259 (0.278)	2.432 (0.421)	2.756 (0.528)	3.008 (0.814)	2.516 (0.548)

Notes.
1. Based on New Earnings Survey Micro-data.
2. NC denotes that we could not obtain convergence. This normally means that the estimates of the parameters were heading in a direction that would make the estimate of ϕ very large.

Table 6.4
Kolmogorov-Smirnov Test of Estimated Distribution (P-Values)
Assuming Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	-	0.244	-	0.450	0.001	0.519	NC	0.468
1988	-	0.171	-	0.777	0.008	0.734	0.192	0.715
1989	-	0.052	-	0.164	NC	0.538	NC	0.539
1990	-	0.160	-	0.808	0.155	0.960	0.147	0.981
Males								
1987	0.027	0.195	0.016	0.865	0.239	0.992	0.997	0.992
1988	0.007	0.084	0.047	0.368	0.483	0.392	0.987	0.358
1989	0.035	0.022	0.050	0.454	0.063	0.844	0.791	0.952
1990	0.028	0.100	0.251	0.806	0.701	0.958	0.556	0.908

Notes.
1. Based on New Earnings Survey Micro-data.
2. To accept the hypothesis of correct functional form at the 5% level one needs a value of the test statistic above 0.95.

Table 6.5
Maximum Likelihood Estimates of Employment Parameter ϕ,
Assuming Singh - Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	_	1.221 (0.113)	_	1.188 (0.184)	0.792 (0.056)	1.504 (0.627)	14.225 (10828.2)	1.124 (0.458)
1988	_	1.149 (0.081)	_	2.039 (0.781)	16.020 (12417.2)	1.857 (0.868)	4958.202 (94493.3)	1.542 (0.837)
1989	_	1.157 (0.080)	_	1.081 (0.120)	16.499 (17207.0)	1.559 (0.667)	15.879 (25761.7)	1.067 (0.376)
1990	_	1.209 (0.095)	_	1.615 (0.416)	12.374 (24.867)	1.960 (0.972)	4.400 (5.704)	2.459 (2.194)
Males								
1987	1.199 (0.057)	1.368 (0.115)	1.078 (0.067)	2.042 (0.525)	1.699 (0.452)	2.491 (1.106)	4.718 (4.328)	3.175 (2.402)
1988	1.129 (0.048)	1.441 (0.124)	1.170 (0.112)	2.343 (0.616)	4.050 (3.107)	3.957 (2.276)	78.074 (381.979)	4.356 (3.412)
1989	1.146 (0.049)	1.255 (0.080)	1.327 (0.156)	2.353 (0.714)	1.218 (0.196)	5.543 (4.851)	3.260 (2.737)	17.832 (42.172)
1990	1.142 (0.050)	1.449 (0.135)	1.343 (0.168)	2.959 (0.981)	1.641 (0.442)	5.743 (3.829)	2.242 (1.242)	4.819 (3.519)

Notes.
1. As for Table 6.3.

Table 6.6
Kolmogorov-Smirnov Test of Estimated Distribution (P-Values)
Assuming Singh-Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	-	0.850	-	0.785	0.299	0.723	0.335	0.702
1988	-	0.910	-	0.952	0.053	0.950	0.207	0.877
1989	-	0.981	-	0.900	0.098	0.964	0.040	0.924
1990	-	0.778	-	0.903	0.210	0.941	0.161	0.967
Males								
1987	0.577	0.696	0.787	0.916	0.650	1.000	0.998	0.995
1988	0.706	0.076	0.602	0.299	0.591	0.494	0.999	0.442
1989	0.982	0.495	0.740	0.617	0.740	0.706	0.972	0.986
1990	0.935	0.426	0.922	0.753	0.943	0.961	0.842	0.958

Notes.
1. As for Table 6.4.

Table 6.7
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1990
Assuming Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	1.151 (0.082)	–	1.161 (0.144)	4.577 (1.862)	1.127 (0.271)	5.121 (2.619)	1.001 (0.206)
Age 25-34	–	1.224 (0.103)	–	1.323 (0.205)	78.515 (135.366)	1.736 (0.555)	49.318 (79.985)	1.603 (0.615)
Age 35-44	–	2.027 (0.511)	–	4.874 (3.968)	638.466 (2083.450)	8.325 (12.091)	157.248 (389.925)	17.366 (45.599)
Age 45+	–	1.373 (0.194)	–	2.206 (0.910)	NC	1.490 (0.538)	NC	2.458 (2.012)
Males								
Age 21-24	1.110 (0.063)	1.770 (0.443)	1.150 (0.139)	8.664 (12.576)	1.202 (0.266)	9.577 (20.686)	1.351 (0.563)	85.340 (612.918)
Age 25-34	1.258 (0.064)	1.580 (0.155)	1.415 (0.138)	2.425 (0.602)	1.605 (0.258)	3.102 (1.283)	1.591 (0.339)	2.779 (1.327)
Age 35-44	1.243 (0.068)	1.251 (0.061)	1.492 (0.172)	1.326 (0.105)	1.458 (0.212)	1.413 (0.168)	1.516 (0.300)	1.442 (0.230)
Age 45+	1.631 (0.193)	1.697 (0.179)	2.109 (0.500)	2.042 (0.369)	3.187 (1.473)	2.888 (0.093)	5.472 (4.808)	2.307 (0.729)

Notes.
1. Based on New Earnings Survey Micro-data.
2. The percentiles refer to the percentiles of the aggregate wage distribution so are the same as in the earlier Tables.

Table 6.8
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1990
Assuming Singh-Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	1.370 (0.254)	–	1.495 (0.523)	2.448 (1.522)	2.048 (1.578)	2.379 (1.812)	1.246 (0.684)
Age 25-34	–	1.250 (0.196)	–	1.696 (0.824)	3894.709 (92589.50)	4.597 (9.870)	3228.072 (81403.51)	4.328 (11.218)
Age 35-44	–	1.122 (0.144)	–	1.999 (1.937)	7.121 (22.524)	2.832 (6.453)	1.233 (0.928)	426.697 (18997.19)
Age 45+	–	1.225 (0.242)	–	7.312 (22.763)	24.609 (247.393)	1.701 (1.787)	13.296 (110.934)	11.814 (97.286)
Males								
Age 21-24	1.169 (0.123)	1.024 (0.171)	1.121 (0.235)	3.231 (7.835)	1.108 (0.456)	0.780 (0.561)	1.407 (1.449)	0.395 (0.057)
Age 25-34	1.180 (0.085)	1.116 (0.082)	1.425 (0.270)	2.418 (1.349)	1.678 (0.609)	5.337 (8.303)	1.482 (0.640)	3.887 (6.144)
Age 35-44	1.276 (0.130)	1.324 (0.129)	1.885 (0.589)	1.537 (0.299)	1.820 (0.709)	2.058 (0.828)	2.099 (1.277)	2.652 (1.795)
Age 45+	1.139 (0.111)	1.647 (0.325)	1.035 (0.151)	2.311 (0.983)	1.000 (0.248)	4.855 (4.837)	0.776 (0.190)	3.108 (2.713)

Notes.
1. As for Table 6.7.

Figure 6.1a
The Meyer-Wise Technique with no Spillover Effects

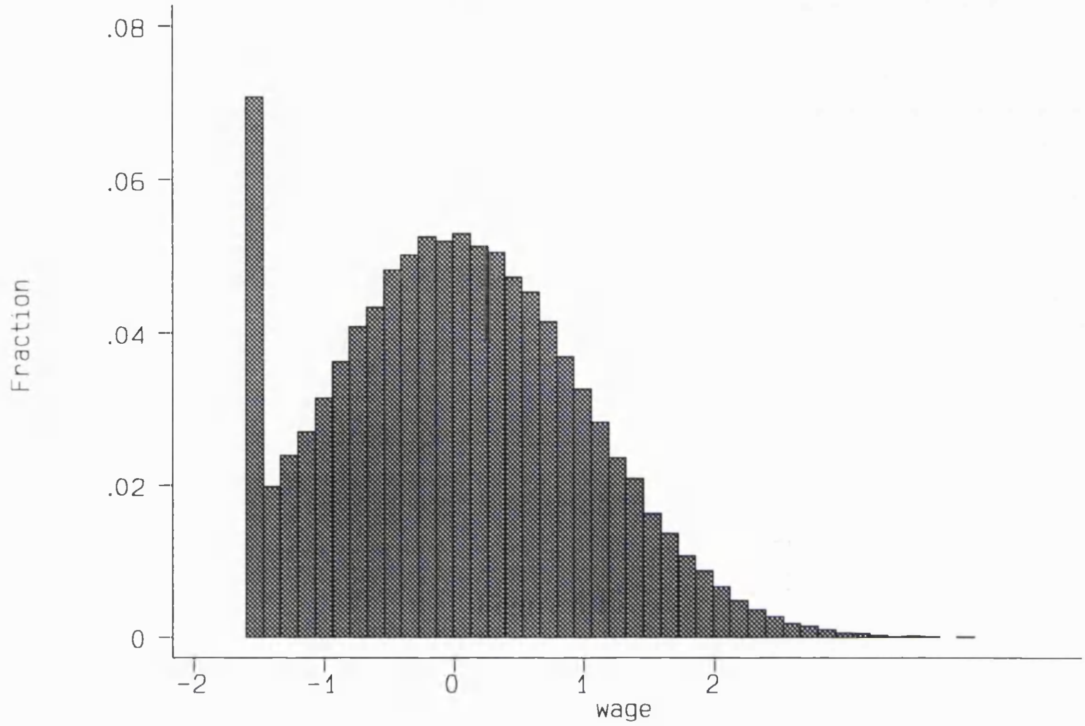


Figure 6.1b
The Meyer-Wise Technique with Spillover Effects

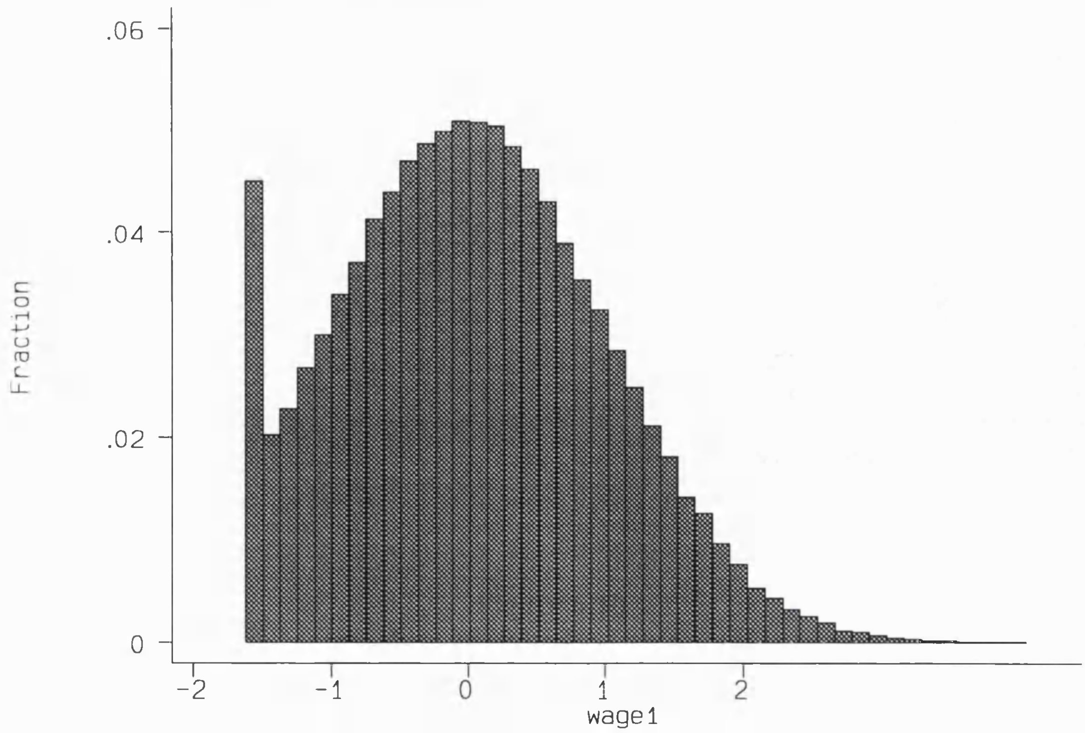


Figure 6.2a

Log hourly wage distribution for female retail employees in 1990

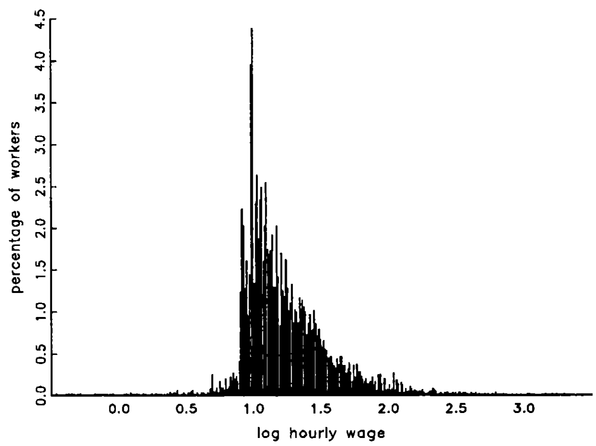


Figure 6.2b

Log hourly wage distribution for male retail employees in 1990

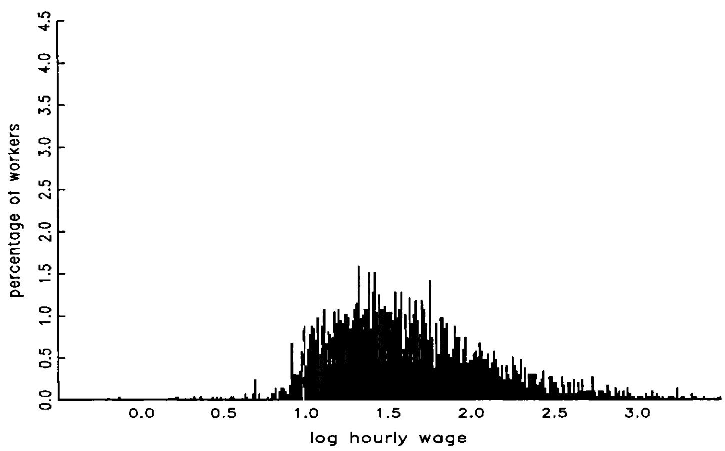


Figure 6.2c

Log hourly wage distribution for female wholesale employees in 1990

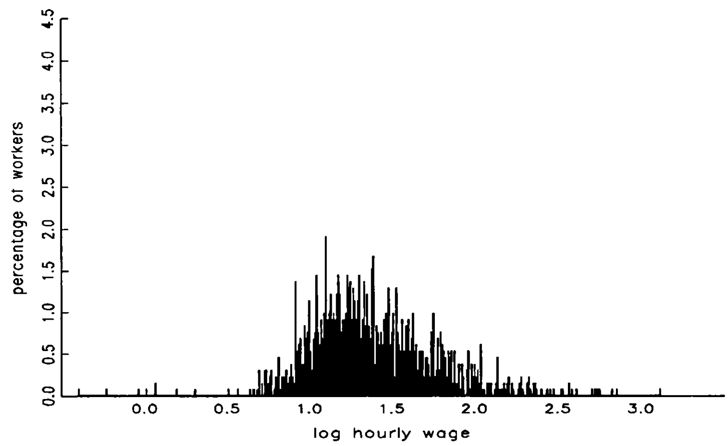
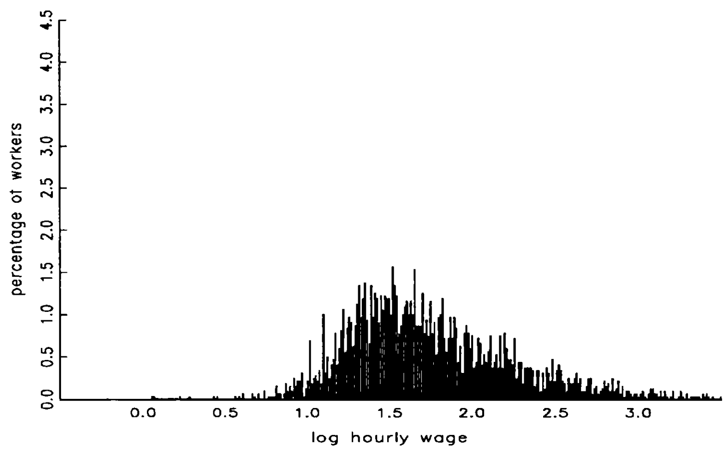


Figure 6.2d

Log hourlywage distribution for male wholesale employees in 1990



Chapter 7 - Conclusions

Wage dispersion has risen dramatically in the UK since the late 1970s. This increase occurred after a long period of relative stability in the wage distribution, so that wage inequality is now greater than it was 100 years ago (Machin, 1996a). The rise in wage inequality has been extensively documented in the literature by labour economists. However, there is relatively little analysis of the dynamics of the earnings process experienced by individuals. This is an important issue, since the degree of movement within the distribution of wages from one period to the next will have potentially serious welfare implications concerning the rise in inequality. Cross section studies of inequality provide only a snapshot of the distribution at a point in time. It is possible that the observed differences in a given year are transitory and there is a high level of movement within the distribution. Cross section inequality is, in a sense, being shared out. However, it is also possible that cross section differences are reflective of permanent (lifetime) differences and there is little movement from one year to the next. The welfare implications in this case are potentially far more serious.

The first half of this thesis addressed the question of the degree of persistence of earnings and the level of wage mobility in Great Britain. In chapter 3, I studied the dynamic structure of individual (male) wages using the NES from 1975 to 1994. I provide an analysis of the auto-covariance structure of wages within year of birth cohorts. The results suggest that individuals' earnings contain a permanent element, modelled by a random walk in age, and a highly persistent transitory component, an ARMA(1,1). Consequently, the proportion of earnings variation within a cohort that is permanent increases as the cohort ages. In addition, I find that the rise in inequality since the late

1970s appears to be driven by similar increases in both the permanent and transitory components. These results imply that the observed increase in the cross sectional distribution of wages is largely reflective of increases in persistent differences between individuals. This is potentially worrying from a welfare perspective.

In chapter 4, I studied wage mobility and labour market transitions in Great Britain from 1975 to 1994, for males and females using the NES, the BHPS and the LFS. Using a decile transition matrix approach I find quite high levels of persistence in wages, with many individuals remaining in the same or adjacent decile from one year to the next. Mobility is higher when measured over periods of more than one year, but there are still quite high levels of persistence. Furthermore, there is some evidence that mobility rates may have fallen over time. This result emerges from an examination of decile matrices and from my preferred measure of mobility, which measures the change in actual ranking of individuals within the wage distribution between time periods.

The results obtained from chapters 3 and 4 paint a picture of increasingly permanent differences between individuals, with persistent wage differences rising at least as fast as cross sectional differences. In addition, there is some evidence that individuals find it more difficult to progress up the distribution of wages than they did twenty years ago. So, not only have observed wage differences between individuals each year risen massively, the degree of movement within the distribution each year has probably fallen. The welfare implications of these results are potentially very alarming and may have serious consequences for the lifetime distribution of income and poverty.

As more panel data become available, the work in this field will undoubtedly grow. Initially, more research documenting the trends in earnings dynamics would be extremely valuable. The Department of Social Security's Lifetime Earnings Database would be suitable for a verification of the results presented here. Further work on international differences in earnings dynamics is also important. An analysis of the determinants of mobility would also be helpful. Research may then turn to the question of what might be causing the changes in earnings dynamics that are observed.

Recently there has been a resurgence of interest in the economic effects of minimum wages. This has been driven in part by recent studies that have found, contrary to the predictions of the conventional competitive model of the labour market, zero or even positive effects of increases in the minimum wage on employment. Interest has also been fuelled by the huge increase in wage inequality, making the minimum wage a more attractive policy instrument for tackling low pay and poverty.

In chapter 5 of this thesis, I studied the economic effects of minimum wages in Great Britain between 1975 and 1992. This chapter analyses wage and employment effects in a panel of Wages Council industries. The results indicate that increases in the minimum wage raise wages at the bottom of the wage distribution by more than those at the top, compressing the wage distribution. I could find no evidence that increases in the minimum wage over this time period reduced employment.

Chapter 6 provided a critique of a paper by Meyer and Wise (1983a, 1983b) which estimates the employment effects of minimum wages for US youth, using data from a single cross section. I use their approach to study employment effects in the British Wages Councils between 1987 and 1990. The Meyer-Wise methodology is shown to be highly sensitive to certain key assumptions required. In particular, the assumed functional form of the distribution of wages and the assumption about how the minimum wage affects the distribution of wages. The results suggest that, for British data at least, the estimates are not robust.

The results on the economic effects of the British Wages Councils from chapters 5 and 6 indicate that a minimum wage is effective in raising the pay of those at the bottom of the wage distribution. Despite this, there is no evidence of any adverse employment effects from increases in the minimum wage. In an era of increasing wage dispersion, these results suggest that a minimum wage may be a desirable method of reducing the incidence of low pay.

Further work on the minimum wage issue is bound to follow. The recently legislated increases in the US Federal minimum will undoubtedly induce more research into the employment effects. If the Labour (and/or Liberal) Party win the next election they are committed to the introduction of a national minimum wage. This would provide the opportunity for an "impact" study, similar to those recently conducted in the US. Whatever results may emerge, the debate is set to continue for a long time.

Appendix 1

The Computation of Auto-Covariances and Estimation of Error Component Models

In this appendix I present the statistical methods employed in chapter 3 for computing the covariances of earnings for each cohort and for estimating error component models for individual earnings. The methodology used is the same as that utilised by Abowd and Card (1989), except that here I have an unbalanced panel of individuals. For each cohort c and individual i, define a vector:

$$d_{ci} = \begin{pmatrix} d_{ci1} \\ \cdot \\ \cdot \\ \cdot \\ d_{ciT_c} \end{pmatrix}$$

where d_{cit} is an indicator variable such that:

$d_{cit} = 1$ if the individual is present in year t of the panel.

$d_{cit} = 0$ otherwise.

and T_c is the total length of the panel for each cohort (Between 1 and 20 years).

Analogously to d_{ci}, define a vector:

$$w_{ci} = \begin{pmatrix} w_{ci1} \\ \cdot \\ \cdot \\ \cdot \\ w_{ciT_c} \end{pmatrix}$$

where w_{cit} are log hourly earnings for cohort c and individual i in year t, in mean deviation form for each cohort and year. Since the panel is unbalanced the elements of w_{ci} corresponding to missing years of data will be set to zero.

The covariance matrix of log hourly earnings for each cohort is then computed as:

$$C_c = \frac{\sum_{i=1}^{i=N_c} w_{ci} w_{ci}'}{D_c}$$

where N_c is the total number of individuals in the cohort and

$$D_c = \sum_{i=1}^{i=N_c} d_{ci} d_{ci}'$$

Define m_c to be a vector of the distinct elements of the covariance matrix C_c, m_c = vech(C_c). Since C_c is symmetric there are T_c (T_c +1)/2 elements in m_c. Conformably with m_c, define m_{ci} to be the distinct elements of the individual cross product matrices $w_{ci}\, w_{ci}'$. Similarly, let p_c be a vector of the distinct elements of D_c. Chamberlain (1984) proves that, under some fairly general conditions, independence of the w_{ci} implies that m_c has an asymptotic normal distribution $m_c \sim \mathrm{N}(m_c,V_c)$.

Where V_c can be estimated by:

$$V_c = \frac{\sum_{i=1}^{i=N_c} (m_c - m_{ci})(m_c - m_{ci})'}{p_c\, p_c'}$$

Now define the vector m to be the vertical concatenation of all the m_c vectors. To estimate the error components models of Section 3.5, I want to fit the elements of m to a parameter vector b, so that $m = \mathrm{f}(b)$. Minimum distance estimation involves minimising the following quadratic form: $(m - \mathrm{f}(b))\ A\ (m - \mathrm{f}(b))'$ where A is an appropriate weighting matrix.

Chamberlain (1984) shows that the optimal choice for A is V^{-1}, where V is a block diagonal matrix which is constructed from all the V_c matrices. However, Altonji and Segal (1994) provide Monte Carlo evidence that optimal minimum distance (OMD) is seriously biased in small samples. This bias arises from the correlation between sampling errors in the second moments, m, and the weighting matrix of fourth moments, V^{-1}. They present an alternative estimator, the independently weighted optimal minimum distance estimator (IWOMD) but conclude that equally weighted estimation (where A is an identity matrix) is often preferable. I follow their procedure and use equally weighted minimum distance estimation.

Following Chamberlain (1984), the standard errors of the estimated parameters are obtained from the following formula:

$$(G'AG)^{-1}\ G'AVAG\ (G'AG)^{-1}$$

where G is the T^*P gradient matrix $\delta \mathrm{f}(b)/\delta b$ evaluated at b^*, the estimated value of b, where T is the sum across cohorts of $T_c(T_c+1)/2$ and P is the number of parameters.

Under the hypothesis of a correct specification the minimised quadratic form:

$$(m - \mathrm{f}(b^*))\ V^{-1}\ (m - \mathrm{f}(b^*))'$$

has a chi-squared distribution with degrees of freedom equal to the dimension of m ($=T$) minus the number of parameters P. This is the test statistic presented in Table 3.3.

Appendix 2

Figure A3.1: Auto-Covariances for all Cohorts: 1975-94

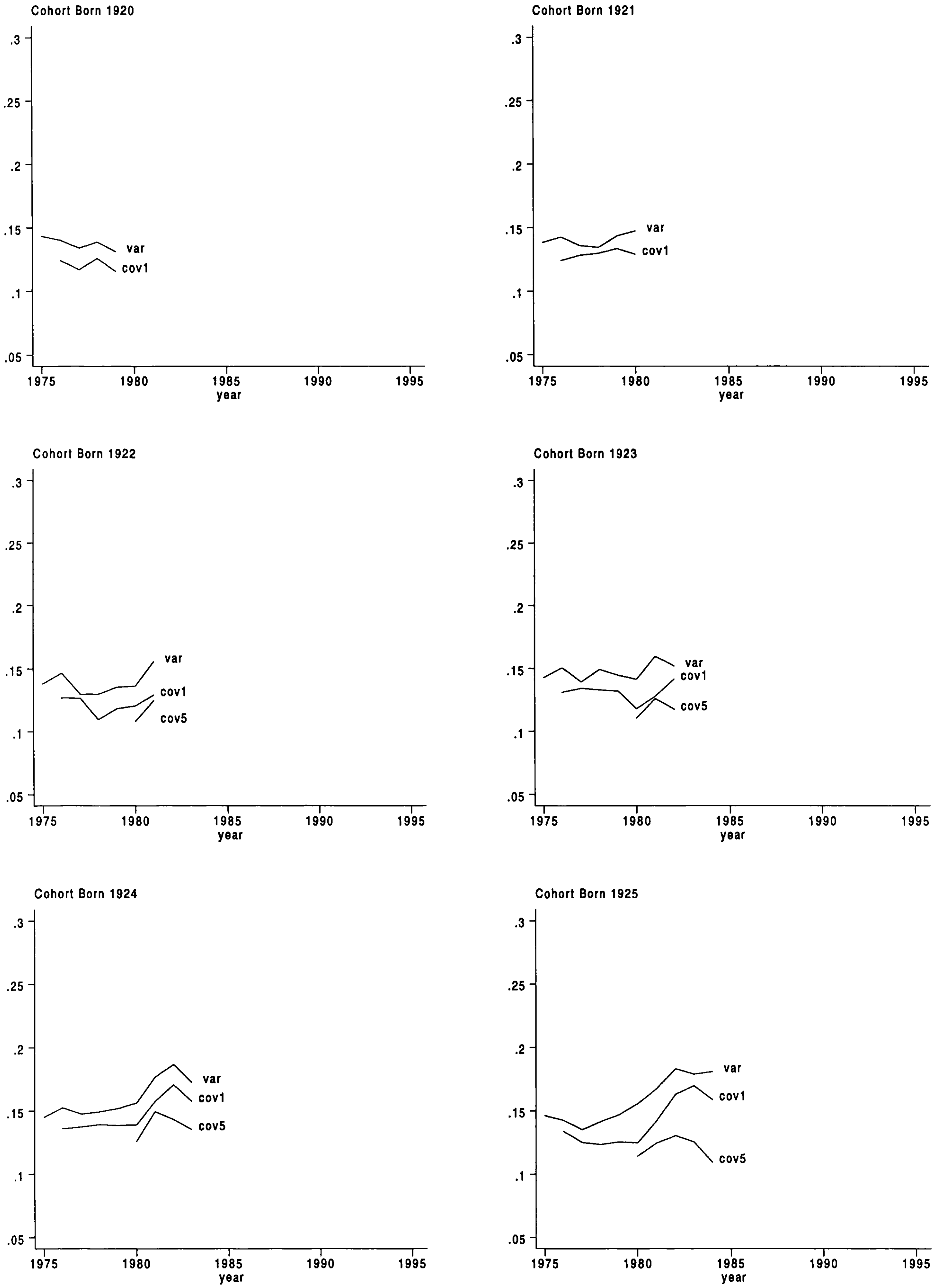


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94

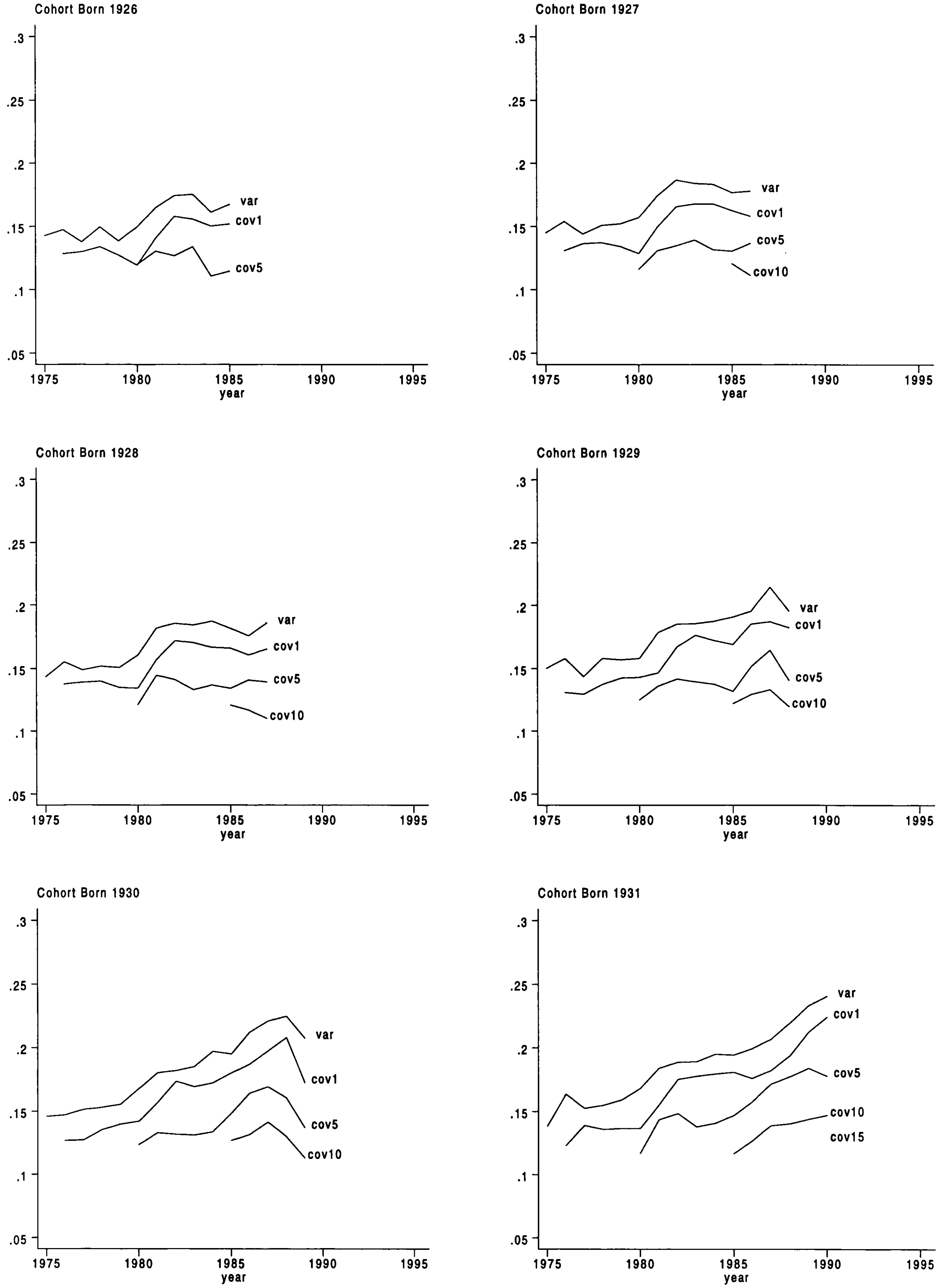


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94

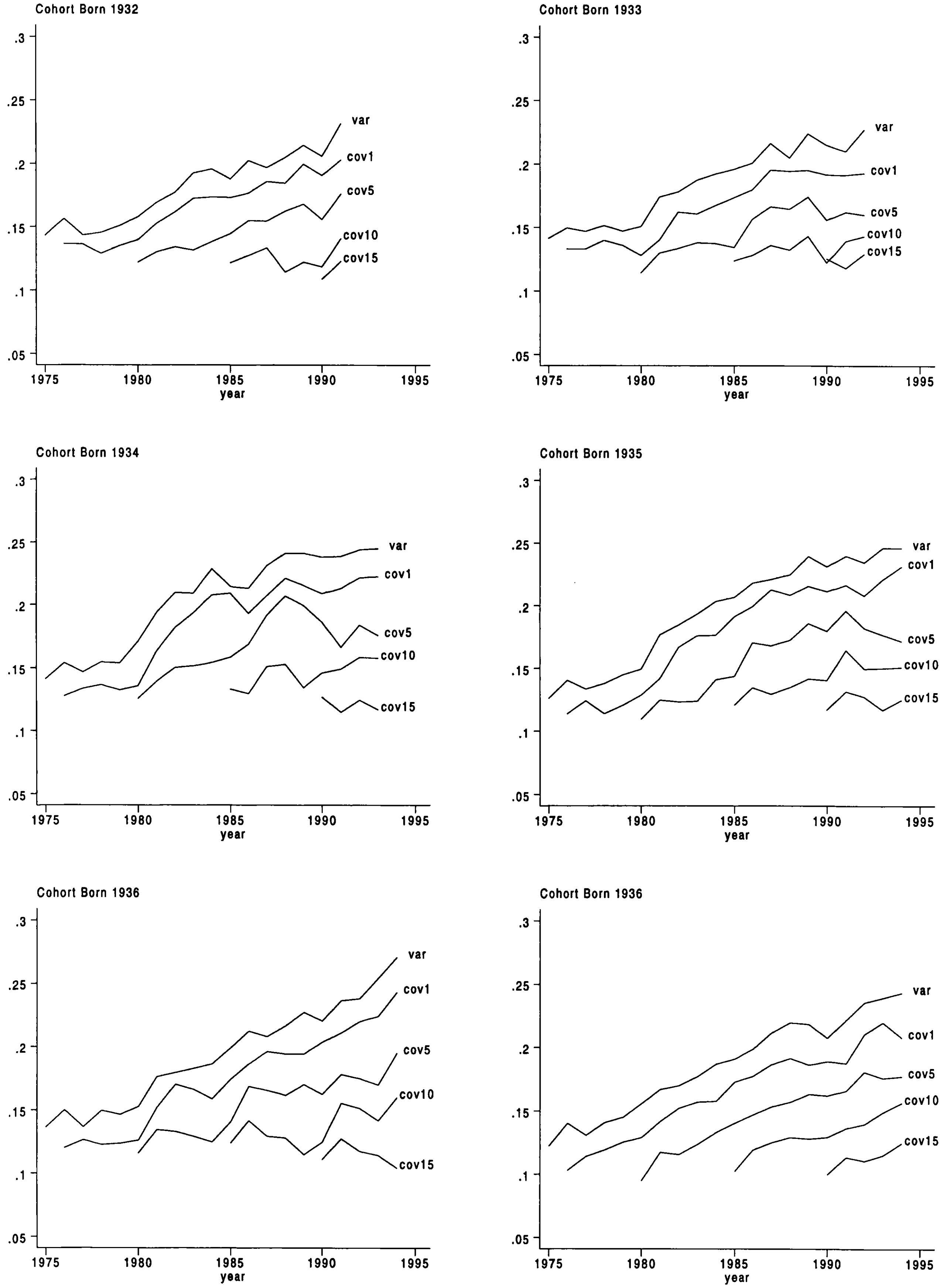


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94

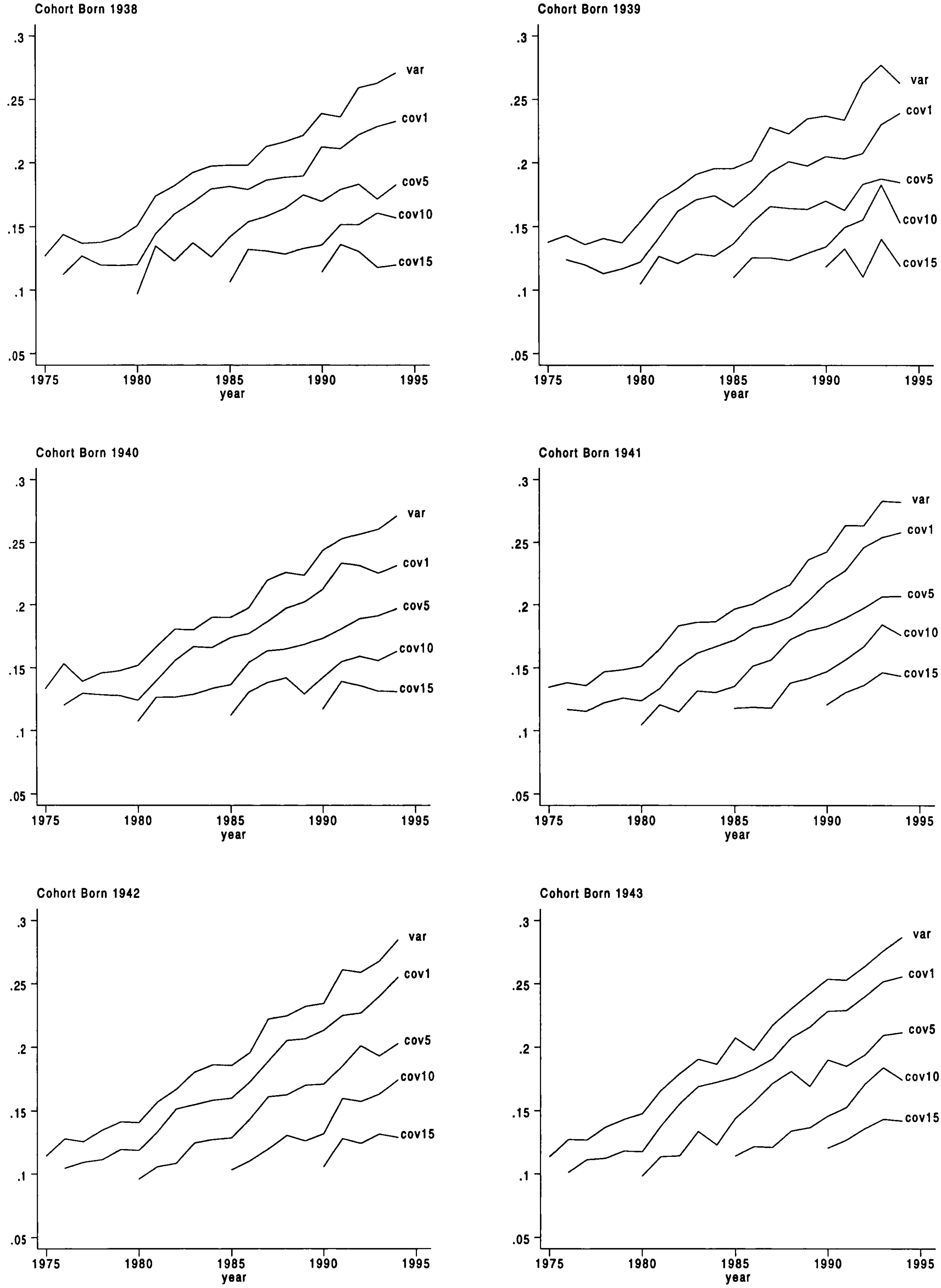


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94

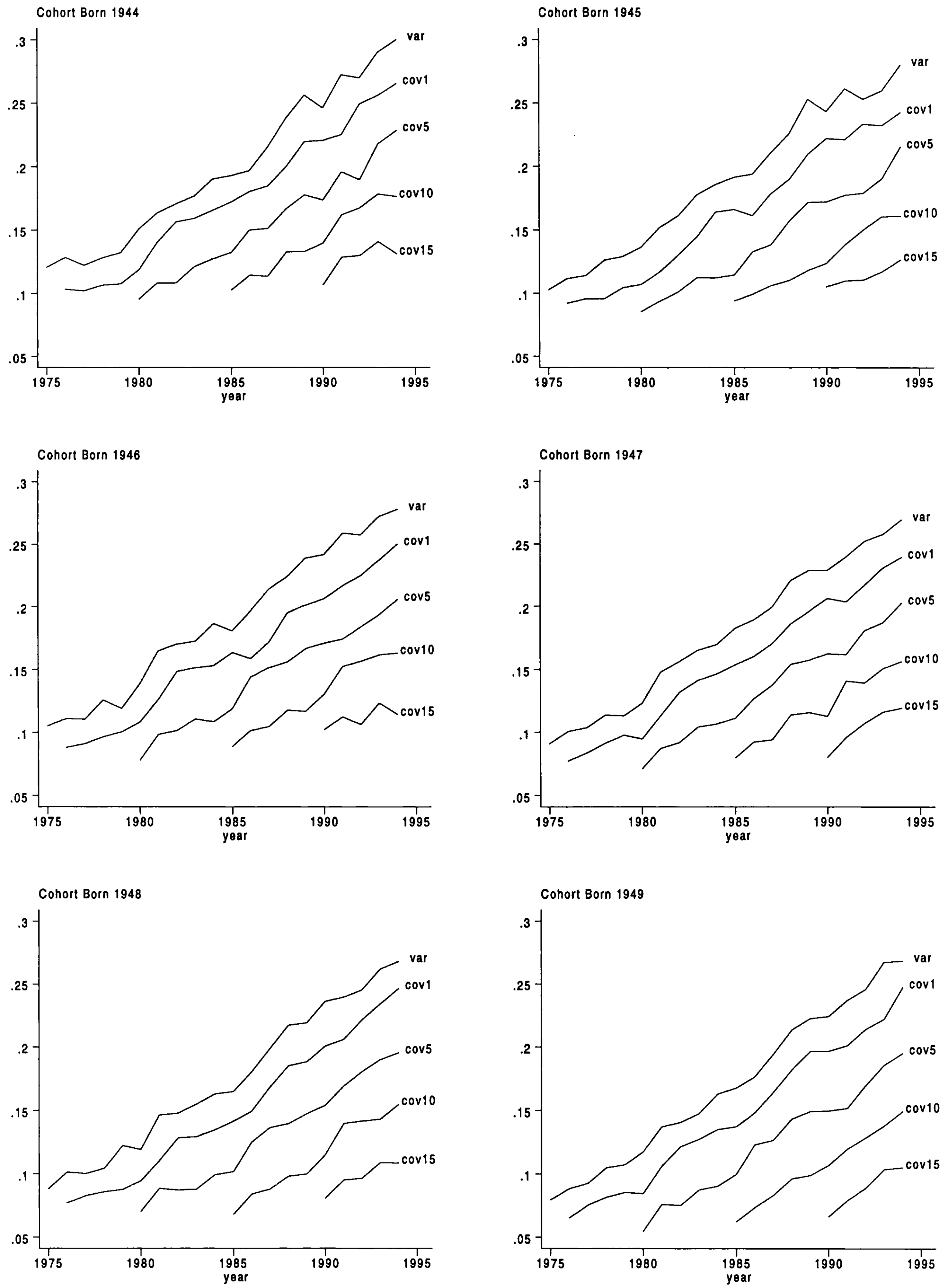


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94

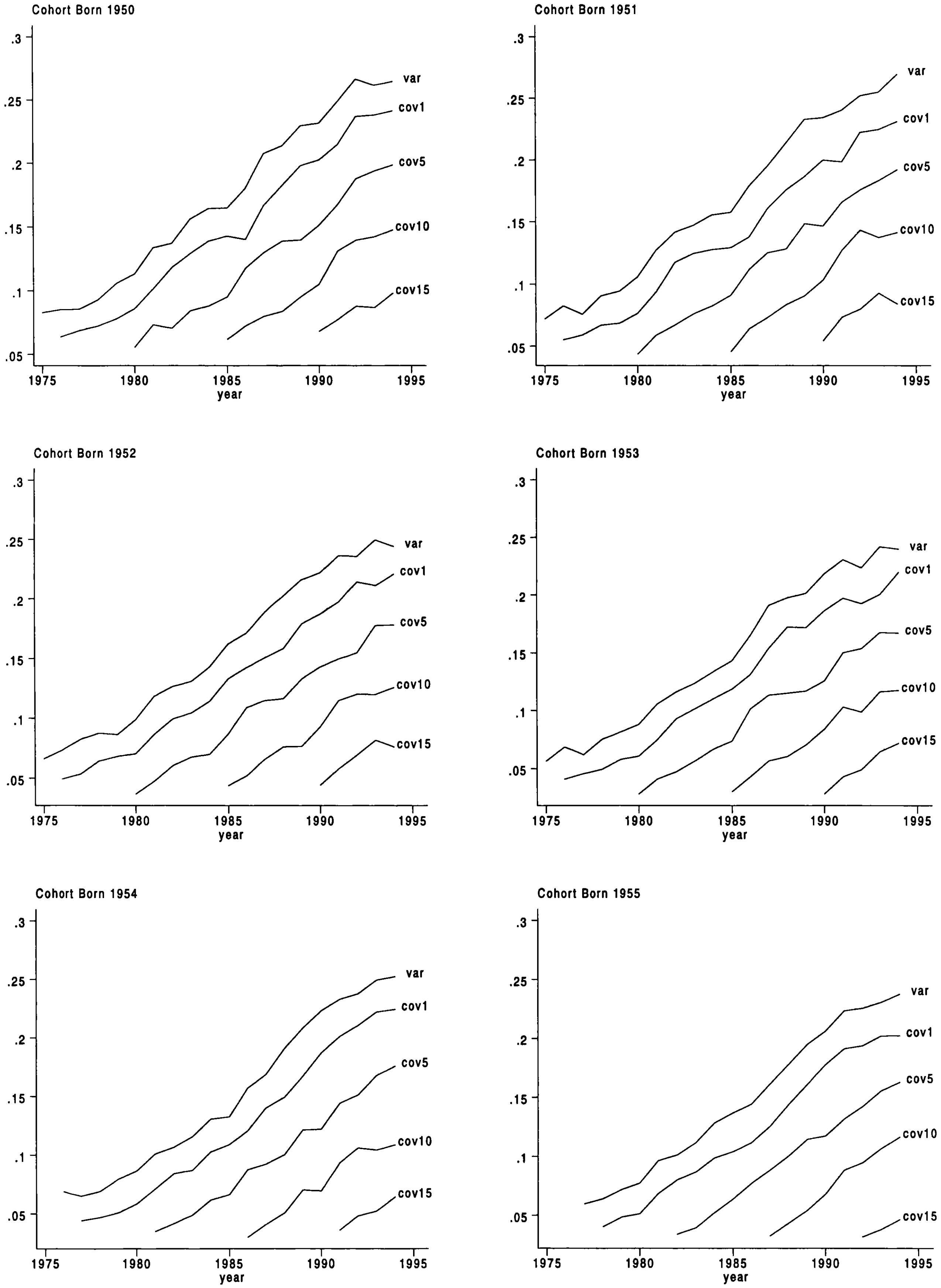


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94

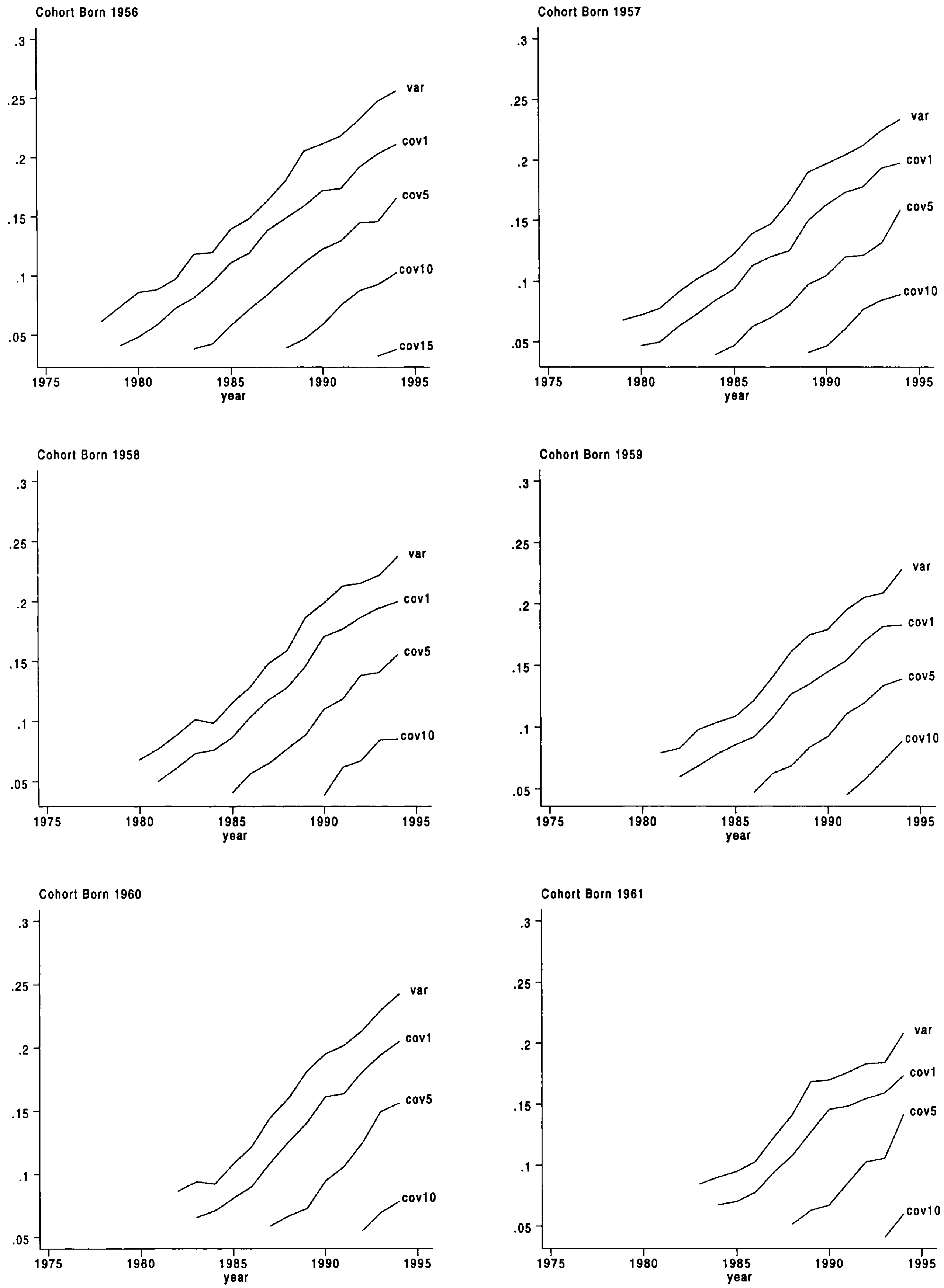


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94

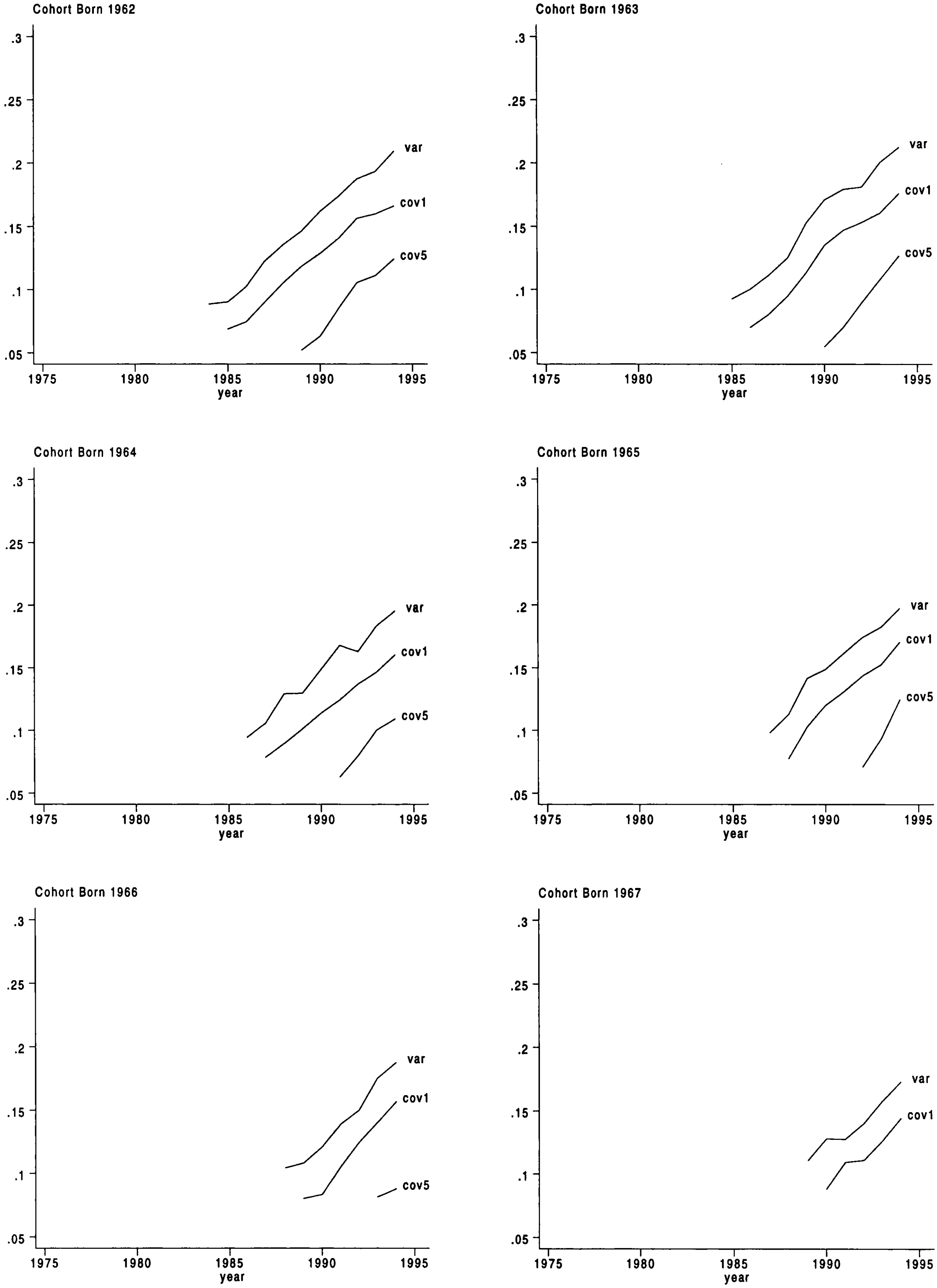
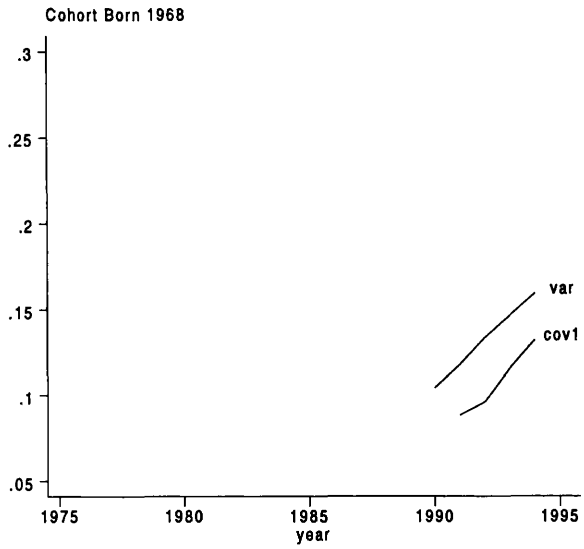


Figure A3.1 continued: Auto-Covariances for all Cohorts: 1975-94



Notes: var - variance(w_t)
cov1 - covariance(w_t,w_{t-1})
cov5 - covariance(w_t,w_{t-5})
cov10 - covariance(w_t,w_{t-10})
cov15 - covariance(w_t,w_{t-15})

Figure A3.2: The Life Cycle Profile of Variances and Covariances for all Years

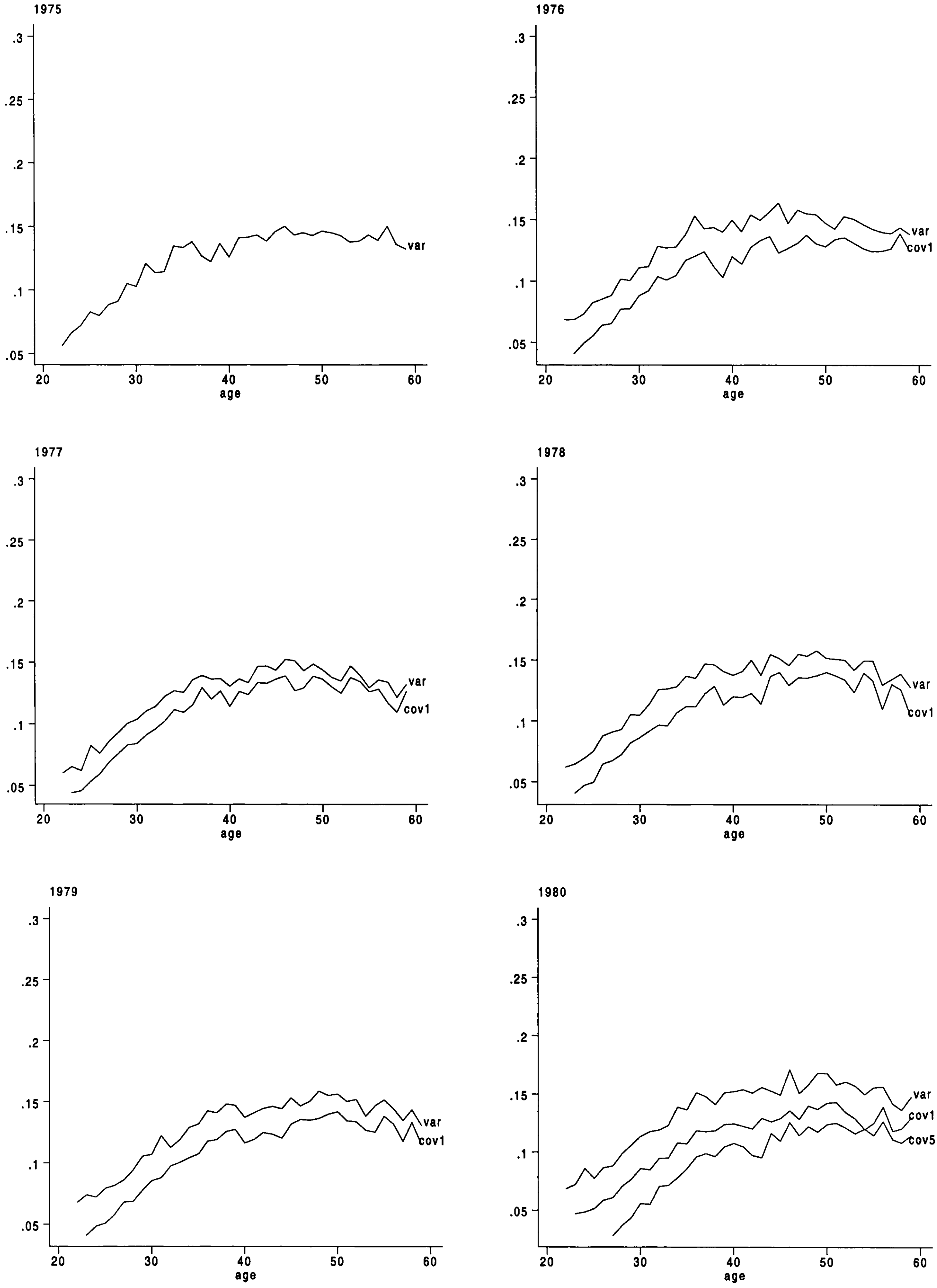


Figure A3.2 continued: The Life Cycle Profile of Auto-Covariances for all Years

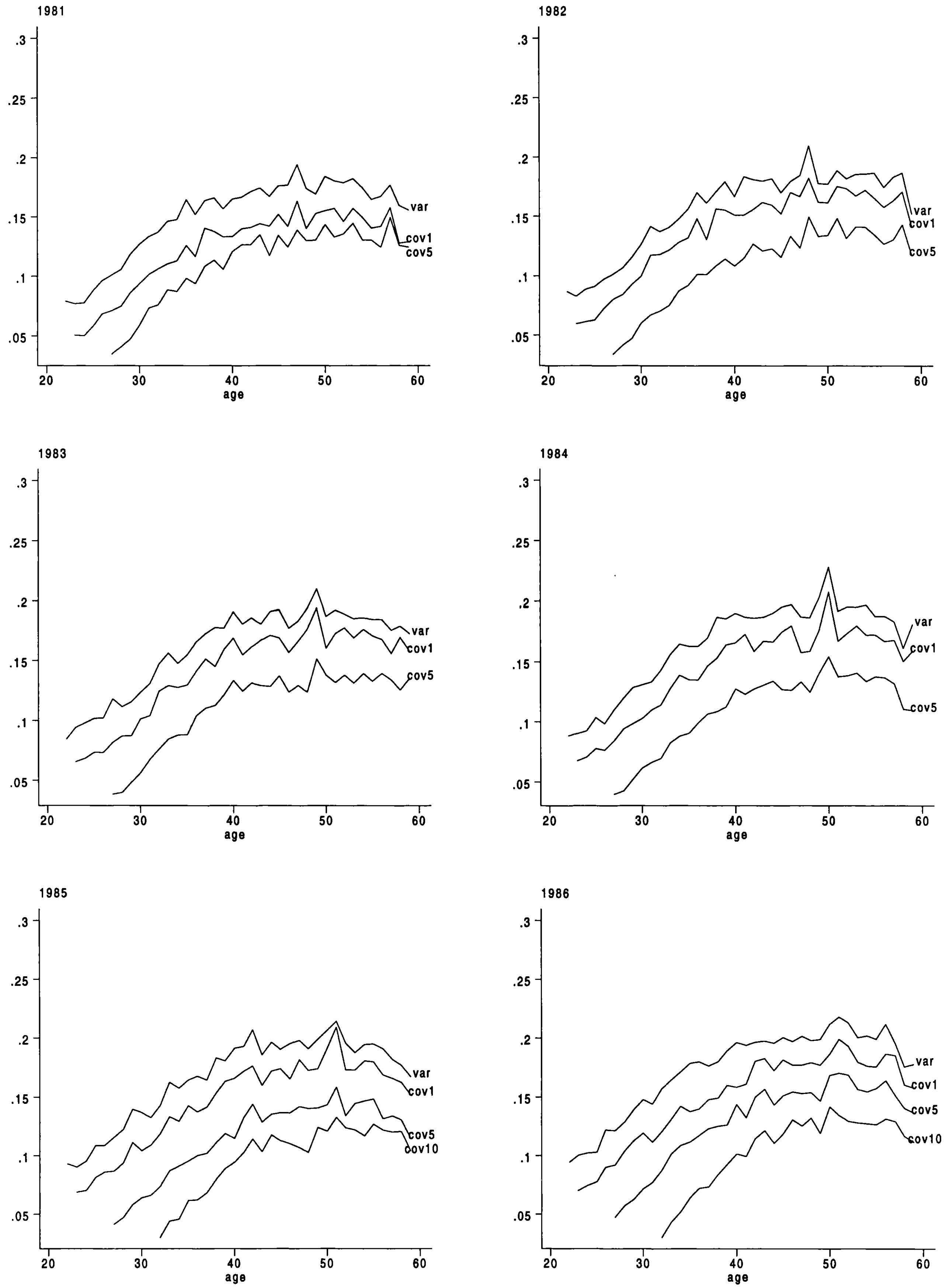


Figure A3.2 continued: The Life Cycle Profile of Auto-Covariances for all Years

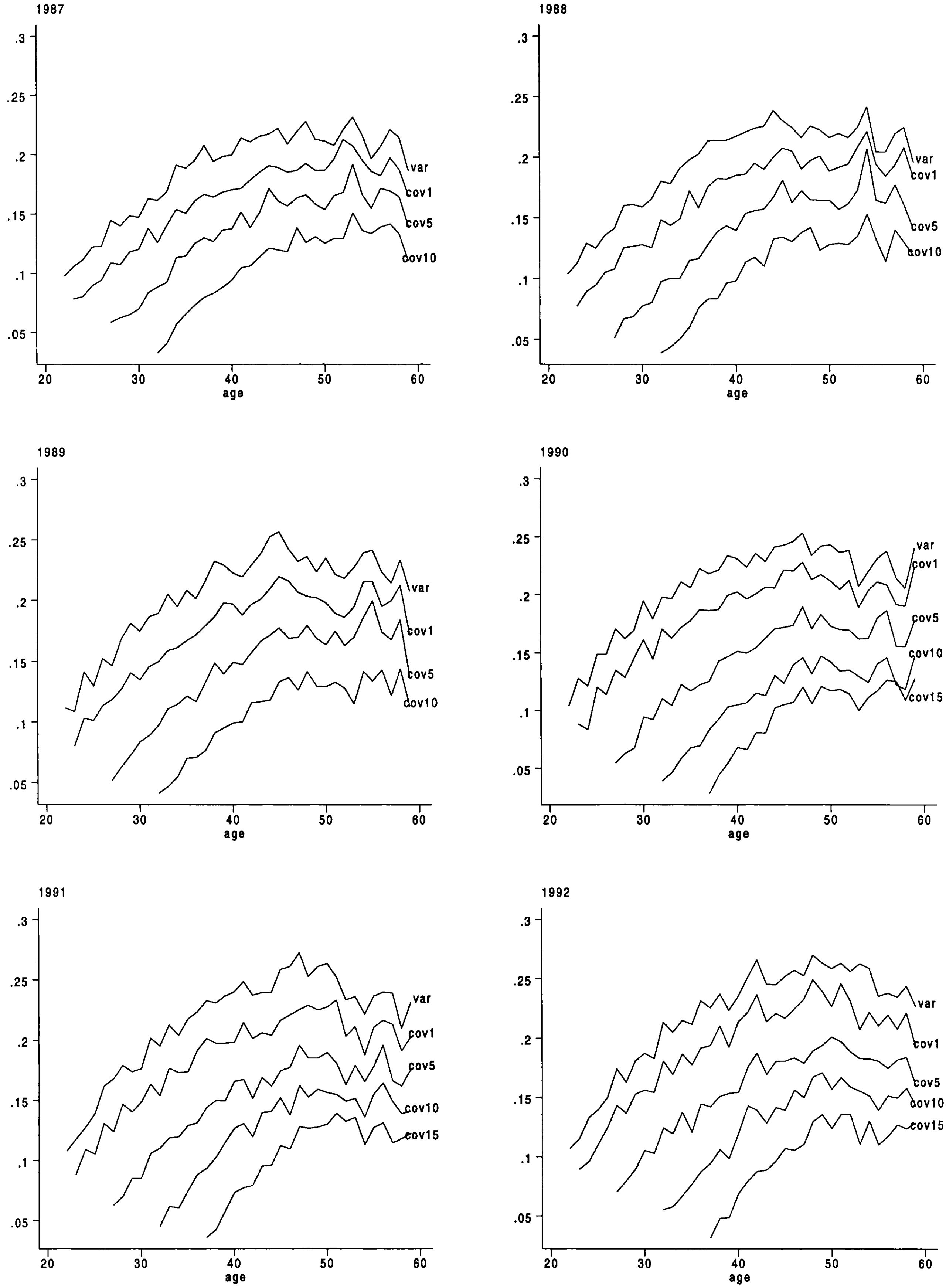
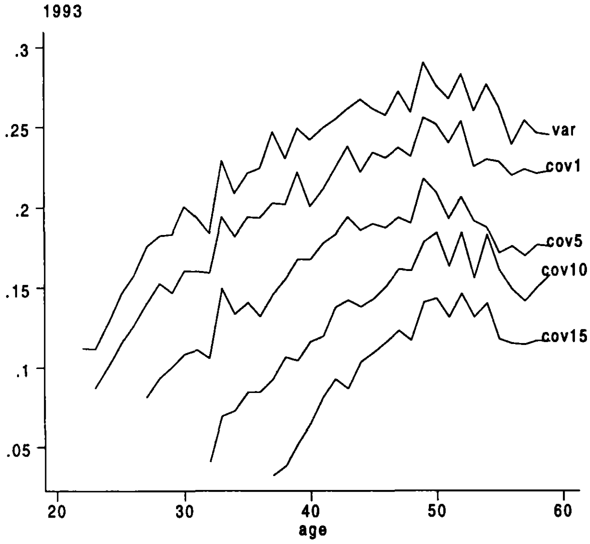
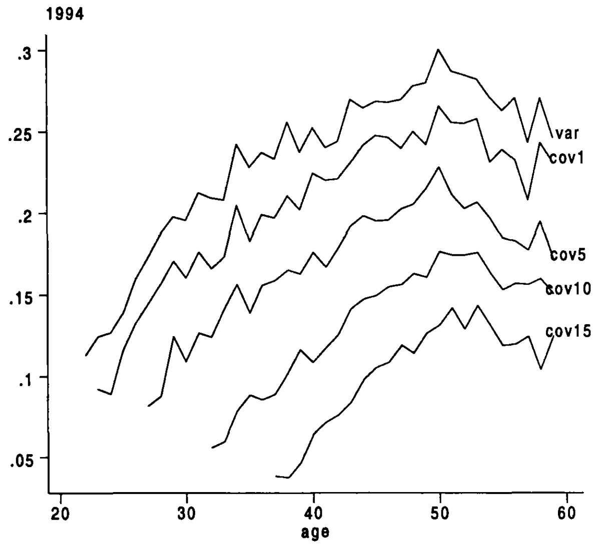


Figure A3.2 continued: The Life Cycle Profile of Auto-Covariances for all Years





Notes: var - variance(w_t)
cov1 - covariance(w_t,w_{t-1})
cov5 - covariance(w_t,w_{t-5})
cov10 - covariance(w_t,w_{t-10})
cov15 - covariance(w_t,w_{t-15})

Appendix 3

Table A6.1
Maximum Likelihood Estimates of Mean of Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	0.748 (0.074)	–	0.552 (0.134)	-4.700 (0.178)	0.140 (0.294)	NC	-0.011 (0.413)
1988	–	0.973 (0.051)	–	0.730 (0.119)	-2.113 (0.258)	0.710 (0.152)	-2.558 (0.209)	0.697 (0.194)
1989	–	0.930 (0.066)	–	0.724 (0.121)	NC	0.128 (0.326)	NC	0.007 (0.428)
1990	–	1.151 (0.050)	–	0.963 (0.105)	-2.499 (0.960)	0.866 (0.156)	-2.075 (0.867)	0.760 (0.225)
Males								
1987	1.110 (0.038)	1.119 (0.052)	1.041 (0.058)	0.943 (0.093)	0.726 (0.133)	0.873 (0.128)	0.407 (0.209)	0.821 (0.171)
1988	1.064 (0.053)	1.215 (0.047)	0.809 (0.108)	1.037 (0.084)	0.336 (0.337)	0.906 (0.127)	-0.184 (0.455)	0.877 (0.161)
1989	1.221 (0.045)	1.244 (0.054)	0.979 (0.093)	0.994 (0.106)	0.848 (0.141)	0.848 (0.160)	0.312 (0.305)	0.661 (0.246)
1990	1.283 (0.045)	1.273 (0.059)	1.067 (0.088)	1.026 (0.110)	0.873 (0.145)	0.868 (0.165)	0.711 (0.218)	0.937 (0.181)

Notes.
1. As for Table 6.3.

Table A6.2
Maximum Likelihood Estimates of Standard Deviation of Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	0.576 (0.028)	–	0.637 (0.042)	1.309 (0.024)	0.742 (0.074)	NC	0.774 (0.095)
1988	–	0.525 (0.024)	–	0.609 (0.043)	1.028 (0.034)	0.615 (0.051)	1.090 (0.034)	0.618 (0.061)
1989	–	0.593 (0.025)	–	0.658 (0.038)	NC	0.807 (0.079)	NC	0.833 (0.096)
1990	–	0.514 (0.025)	–	0.580 (0.040)	1.151 (0.134)	0.609 (0.052)	1.094 (0.126)	0.637 (0.067)
Males								
1987	0.623 (0.020)	0.695 (0.024)	0.648 (0.025)	0.756 (0.035)	0.745 (0.044)	0.777 (0.044)	0.826 (0.056)	0.792 (0.054)
1988	0.712 (0.025)	0.684 (0.022)	0.796 (0.039)	0.746 (0.032)	0.922 (0.093)	0.785 (0.043)	1.037 (0.105)	0.793 (0.051)
1989	0.679 (0.022)	0.725 (0.024)	0.763 (0.035)	0.808 (0.039)	0.801 (0.047)	0.850 (0.052)	0.934 (0.077)	0.898 (0.070)
1990	0.690 (0.021)	0.747 (0.025)	0.765 (0.033)	0.826 (0.039)	0.823 (0.046)	0.870 (0.052)	0.866 (0.062)	0.853 (0.055)

Notes.
1. As for Table 6.3.

Table A6.3
Maximum Likelihood Estimates of Parameter θ_1, Singh - Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	-	4.262 (0.894)	-	4.420 (1.283)	32.695 (13.456)	3.420 (1.635)	8.560 (2024.80)	4.489 (2.446)
1988	-	4.167 (0.776)	-	2.034 (0.798)	8.333 (2032.71)	2.203 (1.020)	0.477 (1.543)	2.599 (1.424)
1989	-	4.473 (0.809)	-	5.127 (1.320)	8.085 (2625.26)	3.266 (1.540)	8.048 (3926.30)	4.717 (2.390)
1990	-	3.795 (0.694)	-	2.606 (0.836)	1.821 (1.424)	2.206 (1.031)	2.675 (1.814)	1.880 (1.259)
Males								
1987	3.073 (0.345)	2.389 (0.364)	3.766 (0.546)	1.531 (0.404)	2.144 (0.593)	1.305 (0.480)	1.128 (0.568)	1.114 (0.578)
1988	3.771 (0.461)	2.127 (0.301)	3.528 (0.673)	1.318 (0.316)	1.146 (0.559)	0.952 (0.357)	0.380 (0.588)	0.898 (0.417)
1989	3.374 (0.392)	2.827 (0.390)	2.671 (0.500)	1.360 (0.382)	2.971 (0.713)	0.784 (0.406)	1.379 (0.743)	0.487 (0.492)
1990	3.376 (0.403)	2.236 (0.344)	2.580 (0.505)	1.135 (0.293)	2.043 (0.595)	0.787 (0.286)	1.571 (0.681)	0.850 (0.339)

Notes.
1. As for Table 6.3.

Table A6.4
Maximum Likelihood Estimates of Parameter θ_2, Singh - Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	_	2.570 (0.129)	_	2.576 (0.123)	2.202 (0.037)	2.517 (0.184)	1.000 (207.7)	2.634 (0.173)
1988	_	2.865 (0.167)	_	3.501 (1.092)	1.000 (223.2)	3.379 (0.933)	3.302 (40.6)	3.223 (0.618)
1989	_	2.983 (0.128)	_	2.972 (0.107)	1.000 (319.1)	2.863 (0.212)	1.000 (500.9)	3.055 (0.198)
1990	_	3.507 (0.235)	_	3.792 (0.606)	1.547 (0.459)	3.968 (1.046)	1.912 (0.463)	4.206 (1.900)
Males								
1987	3.479 (0.191)	3.952 (0.374)	3.360 (0.136)	5.103 (1.619)	3.625 (0.455)	6.017 (3.412)	5.078 (3.646)	7.506 (7.977)
1988	3.268 (0.117)	4.663 (0.535)	3.276 (0.131)	7.024 (2.964)	4.507 (2.763)	12.976 (16.687)	41076.2 (5076591)	15.769 (28.186)
1989	3.775 (0.165)	4.133 (0.251)	3.891 (0.267)	6.105 (2.362)	3.870 (0.220)	21.898 (58.293)	4.181 (1.494)	21082.62 (2130598)
1990	4.006 (0.177)	4.859 (0.461)	4.181 (0.316)	8.572 (4.380)	4.397 (0.575)	20.686 (32.762)	4.795 (1.316)	16.526 (22.824)

Notes as for Table 6.3.

Table A6.5
Maximum Likelihood Estimates of Parameter θ_3, Singh - Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
1987	–	0.833 (0.233)	–	0.799 (0.291)	0.112 (0.047)	1.070 (0.628)	0.428 (101.246)	0.794 (0.503)
1988	–	0.859 (0.232)	–	2.323 (1.562)	0.417 (101.621)	2.066 (1.519)	14.215 (87.457)	1.643 (1.288)
1989	–	0.740 (0.178)	–	0.630 (0.200)	0.404 (131.228)	1.052 (0.602)	0.402 (196.308)	0.703 (0.409)
1990	–	1.006 (0.276)	–	1.670 (0.829)	2.074 (1.865)	2.101 (1.532)	1.372 (1.034)	2.635 (2.812)
Males								
1987	1.041 (0.180)	1.313 (0.317)	0.799 (0.159)	2.562 (1.231)	1.645 (0.655)	3.344 (2.374)	4.143 (3.656)	4.438 (4.808)
1988	0.685 (0.114)	1.605 (0.387)	0.742 (0.181)	3.509 (1.740)	3.312 (2.719)	6.685 (6.657)	170.301 (7130.66)	7.752 (10.030)
1989	0.821 (0.136)	0.967 (0.195)	1.103 (0.287)	2.833 (1.474)	0.968 (0.301)	9.039 (14.901)	2.552 (2.019)	213.668 (9696.51)
1990	0.801 (0.136)	1.333 (0.319)	1.131 (0.311)	3.914 (2.060)	1.537 (0.636)	8.342 (8.381)	2.199 (1.414)	7.076 (6.934)

Notes as for Table 6.3.

Table A6.6
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1987
Assuming Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	1.160 (0.104)	–	1.282 (0.231)	4.544 (2.551)	1.246 (0.338)	3.831 (2.316)	1.045 (0.341)
Age 25-34	–	1.721 (0.386)	–	2.075 (0.796)	NC	1.727 (0.688)	NC	2.011 (1.206)
Age 35-44	–	1.406 (0.128)	–	1.386 (0.176)	4754.132 (31269.02)	2.281 (0.715)	NC	2.757 (1.299)
Age 45+	–	2.325 (0.687)	–	4.444 (3.072)	2675.23 (10368.7)	69.455 (241.330)	NC	37.381 (120.658)
Males								
Age 21-24	1.428 (0.178)	6.377 (7.427)	1.217 (0.199)	NC	1.148 (0.309)	NC	2.623 (2.472)	NC
Age 25-34	1.175 (0.042)	1.289 (0.081)	1.255 (0.080)	1.495 (0.187)	1.704 (0.260)	1.516 (0.268)	1.858 (0.423)	1.461 (0.343)
Age 35-44	1.147 (0.041)	1.202 (0.052)	1.176 (0.069)	1.336 (0.108)	1.529 (0.214)	1.413 (0.169)	1.514 (0.276)	1.486 (0.254)
Age 45+	1.527 (0.148)	1.511 (0.138)	1.930 (0.363)	1.884 (0.330)	3.494 (1.617)	2.354 (0.688)	13.085 (17.684)	2.675 (1.134)

Notes as for Table 6.3.

Table A6.7
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1988
Assuming Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	1.210 (0.098)	–	1.500 (0.306)	3.970 (1.585)	1.983 (0.789)	3.354 (1.616)	2.259 (1.407)
Age 25-34	–	1.255 (0.114)	–	1.554 (0.323)	6889.95 (42621.7)	1.433 (0.345)	86223.4 (109695)	1.789 (0.769)
Age 35-44	–	1.419 (0.197)	–	1.829 (0.565)	125.15 (264.36)	1.383 (0.389)	91.081 (226.315)	1.381 (0.535)
Age 45+	–	1.737 (0.334)	–	4.475 (3.262)	1548.68 (4981.33)	1.381 (0.535)	11321.0 (69397.9)	3.943 (3.974)
Males								
Age 21-24	1.563 (0.180)	4.740 (3.401)	1.898 (0.456)	242.592 (1486.77)	8.627 (9.167)	NC	2324.93 (19602.7)	NC
Age 25-34	1.196 (0.051)	1.352 (0.098)	1.370 (0.116)	1.672 (0.273)	1.683 (0.269)	2.202 (0.712)	2.881 (1.045)	2.782 (1.527)
Age 35-44	1.209 (0.064)	1.176 (0.044)	1.449 (0.162)	1.324 (0.096)	1.809 (0.377)	1.395 (0.148)	2.066 (0.632)	1.226 (0.138)
Age 45+	1.657 (0.186)	1.415 (0.101)	2.286 (0.552)	1.696 (0.230)	4.222 (2.361)	1.888 (0.386)	5.299 (4.384)	2.279 (0.726)

Notes as for Table 6.3.

Table A6.8
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1989
Assuming Log-Normal Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	1.165 (0.098)	–	1.026 (0.106)	27.023 (27.912)	0.968 (0.146)	8.420 (5.337)	0.747 (0.099)
Age 25-34	–	1.524 (0.242)	–	2.000 (0.670)	NC	3.590 (2.956)	NC	11.242 (24.766)
Age 35-44	–	1.802 (0.396)	–	4.737 (3.410)	NC	32.665 (73.259)	2225.42 (12245.6)	76.932 (398.590)
Age 45+	–	2.148 (0.518)	–	2.522 (0.979)	NC	12.385 (18.769)	NC	4.546 (4.622)
Males								
Age 21-24	1.516 (0.169)	28.903 (45.457)	2.336 (0.711)	NC	14.390 (19.717)	NC	NC	NC
Age 25-34	1.180 (0.052)	1.399 (0.106)	1.429 (0.143)	2.343 (0.568)	1.432 (0.198)	3.318 (1.534)	1.446 (0.288)	5.025 (4.274)
Age 35-44	1.187 (0.052)	1.193 (0.045)	1.393 (0.130)	1.282 (0.087)	1.424 (0.180)	1.266 (0.114)	1.623 (0.331)	1.355 (0.186)
Age 45+	1.678 (0.184)	1.640 (0.181)	2.259 (0.519)	1.869 (0.347)	2.740 (1.006)	2.338 (0.717)	14.569 (21.022)	2.540 (1.064)

Notes as for Table 6.3.

Table A6.9
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1987
Assuming Singh-Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	1.207 (0.195)	–	1.261 (0.385)	23.809 (116.623)	1.072 (0.408)	21.271 (117.737)	0.548 (0.037)
Age 25-34	–	3.793 (5.639)	–	5.081 (13.148)	NC	4.408 (12.444)	NC	5.722 (25.205)
Age 35-44	–	1.235 (0.146)	–	1.042 (0.132)	NC	1.158 (0.313)	NC	0.951 (0.265)
Age 45+	–	1.133 (0.197)	–	1.153 (0.431)	0.784 (0.098)	5.764 (28.291)	NC	2.008 (4.741)
Males								
Age 21-24	1.700 (0.539)	0.924 (0.161)	1.173 (0.352)	0.712 (0.377)	0.694 (0.146)	0.398 (0.068)	NC	NC
Age 25-34	1.136 (0.057)	1.234 (0.124)	1.111 (0.092)	1.502 (0.363)	1.538 (0.416)	1.401 (0.442)	1.521 (0.603)	1.011 (0.299)
Age 35-44	1.156 (0.069)	1.237 (0.101)	1.160 (0.114)	1.537 (0.311)	2.255 (0.979)	1.805 (0.635)	2.375 (1.396)	2.211 (1.311)
Age 45+	1.095 (0.079)	1.301 (0.160)	0.994 (0.098)	1.825 (0.680)	0.832 (0.103)	4.200 (5.305)	217.127 (2541.58)	11.984 (41.554)

Notes as for Table 6.3.

Table A6.10
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1988
Assuming Singh-Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	1.044 (0.074)	–	1.081 (0.200)	65.018 (378.836)	1.122 (0.384)	7.464 (15.330)	0.782 (0.180)
Age 25-34	–	1.185 (0.150)	–	2.299 (1.696)	NC	1.645 (1.003)	NC	5.473 (17.093)
Age 35-44	–	1.324 (0.303)	–	2.100 (1.725)	NC	1.053 (0.361)	4793.52 (183621.4)	0.816 (0.241)
Age 45+	–	0.923 (0.042)	–	9.540 (31.886)	3.628 (9.515)	75.243 (926.540)	1.382 (1.436)	10.425 (58.197)
Males								
Age 21-24	1.247 (0.182)	1.067 (0.301)	0.891 (0.140)	0.764 (0.351)	0.770 (0.263)	1.035 (7.058)	1.187 (2.647)	NC
Age 25-34	1.091 (0.055)	1.215 (0.113)	1.101 (0.104)	2.532 (1.676)	1.093 (0.185)	7.541 (20.074)	1.336 (0.534)	11.019 (52.381)
Age 35-44	1.304 (0.152)	1.230 (0.090)	2.668 (1.239)	1.499 (0.251)	4.174 (4.007)	1.644 (0.428)	NC	1.186 (0.233)
Age 45+	1.131 (0.089)	1.310 (0.143)	1.177 (0.212)	1.741 (0.496)	3.876 (5.645)	2.043 (1.012)	37.020 (261.133)	3.078 (3.062)

Notes as for Table 6.3.

Table A6.11
Maximum Likelihood Estimates of Employment Parameter ϕ by Age Group, 1989
Assuming Singh-Maddala Wage Distribution

Cutoff Wage (Percentile)	10th Percentile		20th Percentile		30th Percentile		40th Percentile	
Industry	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale	Retail	Wholesale
Females								
Age 21-24	–	NC	–	NC	8.502 (16.254)	NC	2.306 (1.833)	1.008 (0.445)
Age 25-34	–	1.028 (0.063)	–	0.927 (0.069)	NC	NC	NC	NC
Age 35-44	–	1.023 (0.078)	–	1.209 (0.349)	NC	1.258 (0.770)	NC	0.750 (0.192)
Age 45+	–	1.412 (0.377)	–	1.117 (0.333)	13.246 (118.730)	3.113 (6.779)	3.377 (13.347)	1.000 (0.653)
Males								
Age 21-24	1.060 (0.096)	0.996 (0.180)	0.845 (0.098)	0.872 (0.397)	0.682 (0.098)	0.596 (0.275)	0.924 (2.014)	NC
Age 25-34	1.222 (0.101)	1.031 (0.038)	2.007 (0.660)	1.379 (0.335)	2.292 (1.201)	14.860 (56.807)	2.839 (2.570)	40.306 (373.515)
Age 35-44	1.169 (0.082)	1.221 (0.083)	1.582 (0.335)	1.391 (0.200)	1.620 (0.473)	1.279 (0.216)	2.111 (1.171)	1.386 (0.389)
Age 45+	1.177 (0.105)	2.208 (0.757)	1.051 (0.131)	4.867 (5.161)	0.802 (0.068)	NC	0.696 (0.092)	NC

Notes as for Table 6.3.

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