DEPARTMENT OF ECONOMICS
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LABOUR MARKET HETEROGENEITY: WAGE DETERMINATION & UNEMPLOYMENT DURATION

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Abstract

The last twenty years has witnessed an unprecedented growth in the development and application of non-competitive models of labour market behaviour. These models have emerged in response to the apparent failure of the competitive paradigm to adequately explain the observed stability of the wage structure and the persistence of unemployment in the past two decades. They also help to explain observed empirical regularities that lie outside of the orthodox domain. Identifying the role of competitive and non-competitive forces in the determination of labour market outcomes necessitates that differences between individuals are suitably accounted for. Our ability to control for such differences is limited in both cross-section and time-series data. Panel data, however, can provide new insights in that both observed and unobserved differences between individuals can be accounted for in empirical modelling.

This thesis addresses the importance of individual heterogeneity in the determination of wages and unemployment durations in the UK using longitudinal data drawn from the first eight waves of the British Household Panel Survey (BHPS). The BHPS provides comprehensive information at the individual and household level. It also provides extensive information on individual labour market activity both during the panel and retrospectively from labour market entry. We utilise both aspects of this data to fully explore the impact of individual heterogeneity. Our findings suggest that individual heterogeneity is of critical importance to observed labour market behaviour. We show that over 90 percent of the variation in individual earnings can be explained by observed and *unobserved* individual heterogeneity. We also demonstrate that the failure to incorporate individual heterogeneity results in a significantly upward bias in the magnitude and dispersion of inter-industry wage differentials. The neglect of individual heterogeneity is also observed to significantly bias econometric estimates that measure the conditional probability of exit from unemployment. We show that the failure to incorporate unobserved individual characteristics results in a significant downward bias in the hazard rate from unemployment, thus implying spurious negative state dependence.

The central conclusion of the thesis is that empirical work which is not founded on techniques which utilise panel data can give rise to seriously misleading conclusions regarding the operation of labour markets, and, in particular, the nature of the wage determination process and the likelihood of exit from unemployment.

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Prologue - Thesis Research Methodology

The approach to this thesis has been to treat the research topics independently. Thus, each chapter is self-contained but clearly linked through the theme of individual heterogeneity in the study of wage determination, (un)employment and unemployment durations. The rationale for this approach is to facilitate the acquisition of the ability to write academic papers suitable for submission to peer-reviewed journals, while retaining a clear thematic approach throughout the thesis.

The thesis utilises two datasets to investigate the role of individual heterogeneity in the determination of both wages and (un)employment. The regional survey of individual job seekers in the English County of Kent was made available by the Kent Employment Service and Kent County Council Planning Department. The BHPS data were made available through the ESRC Data Archive. The data were originally collected by the ESRC Research Centre on Micro-Social Change at the University of Essex, now incorporated within the Institute for Social and Economic Research. Neither the original collectors of the data nor the Archive bear any responsibility for the analyses or interpretations presented here.

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Chapter 1 - Introduction and Thesis Overview

1.1. The Research Agenda

The last 20 years has witnessed an unprecedented growth in the development of non-competitive explanations of labour market behaviour. These non-competitive models have emerged largely in response to the apparent failure of the competitive paradigm to adequately explain the observed stability of the wage structure and the persistence of unemployment in the past two decades. They also help to explain observed empirical regularities, in particular the wage curve, which exist outside of the orthodox domain. Many of these models emphasise that, for certain reasons, firms find it profitable to ration labour and pay above the market clearing wage. Such rationales are certainly consistent with observed labour market phenomena. Their ability to explain *the labour market* remains, however, to be seen.

An alternative explanation for observed phenomena is that the competitive paradigm is largely correct. Arguments here focus on the role of unobserved heterogeneity, that is differences across workers and/or firms that are otherwise important in the determination of wages and employment but which are not captured by the econometrician. The failure to control for unobserved heterogeneity runs the risk of specification bias. This may additionally entail spurious inference decisions. Competitive and non-competitive analyses of the wage structure and unemployment persistence necessitate that individual heterogeneity is suitably accounted for. Thus, controlling for unobserved individual-specific characteristics is of vital importance.

Competitive and non-competitive models of the labour market yield distinct positive and normative implications regarding individual welfare. They also generate specific conclusions regarding policy formation. Understanding the true nature of the labour market is thus of fundamental concern in both of these latter regards.

The aim of this thesis is to examine the role of individual heterogeneity in the determination of both wages and (un)employment. We utilise genuine UK longitudinal data in the form of the British Household Panel Survey (BHPS) to explore both dimensions of the labour market. Longitudinal or panel data have witnessed an increasing role in empirical labour research in recent years. Most of this reflects the availability of such data and advances in econometric techniques designed for such data. The remainder, however, has arisen from a growing dissatisfaction with standard cross-section and time-series data when used in microeconomic investigation.[1] Time series data is frequently plagued by strong collinearities amongst explanatory variables that imply that minor redefinitions of the data and/or atheoretical changes of the lag structure result in structural instability. The use of such data is also found to frequently lack microeconomic foundations: economic theory provides little insight into the use of aggregate data when identifying individual and macroeconomic behaviour. Furthermore, empirical analyses derived from the use of such data are often susceptible to the *Lucas Critique*. Cross-section data provides more information in this regard. A major weakness of cross-section data, however, is that it is static and therefore unable to identify important time-varying processes. This stationary aspect of the data prevents an analysis of the dynamics of adjustment. It also prevents the identification of unobserved

[1] See Stafford (1986) for a discussion of the relative merits of these alternative types of data.

individual heterogeneity. Time-series and cross-section studies not controlling for individual heterogeneity run the risk of obtaining biased results.[2]

Panel data, that is data that follow a given sample of individuals over time, provide a number of significant advantages in this regard.[3] Data that record multiple observations for an individual provide more informative data, more degrees of freedom and less collinearity amongst explanatory variables.[4] They also allow one to examine individual life histories. These allow an analysis of how conditions, life events, individual and household experiences are linked dynamically over time. Repeated information collected at different time points allows for a greater control of observed characteristics. It also allows the researcher to control for unobserved individual fixed-effects, that is, time-invariant effects that are missing or unobserved but correlated with the observed explanatory variables. The ability to control for missing or unobserved data significantly reduces the probability of specification bias. It also allows the researcher to identify and measure effects that are simply not detectable in cross-section or time-series data.[5]

The first part of the thesis examines the industry wage structure and the role of regional unemployment in wage determination. We investigate inter-industry wage differentials and test the relevance of competing and non-competing labour market models as an explanation for observed wage dispersion. We also examine the existence of a UK 'Wage Curve' to explore the role of regional unemployment in the determination of individual pay. Both investigations utilise fixed effects models to exploit the panel

[2] See Moulton (1986) for details.
[3] Hsiao (1989) and Baltagi (1995) provide the standard references for panel data analysis.
[4] These help to improve the economic efficiency of econometric estimates.
[5] For example, the analysis of inter-industry wage differentials necessitates that individuals' characteristics are held constant. This simply cannot be achieved in pure cross-section or time-series data.

dimension of the data and take account of the role of individual heterogeneity in the wage determination process. These models are able to capture unobserved heterogeneity inherent in the determination of individual pay. They also enable us to explain a substantial proportion of the variation in earnings between individuals.

The second part of the thesis focuses specifically on the role of individual heterogeneity in determining unemployment duration. We utilise unique regional data and BHPS labour history files to estimate duration models for regional and UK unemployment. The preference to analyse the duration aspect of unemployment derives from considerations regarding its implications for economic welfare. Frequency and average duration of completed spell lengths are revealing indicators of unemployment in that they provide information on the dispersion of unemployment across individuals. They also allow one to examine the impact of socio-demographic factors on the exit probability from unemployment and whether the duration of unemployment itself partly determines how and when labour market transitions are made. The issue of 'state-dependence' or 'scarring' as it has become known in the economic literature attracts considerable attention in empirical studies concerning labour market transitions. Identifying the true impact of worker heterogeneity on scarring, however, remains to be fully defined.

This thesis identifies that observed and unobserved individual heterogeneity is of critical importance in understanding the true nature of observed labour market behaviour. Cross-section wage equations rarely account for more than half of the total variance in earnings across individuals. The remainder is often attributed to non-competitive forces in wage determination. Our results cast considerable doubt over non-competitive explanations of wage determination in Britain. We show that over 90 percent of the variation in individual earnings can be explained by observed and unobserved individual heterogeneity. We also demonstrate that the failure to incorporate individual heterogeneity results in a significantly upward bias in the magnitude and dispersion of inter-industry wage differentials. Thus, one interpretation of our results is that they support standard competitive theory and that wages are paid according to observed and unobserved individual characteristics.

The neglect of unobserved individual heterogeneity is also observed to significantly bias econometric estimates that measure the conditional probability of exit from unemployment. We show that the failure to incorporate unobserved individual characteristics results in a significant downward bias in the hazard rate from unemployment. Most of the empirical literature concerning unemployment durations emphasise that a flexible specification of the baseline hazard is often enough to mitigate the effects of unobserved individual heterogeneity. Our results reveal that a flexible specification of the baseline hazard is not sufficient in this regard. Non-parametric estimation of the baseline hazard removes the restriction of monotonicity imposed by a parametric specification on the conditional probability of exit. The omission of gamma "frailty" continues, however, to result in spurious negative state dependence. State dependence in unemployment implies significant implications for labour market policy. Incorporating individual heterogeneity is thus shown to be of critical labour market importance.

1.2. Research Questions to be Addressed

This section provides a more detailed breakdown of the remainder of the thesis. A short description of the aims and objectives of each chapter follows.

Chapter 2 – Competitive and Non-competitive Models of the Labour Market.

This chapter attempts to provide a brief overview of the theoretical literature relevant to the empirical work in this thesis. For the first part of the thesis, the competitive paradigm is explored and compared with a range of non-competitive models that attempt to explain the determination of wages and (un)employment. These theoretical constructs include efficiency wages, wage bargaining and other rent-sharing explanations. For the second part of the thesis, the use of 'Job-Search' methodology and its emphasis on labour market flows in the matching or workers to jobs is developed. Job search theory dominates the theoretical and empirical literature with regard to the analysis of unemployment spell lengths. Established findings in the literature are reviewed, the consequence of unobserved heterogeneity in the offer distribution and arrival rate of offers is additionally explored.

Chapter 3 – Inter-Industry Wage Differentials in the UK

This chapter investigates the relationship between wage structure and industry affiliation in the UK. We adopt the standard procedure popularised by Krueger Summers (1988) and recently improved by Haisken-DeNew and Schmidt (1997) to examine both cross-section and pooled evidence for British inter-industry wage differentials using BHPS data between 1991 and 1998. In addition, we utilise the panel dimension of the data to assess the importance of unobserved worker heterogeneity on the cross-section and pooled results. There are extremely few panel studies of the inter-industry wage structure in the existing literature and, to our knowledge, none for Britain. The use of the BHPS data allows us to assess the relevance of competitive and non-competitive explanations for observed dispersion in the inter-industry wage structure. It also enables us to provide an original contribution to an otherwise sparse literature.

Chapter 4 – Individual Wage Determination and Regional Unemployment in the UK

This chapter investigates the relationship between wages and regional unemployment in the UK. We adopt the Blanchflower & Oswald (1994) concept of the wage curve and estimate a panel fixed effects model using BHPS data and information on regional unemployment rates between 1991 and 1998. There are extremely few panel studies of the Wage Curve and, to our knowledge, none for Britain. Previous studies for the UK rely on pooled and cross-section data for the 1970's and 1980's. Both of these types of data run the risk of obtaining misleading results. They also give rise to the increased likelihood that observed effects are the consequence of errors in model specification. Panel data overcomes many of these disadvantages. It also allows for the control of unobserved individual heterogeneity in the wage determination process. The ability to control for missing or unobserved data significantly reduces the probability of specification bias. It also helps capture inter and intra-individual differences in the determination of individual pay.

Chapter 5 – Regional Unemployment and Individual Heterogeneity

This chapter investigates the impact of worker heterogeneity on regional unemployment using a unique regional dataset that provides individuals' responses to questions regarding demographic characteristics, reservation wages, and method of job search employed. We specify an empirical model that is closely tied to the theory of job search and utilise the data to assess the relative importance of such factors in the determination of incomplete unemployment spells. There are extremely few empirical studies that contain responses concerning individual reservation wages and search methods for the UK. In addition, we are unaware of any such analyses undertaken at the regional level. Thus, the ability to investigate such facets provides an original contribution to an otherwise extensive literature.

Chapter 6 – Unemployment Duration, State Dependence and Individual Heterogeneity in the UK

This chapter investigates the issue of state dependence and the role of individual heterogeneity in the determination of UK unemployment spell lengths in the 1990's. We use work-life history information taken from the BHPS between 1991 and 1998 to estimate discrete time proportional hazard models and examine the impact of unobserved individual heterogeneity on the conditional probability of exit from unemployment. The use of discrete time proportional hazard models enables us to overcome two potential weaknesses observed in the empirical literature. First, it allows us to estimate the underlying hazard non-parametrically. This generates a very flexible baseline hazard that can circumvent the bias that arises from misspecifying the underlying hazard. Second, evidence suggests that spurious state dependence arising from unobserved heterogeneity in duration models can also be mitigated if a sufficiently flexible baseline hazard is employed. Correct identification of those characteristics that are associated with prolonged spells of unemployment necessitates that econometric estimates are unbiased. Thus, controlling for the potential bias of omitted heterogeneity and spurious state dependence is of considerable importance for individual welfare.

Chapter 7 - Conclusion

This chapter contains a summary of the main findings from the thesis and provides research and policy avenues for further work.

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Chapter 2 - Competitive & Non-competitive Models of the Labour Market

2.1 Introduction

The standard competitive model of the labour market built upon the marginalist principles of neoclassical Marshallian analysis imparts two fundamental implications for the economic analysis of the allocation of labour: first, that there should be a uniform distribution of wages across individuals; second, that there should be no involuntary unemployment. This orthodox interpretation of the labour market has long been the subject of controversy and debate. Casual observation of the labour market reveals that wage differentials and unemployment *do* exist. Moreover, both of these phenomena appear to *persist* over time. Reconciling these facts with a comprehensive understanding of the labour market is an interesting task. Few economists would disagree that the simple competitive paradigm is too extreme to provide an effective rationale of labour market behaviour. Most economists recognise that the market for labour consists of a number of special characteristics and peculiarities that distinguish it from the spot markets that are analysed elsewhere. How one responds to this distinction within the pedagogic and research realms that uphold the field of economics as a major discipline is, however, problematic. The main debates about wage and (un)employment determination take place between two distinct groups of economists: those who feel that the competitive model, suitably modified, can explain most of the stylised facts of labour markets; and those who reject the competitive model in favour of non-competitive and institutional considerations. Neither of these groups can lay claim to explaining the labour market *per se*. That, of course, remains the domain of the econometrician.[1] Both of these groups have, however,

[1] It is the role of the econometrician to test and validate theoretical constructs as and when econometric techniques and data permit.

had a lasting impact on the development of labour economics as a legitimate field of theoretical and empirical enquiry.

The orientation of labour economics thirty years ago was typically descriptive. It's emphasis lay with historical developments, institutional arrangements and legal considerations. Neoclassical price theory sat rather uncomfortably alongside. Contemporary labour economics, in contrast, is more robust. It embodies theories of choice to analyse and predict the behaviour of labour market participants and the economic consequences of their decisions. The simplifying assumptions of the perfectly competitive paradigm are replaced, however, with recognition of the labour market as a noisy, uncertain, yet dynamic arena where transitions between alternative labour market states appear the consequence of sequential, rational decision making in a world of stochastic change. This analytical breakthrough undoubtedly accounts for the labour market as the principal consideration of the theoretical and empirical work undertaken today. It is equally responsible for the upsurge in theoretical literature that identifies itself in a discerning rather than complementary manner. At a glance, competitive and non-competitive models of the labour market appear to be mutually distinct: both are frequently grounded in abstract mathematical constructs that utilise somewhat tenuous assumptions to attain distinct labour market behaviour. They are, however, more similar than one might readily perceive. Many of these models can explain observed labour market phenomena. Most of them are difficult, however, to tractably test or reconcile with *the labour market*. Furthermore, even when such models may be tested, they often yield predictions that are difficult to empirically distinguish from one another. This chapter presents a brief overview of a number of theoretical constructs that attempt to explain the determination of wages and (un)employment. These constructs provide an insight into the theoretical and empirical debates that provide the focus of this thesis.

Many of them are able to explain some of the perceived regularities regarding the wage structure. None of them, however, are consistent with all of the stylised facts.

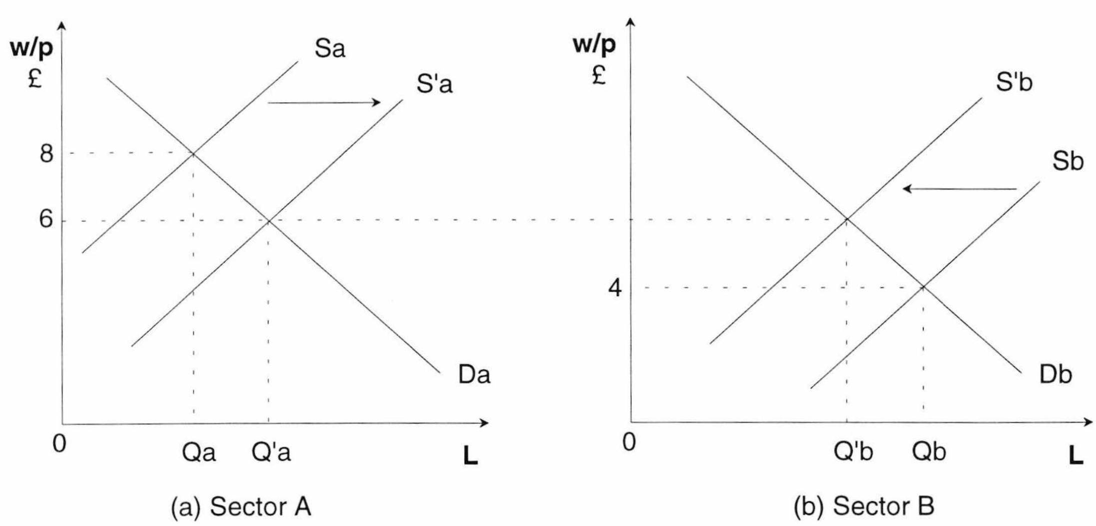
2.2 Competitive Theory, Equalising Differences and Individual Heterogeneity

In the standard competitive model of the labour market the equilibrium wage and associated level of employment are determined by the intersection of labour demand and supply. The forces of supply and demand respond instantaneously to surpluses or shortages of labour to determine a market clearing wage that reflects the willingness of labour to supply themselves to the various jobs on offer and the willingness of employers to remunerate workers for their marginal products. The market for labour is, of course, a theoretical abstraction: one tends to think of markets for different types of labour. The analogy of a single market is used, however, to depict a scenario where the buyers and sellers of labour meet to determine a price at which they are willing to exchange labour services and allocate labour to its area of highest value. If information is perfect, workers and jobs *homogeneous*, and the costs of job search and migration equal to zero, then the market wage will equal the value marginal product (VMP) of labour, and labour will allocate itself across industries and regions until the array of wage rates paid to workers is uniform. Thus, competitive theory predicts no variability in the wage structure.

The process whereby wages equalise across homogeneous workers and jobs is demonstrated in Figure 1. Assume a two-sector economy, A and B, where the forces of labour supply and demand determine the equilibrium wage and employment in each sector respectively. Suppose that these supply and demand conditions produce a real hourly wage of £8 in sector A compared to £4 in sector B. In each sector, the hourly wage is a market-clearing wage that equals the VMP of labour. However, the VMP of the Q_b worker in sector B is less than the hourly wage and VMP of the Q_a worker in sector A. Given homogeneous workers and jobs, and costless migration, workers in sector B have a strong incentive to exit and take employment in high-paying sector A. This movement of workers results in a decline in the labour supply of sector B from S_b to S'_b and an increase in sector A from S_a to S'_a. The decline in labour supply of sector B reduces the equilibrium wage in sector A but increases the equilibrium wage in sector B. This process continues until all potential gains from migration are exhausted and wages across the two sectors are equalised.

Figure 1

Equalising Wages in a 2 Sector Perfectly Competitive Labour Market



The preceding analysis raises three important points. First, an exogenous rise in the VMP of labour in one sector of the economy should generate a wage rise in every sector. This point is not well understood. It is not that a wage rise in every sector must necessarily be matched by productivity increases in each sector. Rather, the higher market-clearing wage in the sector with the initial increase in VMP signals a reallocation of labour across every sector until a new equilibrium market-clearing equal-wage is attained. Second, the market-clearing equal-wage is the social optimum wage; it maximises social welfare. In a perfectly competitive environment the market-clearing equal-wage is also the opportunity cost or price of labour. In each sector, this wage is equal to the VMP of labour., and the VMP of labour is the same in every sector. Thus, all VMPs are equal to the price of labour. The equality of VMPs and the price of labour yields an efficient allocation of labour. The market equilibrium is thus a Walrasian equilibrium and is Pareto efficient. Third, unemployment is an equilibrium phenomenon that is voluntary in nature. The assumption of instantaneous employment at the market-clearing wage precludes discussion of involuntary unemployment. All of those workers who want to work at the market-clearing wage are able to find work. Remaining members of the labour force not in employment are thus voluntarily unemployed. This voluntary or equilibrium level of unemployment will be unique for any given structure of the labour market. It will also be efficient in that it exists at a market-clearing wage where *available* workers are allocated to their highest valued uses. The concept of *idle* resources being 'efficient' is controversial. It is, however, a natural consequence of the perfectly competitive paradigm.

Casual observation of the labour market reveals that wage differentials do exist. Moreover, these differentials are often significant and appear to persist over time. How then does one reconcile this evidence with the competitive story? One obvious approach is to relax the assumption of homogeneity in employment and investigate the total compensation package that constitutes the rewards to work. The preceding analysis assumes that all jobs are identical. Pecuniary and non-pecuniary aspects of jobs are thus not important and utility maximising workers need only consider the wage rate when deciding where to work. In reality, jobs are heterogeneous rather than homogeneous. Such heterogeneity may arise from a number of sources. Some jobs offer employment security, fringe benefits and/or job prestige. Others require additional training or offer a pleasant and safe working environment. These non-wage attributes must also be considered in a competitive analysis of the wage structure. The theory of equalising differences or 'compensating differentials' provides a cornerstone here. This theory recognises that competition will only equalise wages between jobs in which all other conditions are the same. As such, it asserts that competitive forces instead operate to equalise the pecuniary and non-pecuniary advantages and disadvantages of alternative employments. The belief that it is the *net advantages* of employment that are equalised by competition may be traced back to the writings of Adam Smith (1776). Smith argued that the advantages of alternative employments comprised much more than the paid wage. He recognised that workers were less willing to supply their labour for any given wage when employment was unsocial or imparted a greater risk of job loss, injury or death. Thus, firms must compensate workers for the disutility of undesirable job characteristics that do not exist in alternative employment. If all workers view the pecuniary and non-pecuniary advantages and disadvantages of employments similarly, such compensation should generate a structure of wage differentials that just compensates workers for the non-pecuniary disadvantages of their employment. These compensating differentials ensure that labour is allocated to employment that is not as pleasant as others. They also inflict financial penalties on firms who offer unfavourable working conditions. Significantly, compensating differentials are equilibrium differentials. They equalise the net advantages of employment so that workers have no incentive to move to higher pay jobs.

The competitive model may be relaxed further by allowing heterogeneity across workers. The theory of equalising differences generates a structure of wage differentials for workers that are 'comparable'. Many workers, however, are clearly not comparable. Individuals have different innate abilities and/or stocks of human capital. They also differ in their taste for non-wage attributes and preference for future versus current earnings. Such facets are difficult to reconcile with a competitive theory that predicts equal wages. The acquisition of human capital improves workers' marginal products. It is, however, costly. Therefore, jobs that require such an investment should pay a higher wage than those that do not. To illustrate, consider two jobs with identical non-wage attributes. Furthermore, suppose that all workers have the same preference for future versus current earnings. If both jobs pay the same but one of them requires a greater investment in human capital, then the present value of gained earnings will be zero and the return on such an investment will be negative. In this instance, wage equality is not sustainable. Workers would have no incentive to invest in human capital and, as a consequence, would choose not to enter that particular industry. Firms looking to recruit such workers must thus pay higher wages. These higher wages should just compensate workers for the cost of human capital acquisition. They should also generate a wage differential that will persist between the two occupations. If the wage is too low, too few workers will enter employment and the wage differential will rise. If the wage is too high, too many workers will invest in human capital, labour supply will increase and the wage differential will fall. The sustainable wage is thus an equilibrium wage. Once again, workers have no incentive to move jobs.

The above extensions to the competitive model are not mutually exclusive. Wage differentials created by differing skill requirements may increase, reverse or lessen the observed variation in wages generated by the equalisation of net advantages. The theory of equalising differences predicts that employers offering unpleasant employment should pay higher wages than those offering more pleasant opportunities. Evidence to support this outcome is weak.[2] Indeed, one tends to observe a positive correlation between pay and working conditions.[3] The observation that higher paid workers tend to have better working conditions does not refute this theory. Instead, it suggests that wage gaps generated by differences in human capital may offset compensating differentials that operate in the opposite direction. Thus, the absence of compensating differentials would make the skilled wage gap even larger. This consideration is even more valid if we consider working conditions to be a normal good. Then, highly skilled workers with higher pay will be able to 'buy' better working conditions as part of their overall compensation package. Hence, they may choose to sacrifice some of their higher pay for an improved endowment of non-wage amenities. Resulting wage differentials are again equilibrium differentials. They are, however, adjusted for individual preferences. Such preferences are important. They help to explain why workers with similar abilities and access to financial resources choose to invest in different levels of human capital. Different preferences lead to different stocks of human capital. Different stocks of human capital (and hence marginal products) yield different wages. A pattern of non-equalising wage differentials may thus be derived from competitive theory after all.

2.3 The Theory of Job Search

The analysis in the previous section provides a competitive justification of wage differentials that is based on heterogeneous jobs and workers. Wage differences can, however, also be explained via labour market imperfections that impede labour mobility. Imperfect information, costly migration and the time and effort that are required to locate employment also serve to create and maintain a disparate wage

[2] See, for example, McNabb (1989) and Blanchflower (1991).

[3] Krueger and Summers (1988) include a variety of controls for job characteristics, such as unsociable work hours, health hazards, commuting time, whether one has to work two or three shifts per day, and so on. None of these eliminate, or in most cases even reduce, observed wage differentials across industries.

structure. The competitive model assumes employment to be instantaneous: there are no problems or costs associated with acquiring information. In reality, information is imperfect. The acquisition and processing of information takes time. Workers have only a limited knowledge of the opportunities available to them. They must search and learn the range of opportunities from which they may prospect. Employers likewise have only a limited knowledge of the abilities of such workers. Successful applicants must be 'screened' to ensure that the most suitable match is found. Acquiring such information is costly. In addition, the potential payoffs are variable. Even after workers and firms find a match, additional information may accumulate that forces agents to separate and realise a better trade than the one with which they are presently engaged. Understanding the nature of information imperfections provides the basis for the theory of search. Search theory extends the neoclassical doctrine of worker experience. Workers maximise utility subject to prevailing constraints such that no better opportunity is forgone; the assumption of complete information and simultaneous transactions is replaced, however, by an assumption of rational expectations in an uncertain environment. Relaxing the competitive framework in this manner yields a distribution of wages that is far from uniform. It also provides the theoretical basis for the analysis of equilibrium unemployment by way of worker separations and flows. This theoretical construct provides an analytical champion to the debate concerning the determination of unemployment spell lengths. However, the theory is limited when one considers the unemployment experience of Europe over the past thirty years.

The search approach was initially developed as an attempt to explain the persistence of observed wage differentials between workers with similar jobs, skills and work histories.[4] The central tenet of this early literature lies in the consideration of unemployment as

[4] See Feinberg (1978) for a discussion of the antecedents of modern job search theory.

consisting of investment aspects. Hicks (1932) contemplates the time spent seeking information where individuals face imperfect knowledge about employment opportunities. Hutt (1939), by contrast, considers the case where the cost of suboptimal employment exceeds the cost of idle labour. The motive for unemployment here is the pursuit of improved employment. Workers who actively prospect for remunerative employment are not idle. They search for remuneration to raise their future hire value.

> *When actively searching for work, the situation is that he is really investing in himself by working on his own account without immediate remuneration. He is prospecting.........He judges that that the search for a better opening is worth the risk of immediately foregone income.* (Hutt 1939, pp.60)

The notion that waste generated by suboptimal employment could be more important than the unutilised or 'idle capacity' associated with unemployment provides the original rationale for search theory. Formal analysis of the behaviour of unemployed workers originates, however, from the classic work of Stigler (1961, 1962). It is here that unemployment receives its first consideration within the standard microeconomic approach.

Stigler's 1961 paper "The Economics of Information" analyses the effect of price dispersion on markets of incomplete information and homogenous products. The companion 1962 paper "Information in the Labor Market" examines the relationship between dispersed wage rates and heterogeneous labour. Stigler justifies the existence of price dispersion as the consequence of information asymmetries and ignorance in the market place. Wage dispersion arises likewise from the cost of acquiring accurate information on the prospective earnings from potential employers. The fact that information is imperfect and costly to obtain increases the likelihood that a *range* of equilibrium wages will be observed for any given occupation. Employers will set wages according to their circumstances and perception of the 'market' wage. Thus, some firms will pay slightly higher than the market wage whilst others will pay slightly less. Since information is imperfect and costly to obtain, some workers and firms will be unaware that greater or lesser wages are being paid to similar workers. Others will recognise that there is variation in wages but will also realise the costs associated with acquiring such information. If the marginal cost of acquiring information exceeds the expected gains then neither workers nor firms will have an incentive to deviate from their original allocation. Thus, a non-uniform distribution of equilibrium wages may persist.

Stigler argues that unemployed workers know the distribution of wages. The problem that they face is determining the optimal strategy with which to provide their labour. He proposed that the optimal search strategy involves visiting a predetermined number of firms and accepting the best offer obtained. The number of firms sampled is determined by comparing the expected gain from additional search relative to the cost involved. If expected gains prove greater (less) than the costs then the number of firms is increased (decreased). The optimal sample size is thus that number that equates the expected marginal return to the marginal cost of search. Stigler's strategy appears intuitively appealing. Perfect information, for example, entails a sampling cost of zero with an optimal strategy of sampling the entire wage distribution and choosing the employment offering the highest wage. Such a strategy may, however, result in sub-optimal behaviour. If, for example, the first firm sampled from the predetermined set offers the highest wage in the distribution, the optimal strategy should be to stop searching. Un der Stigler's rule the worker continues to search the entire set. McCall (1970) asserts that this problem arises from the adoption of an erroneous stopping rule.[5] He argues that non-sequential search is incorrect. The correct solution to the behaviour of unemployed workers involves a sequential search rule where the worker decides whether to continue to search after each job offer has been obtained.[6] Here the worker knows the distribution of wages and the cost of search. Search time (and hence the expected length of unemployment) depends, however, on the critical value (acceptance wage) associated with the worker's optimal search policy. Thus, each worker faces a two-stage problem. First (s)he must determine a critical value to place on employment. Second, this value must be compared with the associated wage of job offers. Only when the wage rate exceeds the critical value should an offer be accepted and employment commence.

The simple model of McCall is a partial equilibrium model: only worker search is considered. The model itself provides, however, the basis from which subsequent theoretical analyses have grown. Partial equilibrium models assume the wage offer distribution as given. Equilibrium search models (e.g. Albrecht & Axell,1984; Burdett & Mortensen,1989), in contrast, endogenise the wage offer distribution and provide a structure where wages and the duration of alternative labour market states may be interpreted as a general equilibrium outcome dependent upon an underlying matching technology.[7] These equilibrium models overcome the deficiency of an exogenous wage structure and thereby ensure that wage policy matters. Nevertheless, even the most complex of models shares at least some characteristics with the simplest of search frameworks.

[5] See Hirschleifer (1973) for a discussion of the superiority of a sequential decision rule over Stigler's fixed sample size rule.
[6] Mortensen (1970) derives an equivalent outcome.
[7] See Jovanovic (1979, 1984) for early examples of the theoretical literature concerning job matches.

Devine and Kiefer (1991) present a 'standard' model of sequential job search set in continuous time. Analysis begins with each worker receiving job offers according to a Poisson process with parameter δ the arrival rate of offers.[8] The probability of receiving at least one offer within a short interval of length h is thus $\delta h + o(h)$ where $o(h)$ is the probability of receiving more than one offer in that interval and $o(h)/h \to 0$ as $h \to 0$. The decision to accept or reject job offers is determined solely by the associated wage and occurs regardless of other job characteristics such as hours, benefits, working conditions, or non-pecuniary rewards. Hours are assumed fixed such that 'wages' and 'earnings' are equivalent characterisations denoted by the wage rate w. The worker identifies with the general characteristics of the local labour market, (S)he remains unaware, however, where which jobs, and hence values of w are available. Successive job offers thus arrive as independent realisations from a known wage offer distribution with finite mean and variance, cumulative distribution function $F(w)$, and density $f(w)$. When accepted a job lasts forever. Once an offer has been rejected it cannot, however, be recalled. Workers are assumed to be risk neutral with income while unemployed (and net of search costs) b constant and given over a spell. Each worker wishes to maximise the expected present discounted value of income. This is achieved by discounting future income at a known and constant rate r such that the expected present value of accepting an offer, $V^e(w)$, is simply the present value of expected lifetime income at that wage:

$$V^e(w) = \frac{w}{r} \qquad (2.1)$$

The value of declining an offer and continuing search may be derived likewise. Having assumed that net income while unemployed is constant, offers are independently and identically distributed, and that the offer distribution and arrival rate of offers are both

[8] The Poisson distribution is a natural specification for the offer arrival rate if one considers offers to arrive one at a time and that the probability of receiving an offer is independent of the time spent unemployed.

known, then the value of unemployed search for the worker, V^u, must be constant over the duration of a spell. We also know that this value is implicitly determined by four factors: the discounted present value of net unemployed income over the spell; the probability of receiving an offer in the spell times the discounted expected value of following the optimal policy if an offer w is received; the probability of no offer in the spell times the discounted value of optimal search thereafter; and the returns to search in the event of more than one offer, as denoted by the probability of receiving more than one offer times the value of following an optimal policy if more than one offer is obtained. The value of unemployed search, V^u, is thus:

$$V^u = \frac{1}{1+rh} bh + \frac{\delta h}{1+rh} E[\max\{V^e(w), V^u\}] + (1-\delta h)\frac{1}{1+rh} V^u + o(h)k \qquad (2.2)$$

Since V^u is independent of the offer w, and $V^e(w)$ is continuous and strictly increasing in w, it follows that the optimal strategy for the worker is a time-invariant reservation wage policy where the reservation wage is the minimum acceptable offer as defined by equating the expected present value of employment with the expected present value of continued search:

$$V^e(w^r) = \frac{w^r}{r} = V^u \qquad (2.3)$$

Substituting Equations (2.1) and (2.3) for $V^e(w)$ and V^u in Equation (2.2), rearranging terms, and passing to the limit thus yields the optimality condition:

$$w^r = b + \frac{\delta}{r}\int_{w^r}^{\infty} (w - w^r) dF(w) \qquad (2.4)$$

which, evaluating the integral and rearranging terms may be rewritten into a more intuitive interpretation of w^r:

$$(w^r - b)r = (E[w \mid w \geq w^r] - w^r)[1 - F(w^r)]\delta \qquad (2.5)$$

The left hand side of Equation (2.5) represents the marginal cost of rejecting an offer equal to w^r and continuing search. The right hand side represents the marginal expected gain in future earnings from continued search times the probability that an acceptable offer is received. The reservation wage thus represents an equality between the marginal costs and marginal benefits of search activity where the worker is indifferent between accepting an offer or continuing to search. The optimal policy therefore is to accept any wage offers greater than the reservation wage and to reject all those that fall below it.

A distinction must be made here between the reservation wage as an acceptance wage and the reservation wage generated by deterministic models of labour force participation. In deterministic environments, the reservation wage is derived from a variety of non-market factors such as the real wage, non-labour income and worker preferences. In the search framework the reservation wage is solely and endogenously determined by market opportunities as reflected by the wage offer distribution and the arrival rate of job offers. This distinction enables the search model to generate a number of 'derivative' restrictions with regard to net income while unemployed, the discount rate, the arrival rate of offers and the mean offer distribution, restrictions that may be simply derived by differentiating the optimality condition with respect to each term.

The most basic restriction that may be derived from every search model concerns the realisation that an increase in the cost of search directly reduces the worker's reservation wage thereby reducing the duration of search and hence unemployment. An increase in the cost of search reduces the attractiveness of continued search. Workers wish to increase the probability of finding an acceptable job offer. Enlarging the acceptance set and becoming less choosy can only achieve this. Consequently, the reservation wage falls and the duration of search declines. This result has long been recognised for its seductive policy conclusion regarding the level of unemployment insurance. Increasing search costs or namely lowering unemployment insurance can directly reduce the duration of unemployment. The same result is, of course, obtained from static neoclassical analysis. A fall in non-labour income increases the opportunity cost of leisure thereby increasing the relative attractiveness of work. The search framework shows, however, that so long as benefits operate as a subsidy for search then, for a given distribution of employment opportunities, the search process will be shorter the lower the level and duration of unemployment benefit.[9] An equivalent result holds for an increase in the discount rate. An increase in the discount rate represents a decrease in the weight attached to future income. As such, it too reflects less choosiness on the behalf of unemployed workers. A reduction in the reservation wage should again follow.

Other well-known results from the model concern the response of reservation wages to a change in the distribution of wage offers. Mortensen (1986), for example, shows that a mean preserving increase in the riskiness of the distribution (where wage offers become more dispersed but leave the mean offer unchanged) can actually increase the reservation wage. This result appears surprising. The searcher is, after all, a risk-neutral income maximiser. It arises, however, because an increase in mean preserving dispersion actually increases the conditional mean of acceptable wages thereby improving the expected returns to search and hence a reservation wage rise. A similar result holds for a rightward translation of the wage offer distribution. An increase in the worker's wage aspirations raises the mean wage offer. This in turn raises the reservation wage making the worker more choosy. The expected duration of unemployment depends on the size of the

[9] The theoretical and empirical literature concerning the level and duration of unemployment benefit receipt is extensive. See Atkinson & Micklewright (1992) for a critical review.

reservation wage increase relative to the initial change in the distribution. A leftward translation of the wage offer distribution accordingly yields the opposite result.

Much of the above analysis rests on a number of highly restrictive assumptions. However, many of these restrictions serve to permit only a simple exposition of the worker's problem. Relaxing the model yields little impact on any of even the most basic of implications. This result ensures that the model is highly adaptive in structure. It also allows a variety of extensions and modifications to be made. The surveys by Lippman and McCall (1976), and Mortensen (1986) provide considerable details of the types of microeconomic models that may be regarded here. Models with recall, systematic search, finite time horizon, utility maximisation, risk aversion, liquidity constraints, quits and lay-offs, and intertemporal variation in job search parameters (nonstationarity) may all be considered.[10] Such variety is indicative of the literature's maturity. So too is the excellent monograph by Devine and Kiefer (1991) that provides an annotated bibliography of over one hundred empirical studies and a reference list of a further five hundred. Most of these studies utilise the simple search models of McCall (1970) and Mortensen (1970) to motivate their analyses. Many utilise the framework to focus on the determination of unemployment duration. In the search framework, the duration of search and hence unemployment depends entirely on the value the worker places on employment. Knowing that the probability that a worker becomes re-employed in a short interval, τh, depends upon: firstly, the probability that an offer is received in that interval

[10] Many models impose that the reservation wage be constant throughout an unemployment spell. Many, however, reject this constraint. Salop (1973), for example, presents a model of systematic search where workers learn of the wage offer distribution as job offers arrive and simultaneously revise their estimate of the distribution as they decide whether or not to accept or reject each offer. This model generates non-uniqueness in the reservation wage since the reservation wage depends on the return to search and the duration of the search process. These in turn depend upon the current wage offer and the values of those offers rejected in the past. Burdett and Vishwanath (1988), in contrast, suggest a declining trend. Low value job offers sustain the existence of an unemployment spell. Thus, continued unemployment forces the worker to revise downward his perception of the offer distribution and hence the reservation wage.

$(\delta h + o(h))$; and secondly, the conditional probability that once an offer is received that it is accepted and becomes the optimal policy $1 - F(w^r) = \pi(w^r)$, then the probability of re-employment may be written:

$$\tau h = (\delta h + o(h))\pi(w^r) \tag{2.6}$$

Dividing Equation (2.6) through by h and taking limits as $h \to 0$ results in the instantaneous probability of re-employment or hazard rate:

$$\tau = \delta\pi(w^r) \tag{2.7}$$

The hazard rate captures the transition rate between the states of unemployment and employment. Significantly, this rate is independent of elapsed duration. Workers who commence a spell of unemployment receive offers randomly and decide whether to accept or reject them without reference to the time spent unemployed. This distinction proves vital to the analysis of unemployment spell lengths. Viewed as the consequence of a sequence of single stage decisions, differences in the duration and frequency of unemployment appear to arise because of worker heterogeneity and variation in local labour market conditions. Search theory itself does not presuppose what such factors ought to be. In practice, they include human capital, unemployment insurance, labour market tightness and demographic characteristics. In principle, they may include any feature deemed to produce variation in the reservation wage, the arrival rate of offers or the offer distribution. The existence of unobserved or unmeasured heterogeneity provides a cause for concern here. Empirical studies implicitly assume that for a specified distribution of duration and choice of functional form, explanatory variables will adequately control for worker heterogeneity. Failure to capture unobserved or unmeasured heterogeneity may, however, result in spurious duration dependence. Duration dependence implies that the conditional probability of exiting unemployment varies with the duration of an unemployed spell. If $\partial\tau/\partial t > 0$, positive duration dependence is observed and the conditional probability of leaving unemployment increases with spell length. If $\partial\tau / \partial t < 0$, negative duration dependence is observed and departure from unemployment becomes less likely the longer duration continues. Unobserved heterogeneity induces negative duration dependence. It lowers the hazard rate for some workers and thereby lengthens their unemployment spells. Failure to incorporate such characteristics results in the hazard rate for each spell being averaged but not recognised as such. Since no explanation for longer spells is provided other than a decline in the hazard, negative duration dependence is incorrectly assumed. This assumption imparts spurious but significant implications for the formation of effective unemployment policy. Thus, controlling for heterogeneity now lies at the forefront of the hazard approach.

2.4 Efficiency Wage Theory

The competitive paradigm outlined in section 2.2 and the theory of job search outlined in section 2.3 make strong predictions about the wage structure and unemployment. Both of these theories assert that unemployment is voluntary in nature: it is an equilibrium phenomenon that arises from the law of the market-clearing price. They also claim that workers are compensated according to their respective opportunity cost (outside opportunities or alternative wage). The opportunity cost of a worker is determined by accumulated human capital and non-pecuniary factors associated with the firm's work environment. Thus, job characteristics that do not affect the utility of workers should not influence wage outcomes. Non-competitive models of the labour market disagree with this latter facet. They abandon the notion that the forces of supply and demand solely determine wages and unemployment and instead argue that there are non-competitive forces involved in the wage determination process. These non-competitive forces may help to explain the observed regularity of the (industry) wage structure and the existence of wage differentials for workers with equivalent characteristics in identical occupations. They may also operate to prevent the wage from freely adjusting, an attribute that may in turn give rise to involuntary unemployment. Theoretical constructs regarding the payment of efficiency wages, union bargaining and industry rent-sharing provide the principal motivations here.

The fundamental idea underlying the theory of efficiency wages is that firms may find it profitable to pay wages in excess of the market-clearing (competitive) wage if higher wages induce productivity gains. In the competitive model, the market-clearing wage is the firms' optimal wage: it maximises profit and minimises the firms' wage costs per effective unit of labour. Firms that pay lower than the market-clearing wage fail to attract workers. Firms that pay above the market-clearing wage face rising wage costs per effective unit of labour (equally productive workers can be hired at the lower market-clearing wage). Thus, the only effective decision the firm faces regarding labour is how much labour to employ. In efficiency wage theory, the market-clearing wage is not the firms' optimal wage. This arises because the wage that workers receive affects their productivity. Asserting worker effort to be a positive function of the wage, the profit maximising dilemma for firms is to determine not only the quantity of labour to employ but also the quality of labour as measured in efficiency units. An increase in the wage rate improves worker productivity. For a given product price, this increase in worker productivity raises the firms marginal revenue product of labour (MRPL). The increase in MRPL yields benefits to the firm such that increases in wages have less than proportionate effects on firms' costs. Hence, the optimal behaviour for firms in this framework is to find the wage rate that minimises the cost per efficiency unit of labour.

The tenet of efficiency wage theory rests, of course, with the assumption that effort per worker is a positive function of the wage rate. Akerlof & Yellen (1986) provide the generic model. Assume an economy with identical, perfectly competitive firms, each having a multiplicative production function of the form $q = f(e(w)n)$, where n is the number of employees, e is effort per worker, and w is the real wage. Assume also that $e' > 0, e'' \leq 0$, and that the elasticity of $e(w)$ with respect to w is declining in w. These two assumptions ensure that output depends not only on employment but also on the quality of work. Thus, a profit maximising firm will choose the wage that minimises the wage cost per efficiency (effective) unit of labour. A firm that can hire all the labour it wants at the wage it chooses to offer will offer a real wage w^* (the efficiency wage) that induces just enough additional effort to compensate for the additional wage cost. This wage satisfies the Solow condition: the elasticity of effort with respect to the wage is unity.[11] The optimal quantity of labour is determined by hiring labour until the marginal product, $e(w^*)f'(e(w^*)n^*)$, equals w^*.

The Solow condition may be formally derived from the above model by considering the firm's maximisation problem in more detail. For a constant product price p, the firm's profit function may be written:

$$\max_{w,n} \pi = pq - wn \tag{2.8}$$

Differentiating the profit Equation (2.8) with respect to n and w provides the two first-order conditions (FOCs):

$$\frac{\partial \pi}{\partial n} = p\frac{\partial q}{\partial n} - w = 0 \tag{2.9}$$

$$\frac{\partial \pi}{\partial w} = p\frac{\partial q}{\partial e} \cdot \frac{\partial e}{\partial w} - n = 0 \tag{2.10}$$

[11] The origin of what is now termed efficiency wage theory can be traced back to Solow (1979).

Combining Equation (2.9) and (2.10) gives:

$$\frac{\frac{\partial q}{\partial n}}{\frac{\partial q}{\partial e}\cdot\frac{\partial e}{\partial w}}=\frac{w}{n} \tag{2.11}$$

Which may be rearranged to obtain:

$$w\frac{\partial q}{\partial e}\cdot\frac{\partial e}{\partial w}=n\frac{\partial q}{\partial n} \tag{2.12}$$

A multiplicative production function ensures that Equation (2.12) may be rewritten:

$$wn\frac{\partial e}{\partial w}=ne \tag{2.13}$$

Dividing each side of Equation (2.13) by ne yields the Solow condition:

$$\frac{w}{e}\cdot\frac{\partial e}{\partial w}=1 \tag{2.14}$$

The Solow condition (Equation 2.14) yields a number of interesting results. The condition itself, of course, implies that at the optimal wage a given percentage change in the wage should result in an identical percentage change in effort. This, in turn, implies that the real wage will be sticky and that there will be involuntary unemployment. Both of these results occur because the optimal (efficiency) wage depends only on the wage-effort relationship. Thus, neither a change in the firm's product price or the market-clearing wage will induce the firm to change the wage that it pays. If one considers variations in product prices to represent business cycle fluctuations, the efficiency wage should generate real wage rigidity regardless of the level of output.[12] In addition, if the efficiency wage is greater than the market-clearing wage, there will be an excess supply of labour and hence involuntary unemployment. Some unemployed workers would be

[12] In this instance, and with the efficiency wage already defined, contractions and expansions in product demand are met as in the standard competitive model of the labour market. Changes in product prices result in shifts of the firm's MRPL. For a specified wage, each firm thus decides whether it should simply employ more or less workers.

willing to work for a wage less than the efficiency wage. The firm, however, will not cut pay because it knows that employees would reduce their effort and thereby increase the wage cost per efficiency unit.

The original Solow model made no attempt to explain the existence of a positive association between the real wage and worker effort. The need to provide microeconomic foundations for such behaviour has, however, subsequently resulted in a number of alternative economic rationales. Four conceptually distinct though analogous motivations may be identified in this regard. Each of these motivations underpins a model that is built upon the principal-agent problem that arises from the informational imperfection that worker effort is not perfectly observable. Each model generates a prediction as to why firms may find it profitable to raise wages above the competitive level. In addition, all of the models engender an outcome of involuntary unemployment.

Shapiro & Stiglitz (1984) present a model where firms wish to prevent shirking. This model recognises that imperfect information and costly monitoring make it difficult to identify how well workers are performing their duties. It also assumes that work is a source of disutility to workers. Under such conditions, the possibility arises that workers may choose to shirk. To counter the possibility of shirking, firms may opt to pay higher than market-clearing wages. The higher wage raises the relative value of the job as viewed by each worker. It also raises the cost of the job being terminated if caught shirking. A higher opportunity cost of shirking reduces the amount of shirking occurring. It also gives rise to the existence of involuntary unemployment. Involuntary unemployment acts as a *worker discipline device*. It prevents workers form shirking and ensures that firms only have to pay as much as each other to elicit worker effort.

Salop (1979) and Stiglitz (1974, 1985) present models that emphasise firms' desire to minimise labour turnover. The formal structure of these models is very similar to that of the shirking model proposed by Shapiro & Stiglitz. The desire here, however, is not to minimise shirking but rather to reduce the level of quits. Workers who quit employment have to be replaced. Replacing workers means that firms incur recruitment and training costs. Higher wages and the threat of unemployment raise the relative wage paid by the firm. A higher relative wage induces workers to be less inclined to quit. Thus, labour turnover rates (and hence costs) should fall.

Weiss (1980) develops a model built upon the principles of adverse selection. The emphasis here lies in the role of the wage not only as a compensation factor for labour supply, but also as a sorting device for workers' ability. Firms find it costly to find out the ability of prospective workers. If ability and workers reservation wages are, however, positively correlated, firms that offer higher wages should attract higher quality workers. The willingness of a worker to work for less than the higher wage places an upper bound on their ability and hence productivity. In contrast, the higher productivity of workers who accept higher wages should compensate firms for the additional cost of offering higher wages. In this instance, the optimal policy for a firm is thus to pay an efficiency wage and turn away applicants that are willing to work for less than that wage.

Finally, Akerlof (1984) presents a model where efficiency wage payments serve to improve worker morale. The motivation here is sociological rather than individualistic. Each worker's effort depends on group norms and whether they perceive their treatment to be equitable or fair. Workers' ideas of equity depend on their relative wage, the rate of unemployment and the ability of the firm to pay (as measured by the firm's profits).

In such situations, firms can raise worker productivity by paying a 'gift' of wages in excess of the minimum required. These higher wages result in a 'gift exchange' of higher efforts. Higher efforts raise worker productivity and lower the cost of labour per efficiency unit.

Each of the above models explains why firms may find it profitable to pay in excess of market clearing wages. Since the circumstances for paying efficiency wages differs across models, and the application of these models may vary both within and across industries, efficiency wage theory may also be used to explain wage differentials for workers possessing similar qualifications and characteristics. Wage differentials that arise from efficiency wages are equilibrium differentials: no firm has an incentive to reduce the wage even though qualified workers may offer to work for less. They are also assumed to be unrelated to skill differentials and/or non-wage amenities. Efficiency wage theory sets out to explain wages established in excess of the market-clearing wage where the market-clearing wage reflects differences in human capital and net advantages. The theory elicits to the existence of productive characteristics that provide motivations to devise contracts that induce workers to deliver optimum level of efficiency units. These characteristics are largely unobservable. As such, it could be argued that efficiency wage differentials merely identify those differentials explained by unobserved heterogeneity in the competitive paradigm. In this regard, efficiency wage theory may be considered as an additional extension to the theory of equalising differences rather than an alternative. This is certainly a plausible (if somewhat unpalatable) conclusion. It remains, however, difficult to reconcile with industry specific factors such as the degree of capital intensity, profitability and firm size which have been found to significantly influence individual wages but which otherwise have no role in competitive labour market theory.

Efficiency wage theory is not without criticism. One major criticism that arises concerns the Solow condition. The Solow condition depends crucially on the assumed multiplicative form of the production function. A multiplicative production function ensures that the optimal (efficiency) wage is independent of output: it ensures that wages do not depend on product prices or employment. Relaxing this production function raises significant issues with regard to real wage stickiness. Furthermore, even when the multiplicative function is accepted, some critics argue that an effort-wage elasticity of unity is likely to be too high. If this is correct, there cannot be an equilibrium with involuntary unemployment. Fortunately, alternative specifications where the equilibrium effort-wage elasticity is lower can be derived.[13] Thus, profit-maximising supra-competitive equilibrium wage differentials may be consistent after all.

A further criticism arises from the realisation that efficiency wage models are inefficient. Efficiency wage models provide a solution to a contractual problem that arises due to principal-agent concerns. However, in each instance the proposed contract generates involuntary unemployment. The existence of involuntary unemployment poses the threat that more 'efficient' employment contracts may exist. The most widely discussed contract in this regard concerns the payment by workers of a bond on entry to the firm that they forfeit if they fail to deliver the required productivity or quit.[14] The threat of losing the bond substitutes for the threat of unemployment. Thus, unemployment as a worker discipline device is not required. Bond payments appear to work reasonably well in tenancy agreements. They do not, however, appear in employment contracts for two reasons. First, capital market imperfections typically

[13] See Akerlof & Yellen (1986) for details.
[14] See Eaton & White (1982) for a detailed analysis.

prevent workers from financing a bond. Second, bond payments present a moral hazard problem in that firms have an incentive to appropriate the bond by declaring workers as shirking or by harassing them to quit. Such considerations prevent the posting of bonds. Other contractual arrangements may, however, be observed. Where productivity is difficult to measure, firms can pay workers a bonus that is related to team performance. Where monitoring is costly, firms can pay workers on the basis of piece rates or commission. Alternatively, they could also pay seniority wages.[15] An upward sloping age-earnings profile provides a penalty for shirking: the re-employment wage would be the market-clearing wage. This payment scheme again, however, raises the issue of moral hazard in that firms could renege on the entry fee deal of lower wages at first with rising wages thereafter, by firing older workers.[16] In this instance, firms may be forced to use the general level of wages as an incentive device to motivate its employees. Whether efficiency wages matter then depends entirely on how strongly wages affect worker behaviour.

2.5 Wage Bargaining and Rent Sharing

Firms operating in an efficiency wage environment pay higher than market-clearing wages because the payment of such wages yield economic rents that make it both profitable and viable do so. Recent years have witnessed growth in a number of alternative models that again emphasise the firm's self-interest and ability to share economic rents. These models differ from efficiency wage models in that they emphasise the rent-sharing process as a consequence of economic bargaining rather than autonomous wage setting by the firm. This class of wage bargaining models has become

[15] See Lazear & Moore (1984) for a summary of this early literature.

[16] Lazear (1981) has shown that the moral hazard issue may, in this scenario, be overcome by the firm's concern for its reputation.

known as insider-outsider models.[17] Insider-outsider models may again be used to explain the existence of a disparate wage structure. The principal emphasis of such models rests again, however, with justifying involuntary unemployment and explaining why equally qualified unemployed workers do not compete for existing jobs by offering to work at a lower wage.

In efficiency wage theory, all labour market power rests with the firm. The firm decides the optimal wage to pay, and this, in turn, determines the optimal level of efficiency units to employ. The firm has no incentive to accept underbidding of the efficiency wage by unemployed workers since the efficiency wage acts as a sorting device for productivity. Any worker accepted on a lower wage will be less inclined to fear being fired. As such, (s)he will be inclined to deliver less than the appropriate level of efficiency units (productivity). Insider-outsider models contrast from this approach in that they deliver labour market power directly into the hands of incumbent employees. The source of such power may vary. Each source arises, however, from the realisation that new employees may be imperfect substitutes for existing workers. Incumbent workers may have better information than management about work effort. Alternatively, they may be better informed as to how to implement their skills (generic and specific) within the firm's production technology. In either scenario, incumbent workers may refuse to reveal such information to management or new employees unless it is in their interest to do so. This informational asymmetry yields incumbent workers with bargaining power. Hence, where it is costly for the firm to replace workers, incumbent workers will exercise a degree of labour market power.

[17] Lindbeck & Snower (1988) provide the seminal contributions here.

There is no formal consensus as to what constitutes an insider-outsider model. Consequently, many variants have been proposed. Some models interpret the insider-outsider approach broadly and present simple bargaining models that predict wages to be a function of insider variables such as firm or industry profitability and productivity, or outsider variables such as unemployment (Blanchflower *et al* (1988), Carruth & Oswald (1989)). Others focus on trade unions and membership dynamics to explain wage determination (Blanchard & Summers (1986)). Wage bargaining does not, of course, require the existence of unions. Lindbeck & Snower (1988) present models that demonstrate that incumbent workers operating in labour markets characterised by high transaction costs and/or labour turnover may possess a degree of market power that can be exercised through individual or collective bargaining. Dickens (1986) presents a model where the *threat* of unionisation serves to induce firms to share their economic rents: higher wages reduce the need for workers to organise collectively thereby removing the threat of restrictive work rules and disruptive collective action. A comprehensive or indeed partial analysis of labour markets without due consideration of trade unions is, however, incomplete. Unions play a vital role in labour markets. They provide the foundation to the degree of centralisation or decentralisation of wage determination.[18] They also help to determine the degree of regulation of wage and employment outcomes.

The orthodox view of trade unions is that they exist as organisations whose purpose is to improve the material welfare of members by improving working conditions and raising wages above the market-clearing level. There is little dispute that unions are

[18] See Calmfors & Driffill (1988) for an analysis of centralised collective bargaining. See Henley & Tsakalotos (1993) for an assessment of corporatism and economic performance in OECD economies.

reasonably successful in this regard. How one models the role that unions play in the wage determination process is, however, rather more difficult to discern.

The simplest model of trade union behaviour is the monopoly union model. In this model, the union acts a monopolist in the supply of labour and unilaterally determines the wage rate subject to the labour demand curve of the firm.[19] The union understands how the firm will behave in response to the chosen wage. The union itself, however, has no influence on the level of employment. The firm determines the optimal level of employment by equating the MVPL to the marginal cost of labour (the union wage). Thus, the union chooses the wage and the firm determines the level of employment. Since the union wage is higher than the market-clearing wage, the level of employment will be less than that obtained under perfect competition. The extent to which these union effects dominate depends on the union's utility function and the relative importance it places on wages rather than employment.

The monopoly union model is certainly able to explain the existence of higher than market-clearing wages and involuntary unemployment. It is, however, not without criticism. The main criticism of the model rests in its simplicity. There is no bargaining in the model: the union determines the wage to set and the firm obliges by paying that wage. A further criticism rests in the model's inability to relate wage determination to issues concerning productivity and profitability. A necessary condition for unions to achieve higher than competitive wages for their members is that the union has the necessary power to force the firm to share any surplus or economic rent. An alternative is that the firm is willing to pay higher wages in return for higher productivity that

[19] In this framework, the optimal wage for the union to set is determined by equating the union's marginal rate of substitution of employment for wages (the union's preferences) to the firm's labour demand curve.

increases the available surplus to the firm. These conditions are unlikely to exist in isolation. More sophisticated analysis must thus provide a framework where bargaining outcomes are determined by both the union and the firm. Here, the bargaining outcome is indeterminate: it depends on the relative strengths of both employers and unions. Thus, the solution to this scenario requires the identification of what bargaining strength really is and how it may be used to generate agreements.

Two broad approaches to modelling bargaining behaviour may be found in the literature. The first of these is the axiomatic approach to bargaining. The axiomatic approach focuses on the outcome of the bargaining process. It is normative and static by nature and assumes that the bargaining outcome should satisfy a set of axioms that might be utilised by an independent arbitrator in the event of an impasse. The most well know solution to this approach is due to Nash (1950, 1953) and is normally referred to as the Nash Bargaining Solution.[20] The Nash bargaining solution has become the standard method of predicting bargaining outcomes in economic theory and is best understood as a prediction of the kind of agreement two parties would arrive at if they had to share a given amount. The second and more recent approach to bargaining behaviour concerns the game-theoretic approach. This approach is more dynamic by nature and involves modelling the bargaining process directly in order to determine the actual outcome. Rubinstein's (1982) model where the union and firm alternate in making offers that are either accepted or rejected provides the seminal contribution. This model provides an advantage over the axiomatic approach in that the eagerness of either party to attain a bargaining arrangement may be considered by examining the discount rate that each party places on future payoffs and the length of time that elapses

[20] The Nash bargaining solution is the theoretical equivalent of the well known concept of Nash equilibrium derived in non-cooperative game theory.

between each round. An additional feature here is that in a model with no uncertainty, the game theoretic solution is identical to the generalised Nash bargaining solution.

Having determined the alternative approaches to providing the solution to the wage bargaining process, the only remaining consideration involves identifying what the relative bargaining positions of both the union and the firm are going to be. The literature is characterised by two sets of popular models in this regard. First, there is the right to manage model (Nickell 1982) where unions and firms bargain over wages but employment is determined unilaterally by the firm. This model retains the union as a monopoly but introduces an employer that, constrained by its demand curve, also exercises bargaining power over wages.[21] Utilising a generalised form of the Nash bargaining approach provides the typical solution. In this instance, the wage bargain is determined such that the proportional marginal benefit to both parties from a unit increase in wages is exactly equal to the proportional marginal cost to each party, weighted by each party's bargaining strength. Second, there is the efficient bargaining model (Leontief (1946), MacDonald & Solow (1981)) where unions and firms bargain over wages and employment simultaneously. The efficient bargain may also be derived using the generalised Nash bargaining solution.[22] However, the model contrasts with the monopoly union and right to manage models in that it delivers both higher wages and employment than that obtained under the competitive paradigm. It is also superior to either of the aforementioned models in that a move from either outcome to an efficient bargain will result in a Pareto improvement.[23] This latter point is of considerable importance. However, there is

[21] The monopoly union model turns out to be a special case of the right to manage model where the firm's wage bargaining power is set to zero.
[22] Under the generalised Nash bargain, the union and firm set wages and employment such that the wage is equal to the sum of the average and marginal revenue products of labour, weighted by either party's bargaining strength.
[23] See Booth (1995) for an extensive analysis of the economics of trade unions and discussion as to which model of the unionised sector is the most appropriate.

considerable evidence to suggest that unions and firms do not bargain simultaneously over wages and employment. Indeed, Oswald and Turnbull (1985) argue that the institutional arrangements necessary to negotiate such agreements simply do not exist. The right to manage model, for this reason, is thus often preferred.

The activities of trade unions and the nature of the bargaining process outlined in the preceding analysis yield significant impacts on the operation of labour markets and the determination of both wages and (un)employment. These effects are not, however, without criticism. Two principal weaknesses may be found in this regard. First, do unions cause higher wages or are unions prone to organise industries that already pay high wages? Significant higher wages are certainly consistent with unionised activity. Mitchell (1980), however, presents evidence to suggest that the observed wage differential between industries that are highly or weakly unionised may be partially demographic or technological in nature.[24] Weakly unionised industries usually have smaller plants and are less capital-intensive than strongly unionised industries. They also tend to consist of a larger proportion of female workers. Theoretical and empirical literature concerning the effects of discrimination indicates that female employees tend to be paid less than male employees. Employees involved in industries with low capital utilisation also tend to require lower levels of skill. Lesser skills entail lower wages. Thus, low levels of capital utilisation and/or a high proportion of female workers both serve to reduce the average industry wage. Second, do unions raise or lower firm and industry profitability? Freeman & Medoff (1984) and Addison & Hirsh (1989) report significant reduction in profits due to unionisation. Voos & Michell (1986), utilising data for manufacturing industries, estimate the size of this reduction to be between 20

[24] Brown & Medoff (1989) present evidence to suggest that observed wage differentials may be further confounded by an employer size wage effect.

and 23 percent. Addison & Hirsch more generally conclude the magnitude of the reduction in profits to be large.

Other criticisms regarding wage and employment outcomes derived from models of unionisation concern limitations that may be applied to wage bargaining models as a whole. Rent-sharing models are extremely useful in contributing to explanations of involuntary unemployment and why equally qualified workers in different industries but identical occupations receive different wages.[25] A problem arises, however, in that the predicted effects are often similar to those of efficiency wage theory. For example, both sets of models predict an inverse relationship between wages and unemployment. Both, similarly derive a positive association between profitability and pay. This high degree of correlation between the models makes it difficult to accurately discern the true source of observed effects. The similarity in predictions does, however, at least make one aware to treat competitive theory with caution.

2.6 Conclusion

This chapter has provided a brief overview of a number of theoretical constructs that attempt to explain the determination of wages and (un)employment. The analysis is by no means exhaustive. Neither is it comprehensive with regard to the explanation of perceived labour market phenomena. There are many models outside those presented here that play an important role in the determination of stylised labour market facts. Theories of discrimination, hedonic wages, implicit contracts, dual and internal labour markets and government intervention may all be considered in this regard. The models

[25] In rent sharing models, all workers are assumed to grab or are given similar shares in economic rents or shares of rents in proportion to their relative skill. Thus, workers that might not otherwise be paid higher wages on efficiency (wage) grounds may still appropriate higher pay and thus induce wage differentials that might otherwise be difficult to explain.

presented in this chapter provide, however, an insight into the theoretical and empirical debates that provide the focus of this thesis. Efficiency wage theory and models of wage bargaining have taken precedence in recent years as explanations for the existence of stable and significant industry wage differentials and an inverse relationship between wages and regional unemployment. Job search theory, in contrast, dominates the theoretical and empirical literature with regard to the analysis of unemployment spell lengths. These topics, outlined in Chapter 1, provide the core elements to be considered in the remainder of the thesis.

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Chapter 3 - Inter-Industry Wage Differentials in the UK

3.1 Introduction

A major empirical regularity in the literature on the analysis of wage structure is the existence of large and persistent inter-industry wage differentials for workers of equal quality in equivalent occupations (Dickens and Katz, 1987a, 1987b; Krueger and Summers, 1987, 1988; Katz and Summers, 1989). These differentials exhibit a high degree of stability over time and appear to hold across a variety of countries with distinct institutional and structural arrangements (Gittleman and Wolff, 1993; Kahn, 1998). They also persist across different types of workers and establishment size. Such disparities are difficult to explain by the distribution of human capital accumulation across industries or by compensating differentials for non-pecuniary job attributes affecting the utility of workers. Their persistence is also inconsistent with the notion of transitory disequilibrium phenomena brought about by adjustments to labour supply or demand in the presence of imperfect short-run labour mobility. Accordingly, a number of non-competitive explanations have been proposed.

Standard human capital theory asserts that job attributes that do not directly affect the utility of workers should have no effect on the determination of individual wages. In contrast, non-competitive theories of wage determination assert that such attributes can have a systematic effect on wages because they influence the optimal wage for firms to set. The purpose of these theories is to determine why firms may find it profitable (and are able) to pay wages higher than the market-clearing rate. In addition, such explanations must also explain why the importance of such factors differs by industry. A number of possibilities have been suggested. Efficiency wage models embody the need for high wages to elicit worker effort. Motivations here are varied but include the firm's wish to prevent shirking (Shapiro and Stiglitz, 1984), minimise turnover costs (Stiglitz, 1985), diminish adverse selection (Weiss, 1980) and improve worker morale (Akerlof, 1984). Insider-outsider models (Lindbeck and Snower, 1986) stress the incumbent power of employees when bargaining for a share of industry rents. Finally, union threat models (Dickens, 1986) emphasise the threat of collective action as a reason for firms paying higher than competitive wages.

An alternative competitive explanation is that observed wage differentials are *true* differentials that reflect *unobserved* differences in worker quality. Several studies (Murphy and Topel, 1987; Krueger and Summers, 1988; Gibbons and Katz, 1992; Keane, 1993; Shippen, 1999; Abowd *et al.*, 1999) have utilised longitudinal data and fixed effects models to test this hypothesis, with mixed results. Krueger and Summers (1988), for example, present little evidence to support the importance of unobserved heterogeneity in the determination of industry pay. In contrast, Murphy and Topel (1987), Keane (1993), and Abowd *et al.* (1999) find that unobserved heterogeneity explains 66%, 84%, and about 90% respectively of the apparent differential in log wages across industries. Gibbons and Katz (1992) provide an experiment that does not rule out an unobserved ability explanation, but another experiment is sympathetic to the Krueger and Summer thesis that true industry differentials exist across industries, even for identical workers.

Identifying the true nature and source(s) of observed inter-industry wage differentials is important on both research and policy grounds and also with regard to individual welfare. Renewed interest in the structure of wages has occurred at a time when wage inequality in both the US and the UK is higher than at any other time this century (Katz *et al.*, 1995; Machin, 1996). This increased dispersion has occurred both between and within groups with the same observable characteristics. Competitive models of the labour market imply that changes in dispersion should be largely transitory in nature. Increased inequality, in this regard, may be considered as being shared amongst individuals. In contrast, non-competitive models of the labour market imply that such changes may be largely permanent. The acceptance of such explanations thus has significant positive and normative implications.

This chapter sets out to examine the existence, magnitude and stability of inter-industry wage differentials for Britain using longitudinal data drawn from the first eight waves of the British Household Panel Survey (BHPS). The BHPS is a nationally representative sample of more than 5,000 households (approximately 10,000 individual interviews) and provides a rich source of socio-economic information for issues concerning household organisation, labour market activity, income and wealth, housing, health and education amongst others. We take advantage of the data's features and examine both cross-section and pooled evidence for British inter-industry wage differentials between 1991 and 1998. In addition, we utilise the panel dimension of the data to assess the importance of unobserved worker heterogeneity on the cross-section and pooled results. There are extremely few panel studies of the inter-industry wage structure in the existing literature and, to our knowledge, none previous for Britain. Thus our use of the BHPS data to examine this issue provides an original contribution to a sparse literature.

The remainder of the chapter proceeds as follows. Section 3.2 presents a brief overview of recent research and a more detailed discussion of the theoretical explanations for the inter-industry wage structure. Section 3.3 outlines the methodology employed while section 3.4 discusses the data and its relative merits. Empirical results are reported in section 3.5. Section 3.6 concludes.

3.2 Inter-industry Wage Differentials: An Overview

The existence of inter-industry wage differentials is not a new phenomenon.[1] Slichter (1950) provides the seminal paper concerning 'regularities' in the US wage structure. Using hourly wage data for unskilled male workers of 20 US manufacturing industries over the period 1923-1946, he reports the rank order correlation of average hourly earnings to be 0.73. He also reports significant correlations between earnings and a number of financial variables. Unskilled male earnings appear to be positively correlated with value added per worker, value product of labour, and firms' profit margins. This, he concludes, provides evidence of 'managerial discretion' in wage determination. Such discretion undermines the role of competitive forces in determining wage outcomes. Consequently, it may also account for the apparent stability over time.

Recent literature revolves around American research by Krueger and Summers (1987) and Dickens and Katz (1987a). Neither of these papers utilises panel data in their analyses. Instead, they use both historical data on average industry earnings and large cross-section Current Population Survey (CPS) data on individual earnings to investigate the importance of inter-industry wage differentials across different occupations. Their findings suggest inter-industry differentials to be both substantial and significant, even when controlling for observable characteristics such as human capital and other demographics. They too report remarkable stability in the wage structure over long periods of time.

Krueger and Summers (1987) extend Slichter's analysis of manufacturing data and match the original 1923 data to wage differentials estimated from May 1984 CPS data. They observe that relatively high wage industries in 1923 continued to be high wage

[1] See Carruth and Oswald (1989) for an overview of the early literature on wage structure.

industries in 1984, whilst low wage industries continued likewise.[2] This finding is not confined to manufacturing. They present evidence that the industry wage structure for all industries has also remained constant.[3] Such stability is surprising but it is not unique. Papola and Bharadwaj (1970) study the rank correlation of industry earnings for 17 countries in the period 1948 to 1965 and report a high degree of stability for developed countries. Tarling and Wilkinson (1982) and Lawson (1982) similarly remark on the stability of the UK industry wage structure in the years after World War II. Thus, the structure of relative industry wages appears to change only moderately over time.

Evidence concerning the pattern of industry wages is equally pervasive. Krueger and Summers (1987) present evidence of similarity in the industry wage structure for both the south and non-south regions of the US. They also provide evidence of similarity in manufacturing industry wages across 14 countries in 1982. Correlations amongst developed, capitalist countries are particularly high.[4] The UK has the strongest correlation with US industry wages (0.95) while the former USSR has the weakest (0.33). Such findings are broadly consistent with the earlier work of Lebergott (1947) who finds a high rank correlation for industry wages between the US and Canada, the UK, Switzerland and Sweden in the 1940's. They are also consistent with the more recent results of Gittleman and Wolff (1993) and Kahn (1998) who both report considerable stability in the rank order of industries for a variety of countries.

It is important to note that the existence of inter-industry wage differentials is not necessarily inconsistent with competitive labour market theory. Several plausible

[2] The rank correlation coefficient is 0.56, which is remarkable given the length of time between the two periods and subsequent changes in industry definition. Moreover, changes in industry definitions and sampling error suggest this correlation could be an underestimate. The wage structure thus appears to have remained stable for a very long time.

[3] Correlations in the wage structure between 1984 and 1915 range from 0.76 to 0.98.

[4] Eight of the thirteen correlations exceed 0.8 and eleven are above 0.6.

explanations for observed differences in industry pay can be hypothesised in such a framework, for instance, industry wage differences may reflect unobserved heterogeneity, or compensating differentials for non-pecuniary job attributes, or transitory phenomena as an adjustment to sectoral change. However, the stability of the industry wage structure over long periods of time is inconsistent with transitory skill premia in periods of rapid sectoral change. Moreover, the evidence in favour of compensating differentials is also rather weak. If wage premia do serve to compensate for non-pecuniary job attributes, one would expect to find the inclusion of job characteristics in wage equations to significantly reduce observed industry effects. Similar findings should also hold for fringe benefits. Krueger and Summers (1988) find no evidence to support either of these hypotheses. Results of 1984 CPS wage equations with the dependent variable adjusted to reflect non-wage compensation reveal an increase in industry wage dispersion. The inclusion of a number of potentially important job attributes[5] using cross-section data from the 1977 Quality of Employment Survey (QES) produces a similar result: estimates with and without controls differ little in the observed pattern of industry wages.[6]

The importance of unobserved heterogeneity is more difficult to ascertain. Krueger and Summers (1988) adopt two methods to test for the presence of unobserved differences in labour quality. First they compare cross-section wage equations for May 1979 CPS data both with and without controls for human capital (age, gender, race, education, tenure and occupation). The inclusion of labour controls is reported to have no impact

[5] These are weekly hours, commuting time, choice of overtime, health hazards (2), shift work (2), and working conditions (2).

[6] Evidence from quit rates provides an additional argument against compensating differentials. Industry wage effects which are truly compensating should not yield any observable correlation with industry quit rates. However, Krueger and Summers (1988) and Katz and Summers (1989) find evidence that high wage industries tend to be those with the lowest rate of quits. Such evidence appears to suggest that workers feel that they are being paid in excess of their opportunity costs.

on estimated industry differentials.[7] Second they use matched CPS data sets along with the 1984 Displaced Workers Survey (DWS) to estimate first-difference equations on industry movers. These estimates appear broadly similar to their cross-section results. Both methods thus lead the authors to reject arguments for unobserved differences in labour quality. Gibbons and Katz (1992) add some support to this conclusion. They estimate first-difference models using data from the DWS for the period 1984-1986 and report that industry switchers appear to earn, on average, 97% of the relevant cross-section differential. The authors accordingly reject unobserved ability explanations and conclude that industry effects are indeed important in explaining inter-industry wages. In a different experiment Gibbons and Katz demonstrate that "pre-displacement industry affiliation plays an important role in post-displacement wage determination", which is sympathetic to an unmeasured ability story.

Murphy and Topel (1987) present evidence to the contrary. They use first-differences equations on a sample of matched CPS data for the period 1977-1984 and report industry switchers to receive only 27 to 36% of the cross-sectional differential. They conclude "that nearly two-thirds of the observed industry differences are estimated to be caused by unobserved individual components" (p. 135). Similar findings are reported in Keane (1993) and Shippen (1999). Keane estimates inter-industry wage differentials using a fixed-effects estimator on a long panel, namely the National Longitudinal Survey of Young Men (NLS). His results indicate that unobserved differences in labour quality account for a substantial 84% of the inter-industry log wage variance. Shippen reports likewise. He uses matched CPS data from 1983-1995 and retrospective data from the DWS from 1984-1992 to determine the effects of unmeasured skill on wages

[7] Krueger and Summers argue that unmeasured labour quality is probably correlated with measured quality. As such, one would expect the inclusion of labour quality controls to reduce considerably the dispersion of industry wages.

in the apparel industry. Results indicate that between 64 and 80% of the earnings differential between displaced apparel workers and other displaced workers can be attributed to unobserved heterogeneity not captured in standard cross-section wage equations.

Abowd *et al.* (1999) utilise a very large panel of matched employer-employee data for the private sector in France to provide further evidence on this issue. The nature of their data implies that they can separate the impact of observed and unobserved firm effects in the determination of wages from observed and unobserved individual (person) effects. Thus the importance of individual heterogeneity can be identified separately from any impact on wages from firm heterogeneity (both measured and unmeasured). Their results indicate that unobservable individual effects are a very important source of wage variation. Moreover, unobserved individual heterogeneity is seen to explain about 90% of the estimated inter-industry differences in wages, while firm effects contribute relatively little.[8]

Perhaps the most convincing argument against unobserved heterogeneity comes from evidence concerning inter-industry wage differentials and the industry's ability to pay. Dickens and Katz (1987a) provide a comprehensive review of this literature. They report industry wages to be highly correlated with a wide range of industry characteristics including the capital to labour ratio, firm and establishment size, union density, monopoly power and several measures of industry profit. These correlations appear to account for a large proportion of inter-industry wage variation across both time and space. They also hold after controlling for personal and demographic

[8] More precisely, industry-averaged individual heterogeneity can explain 84% or 92% of inter-industry wage variation, depending on specification (see Abowd *et al.*, 1999, Table VII for details) while industry-averaged firm-effects explain only 7% or 25%. Moreover, individual and firm heterogeneity are not highly correlated.

characteristics. Blanchflower *et al.* (1990) and Nickell and Wadhwani (1990) report similar findings for the UK. They show that product market characteristics and the prosperity of the employer positively affect the level of pay. Since there are no identifiable reasons why unmeasured labour quality and product market characteristics should be correlated, these findings serve to undermine the role of unobserved heterogeneity as an explanation for inter-industry differentials.[9]

Efficiency wage theories may provide a theoretical explanation for inter-industry wage differentials and the observed correlation between profitability and pay. These theories predict that higher than competitive wages can be profitable for firms where induced productivity gains ensure that changes in wages have less than proportionate effects on firms costs. Yellen (1984) provides the generic model. The central premise of these models is that effort per worker is a positive function of the wage rate. Four conceptually distinct though analogous motivations may be identified. These are that: firms wish to prevent shirking (Shapiro and Stiglitz, 1984); minimise turnover costs (Stiglitz, 1985); diminish adverse selection (Weiss, 1980); and improve worker morale (Akerlof, 1984). Each of these motives predicts correlations between industry wage premia and industry characteristics consistent with the available evidence although none of these models attest to all of the evidence. The shirking, turnover and adverse selection models, for example, are difficult to reconcile with the uniformity of industry wages across occupations. Fair wage models, in contrast, are difficult to reconcile with cross-national evidence regarding similarities in wage setting between former Eastern bloc and Western industrialised countries.

[9] A related study by Blackaby and Murphy (1991) correlates industry-regional wage differentials for the UK with a number of industry and regional characteristics including the average age and experience of the local labour force, various dimensions of employer-employee bargaining and regional prices and unemployment. A number of these factors are found to be significant determinants of industry-regional differentials, and, in total, can explain about 75% of the variation. They interpret this result as providing weak support for non-competitive models of wage determination.

The threat of collective action provides an alternative rationale for employee receipt of industry rents. Dickens (1986) argues that threat of unionisation can benefit non-union workers if employers pay above the competitive wage to prevent collective action.[10] His model predicts industries with high wages to be those where the threat of unionisation is high and the costs of collective action to workers low. Evidence concerning correlates of industry wage premia support this hypothesis.[11] Krueger and Summers (1987), however, argue against this threat of unionisation. They report that historical evidence for the US suggests that high wage industries paid relatively high wages before the advent of widespread unionisation. Furthermore, the inter-industry wage structure appears highly correlated across both union and non-union workers. This latter evidence is contrary to the predictions of the union threat model. It also conflicts with the predictions of a range of union bargaining models that argue that 'strong' unions are the source of inter-industry wage differentials.

A further rent sharing explanation of inter-industry wage differentials comes from the concept of insider power (Lindbeck and Snower, 1986; Solow, 1985).[12] Insider-outsider models emphasise the incumbent market power of employees whose positions are protected by significant costs of turnover. These models assert that the presence of large transactions costs in the hiring and firing of workers provide firms with the incentive to pay current employees supra-competitive wage premia in order to retain their services. This view of rent sharing is again consistent with observed correlates for the inter-industry wage structure. Krueger and Summers (1987) argue that it is also consistent with the existence of inter-industry wage differentials for workers of different *occupations*. Rent sharing models in which firms are willing to share rents equally

[10] Collective action can take several forms including threat of strike and work-to-rule measures.
[11] High wages in the US are strongly correlated with both union density and industry profits.
[12] Blanchflower *et al.* (1990) report evidence of both insider and outsider power in the UK.

across all types of workers certainly support this claim. Equality constraints based on sociological 'norms' provide the most feasible argument.

This chapter explicitly addresses the role of unobserved heterogeneity as an explanation of the observed inter-industry differentials. We utilise genuine panel data (rather than matched data) to show explicitly that much of the observed cross-section inter-industry wage differentials can be accounted for by unobserved individual-specific effects. Thus, the chapter is most similar in spirit to that of Keane (1993). However, using the BHPS means that we can also largely dismiss the compensating differentials argument since, unlike in his data, we can also control for (observed) job and workplace characteristics. Of course, it remains to be explained why these unobserved individual effects should be correlated with industry affiliation, although we suggest some possible explanations in our discussion and conclusion.

3.3 Methodology

We adopt a two-step approach to the analysis of inter-industry wages. Our first approach follows the standard procedure popularised by Krueger and Summers (1988), and recently improved by Haisken-DeNew and Schmidt (1997).[13] We estimate cross-section and pooled wage equations of the form:

$$\ln w_{ij} = \alpha + \beta x_i + \varphi Z_j + \varepsilon_{ij} \tag{3.1}$$

where $\ln w_{ij}$ is the natural logarithm of the real hourly wage of worker i in industry j, α is the constant, x_i is a vector of personal and workplace characteristics, occupations and regions, Z_j is a vector of industry dummies which includes *all* industries, β and φ are

[13] See Arbache (1998) for a detailed discussion of the Krueger & Summers and Haisken-DeNew & Schmidt methodologies and a comparison of both methodologies using Brazilian manufacturing data.

vectors of parameters to be estimated, and ε_{ij} is a random disturbance term. Since in equation (3.1) the cross-product matrix of regressors is not of full rank, a linear constraint is imposed on the φ's as follows:

$$\sum_j n_j \varphi_j = 0 \qquad (3.2)$$

where n_j is the employment share in industry j.

Krueger and Summers utilise a two step procedure. First, they estimate standard cross-section wage equations that include a vector of dummy variables indicating industry affiliation and a constant term that corresponds to an omitted industry. Second, they renormalise the estimated industry differentials to yield deviations from a hypothetical employment-share weighted mean. Instead of calculating the standard errors of the renormalised coefficients, Krueger and Summers suggest approximating them by the unadjusted standard errors of the coefficients in the original regression, and using the standard error of the constant term to approximate the standard error of the omitted industry. Hausken-DeNew and Schmidt argue that the above procedure overstates both the standard error of renormalised coefficients and their variance. They also demonstrate empirically that the estimated standard errors vary drastically depending on the choice of omitted industry, irrespective of sample size. Such variation inevitably inhibits sensible economic interpretation of individual elements of the renormalised coefficient vector and the estimated summary measure of overall wage dispersion.[14] In contrast, the Hausken-DeNew and Schmidt procedure described in equations (3.1) and (3.2) provides economically sensible coefficients and their correct standard errors in a single regression step.

[14] Hausken-DeNew and Schmidt also show that the overall measure of industry wage dispersion is always underestimated using the Krueger and Summers methodology

Our second approach considers a panel fixed-effects model also using the improved methodology of Hausken-DeNew and Schmidt.[15] In this case, the constraint of equation (3.2) is imposed on a regression model of the form:

$$\ln w_{ijt} = \alpha_i + \beta x_{it} + \varphi Z_{jt} + v_{it}, \quad i = 1,\ldots,N \qquad t = 1,\ldots,T \tag{3.3}$$

where $\ln w_{ijt}$ is the natural logarithm of the real hourly wage of worker i in industry j at time t, α_i is an individual-specific component of wages reflecting observed time-invariant individual heterogeneity such as gender and race, and v_{it} is a random error term independently and identically distributed over i and t.

Assuming unobserved individual-specific heterogeneity to be time-invariant, the error term v_{it} can be decomposed as:

$$v_{it} = u_i + e_{it} \tag{3.4}$$

where u_i denotes the individual-specific unobserved effect and e_{it} denotes the remainder disturbance.

Equation (3.3) may now be written:

$$\ln w_{ijt} = \alpha_i + \beta x_{it} + \varphi Z_{jt} + u_i + e_{it} \tag{3.5}$$

Averaging over time gives:

$$\ln \overline{w}_{ij.} = \alpha_i + \beta \overline{x}_{i.} + \varphi \overline{Z}_{j.} + u_i + \overline{e}_{i.} \tag{3.6}$$

Subtracting equation (3.6) from (3.5) thus yields:

$$\ln w_{ijt} - \ln \overline{w}_{ij.} = \beta\left(x_{it} - \overline{x}_{i.}\right) + \varphi(Z_{jt} - \overline{Z}_{j.}) + \left(e_{it} - \overline{e}_{i.}\right) \tag{3.7}$$

[15] As far as we are aware, this improved methodology has never before been implemented using panel data.

This is the fixed-effects (or within) estimator. The within estimator produces consistent and efficient estimates of the parameters when the time-invariant effects are assumed correlated with x_{it}.

Having controlled for other factors important in the determination of wages, the reported industry coefficients, φ_j, may be interpreted as the proportionate difference in wages between a worker in industry j and the average worker across all industries. To describe the overall variability in industry wages, we use two different summary measures. First, as in the standard literature, we calculate the standard deviation of the industry wage differentials:

$$SD(\varphi) = \sqrt{\sum_j n_j \varphi_j^2 - \sum_j n_j \sigma_j^2} \qquad (3.8)$$

where σ_j^2 are the variances of the estimated φ_j. $SD(\varphi)$ gives the weighted and adjusted standard deviation of industry coefficients.[16]

Our second summary statistic for the inter-industry variation in wages is the weighted average absolute differential:

$$|\varphi| = \sum_j |n_j \varphi_j| \qquad (3.9)$$

Thus, $|\varphi|$ is the weighted average proportionate deviation from the mean for a randomly chosen worker.

[16] The second term in equation (3.8) is the correction for the least squares sampling error - see Krueger & Summers, and Haisken-DeNew & Schmidt.

3.4 Data

We estimate British inter-industry wage differentials using longitudinal micro data drawn from the 1991-1998 (eight) waves of the BHPS, a nationally representative survey of households randomly selected south of the Caledonian Canal.[17] The BHPS was designed as an annual survey of each adult member (age 16 or over) from a nationally representative sample of more than 5,000 households, providing a total of approximately 10,000 individual interviews. The first wave of the BHPS was conducted from September 1991 to January 1992, subsequent waves have been collected annually thereafter. [18,19]

The BHPS provides a rich source of socio-economic information at the individual and household level. The dependent variable that we derive from these data is the natural logarithm of the real hourly wage. This is calculated as the ratio of usual gross pay per month (a derived variable that measures usual monthly wage or salary payment before tax and other deductions in current main job for employees), and the total number of hours normally worked per week, scaled by average weeks per month.[20] This is then deflated by the RPI in the month of interview (base January 1991).

The richness of the BHPS permits a wide variety of both personal and workplace controls in our wage equations. Personal controls include gender, race, marital status, highest educational qualification achieved, head of household indicator, and the number of children in the household and their age profile. Additional information regarding an

[17] The very north of Scotland is thus excluded.

[18] From wave 7, the BHPS has incorporated a sub-sample of the original United Kingdom European Community Household Panel (UKECHP), including all households still responding in Northern Ireland. For consistency across the panel, these new sample members are excluded from the analysis below.

[19] See Taylor *et al.* (1998) for details.

[20] The data provide separate information regarding the number of hours normally worked per week (excluding overtime and meal breaks), the number of overtime hours worked in a normal week, and the number of overtime hours worked as paid overtime. We define total hours as normal hours plus overtime.

individual's health along with their recent labour market history are also included. A piecewise linear spline for age is used to capture the expected profile of lifetime earnings.[21]

Workplace and workforce controls which can be expected to impinge upon earnings include unionisation (both recognition and membership), full or part time job status, promotion opportunities, a number of variables capturing the structure of pay and pay increases, seasonal or temporary work, rotating shifts, managerial duties and supervisory tasks and travel to work time. Any remaining firm-specific effects are captured by the inclusion of firm size and public-private sector indicators.[22] Occupational affiliation is coded to the 1990 OPCS Standard Occupational Classification and we utilise 1-digit occupational dummies to control for variation of wages across occupation. Regional dummies and time dummies are also included to capture any remaining effects on wages brought about by geographical differences in industry and institutional structure, and cyclical effects on wages.[23]

The data report industry affiliation at the 4-digit level using the 1980 Standard Industrial Classification (SIC). We report two sets of estimates in the results presented below. First we use 1-digit industry identifiers. While these are sufficient to illustrate the principal findings of the chapter, we also present results using 2-digit industry dummies (after appropriate aggregation of comparable industries where cell size is small). For panel purposes, this finer disaggregation permits a greater number of inter-industry

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[21] The linear spine is preferred to imposing the constraints implied by the usual quadratic in age or experience.

[22] A positive association between wages and firm size is well established. See Brown and Medoff (1985) and Green *et al.* (1996) for details.

[23] The BHPS distinguishes 18 standard regions. We reclassify this regional information in accordance with the 11 Standard Regions of the UK.

transitions to be observed. However, as will be seen below, our central results are not sensitive to the level of disaggregation of the industry identifiers.

The sample is selected on the basis that the individual is of working age (aged 16 to retirement) and has a current status of 'employee'. Retired and self-employed workers, the unemployed, individuals working on government schemes and 'inactive' members of the working-age population are thus excluded. Individuals who have missing relevant information or who are not interviewed at a particular wave are also excluded. However, individuals who enter and exit the sample across the panel are included. While this results in an unbalanced panel, it does serve to minimise potential attrition biases and yields greater numbers of observations in the panel when controlling for fixed-effects (and also maximises the number of inter-industry transitions recorded). Finally, to alleviate potential biases from serious over or under estimation of earnings, we symmetrically trim the data of extreme outliers and omit the 0.5% of observations with the highest and lowest real hourly wages.[24]

The resulting sample available for estimation has 34,500 data points across the eight waves, comprising observations on 8,508 individuals. The gender distribution across the panel is presented in Table 1, while Table 2 details the total number of waves for which each individual is observed. Data definitions and summary statistics are presented in Table A1 of the Appendix.

[24] We also investigate the robustness of our results to a number of other specification and sample selection criteria.

3.5 Empirical Results

Table 3A, column 1 reports the 'raw' 1-digit inter-industry wage differentials for the pooled data across all eight waves taken together. All but two of the differentials are statistically significant at 1% levels and the point estimates for the individual industry differentials are economically important. Taken across all eight waves, workers in energy and water supplies earn 47% above the average wage, while those in distribution, hotels and catering earn 27% below the average.[25] The employment-weighted adjusted standard deviation of the raw industry log differentials is 17% and the average absolute deviation is 14%. Table 4A, column 1 reports similar findings based on the 2-digit classification; 33 of the 35 differentials are statistically significant at the 1% level, and workers earn from between 55% above (solid fuels, oil etc.) to 42% below the average (personal and domestic services).

The differentials are remarkably stable and persistent across the eight waves (cross-sections) treated separately. The rank order correlation of 1-digit (2-digit) differentials between wave 1 and wave 8 is 0.96 (0.96), and the $SD(\varphi)$ measure of dispersion ranges from between 0.1548 and 0.1829 (0.2106 and 0.2280) compared with the value for the data pooled of 0.1721 (0.2216). These findings are consistent with previous studies which identify the stability and regularity of the wage structure as discussed above.[26]

Table 3A, column 2 reports proportionate industry wage differentials conditional on controls for personal characteristics. Most control variables are individually significant,

[25] Percentage differentials are calculated as $100\times(e^{\varphi_j}-1)$ - see Halvorsen and Palmquist (1980).

[26] The consistency and stability of the inter-industry differentials over time provides evidence against the argument that (the threat of) industrial action by trades unions generates wage differentials through the differential capture of industry rents. Over the period covered by our sample, unions in Britain were in almost continuous decline in terms of membership, coverage, and influence. Our estimated wage differentials for individual cross-sections over the period display no such trend.

and their collective significant is shown by the F-test in the diagnostics at the bottom of the table. However, their inclusion has relatively little impact on the ranking of industries in that the rank order is broadly similar to that observed in column 1 (the rank order correlation coefficient is 0.99). A similar pattern in the stability of the wage structure is observed when we consider the analogous results for the 2-digit industry categorisation in Table 4A, column 2. Again, the personal controls are individually and jointly significant, but the ranking of the inter-industry differentials is little affected.

The main effect of personal controls is to reduce the size, significance and dispersion of the estimated industry wage differences - most industry coefficients are reduced by a factor of between one quarter and two thirds when personal controls are included.[27] The standard deviation of the 1-digit differentials falls to 10%, and to 14% for the 2-digit differentials. This represents a decrease of around 40% in each case, and this is similar to the fall in the alternative measure of dispersion, $|\varphi|$. This decrease in dispersion is very similar to that reported by Krueger and Summers (1987) for US data, and indicates observed labour quality to be an important factor in the determination of inter-industry pay.

Although it is difficult to capture all non-pecuniary job attributes precisely, the inclusion of workplace controls should also affect estimated industry differentials if they are important in the wage determination process. The third columns of Tables 3A and 4A reports the results when workplace controls are also included alongside personal controls in the 1-digit and 2-digit specifications. The addition of such controls again

[27] The highest paying 1-digit industry is still energy and water supplies, but workers in this industry now earn 28% above the average wage, conditional on personal characteristics. Similarly, while solid fuels, oil etc still heads the 2-digit ranking, the associated differential is now 37%. These compare with the raw differentials of 47 and 55% respectively.

alters the size, significance and dispersion of industry wage differences. The number of statistically significant industries is, however, reduced only slightly. Workers in the highest paid 1-digit (2-digit) industry now earn a premium of 22% (30%), while those in the lowest paid 1-digit (2-digit) industry group face wages which are 10% (18%) less than the wage that the average worker receives.

With both personal and workplace controls, the standard deviation of 1-digit (2-digit) industry differentials is 7.6% (10%) across the pooled eight waves of data. This further fall in the calculated dispersion suggests that workplace characteristics can account for about 26% of the observed inter-industry wage variation. Overall, personal and workplace controls explain around 55% of the observed inter-industry wage differences.[28]

These results concerning the importance of personal and workplace variables in explaining wage dispersion are consistent with previous (cross-section) studies investigating the inter-industry wage structure. They differ, however, in that the richness of the BHPS data is such that over one half of the total variation of wages is explained by these control variables as seen in the R^2's reported in the diagnostics. However, there is still a considerable degree of inter-industry wage variation that remains unaccounted for, and it is this residual dispersion that is usually attributed to non-competitive forces in wage determination.

Of course, pooled/cross-section estimates cannot control for *unobserved* differences between individuals which are correlated with their wages. Such differences may reflect

[28] For $\mathrm{SD}(\varphi)$, the proportion of 1-digit differentials explained by personal and workplace controls is $(1-\frac{0.0764}{0.1721})\times 100 = 56\%$, while for the 2-digit differentials, it is $(1-\frac{0.1009}{0.2216})\times 100 = 55\%$. For $|\varphi|$, the corresponding values are 55% and 51% respectively.

productivity-enhancing attributes that are not measured or captured in the data available to the econometrician, innate ability, any job-specific skills not measured by formal qualifications or accounted for by measured job characteristics etc. These unobserved individual-specific differences may, of course, explain the remaining inter-industry differences and the unexplained residual wage dispersion. Thus, in order to gauge the potential importance of such unobserved heterogeneity, we proceed to estimate a fixed-effects model as outlined in equation (3.3) by utilising the panel element of the data.

Tables 3B and 4B present fixed-effects estimates of the three wage equation specifications considered previously for 1-digit and 2-digit industry identifiers respectively. Column 1 reports the raw differentials; column 2 controls for personal characteristics and column 3 includes workplace control variables as well as personal controls. In each case, we estimate by fixed-effects and thus also account for unobserved individual heterogeneity.[29,30]

Contrasting these results with the pooled regression results in Tables 3A and 4A highlights a number of important issues, and reveals some exceedingly interesting findings. Firstly, the inclusion of individual fixed-effects significantly reduces the size and significance of the industry coefficients. It also has a considerable impact on the

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29 Controlling for individual fixed-effects eliminates any workers who do not change industry over the eight waves since their fixed-effect α_i is exactly correlated with the industry identifier. Hence, since these estimates effectively reflect industry 'switchers' only, the coefficient on an industry dummy indicates the 'true' penalty or premium earned in that industry. We provide the comparable pooled estimates for switchers only in the robustness checks we perform below.

30 Full results for pooled and fixed-effects specifications are presented in Table A2 (1-digit) and A3 (2-digit) of the appendix. These reveal that the estimated wage equations appear to be meaningful and appropriate in that the returns to the different personal and workplace characteristics are consistent with the large previous literature on wage determination. Thus, for example, *ceteris paribus*, age-earnings profiles are concave (although earnings increase over any individual's lifetime); women are paid significantly less than men; there are significant private returns to education; recent periods of unemployment or inactivity have a detrimental effect on earnings; unionised workers enjoy a wage premium of about 7% over their non-unionised colleagues; workers are compensated for long travel-to-work times; and wages are significantly higher in the south of Britain.

degree of industry wage dispersion. For the 1-digit classification, comparing the first columns of Tables 3A and 3B, we see that much of the inter-industry wage dispersion can be ascribed to individual characteristics (which do not vary over time). Indeed, only four of the industry dummies are now statistically significantly different from zero at the 1% level (and only five at the 5% level), and the $SD(\varphi)$ measure of industry wage dispersion is only 3.7%. This result indicates that just under 80% of the observed deviation in 'raw' industry wages can be attributed to unobserved heterogeneity not measured in standard cross-sections. The inclusion of personal and workplace controls in columns 2 and 3 reduces the measured inter-industry wage dispersion even further to only 2.7%. Thus observed and unobserved differences between employees can together account for just over 84% of industry wage differentials. Similar findings are evident when we compare Tables 4A and 4B for the 2-digit classification: only ten of the differentials are now significant at 1%, and 82% of the raw inter-industry differentials can be 'explained' by unobserved and observed differences between individuals and the jobs that they do. This result is remarkably similar to those of Keane (1993), Shippen (1999), and Abowd *et al* (1999).[31]

The second notable feature of the results in Tables 3B and 4B is the high proportion of the variation in wages between individuals that is now 'explained'. For the full specification in column 3, the R^2 are 0.93 for both 1-digit and 2-digit industrial classifications. This implies that there is only a very limited residual variation in wages that cannot be accounted for by observed and unobserved characteristics of individuals and the jobs they do within the industries that they are employed. Moreover, as we have

[31] Of course, we cannot control for any differences in returns to unobserved individual ability which vary by industry since industry-specific individual effects cannot be identified separately from true industry effects. If workers are gradually sorted into the industries which reward their particular abilities most highly, then we will observe positive industry wage differentials. Such a process may account for the small degree of inter-industry wage variation that remains (Keane, 1993).

just seen, most of the variation in wages can in fact be attributed directly to differences between individuals (and the characteristics of their jobs) rather than simply their industry affiliation. This contrasts with much of the previous literature on wage determination which finds that there is considerable residual variation in wages that is unexplained by the variables in the wage equation.

Despite the fall in magnitude and significance of the estimated inter-industry wage differentials, there are still some substantial differences in wages between industries. For example, in the 2-digit specification, workers in solid fuels, oil etc earn a premium of almost 18% over the average worker, while those in hotels and catering are paid 9% less than their measured and unmeasured attributes and their job conditions would imply. Of course, it could be argued that these remaining differentials are evidence of non-competitive pressures in wage determination.[32] However, the important result in this chapter is that such non-competitive differences are of a much smaller degree than previously thought. Our findings suggest that much of the variation in wages previously attributed to inter-industry differentials is actually a reflection of unobserved differences between individuals which could not be eliminated in standard cross-section/pooled estimates of wage equations, and that these differences are correlated with industry affiliation (indeed they may indicate a successful matching process between workers and jobs). Thus it would appear that non-competitive forces have only a limited role in explaining the industry wage structure.

[32] Given that the fixed-effects estimates of the inter-industry differentials only reflect the premia earned by individuals who move industry, an alternative explanation for the remaining inter-industry wage differences is that there are unmeasured individual abilities which are not fixed (and thus eliminated by the within transformation) but differ according to the job that the individual is doing (or rather the firm/industry s/he is working in).

One possible counterargument is that our results could equally be explained by unobserved fixed-effects at the firm or establishment level. Given the importance of measured job characteristics in cross-section estimates, and the fact that measured and unmeasured characteristics appear highly correlated in the fixed-effects model, this explanation seems plausible. However, as noted above, Abowd *et al.* (1999), in their extensive study using matched employer-employee data, demonstrate that around 90% of inter-industry differentials can be explained by individual fixed-effects while firm effects can explain very little of the observed differentials. Hence, we are confident in the interpretation of our results as indicating a significant role for unmeasured individual heterogeneity rather than unmeasured firm heterogeneity in the explanation of inter-industry wage differentials. [33]

A summary of our results so far is contained in Panel A of Table 5. For each of the three specifications (specification 1 - raw differentials; specification 2 - conditioned on personal controls; and specification 3 - conditioned on personal and workplace controls), the three summary statistics of interest ($SD(\varphi)$, $|\varphi|$ and R^2) are presented. Row (a) has the OLS results for the pooled data, while row (b) contains the results for the fixed-effects estimator. The 1-digit industry results are in the top half of the table while the 2-digit results are in the bottom half. Reading across the rows of Table 5 demonstrates the importance of personal and workplace/workforce controls in explaining inter-industry differentials, while reading down the columns in each Panel displays the contribution that individual fixed-effects makes to the differentials. We

[33] Of course, our fixed-effects capture the contribution of observed time-invariant characteristics (such as gender and race) as well as unobserved heterogeneity, and hence the comparison above between the pooled and fixed-effects results is not quite accurate. We can gain some insight into the relative contribution of such characteristics by re-estimating the pooled specification without them. Our results show that the central conclusion stated above remains valid. Indeed, gender and race contribute little to the overall dispersion in wages, and hence the improvement in explanatory power evident in the FE estimates derives principally from unobserved rather than observed time-invariant individual characteristics.

now turn to discuss the robustness of our findings, and investigate some possible alternative explanations to those given above using a number of empirical experiments.

Our first experiment is to take account of the fact that the pooled estimates fail to recognise that the observations are not truly independent but contain repeated observations on the same individuals – a feature we exploit for the fixed-effects estimates. Thus we are not precisely replicating the cross-sectional results that appear in the standard literature on inter-industry wage differentials. A fairer comparator for our fixed-effects estimates is with wave-by-wave cross-section estimates. A summary of such estimates is given in Panel B of Table 5 where we present averages for the eight cross-sections taken separately. As noted above, the cross-section estimates produce differentials which are remarkably stable and persistent across the eight waves.

As mentioned previously, the fixed-effects coefficients indicate the true penalty or premia earned in those industries for which switchers are observed. Our pooled results in contrast represent estimations across the whole sample that includes both switchers and non-switchers. Gibbons and Katz (1992) argue that the switching process may not be exogenous. Therefore, comparison of the estimated dispersion in industry wages across the pooled and panel results may suffer from endogeneity bias. The correct modelling of the industry switching process requires identification of a set of variables some of which are independent of the wage formation process. Such variable selection is often weak or infeasible in microeconometric data analysis. Consequently, arbitrary exclusion restrictions may end up driving the results. One way of tackling this issue is therefore to re-estimate the pooled and panel results only for the sub-sample of individuals who are observed to switch industry.[34] The results from this second experiment are presented in Panel C of Table 5. As can be seen, working with this restricted sample makes no difference to the tenor of our results at either the 1-digit or 2-digit industry level. This suggests that the switchers are a fairly random draw from our original sample.[35]

Thirdly, we investigated the sensitivity of our results to the fact that our sample is an unbalanced panel of individuals, some of whom were only interviewed on relatively few occasions (see Table 2). The results obtained from re-estimating the pooled and fixed-effects specifications using a balanced panel for individuals observed in all eight waves are presented in Panel D of Table 5. As can be seen, these are qualitatively identical, and quantitatively very similar to those presented and discussed above.

Fourthly, we examined the impact of using the (individual) weights provided with the BHPS data to correct for the sample design and non-response rates. Technically, these should be used in any analysis utilising the BHPS to ensure that the marginal distributions in the data match the known distribution in the population. Cross-section weights are supplied for each wave, and longitudinal weights (which also correct for possible attrition biases in the panel) are provided for individuals who have been interviewed in all eight waves. Panel E of Table 5 contains the results for the weighted regressions using the longitudinal weights. None of our conclusions are affected by the use of these weights in either the pooled cross-section or fixed-effects results, and indeed, our conclusions hold *a fortiori* in the weighted regression results.

[34] For comparison purposes, industry switchers at the 1-digit (2-digit) level account for 37% (50%) of the original sample.

[35] There are small differences between Panel A, row (b) and Panel C, row (b) even though both rows only reflect switchers due to the fact that the standard errors in the former are based on the full sample rather than the sub-sample, even though the point estimates will be identical.

Finally, we estimated our wage equations separately for men and women. It is well known that rates of return to educational qualifications, for example, can differ markedly between men and women, and that there are important labour force participation decision differences by gender which can impact on wages. Panel F and G of Table 5 contain the summary statistics of interest. The estimated differentials are slightly greater for women than for men, although a higher proportion of the overall variation in wages is explained for men. But, once again, our substantive findings are not sensitive to this dichotomisation of the data, and hence our main results are not driven by aggregation across gender, or the impact of any participation differences between men and women.

3.6 Conclusion

This chapter has investigated the existence, stability and magnitude of British inter-industry wage differentials using longitudinal data drawn from the BHPS. Our results, using the improved methodology of Haisken-DeNew and Schmidt (1997), cast considerable uncertainty over the existence of substantial inter-industry wage differentials in Britain. In turn, this implies that there is little role for non-competitive explanations of the wage structure.

We first show that observed differences in worker and workplace characteristics accounts for about 55% of raw industry wage differentials, and slightly more than half of the total dispersion in wages. However, as in traditional cross-section estimates of the wage distribution, considerable inter-industry dispersion remains unexplained, and there is also still considerable unexplained variation in wages. We then exploit the panel dimension of our data, and re-estimate our earnings functions using fixed-effects. Our fixed-effects estimates which additionally capture unobserved individual heterogeneity suggest that, in total, observed and unobserved differences between individuals account for 84% of the 1-digit industry wage pattern (or 82% if we use the finer 2-digit classification). Moreover, such earnings functions explain well over 90% of the total variation in wages. Hence our results are in line with those of Keane (1993) and Shippen (1999) for the US, and Abowd *et al.* (1999) for France, which emphasise the importance of unobserved individual-specific effects, while they contrast with those papers in the inter-industry wage structure literature which conclude that unobserved heterogeneity is relatively unimportant, and that non-competitive explanations for the wage distribution are apposite.

While much of the inter-industry variation in wages can be attributed to unmeasured individual effects, it is important to note that there are still statistically significant differences in wages between industries, which average around 3-4%. It is these differentials (which are much smaller than those estimated from conventional cross-section regressions) that are possibly generated by non-competitive forces in wage determination. However, they may equally be explained by sorting of individuals into industries which reward unobserved abilities more highly or by fixed firm or individual-industry effects which we cannot capture in the absence of matched employer-employee data. Their analysis is an area of research that we intend to pursue in the near future. Nevertheless, it can be noted that the stability of the inter-industry dispersion over time provides evidence against union threat explanations of wage differentials since the decreasing influence of trades unions in Britain should have led to a narrowing in the inter-industry dispersion over the sample period. The stability in the estimated wage structure is also evidence against efficiency wage theories; industries paying efficiency wages will have relatively rigid real wages *cf.* those that pay competitive wages and hence there should be a widening of the wage distribution in recessions and a contraction in booms while no such changes are evident over our sample period. Whatever their explanation, the important point to note here is that such inter-industry differentials are considerably smaller than those that are obtained from conventional cross-section estimates.

One broad interpretation of our results, especially given that there is very little variation in wages that remains unexplained, is that they give greater support to standard competitive human capital and compensating differentials theories. These presuppose that workers are paid according to their marginal productivity which in turn will be correlated with both observed and unobserved individual characteristics, and the characteristics of their jobs. This finding is in direct contrast to the conclusions of Dickens and Katz (1987a, 1987b) and Krueger and Summers (1987, 1988), who cast doubt on human capital explanations of inter-industry phenomena. The result is consistent, however, with other panel studies reported recently for the US and France.

Table 1

Distribution of Observations for BHPS Waves 1-8

Wave of interview	*Males*	*Females*	*Total*
Wave 1	2,279	2,276	4,555
Wave 2	2,061	2,085	4,146
Wave 3	1,961	2,048	4,009
Wave 4	1,984	2,075	4,059
Wave 5	1,985	2,054	4,029
Wave 6	2,084	2,150	4,234
Wave 7	2,320	2,324	4,644
Wave 8	2,394	2,430	4,824
Total	17,058	17,442	34,500

Table 2

Distribution of Individuals for BHPS Waves 1-8

No. of waves individual is observed	*Males*	*Females*	*Total*
1 wave	1,052	1,017	2,069
2 waves	698	710	1,408
3 waves	411	412	823
4 waves	333	346	679
5 waves	276	326	602
6 waves	282	319	601
7 waves	379	415	794
8 waves	790	742	1,532
Total	4,221	4,287	8,508

Table 3A

1-digit Inter-Industry Wage Differentials 1991-1998: Pooled Regressions

1-digit industry	Specification 1		Specification 2		Specification 3	
Agriculture, forestry and fishing	-0.279	(11.76)	-0.222	(11.72)	-0.004	(0.26)
Energy and water supplies	0.388	(22.16)	0.246	(17.58)	0.198	(15.68)
Minerals, metal manufacture and chemicals	0.140	(10.62)	0.107	(10.11)	0.089	(9.10)
Metal goods, engineering and vehicles	0.112	(14.95)	0.066	(10.83)	0.077	(12.84)
Other manufacturing	-0.079	(10.58)	-0.012	(1.91)	0.010	(1.67)
Construction	0.034	(2.40)	0.005	(0.47)	0.055	(5.38)
Distribution, hotels and catering	-0.308	(60.08)	-0.182	(43.37)	-0.108	(24.35)
Transport and communication	0.023	(2.34)	-0.005	(0.68)	0.001	(0.19)
Banking, finance and insurance services	0.177	(27.47)	0.118	(22.75)	0.111	(21.70)
Other services	0.062	(17.59)	0.024	(7.71)	-0.033	(7.59)
Diagnostics						
R^2	0.1229		0.4495		0.5737	
$SD(\varphi)$	0.1721		0.1037		0.0764	
$\lvert\varphi\rvert$	0.1383		0.0765		0.0629	
F(industry dummies)	536.8 [0.00]		290.1 [0.00]		161.5 [0.00]	
F(personal controls)	-		584.1 [0.00]		264.6 [0.00]	
F(workplace controls)	-		-		286.4 [0.00]	
NT	34,500		34,500		34,500	

Notes

1. Specification 1 reports the raw 1-digit inter-industry wage differentials.
2. Specification 2 includes personal controls: 5 segment piecewise linear spline for age and dummies for gender, race (2), marital status (3), highest qualification (7), registered disabled, health limits work, head of household, own children in household, age of children in household (3), recent labour market experience (2), region (11).
3. Specification 3 includes personal controls (see note 2) and workplace controls: dummies for occupation (9), firm size (8), full-time work, temporary work, contract work, private sector, union recognition, union member, manager, supervisor, shift worker, bonus in pay, annual increments in pay, travel to work time greater than 45 minutes, time (wave) dummies (8).
4. The F-tests are for the joint exclusion of the variables in parentheses; p-values in [ ].
5. For comparison, the R^2's for Specification 2 and 3 excluding the industry effects are 0.4078 and 0.5557 respectively.
6. $SD(\varphi)$ is the weighted and adjusted standard deviation of the inter-industry differentials calculated according to the Haisken-DeNew & Schmidt methodology; $\lvert\varphi\rvert$ is the weighted average absolute differential. See text for details.

Table 3B

1-digit Inter-Industry Wage Differentials 1991-1998:Panel (FE) Regressions

1-digit industry	Specification 1		Specification 2		Specification 3	
Agriculture, forestry and fishing	-0.028	(1.15)	-0.025	(1.10)	-0.010	(0.46)
Energy and water supplies	0.126	(6.53)	0.124	(6.74)	0.102	(5.64)
Minerals, metal manufacture and chemicals	0.035	(2.65)	0.033	(2.59)	0.025	(2.02)
Metal goods, engineering and vehicles	0.019	(2.39)	0.028	(3.69)	0.029	(3.76)
Other manufacturing	-0.001	(0.13)	0.009	(1.17)	0.010	(1.25)
Construction	0.011	(0.82)	0.007	(0.50)	0.022	(1.73)
Distribution, hotels and catering	-0.068	(12.75)	-0.055	(10.70)	-0.042	(7.96)
Transport and communication	0.014	(1.31)	-0.007	(0.65)	-0.014	(1.36)
Banking, finance, and insurance services	0.029	(4.08)	0.018	(2.71)	0.028	(4.26)
Other services	0.009	(1.76)	0.004	(0.81)	-0.007	(1.31)
Diagnostics						
R^2	0.9172		0.9262		0.9293	
$SD(\varphi)$	0.0369		0.0314		0.0271	
$\lvert\varphi\rvert$	0.0267		0.0220		0.0220	
F(industry dummies)	22.87 [0.00]		18.55 [0.00]		13.32 [0.00]	
F(personal controls)	-		94.84 [0.00]		40.13 [0.00]	
F(workplace controls)	-		-		31.81 [0.00]	
NT	34,500		34,500		34,500	

Notes
1. See notes to Table 3A.
2. Specification 1 reports raw 2-digit differentials controlling for unobserved individual heterogeneity; Specification 2 includes personal controls; Specification 3 includes both personal and workplace controls.
3. For comparison, the R^2's for Specification 2 and 3 excluding the industry effects are 0.9257 and 0.9290 respectively.

Table 4A

2-digit Inter-Industry Wage Differentials 1991-1998: Pooled Regressions

2-digit industry	Specification 1		Specification 2		Specification 3	
Agriculture, horticulture, forestry and fishing	-0.279	(12.34)	-0.223	(12.12)	-0.018	(1.05)
Solid fuels, oil and natural gas, nuclear fuel	0.439	(16.79)	0.315	(14.87)	0.262	(13.63)
Energy & water production & distribution	0.352	(16.12)	0.219	(12.31)	0.179	(11.02)
Metallic and non-metallic minerals	0.052	(2.71)	0.073	(4.68)	0.064	(4.45)
Chemicals and man-made fibres	0.209	(12.35)	0.141	(10.29)	0.112	(8.84)
Metal goods	-0.068	(3.04)	-0.006	(0.33)	0.036	(2.15)
Mechanical engineering	0.103	(7.20)	0.055	(4.68)	0.077	(7.09)
Office machinery & data processing equip.	0.160	(5.44)	0.077	(3.22)	0.084	(3.91)
Electrical and electronic engineering	0.097	(6.54)	0.071	(5.84)	0.072	(6.42)
Motor Vehicles and parts	0.155	(7.79)	0.099	(6.09)	0.081	(5.42)
Other transport equipment	0.230	(9.37)	0.155	(7.80)	0.106	(5.83)
Instrument engineering	0.203	(7.07)	0.111	(4.76)	0.148	(7.05)
Food, drink and tobacco	-0.129	(9.35)	-0.055	(4.92)	-0.036	(3.47)
Textiles, footwear & clothing, leather goods	-0.278	(14.68)	-0.113	(7.29)	-0.117	(8.11)
Timber and wooden furniture	-0.152	(7.43)	-0.065	(3.90)	0.021	(1.35)
Paper and paper products	0.121	(8.49)	0.100	(8.61)	0.103	(9.61)
Rubber, plastics and other manufacturing	-0.074	(3.89)	0.013	(0.86)	0.031	(2.17)
Construction	0.034	(2.52)	0.014	(1.24)	0.060	(5.95)
Wholesale distribution, scrap and waste	-0.070	(5.69)	-0.050	(4.95)	0.010	(1.07)
Retail Distribution	-0.314	(44.10)	-0.182	(31.03)	-0.138	(21.03)
Hotels and Catering	-0.499	(45.45)	-0.308	(34.20)	-0.194	(22.03)
Repair of consumer goods and vehicles	-0.252	(10.87)	-0.199	(10.55)	-0.081	(4.65)
Air/land/sea transport services and storage	-0.051	(4.30)	-0.061	(6.35)	-0.035	(3.87)
Postal services and telecommunications	0.153	(9.68)	0.106	(8.28)	0.096	(8.11)
Banking and Finance	0.223	(17.25)	0.200	(18.93)	0.134	(13.16)
Insurance, except for social security	0.210	(12.22)	0.184	(13.22)	0.144	(11.24)
Business Services	0.174	(19.90)	0.089	(12.42)	0.116	(16.81)
Owning and dealing in real estate	-0.010	(0.44)	-0.010	(0.55)	0.007	(0.44)
Public admin, defence, social security	0.280	(34.44)	0.179	(27.01)	0.090	(11.72)
Sanitary Services	-0.334	(13.38)	-0.206	(10.18)	-0.059	(3.15)
Education, R&D	0.141	(19.21)	0.002	(0.37)	-0.059	(7.85)
Hospitals and other medical institutions	0.029	(3.27)	0.066	(9.02)	-0.055	(7.09)
Social welfare, charities etc.	-0.083	(7.93)	-0.080	(9.31)	-0.094	(10.52)
Film, radio & television, literature, museums	-0.136	(7.83)	-0.083	(5.85)	-0.051	(4.03)
Personal and domestic services	-0.551	(26.61)	-0.353	(20.96)	-0.155	(9.87)
Diagnostics						
R^2	0.2041		0.4816		0.5860	
$SD(\varphi)$	0.2216		0.1399		0.1009	
$\lvert\varphi\rvert$	0.1835		0.1127		0.0897	
F(industry dummies)	259.9 [0.00]		144.3 [0.00]		74.05 [0.00]	
F(personal controls)	-		526.8 [0.00]		237.6 [0.00]	
F(workplace controls)	-		-		247.7 [0.00]	
NT	34,500		34,500		34,500	

Notes:

1. See notes to Table 3A.

Table 4B

2-digit Inter-Industry Wage Differentials 1991-1998: Panel (FE) Regressions

2-digit industry	Specification 1		Specification 2		Specification 3	
Agriculture, horticulture, forestry and fishing	-0.037	(1.54)	-0.034	(1.49)	-0.013	(0.58)
Solid fuels, oil and natural gas, nuclear fuel	0.189	(6.80)	0.186	(7.04)	0.161	(6.22)
Energy & water production & distribution	0.078	(2.92)	0.075	(2.95)	0.064	(2.56)
Metallic and non-metallic minerals	0.024	(1.25)	0.003	(1.69)	0.026	(1.49)
Chemicals and man-made fibres	0.059	(3.27)	0.044	(2.55)	0.040	(2.32)
Metal goods	0.042	(2.20)	0.046	(2.56)	0.052	(2.89)
Mechanical engineering	0.015	(1.14)	0.021	(1.67)	0.026	(2.11)
Office machinery & data processing equip.	-0.014	(0.59)	0.017	(0.79)	0.027	(1.23)
Electrical and electronic engineering	0.029	(2.17)	0.038	(2.99)	0.042	(3.29)
Motor Vehicles and parts	0.037	(1.84)	0.043	(2.25)	0.042	(2.26)
Other transport equipment	0.047	(1.87)	0.059	(2.45)	0.052	(2.20)
Instrument engineering	0.019	(0.81)	0.019	(0.86)	0.024	(1.09)
Food, drink and tobacco	-0.001	(0.10)	0.007	(0.52)	0.009	(0.66)
Textiles, footwear & clothing, leather goods	-0.054	(2.46)	-0.042	(1.99)	-0.045	(2.15)
Timber and wooden furniture	0.006	(0.29)	0.012	(0.62)	0.024	(1.32)
Paper and paper products	0.005	(0.28)	0.020	(1.28)	0.030	(1.93)
Rubber, plastics and other manufacturing	0.016	(0.97)	0.022	(1.40)	0.024	(1.53)
Construction	0.019	(1.39)	0.013	(0.94)	0.030	(2.29)
Wholesale distribution, scrap and waste	-0.016	(1.51)	-0.008	(0.80)	0.004	(0.36)
Retail Distribution	-0.080	(10.08)	-0.056	(7.43)	-0.047	(5.85)
Hotels and Catering	-0.122	(11.45)	-0.118	(11.71)	-0.092	(8.95)
Repair of consumer goods and vehicles	-0.064	(3.00)	-0.044	(2.17)	-0.026	(1.30)
Air/land/sea transport services and storage	-0.006	(0.43)	-0.030	(2.42)	-0.029	(2.38)
Postal services and telecommunications	0.083	(3.99)	0.071	(3.58)	0.051	(2.63)
Banking and Finance	0.077	(4.45)	0.083	(5.04)	0.064	(3.93)
Insurance, except for social security	0.043	(2.25)	0.052	(2.85)	0.047	(2.61)
Business Services	0.020	(2.29)	0.007	(0.91)	0.028	(3.39)
Owning and dealing in real estate	0.025	(1.37)	0.003	(0.16)	0.011	(0.63)
Public admin, defence, social security	0.052	(5.28)	0.041	(4.35)	0.020	(2.12)
Sanitary Services	-0.011	(0.55)	-0.020	(1.04)	-0.002	(0.12)
Education, R&D	0.024	(2.41)	0.014	(1.48)	-0.008	(0.78)
Hospitals and other medical institutions	-0.017	(1.40)	-0.026	(2.29)	-0.037	(3.20)
Social welfare, charities etc.	-0.009	(0.84)	-0.021	(2.00)	-0.030	(2.83)
Film, radio/television, literature, museums	-0.043	(2.41)	-0.042	(2.49)	-0.035	(2.12)
Personal and domestic services	-0.161	(6.81)	-0.113	(5.04)	-0.075	(3.36)
Diagnostics						
R^2	0.9178		0.9267		0.9297	
$SD(\varphi)$	0.0530		0.0468		0.0394	
$\lvert\varphi\rvert$	0.0414		0.0378		0.0346	
F(industry dummies)	11.43 [0.00]		10.18 [0.00]		6.76 [0.00]	
F(personal controls)	-		94.65 [0.00]		39.79 [0.00]	
F(workplace controls)	-		-		29.75 [0.00]	
NT	34,500		34,500		34,500	

Notes:

1. See notes to Table 3B.
2. Specification 1 reports raw 2-digit differentials controlling for unobserved individual heterogeneity; Specification 2 includes personal controls; Specification 3 includes both personal and workplace controls

Table 5

Summary of Results and Robustness Tests

	Description	Sample Selection/Definition:	Specification 1			Specification 2			Specification 3		
		1-digit industry definitions	$SD(\varphi)$	$\lvert\varphi\rvert$	R^2	$SD(\varphi)$	$\lvert\varphi\rvert$	R^2	$SD(\varphi)$	$\lvert\varphi\rvert$	R^2
A	Basic results (Table 3A & 3B)	(a) Pooled: NT=34500	0.1721	0.1383	0.1229	0.1037	0.0765	0.4495	0.0764	0.0629	0.5737
		(b) Fixed-effects: N=8508	0.0370	0.0267	0.9172	0.0314	0.0220	0.9262	0.0271	0.0220	0.9293
B	Cross-section	Average of 8 cross-section estimates	0.1717	0.1385	0.1241	0.1030	0.0772	0.4527	0.0757	0.0644	0.5793
C	Switchers	(a) Pooled: NT=12710	0.1513	0.1283	0.0956	0.0894	0.0737	0.4363	0.0624	0.0554	0.5661
		(b) Fixed-effects: N=2354	0.0366	0.0266	0.8815	0.0306	0.0217	0.8960	0.0239	0.0208	0.9034
D	Balanced Panel	(a) Pooled: NT=12256	0.1583	0.1167	0.1254	0.1059	0.0748	0.4426	0.0775	0.0641	0.5776
		(b) Fixed-effects: N=1532	0.0355	0.0269	0.9159	0.0328	0.0258	0.9259	0.0291	0.0228	0.9290
E	Weighted	(a) Pooled: NT=12256	0.1708	0.1362	0.1198	0.1032	0.0759	0.4510	0.0759	0.0622	0.5782
		(b) Fixed-effects: N=1532	0.0396	0.0297	0.8358	0.0353	0.0270	0.8553	0.0312	0.0237	0.8612
F	Men only	(a) Pooled: NT=17058	0.1713	0.1457	0.1274	0.0983	0.0729	0.4514	0.0718	0.0566	0.5545
		(b) Fixed-effects: N=4221	0.0376	0.0281	0.9171	0.0244	0.0174	0.9280	0.0210	0.0182	0.9311
G	Women only	(a) Pooled: NT=17442	0.1688	0.1465	0.1314	0.1028	0.0834	0.3987	0.0762	0.0671	0.5560
		(b) Fixed-effects: N=4287	0.0416	0.0318	0.9036	0.0411	0.0296	0.9131	0.0396	0.0325	0.9174
		2-digit industry definitions	$SD(\varphi)$	$\lvert\varphi\rvert$	R^2	$SD(\varphi)$	$\lvert\varphi\rvert$	R^2	$SD(\varphi)$	$\lvert\varphi\rvert$	R^2
A	Basic results (Table 4A & 4B)	(a) Pooled: NT=34500	0.2216	0.1835	0.2041	0.1399	0.1127	0.4816	0.1009	0.0897	0.5860
		(b) Fixed-effects: N=8508	0.0530	0.0414	0.9178	0.0468	0.0378	0.9267	0.0394	0.0346	0.9297
B	Cross-section	Average of 8 cross-section estimates	0.2214	0.1853	0.2095	0.1392	0.1150	0.4874	0.0999	0.0909	0.5932
C	Switchers	(a) Pooled: NT=17146	0.2030	0.1651	0.1741	0.1242	0.1007	0.4753	0.0867	0.0778	0.4776
		(b) Fixed-effects: N=3150	0.0523	0.0414	0.8894	0.0457	0.0374	0.9031	0.0357	0.0333	0.9091
D	Balanced Panel	(a) Pooled: NT=12256	0.2047	0.1659	0.2109	0.1436	0.1153	0.4847	0.1109	0.0976	0.5995
		(b) Fixed-effects: N=1532	0.0526	0.0447	0.9167	0.0459	0.0395	0.9265	0.0419	0.0371	0.9295
E	Weighted	(a) Pooled: NT=12256	0.2209	0.1819	0.2006	0.1396	0.1117	0.4829	0.1005	0.0895	0.5906
		(b) Fixed-effects: N=1532	0.0567	0.0487	0.8373	0.0489	0.0421	0.8565	0.0441	0.0390	0.8622
F	Men only	(a) Pooled: NT=17058	0.2091	0.1748	0.1907	0.1267	0.1004	0.4774	0.0979	0.0824	0.5715
		(b) Fixed-effects: N=4221	0.0660	0.0503	0.9181	0.0551	0.0398	0.9288	0.0488	0.0363	0.9318
G	Women only	(a) Pooled: NT=17442	0.2168	0.1879	0.2176	0.1447	0.1214	0.4412	0.0957	0.0852	0.5663
		(b) Fixed-effects: N=4287	0.0544	0.0459	0.9045	0.0525	0.0461	0.9139	0.0495	0.0455	0.9179

APPENDIX

Table A1: Data Definitions and Summary Statistics

Variable	*Definition and Description*	*Mean*	*SD*
Dependent Variable:			
Log of real hourly wage	Log of hourly wage deflated by RPI	1.599	0.492
Independent Variables			
Age	Age at December of interview	37.10	11.20
Gender	(1,0) if female	0.506	
Race			
White (reference)	(1,0) if white	0.967	
Black	(1,0) if black ethnic origin	0.010	
Other non-white	(1,0) if other ethnic origin	0.023	
Marital Status			
Never Married	(1,0) if never married	0.203	
Married/Living as a Couple (reference)	(1,0) if married or living as a couple	0.722	
Widowed/Separated/Divorced	(1,0) if widowed, separated or divorced	0.075	
Highest Qualification			
Higher or First Degree, Teaching	(1,0) qualification dummy	0.158	
Other Higher Education	(1,0) qualification dummy	0.199	
GCE A-level	(1,0) qualification dummy	0.132	
GCE O-level (reference)	(1,0) qualification dummy	0.236	
CSE Grade1-5	(1,0) qualification dummy	0.048	
Apprenticeship, Nursing, Other	(1,0) qualification dummy	0.068	
No Qualification	(1,0) qualification dummy	0.159	
Health			
Registered Disabled	(1,0) if registered disabled	0.008	
Limits types of work	(1,0) if health limits work	0.073	
Other Personal Controls			
Head of Household	(1,0) if head of household	0.493	
Own Children	(1,0) if own children in household	0.360	
Children aged 0-4 Years	(1,0) if children aged <5 years in hh	0.123	
Children aged 5-11 Years	(1,0) if children aged 5-11 years in hh	0.197	
Children aged 12-15 Years	(1,0) if children aged 12-15 years in hh	0.133	
Unemployed in Past Year	(1,0) if unemployment spell in past year	0.058	
Non-Participant in Past Year	(1,0) if non-participation spell in past year	0.060	
Size of Establishment			
<10 Employees (reference)	(1,0) if <10 employees	0.172	
10-24 Employees	(1,0) if 10-24 employees	0.161	
25-49 Employees	(1,0) if 25-49 employees	0.147	
50-99 Employees	(1,0) if 50-99 employees	0.117	
100-199 Employees	(1,0) if 100-199 employees	0.107	
200-499 Employees	(1,0) if 200-499 employees	0.131	
500-999 Employees	(1,0) if 500-999 employees	0.067	
>1000 Employees	(1,0) if >1000 employees	0.098	
Workplace and Other Controls			
Full-time	(1,0) if work >30 hours per week	0.813	
Private Sector	(1,0) if private sector employment	0.692	
Seasonal or Temporary Employment	(1,0) if seasonal or temporary emp't	0.034	
Contract or Fixed Term Employment	(1,0) if contract or fixed term emp't	0.031	
Promotion Opportunities	(1,0) if job has promotion opportunities	0.503	
Bonuses or Profit	(1,0) if pay includes bonuses or profits	0.299	
Annual Increments	(1,0) if pay includes annual increments	0.459	
Union or Staff Association	(1,0) if union or staff association at work	0.500	
Member of Union	(1,0) if member of workplace union	0.326	
Rotating Shifts	(1,0) if work involves rotating shifts	0.102	
Manager	(1,0) if manager	0.190	
Supervisor	(1,0) if supervisor	0.172	
Travel 45+ Minutes	(1,0) if travel to work 60+ Minutes	0.131	

Regions of the UK			
Greater London (reference)	(1,0) regional dummy	0.101	
Rest of the South	(1,0) regional dummy	0.198	
East Anglia	(1,0) regional dummy	0.037	
South West	(1,0) regional dummy	0.088	
West Midlands	(1,0) regional dummy	0.090	
East Midlands	(1,0) regional dummy	0.083	
Yorkshire	(1,0) regional dummy	0.093	
North West	(1,0) regional dummy	0.104	
North	(1,0) regional dummy	0.065	
Wales	(1,0) regional dummy	0.048	
Scotland	(1,0) regional dummy	0.093	
Occupation Major Groups			
Managers and Administrators	(1,0) occupation dummy	0.127	
Professional Occupations	(1,0) occupation dummy	0.102	
Associate Professionals & Tech	(1,0) occupation dummy	0.107	
Clerical and Secretarial (reference)	(1,0) occupation dummy	0.200	
Craft and Related	(1,0) occupation dummy	0.109	
Personal and Protective Services	(1,0) occupation dummy	0.108	
Sales	(1,0) occupation dummy	0.072	
Plant and Machine Operatives	(1,0) occupation dummy	0.100	
Other Occupations	(1,0) occupation dummy	0.075	
1-digit industry groups			
Agriculture, forestry & fishing	(1,0) industry dummy	0.011	
Energy and water supplies	(1,0) industry dummy	0.020	
Minerals, metal manufacture & chemicals	(1,0) industry dummy	0.034	
Metal goods, engineering and vehicles	(1,0) industry dummy	0.099	
Other manufacturing	(1,0) industry dummy	0.099	
Construction	(1,0) industry dummy	0.030	
Distribution, hotels and catering	(1,0) industry dummy	0.189	
Transport and communication	(1,0) industry dummy	0.060	
Banking, finance, & insurance services	(1,0) industry dummy	0.129	
Other services	(1,0) industry dummy	0.329	
2-digit industry groups			
Agriculture, horticulture, forestry & fish.	(1,0) industry dummy	0.011	
Solid fuels, oil & natural gas, nuclear fuel	(1,0) industry dummy	0.008	
Energy & water production & distribution	(1,0) industry dummy	0.012	
Metallic and non-metallic minerals	(1,0) industry dummy	0.015	
Chemicals and man-made fibres	(1,0) industry dummy	0.019	
Metal goods	(1,0) industry dummy	0.011	
Mechanical engineering	(1,0) industry dummy	0.027	
Office machinery & data processing equip	(1,0) industry dummy	0.006	
Electrical and electronic engineering	(1,0) industry dummy	0.025	
Motor vehicle parts	(1,0) industry dummy	0.014	
Other transport equipment	(1,0) industry dummy	0.009	
Instrument engineering etc.	(1,0) industry dummy	0.007	
Food, drink and tobacco	(1,0) industry dummy	0.029	
Textiles, footwear and clothing, leather	(1,0) industry dummy	0.015	
Timber and wooden furniture	(1,0) industry dummy	0.013	
Paper and paper products	(1,0) industry dummy	0.027	
Rubber, plastics & other manufacturing	(1,0) industry dummy	0.015	
Construction	(1,0) industry dummy	0.030	
Wholesale distribution, scrap and waste	(1,0) industry dummy	0.035	
Retail Distribution	(1,0) industry dummy	0.099	
Hotels and Catering	(1,0) industry dummy	0.044	
Repair of consumer goods and vehicles	(1,0) industry dummy	0.010	
Air/land/sea transport services/storage	(1,0) industry dummy	0.039	
Postal services and telecommunications	(1,0) industry dummy	0.022	
Banking and Finance	(1,0) industry dummy	0.032	
Insurance, except for social security	(1,0) industry dummy	0.019	
Business Services	(1,0) industry dummy	0.068	

Owning and dealing in real estate	(1,0) industry dummy	0.010	
Public admin., defence, social security	(1,0) industry dummy	0.078	
Sanitary Services	(1,0) industry dummy	0.009	
Education, R&D	(1,0) industry dummy	0.094	
Hospitals and other medical institutions	(1,0) industry dummy	0.068	
Social welfare, charities etc.	(1,0) industry dummy	0.049	
Film, radio/television, literature, museums	(1,0) industry dummy	0.018	
Personal and domestic services	(1,0) industry dummy	0.013	
NT		34,500	

Table A2

Earnings Equations: BHPS 1991-1998: 1-digit Industries

	Pooled		Fixed-Effects	
Dependent Variable: log real hourly wage	**Table 3A Specification 3**		**Table 3B Specification 3**	
Personal Controls				
Age 16-26	0.036	(26.75)	0.085	(0.72)
Age 26-33	0.014	(12.24)	0.050	(0.42)
Age 33-40	0.000	(0.25)	0.037	(0.31)
Age 40-48	-0.000	(0.58)	0.036	(0.30)
Age 48-64	-0.002	(2.64)	0.027	(0.23)
Gender	-0.131	(26.06)	-	
Black	-0.044	(2.51)	-	
Other	-0.053	(4.57)	-	
Widowed, Separated or Divorced	-0.081	(11.25)	-0.015	(1.53)
Never married	-0.054	(9.45)	-0.015	(1.77)
Higher or First Degree, Teaching	0.162	(23.38)	0.116	(5.38)
Other Higher Education	0.061	(11.01)	0.039	(3.35)
GCE A-level	0.041	(6.70)	0.054	(3.84)
CSE Grade1-5	-0.025	(2.83)	-0.024	(0.89)
Apprenticeship, Nursing, Other	-0.040	(5.16)	0.055	(2.56)
No Qualification	-0.116	(18.99)	0.027	(1.34)
Registered Disabled	-0.111	(5.73)	-0.034	(1.37)
Health Limits types of work	-0.042	(6.12)	-0.033	(4.96)
Head of Household	0.056	(11.77)	0.011	(1.69)
Own Children	0.007	(0.82)	0.007	(0.84)
Children aged 0-4 Years	0.033	(4.10)	-0.009	(1.34)
Children aged 5-11 Years	-0.012	(1.74)	-0.007	(1.06)
Children aged 12-15 Years	-0.030	(3.89)	-0.004	(0.58)
Unemployed in past year	-0.082	(10.55)	-0.032	(4.77)
Non-participant in past year	-0.095	(12.08)	-0.062	(9.05)
Workplace Controls				
10-24 Employees	0.102	(16.72)	0.034	(5.64)
25-49 Employees	0.114	(17.98)	0.043	(6.72)
50-99 Employees	0.161	(23.50)	0.061	(8.56)
100-199 Employees	0.165	(23.38)	0.060	(8.24)
200-499 Employees	0.179	(25.99)	0.072	(9.80)
500-999 Employees	0.189	(22.53)	0.077	(8.93)
>1000 Employees	0.205	(26.84)	0.082	(9.65)
Full-time Employment	0.007	(1.21)	-0.108	(16.37)
Private sector	-0.075	(11.21)	-0.033	(4.22)
Seasonal or Temporary Employment	-0.023	(2.23)	-0.039	(4.17)
Contract or Fixed Term Employment	-0.034	(3.31)	-0.010	(1.07)
Promotion Opportunities	0.023	(6.07)	0.006	(1.62)
Bonuses or Profit	0.050	(11.99)	0.029	(7.33)
Annual Increments	0.021	(5.50)	0.013	(3.50)
Union or Staff Association	0.033	(6.13)	0.039	(6.54)
Member of Union	0.079	(14.70)	0.057	(8.79)
Rotating Shifts	0.066	(10.61)	0.021	(3.00)
Manager	0.143	(21.90)	0.041	(6.40)
Supervisor	0.062	(12.64)	0.028	(6.07)
Travel 45+ Minutes	0.081	(15.02)	0.023	(4.03)
Region Dummies				
Rest of the South	-0.105	(15.18)	-0.014	(0.71)
East Anglia	-0.180	(16.73)	-0.032	(0.93)
South West	-0.159	(19.26)	-0.073	(2.57)
West Midlands	-0.219	(26.79)	-0.117	(3.64)
East Midlands	-0.232	(27.55)	-0.047	(1.61)

Yorkshire	-0.221	(27.21)	-0.070	(2.02)
North West	-0.169	(21.36)	-0.048	(1.48)
North	-0.216	(24.01)	-0.101	(2.60)
Wales	-0.210	(21.21)	-0.077	(1.86)
Scotland	-0.174	(21.47)	-0.046	(1.20)
Occupation Major Groups				
Managers and Administrators	0.146	(17.72)	0.030	(3.74)
Professional Occupations	0.201	(24.15)	0.045	(4.42)
Associate Professionals and Technical	0.146	(20.37)	0.041	(4.82)
Craft and Related	-0.027	(3.57)	0.006	(0.62)
Personal and Protective Services	-0.127	(17.52)	-0.061	(6.38)
Sales	-0.065	(7.74)	-0.053	(5.70)
Plant and Machine Operatives	-0.088	(11.29)	-0.016	(1.65)
Other Occupations	-0.189	(23.23)	-0.075	(7.14)
Industry Classes (1-digit)				
Agriculture, forestry and fishing	-0.004	(0.26)	-0.010	(0.46)
Energy and water supplies	0.198	(15.68)	0.102	(5.64)
Minerals, metal manufacture and chemicals	0.089	(9.10)	0.025	(2.02)
Metal goods, engineering and vehicles	0.077	(12.84)	0.029	(3.76)
Other manufacturing	0.010	(1.67)	0.010	(1.25)
Construction	0.055	(5.38)	0.022	(1.73)
Distribution, hotels and catering	-0.108	(24.35)	-0.042	(7.96)
Transport and communication	0.001	(0.19)	-0.014	(1.36)
Banking, finance, insurance & business services	0.111	(21.70)	0.028	(4.26)
Other services	-0.033	(7.59)	-0.007	(1.31)
Time Dummies				
Wave 2	0.020	(2.94)	-0.011	(0.09)
Wave 3	0.019	(2.70)	-0.039	(0.17)
Wave 4	0.020	(2.89)	-0.067	(0.19)
Wave 5	0.018	(2.59)	-0.097	(0.21)
Wave 6	0.025	(3.61)	-0.115	(0.19)
Wave 7	0.016	(2.42)	-0.142	(0.20)
Wave 8	0.024	(3.62)	-0.156	(0.19)
Constant	0.581	(16.49)	-0.942	(0.24)
Diagnostics				
R^2	0.5737		0.9293	
$SD(\varphi)$	0.0764		0.0271	
$\lvert\varphi\rvert$	0.0629		0.0220	
F(industry dummies)	161.5 [0.00]		13.32 [0.00]	
F(personal controls)	264.6 [0.00]		40.13 [0.00]	
F(workplace controls)	286.4 [0.00]		31.81 [0.00]	
NT	34,500		34,500	

Notes: t-ratios in parentheses.

Table A3

Earnings Equations: BHPS 1991-1998: 2-digit Industries

	Pooled		Fixed-Effects	
Dependent variable: log real hourly wage	**Table 4A Specification 3**		**Table 4B Specification 3**	
Personal Controls				
Age 16-26	0.035	(26.01)	0.083	(0.70)
Age 26-33	0.014	(12.24)	0.048	(0.41)
Age 33-40	0.000	(0.27)	0.035	(0.29)
Age 40-48	-0.000	(0.33)	0.034	(0.29)
Age 48-64	-0.002	(2.42)	0.025	(0.21)
Gender	-0.106	(20.93)	-	
Black	-0.033	(1.93)	-	
Other	-0.044	(3.73)	-	
Widowed, Separated or Divorced	-0.073	(10.24)	-0.013	(1.31)
Never married	-0.050	(8.89)	-0.014	(1.72)
Higher or First Degree, Teaching	0.167	(24.31)	0.116	(5.38)
Other Higher Education	0.062	(11.41)	0.039	(3.34)
GCE A-level	0.040	(6.65)	0.054	(3.83)
CSE Grade1-5	-0.023	(2.64)	-0.025	(0.93)
Apprenticeship, Nursing, Other	-0.031	(4.03)	-0.055	(2.59)
No Qualification	-0.105	(17.33)	0.026	(1.33)
Registered Disabled	-0.110	(5.78)	-0.032	(1.30)
Health Limits types of work	-0.041	(6.08)	-0.033	(4.98)
Head of Household	0.056	(11.77)	0.011	(1.72)
Own Children	0.004	(0.47)	0.006	(0.78)
Children aged 0-4 Years	0.037	(4.81)	-0.009	(1.31)
Children aged 5-11 Years	-0.009	(1.36)	-0.007	(1.08)
Children aged 12-15 Years	-0.027	(3.49)	-0.004	(0.52)
Unemployed in past year	-0.078	(10.13)	-0.031	(4.68)
Non-participant in past year	-0.093	(12.01)	-0.061	(9.00)
Workplace Controls				
10-24 Employees	0.097	(16.06)	0.033	(5.46)
25-49 Employees	0.108	(17.05)	0.042	(6.40)
50-99 Employees	0.148	(21.64)	0.058	(8.22)
100-199 Employees	0.151	(21.39)	0.057	(7.79)
200-499 Employees	0.166	(24.18)	0.068	(9.22)
500-999 Employees	0.174	(20.80)	0.072	(8.37)
>1000 Employees	0.191	(24.44)	0.079	(9.19)
Full-time Employment	-0.004	(0.78)	-0.108	(16.47)
Private sector	-0.048	(6.78)	-0.032	(3.98)
Seasonal or Temporary Employment	-0.025	(2.51)	-0.038	(4.11)
Contract or Fixed Term Employment	-0.032	(3.17)	-0.012	(1.26)
Promotion Opportunities	0.020	(5.09)	0.005	(1.41)
Bonuses or Profit	0.045	(10.88)	0.027	(6.96)
Annual Increments	0.019	(4.98)	0.013	(3.43)
Union or Staff Association	0.032	(5.93)	0.038	(6.30)
Member of Union	0.076	(14.35)	0.055	(8.53)
Rotating Shifts	0.065	(10.52)	0.023	(3.24)
Manager	0.145	(22.52)	0.041	(6.45)
Supervisor	0.065	(13.40)	0.028	(6.13)
Travel 45+ Minutes	0.075	(13.99)	0.022	(3.90)
Region Dummies				
Rest of the South	-0.107	(15.73)	-0.011	(0.59)
East Anglia	-0.178	(16.71)	-0.033	(0.97)
South West	-0.162	(19.83)	-0.073	(2.56)
West Midlands	-0.214	(26.40)	-0.115	(3.59)
East Midlands	-0.227	(27.18)	-0.046	(1.58)

Yorkshire	-0.218	(27.12)	-0.077	(2.23)
North West	-0.165	(21.04)	-0.047	(1.47)
North	-0.208	(23.39)	-0.098	(2.53)
Wales	-0.207	(21.12)	-0.084	(2.03)
Scotland	-0.169	(21.05)	-0.048	(1.27)
Occupation Major Groups				
Managers and Administrators	0.169	(20.68)	0.034	(4.15)
Professional Occupations	0.248	(28.77)	0.049	(4.85)
Associate Professionals and Technical	0.179	(24.30)	0.045	(5.33)
Craft and Related	0.007	(0.86)	0.009	(0.91)
Personal and Protective Services	-0.079	(10.42)	-0.044	(4.33)
Sales	-0.047	(5.45)	-0.052	(5.51)
Plant and Machine Operatives	-0.058	(7.43)	-0.016	(1.62)
Other Occupations	-0.151	(17.85)	-0.067	(6.25)
Industry Classes (2-digit)				
Agriculture, horticulture, forestry and fishing	-0.018	(1.05)	-0.013	(0.58)
Solid fuels, oil and natural gas, nuclear fuel	0.262	(13.63)	0.161	(6.22)
Energy and water production and distribution	0.179	(11.02)	0.064	(2.56)
Metallic and non-metallic minerals	0.064	(4.45)	0.026	(1.49)
Chemicals and man-made fibres	0.112	(8.84)	0.040	(2.32)
Metal goods	0.036	(2.15)	0.052	(2.89)
Mechanical engineering	0.077	(7.09)	0.026	(2.11)
Office machinery and data processing equipment	0.084	(3.91)	0.027	(1.23)
Electrical and electronic engineering	0.072	(6.42)	0.042	(3.29)
Motor vehicle parts	0.081	(5.42)	0.042	(2.26)
Other transport equipment	0.106	(5.83)	0.052	(2.20)
Instrument engineering etc.	0.148	(7.05)	0.024	(1.09)
Food, drink and tobacco	-0.036	(3.47)	0.009	(0.66)
Textiles, footwear and clothing, leather goods	-0.117	(8.11)	-0.045	(2.15)
Timber and wooden furniture	0.021	(1.35)	0.024	(1.32)
Paper and paper products	0.103	(9.61)	0.030	(1.93)
Rubber, plastics and other manufacturing	0.031	(2.17)	0.024	(1.53)
Construction	0.060	(5.95)	0.030	(2.29)
Wholesale distribution, scrap and waste	0.010	(1.07)	0.004	(0.36)
Retail Distribution	-0.138	(21.03)	-0.047	(5.85)
Hotels and Catering	-0.194	(22.03)	-0.092	(8.95)
Repair of consumer goods and vehicles	-0.081	(4.65)	-0.026	(1.30)
Air/land/sea transport services and storage	-0.035	(3.87)	-0.029	(2.38)
Postal services and telecommunications	0.096	(8.11)	0.051	(2.63)
Banking and Finance	0.134	(13.16)	0.064	(3.93)
Insurance, except for social security	0.144	(11.24)	0.047	(2.61)
Business Services	0.116	(16.81)	0.028	(3.39)
Owning and dealing in real estate	0.007	(0.44)	0.011	(0.63)
Public admin, defence, social security	0.090	(11.72)	0.020	(2.12)
Sanitary services	-0.059	(3.15)	-0.002	(0.12)
Education, R&D	-0.059	(7.85)	-0.008	(0.78)
Hospitals and other medical institutions	-0.055	(7.09)	-0.037	(3.20)
Social welfare, charities etc.	-0.094	(10.52)	-0.030	(2.83)
Film, radio and television, literature, museums	-0.051	(4.03)	-0.035	(2.12)
Personal and domestic services	-0.155	(9.87)	-0.075	(3.36)
Time Dummies				
Wave 2	0.021	(3.13)	-0.009	(0.08)
Wave 3	0.020	(2.90)	-0.036	(0.15)
Wave 4	0.021	(3.12)	-0.062	(0.17)
Wave 5	0.019	(2.78)	-0.09	(0.19)
Wave 6	0.026	(3.86)	-0.106	(0.18)
Wave 7	0.018	(2.69)	-0.131	(0.18)
Wave 8	0.028	(4.16)	-0.143	(0.17)
Constant	0.574	(16.47)	-0.878	(0.22)

Diagnostics		
R^2	0.5860	0.9297
$SD(\varphi)$	0.1009	0.0394
$\lvert\varphi\rvert$	0.0897	0.0346
F(industry dummies)	74.05 [0.00]	6.76 [0.00]
F(personal controls)	237.6 [0.00]	29.75 [0.00]
F(workplace controls)	247.7 [0.00]	39.79 [0.00]
NT	34,500	34,500

Notes: t-ratios in parentheses.

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Chapter 4 - Individual Wage Determination and Regional Unemployment in the UK

4.1 Introduction

Recent contributions to the literature by Blanchflower & Oswald (1990, 1994a, 1994b, 1995) adhere to the existence of a new empirical law of economics, a stable inverse non-linear relationship between individual pay and the local unemployment rate. They name this new regularity the 'Wage Curve'. The empirical foundation of this relationship is a Mincerian earnings equation augmented with the unemployment rate for an individual's local labour market. The local unemployment rate provides a measure for the degree of joblessness in the local market. The purpose of such equations is thus to examine the role of local unemployment in the determination of local pay, "where causality is to be thought of as running from the amount of joblessness to the level of wages".[1]

Evidence for the existence of a wage curve appears irrefutable. Blanchflower & Oswald (1994b) present evidence utilising information on approximately three and a half million people from a dozen countries. Additional papers utilising datasets from countries as diverse as Belgium, Norway, South Africa and the Ivory Coast extend the result further. The relationship appears virtually identical across a variety of countries, regardless of institutional and industry structure. Results for the US, Britain, South Korea, Canada and a number of other Western European Countries suggest that the unemployment elasticity of pay is –0.1, that is, a 10% increase in local unemployment results in a 1% decrease in local pay. Such uniformity in wage flexibility appears remarkable, particularly in Europe where differences in international wage setting behaviour are frequently cited as a potential explanation of aggregate unemployment.[2] It is not, however, without criticism. Card (1995), in a searching review of the Wage Curve, accepts Blanchflower and Oswald's conclusion of a negative correlation between wages and the local unemployment rate. The origin and interpretation of this correlation remains, however, a source for debate.

Critiques of Blanchflower & Oswald emphasise issues concerning choice of econometric technique. Model specification, sample selection, lagged dependent variables, and endogeneity between unemployment and wages have all been asserted as potential sources of bias in the estimated relationship. Most of these problems arise from the use of repeated cross-section or time-series data. Time-series data frequently suffers from structural instability and the inability to discern important aspects of economic behaviour that are masked by aggregate data. Cross-section data, by contrast, suffers from an inability to study the dynamics of adjustment. Both of these features run the risk of obtaining misleading results. They also give rise to the increased likelihood that observed effects are the consequence of errors in model specification. Panel data, that is, data that follow a given sample of individuals over time, provide a number of significant advantages in this regard. Data that record multiple observations for an individual provide more informative data, more degrees of freedom, less collinearity among explanatory variables and greater control of individual heterogeneity. It also allows for the control of individual fixed effects, effects that are either missing or unobserved but correlated with explanatory variables. The ability to control for missing or unobserved data significantly reduces the probability of specification bias. For the

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[1] Blanchflower & Oswald (1994b), p.3

estimation of earnings equations, such features help capture inter and intra-individual differences inherent in the determination of individual pay. They also alleviate both aggregation[3] and composition bias.[4]

A number of recent studies document the existence of the wage curve using panel data. Bratsberg and Turunen (1996) present panel evidence for the US drawing on data from the National Longitudinal Survey of Youth (NLSY). Janssens and Konings (1998) report evidence using the Belgian Social Economic Panel. Finally, Pannenberg and Schwarze (1998) and Baltagi and Blien (1998) report evidence for Germany utilising the German Socio Economic Panel (GSOEP) and data from the Institut für Arbeitsmarkt und Berufsforschung (IAB). None of these studies provide evidence for the UK. The purpose of this chapter, therefore, is to test for the existence of a wage curve utilising genuine panel data drawn from the first eight waves of the British Household Panel Survey (BHPS). The BHPS is a nationally representative sample of more than 5,000 households (approximately 10,000 individual interviews) and provides a rich source of socio-economic information for issues concerning household organisation, labour market activity, income and wealth, housing, health and education amongst others. We take advantage of the data's features and utilise the panel dimension of the data to assess the existence of a wage curve whilst controlling for the role of unobserved worker heterogeneity in the wage determination process. In addition, we perform a variety of

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[2] See Bean, Layard & Nickell (1989) for details.

[3] Moulton (1986) points out that aggregate variables used as explanatory variables in regressions based on microeconomic data typically result in the substantial downward bias of standard errors. This bias arises from correlation across individuals brought about by a lack of controls for individual heterogeneity.

[4] Solon, Barsky & Parker (1994) demonstrate that the use of wage data from repeated cross sections rather than genuine panel data may result in an upward bias of up to 50 percent in the estimated unemployment elasticity of pay.

diagnostic tests concerning functional form and sample selection to test the robustness of the results.

The remainder of the chapter is organised as follows. Sections 4.2 and 4.3 present a brief overview of recent research on the relationship between wages and unemployment and a more detailed discussion of the theoretical explanations for the Wage Curve. Section 4.4 discusses the data while Section 4.5 outlines the methodology employed. Empirical results and diagnostics are reported in Section 4.6. Section 4.7 concludes.

4.2 The Wage Curve: An Overview

The wage curve challenges economic orthodoxy. Traditional neoclassical analysis built upon the models of Harris-Todaro (1970) and Hall (1970, 1972) posits a positive relationship between regional unemployment and pay. Compensating differentials, it is argued, imply that regions of high unemployment should be regions of higher pay. Firms faced with high unemployment pay higher wages to compensate for higher search costs. Higher wages become affordable since high unemployment reduces quits and thus the costs of hiring and training. A positive locus in wage-unemployment space is therefore predicted.

Table 1 documents early research concerning the spatial distribution of wages and unemployment to support the existence of a positive wage locus.[5] Hall (1970, 1972) reports weak evidence "that wages and unemployment rates are positively related in a

[5] See Blanchflower & Oswald (1994b) for a comprehensive survey of this literature.

Table 1 - A Selective Summary of the Literature on the Relationship Between Wages & Unemployment

Study	Country	Data	Estimation notes	Findings
Hall (1970, 1972)	US	1966 Data for 12 Cities	Descriptive analysis & OLS wage equations	Positive relationship between city pay & city unemployment for men. Weak evidence of a positive relationship between both nominal and real wages & the unemployment rate.
Reza (1978)	US	1967, 1970-74 data for 18 metropolitan areas	OLS wage equations	Positive relationship between both nominal and real wages and unemployment.
Roback (1982)	US	1973 CPS Data for 98 Cities	OLS wage & land rental rate equations	Weak evidence of a positive relationship between male weekly earnings and local unemployment.
Adams (1985)	US	1970-76 PSID Data	OLS wage equations	Positive average unemployment elasticity of pay (≈0.2). Negative industry unemployment elasticity of pay (–0.09).
Marston (1985)	US	1970 CPS Data	OLS wage equations & probit equations for employment	Positive relationship between real area wage and unemployment for both types of equation.
Blackaby & Manning (1987)	UK	1964-84 Regional Data 1974 GHS Data	OLS Phillips Curve & Mincer-Style wage equations	Negative unemployment elasticity of pay (–0.16) for Mincer-style wage equations. Standard Phillips Curve results.
Blackaby & Manning (1990a)	UK	1970-86 Regional data	Dynamic earnings equations	Negative unemployment elasticity of pay for several UK regions
Blackaby & Manning (1990b)	UK	1970-86 Regional data 1975, 1982 GHS data	Mincerian/dynamic earnings equations	Negative unemployment elasticity of pay for both types of equation.
Blackaby & Manning (1990c)	UK	1975, 1982 GHS data	Mincerian/dynamic earnings equations	Negative local unemployment elasticity of pay (–0.13 & -0.19).
Blackaby & Manning (1992)	UK	1972-88 Regional data	Dynamic wage equations	Negative unemployment elasticity of pay .
Layard & Nickell (1986, 1987)	UK	1950-83 Aggregate data	Real dynamic wage equations	Negative unemployment elasticity of wages (-0.06).
Nickell (1987)	UK	1956-83 Aggregate data	Real dynamic wage equations	Negative unemployment elasticity of wages (-0.1)
Carruth & Oswald (1989)	UK	1956-83 Aggregate data	Real dynamic wage equations	Negative unemployment elasticity of wages (–0.05 & -0.1)
Pissarides & McMaster (1990)	UK	1961-82 Regional data	Error Correction models for pooled wage equations	Negative short-run unemployment elasticity of pay. Positive long-run steady-state unemployment elasticity of pay.
Freeman (1988)	US, UK	1979-85 State/County data	OLS real wage equations	Weak negative correlation between changes in regional pay and changes in unemployment.
Holmund & Skedinger (1990)	Sweden	1969-85 Regional data for the wood industry	Regional Panel wage drift equations	Negative unemployment elasticity of pay (zero to -0.04).
Card (1990)	Canada	1963-83 Union Contracts Data	OLS & IV first-differenced real wage equations	Negative unemployment elasticity of pay (–0.05 to -0.1).

cross section of cities".[6] Reza (1978) and Roback (1982) report likewise. Reza extends Hall's analysis to demonstrate that a positive unemployment elasticity of pay is neither the result of sample selection nor model misspecification. Roback, in contrast, provides strong evidence of compensating differences across regional space. The precise role of unemployment in this process remains, however, ambiguous.

Adams (1985) extends the above framework to differentiate between temporary and permanent movements in the analysis of compensating differentials across space. He develops a contract model where employees who lose their jobs in the face of random demand shocks receive unemployment insurance at a level below the full value of their wage. He shows that for a job package offering the going market-utility rate, regional wages will be an increasing function of the risk of unemployment and a decreasing function of the replacement ratio. Empirical work supports this premise. A well-defined and significant average state unemployment elasticity of the wage of 0.2 is reported. This implies that a doubling of state unemployment would raise wages by 20 percent. Curiously, current industry unemployment delivers an elasticity of –0.9. Adams interprets this result as evidence of the need to distinguish temporary from permanent movements in wage-unemployment space. Marston (1985) derives similar conclusions. He reports that shocks that disturb the steady-state relationship between regions' unemployment tend to be eliminated rapidly. Predominant influences on observed unemployment rates appear thus to be the persistent ones of regional amenities

Evidence to the mid 1980's clearly supports the existence of a positive relationship in wage-unemployment space. By the late 1980's this evidence had, however, begun to

[6] Hall (1972), p. 733.

diminish. Blackaby and Manning (1987) estimate Phillips curve and Mincer-style wage equations. They report the rate of wage change to depend upon the rate of change of prices, the rate of change of unemployment and the level of unemployment. Microeconometric earnings level estimations using local unemployment as an independent variable additionally report a significant negative unemployment elasticity of pay of –0.16. Subsequent papers (Blackaby & Manning 1990a, 1990b, 1990c) extend this result to include the impact of regional fixed effects, costs of living and long-term unemployment. These additional inclusions enter individual and regional earnings level equations as significant but reduce only slightly the estimated unemployment elasticity of pay.

The debate regarding the role of the long-term unemployed in the wage determination process is an interesting one. Blackaby & Manning (1990c, 1992) and Blackaby & Hunt (1992) report long-term unemployment to reduce the impact of total unemployment on earnings, a finding which conforms to the prediction of Layard and Nickell (1986, 1987) that the long-term unemployed exert little or no influence in wage determination. Layard & Nickell derive this prediction from two findings in time-series econometric work: first, that the log rather than the level of the total unemployment rate appears to be a more robust specification when entered into a wage equation; second, that estimations including both the total and long-term unemployment rates reveal exactly equal and opposite signs. Both of these findings suggest that it is the short-term unemployed that exert downward pressure on wages. Such findings do not exist in isolation. Nickell (1987), Budd, Levine & Smith (1988) and Carruth & Oswald (1989) also identify the importance of the duration composition of unemployment in the wage determination process. They too report the proportion of long-term unemployed to attenuate the downward pressure on wages exerted by total unemployment. Precisely *when* the long-term unemployed cease to exert downward pressure remains, however, unanswered. Further evidence to support the existence of a negative relationship in wage-unemployment space is found in Pissarides & McMaster (1990). They report changes in a region's relative wage to be correlated with movements in the region's unemployment level; these changes vary, however, between the short and long-run. This result could, of course, reflect incorrect dynamic specification of their model. The result does, however, re-affirm the need to distinguish between temporary and permanent unemployment. As previously discussed, actual wages may be negatively correlated with contemporaneous unemployment. Permanent wages could, however, be positively related to permanent unemployment.

Consensus for the collapse of a positive association between regional unemployment and pay is not constrained to the UK. Freeman (1988) offers weak evidence of a negative unemployment elasticity of pay for both the US and the UK. Card (1990) reports similarly for Canada, while Holmlund and Skedinger (1990) present evidence for Sweden.[7] Most of the debate regarding the wage curve centres, however, around Blanchflower and Oswald (1990). Utilising four microeconomic datasets (one from the US and three from the UK) and controlling for a number of individual and establishment characteristics, Blanchflower and Oswald estimate a series of cross-section and pooled cross-section wage equations and provide evidence of a significant inverse non-linear association between pay and unemployment. They investigate this non-linearity with the inclusion of higher order polynomials for the unemployment rate

[7] This latter finding is particularly interesting given the degree of centralised wage bargaining that has previously been thought to provide little scope for the existence of regional wage premia.

and proffer the level of unemployment and its square or alternatively the natural logarithm of unemployment and its cube as their preferred specifications. An unrestricted specification where the distribution of unemployment is split into intervals of equal width confirms this curvature and again traces out a negative locus in wage-unemployment space. This locus becomes horizontal between 9 per cent and 15 per cent unemployment. Increases in unemployment above these levels fail thus to exert downward pressure on wages.

Subsequent papers (Blanchflower & Oswald 1994a, 1995) and a comprehensive monograph (Blanchflower & Oswald, 1994b) extend this analysis to deliver a simple log-linear function as the preferred specification for the wage curve. Controlling for regional and industry fixed effects and estimating a variety of model specifications for both weekly and hourly earnings, results indicate an inverse relationship between the level of regional pay and local unemployment. The estimated unemployment elasticity of wages is approximately –0.1. This result is robust to changes in the sample period and the inclusion of higher order unemployment measures. It additionally turns insignificant or positive when regional fixed effects are excluded. The failure of previous researchers to identify a negative locus in wage-unemployment space is attributed thus to a failure to adequately control for the influence of regional fixed effects. Regional fixed effects are correlated with the local unemployment rate. Estimations that exclude such effects thus suffer from classic omitted variable bias.

4.3 Theoretical Issues

The evidence and debate summarised in the previous section, together with more recent studies, presents overwhelming support for the existence of a new empirical law of economics. This law appears robust with respect to both specification and country. It also appears stable over time. As such, further investigation into the precise nature of this relationship is clearly warranted. Such investigation requires, however, a theoretical foundation. Competitive theory fails in this regard. Explaining the wage curve is thus a stimulating challenge.

Some commentators argue the wage curve is some form of misspecified labour supply function where unemployment may be regarded as the inverse of employment for a fixed labour force. If the wage curve is such a function, the unemployment rate should perform statistically worse in a wage equation than conventional labour supply variables such as the participation rate or the employment to population ratio. Blanchflower and Oswald (1994a) test this hypothesis using 1973-1990 GHS data for Britain and report no evidence to support the idea of the wage curve as a labour supply function. A variable for the regional participation rate always enters wage equations as insignificantly different from zero. Local unemployment also dominates it. This suggests that it is local unemployment rather than the size of the local labour market that influences wages. Competitive theory is thus rejected.

Instead of being a mismeasured labour supply curve, the wage curve could be a misspecified Phillips Curve.[8] Here, model specification should relate a change in the regional wage to unemployment rather than the level of wages itself. Blanchflower and

[8] See Paldam (1990) and Black & FitzRoy (1997) for detailed discussion.

Oswald (1994b) reject this proposition. They argue that the Phillips Curve is primarily concerned with inflation and the effect of aggregate unemployment. As such, it essentially proposes a disequilibrium adjustment mechanism. The wage curve, in contrast, focuses on the role of local unemployment. It represents an equilibrium locus in wage-unemployment space that is derived from microeconomic analyses rather than macroeconomic analyses.[9] This theoretical distinction is reinforced by econometric consideration where the distinction between the two concepts essentially rests upon wage dynamics. A significant autoregressive component in dynamic wage equations would support the Phillips Curve specification. Blanchflower and Oswald find little evidence, however, to support this. Instead, their results suggest the idea of a Phillips curve to be misleading. Failure to estimate using suitable control variables, particularly those for fixed effects, results in spuriously large coefficients on lagged dependent wage variables. They assert, therefore, that the correct specification should indeed express the level of wages as a function of the unemployment level.

Having rejected the wage curve as a misspecified labour supply curve or indeed a Phillips curve, Blanchflower and Oswald argue that the wage curve may represent a non-competitive account of the labour market. They offer several explanations consistent with this empirical phenomenon including a bargaining model and an efficiency wage model.[10]

[9] The Phillips Curve is traditionally estimated using time-series macroeconomic data. The wage Curve, in contrast, is estimated using longitudinal and pooled cross-sections of microeconomic data.

[10] A labour contract model is also presented. This model, as in the case for labour supply, relies, however, on the movement of wages and employment. As such, it too rests on the key assumption of unemployment as the inverse of employment. See Card (1995) for additional details.

The bargaining model utilises a conventional framework similar to that presented in Carruth & Oswald (1989). This model asserts that a high degree of joblessness might be expected to reduce the ability of workers to bargain for a share of economic rents. High unemployment serves here as a potential threat to the employee. In the event of a permanent impasse, workers may be forced to seek alternative employment. The probability of re-employment falls as local unemployment increases. Assuming that unions have concerns for both employed and unemployed members, rising joblessness might then incline union preferences towards the preservation of jobs rather than the share of rents. A reduced concern for rents may result in a lower level of negotiated pay. An inverse association between the level of wages and unemployment should then be observed.

Efficiency wage models operate in a manner not dissimilar from the arguments presented above. The approach, however, is typically non-union and is thus ideally suited to economies where unionisation and coverage is reported as low. Shapiro and Stiglitz (1984) provide the archetypal model. Firms set pay in a working environment where the wage influences productivity. Workers are risk-neutral and choose between exerting effort or shirking. Utility is derived from wages and disutility from work. Regional equilibrium prevails if firms offer pay packages of equal expected utility across regions. A non-shirking constraint necessitates, however, that firms offer a net wage greater than the value of unemployment. Workers caught shirking are fired. Expected utility when fired depends on the level of unemployment insurance and the probability of re-employment. The probability of re-employment decreases with the level of unemployment. Increases in unemployment serve thus to discipline workers into providing greater efforts. Greater efforts ensure that the non-shirking condition requires a lower wage at higher unemployment. An efficiency wage is thus also consistent with a negative locus in wage-unemployment space.

Theoretical justification of the wage curve by non-competitive models of the labour market does not mean that the Harris-Todaro concept of compensating differentials is necessarily wrong. The Harris-Todaro locus sits comfortably alongside the existence of the wage curve once permanent and transitory movements in pay and unemployment are, for example, accounted for. The above models do, however, pertain to a number of interesting caveats. Card (1995), for example, points out that efficiency wage models comfortably entertain differences in the slope of the wage curve across different groups of workers. He argues that for such models, wages of a particular group of workers are related to the group-specific unemployment rate. High unemployment for one group of workers should thus have no effect on another group. This is an interesting implication, especially with regard to the identification of unemployment elasticities across disaggregated curves.[11] More important, however, is the implication that the models replace the conventional labour supply curve with a wage-fixing function, a function that lies flatter and to the left of the true Marshallian labour supply. This function is compatible with a new generation of macroeconomic models in which an aggregate wage curve is the distinguishing feature.[12] The wage curve may thus provide the missing empirical foundation for such models. There remains, however, much to be learned.

This chapter explicitly addresses the existence of a wage curve by utilising genuine panel data for the UK. Previous studies for the UK rely on pooled and cross-section data for the 1970's and 1980's. This chapter, in contrast, utilises data drawn from the 1990's.

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[11] See, for example, Blanchflower & Oswald (1994a), Card (1995) and Turunen (1998).

Thus, the chapter presents two major additions to the existent UK literature. First, it provides a framework for analysis during the 1990's, a period where the level and structural composition of unemployment has witnessed a marked change from the preceding decades. Second, the panel dimension of the data allows us to take account of the role of unobserved worker heterogeneity in the wage determination process. This latter feature enables us to explain a substantial proportion of the variation in earnings between individuals.

4.4 Data

We estimate the UK wage curve using longitudinal micro data drawn from the 1991-1998 (eight) waves of the British Household Panel Survey (BHPS), a nationally representative survey of households randomly selected south of the Caledonian Canal.[13] The BHPS was designed as an annual survey of each adult member (age 16 or over) from a nationally representative sample of more than 5,000 households, providing a total of approximately 10,000 individual interviews. The first wave of the BHPS was conducted from September 1991 to January 1992, subsequent waves have been collected annually thereafter.[14,15]

The BHPS provides a rich source of socio-economic variables at the individual and household level. The dependent variable that we derive from these data is the natural logarithm of the real hourly wage. This is calculated as the ratio of usual gross pay per

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[12] See Layard et al (1991) for an overview of this literature.

[13] The very north of Scotland is thus excluded.

[14] From Wave Seven the BHPS has incorporated a sub-sample of the original United Kingdom European Community Household Panel (UKECHP), including all households still responding in Northern Ireland. For consistency purposes across the panel, these new sample members are excluded from analysis.

[15] See Taylor (1998) for details.

month (a derived variable that measures usual monthly wage or salary payment before tax and other deductions in current main job for employees), and the total number of hours normally worked per week, scaled by average weeks per month.[16] This is then deflated by the monthly RPI (base period January 1991).

The richness of the BHPS permits a wide variety of both personal and workplace controls in our wage equations. Personal controls include gender, race, marital status, highest educational qualification, head of household indicator, and the presence of children in the household and their age profile. Additional information regarding an individual's health along with their recent labour market history are also included. A piecewise linear spline for age is used to capture the expected profile of lifetime earnings.[17]

Workplace and workforce controls which can be expected to impinge upon earnings include unionisation (recognition & membership), full or part time job status, promotion opportunities, a number of variables capturing the structure of pay and pay increases, seasonal/temporary or contract work, rotating shifts, managerial duties and supervisory tasks. Any remaining firm-specific effects are captured by the inclusion of firm size and public-private sector indicators.[18] Industry and occupational affiliation are coded using the 1980 Standard Industrial Classification (SIC) and the 1990 OPCS Standard Occupational Classification. We utilise 1-digit classification dummies to control for variation of wages across both occupation and industry.

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[16] The data provides separate information regarding the number of hours normally worked per week (excluding overtime and meal breaks), the number of overtime hours worked in a normal week, and the number of overtime hours worked as paid overtime. We define total hours as normal hours plus overtime.
[17] The linear spline is preferred to imposing the constraints implied by the usual quadratic in age or experience.

Regional dummies are included to capture the multitude of effects brought about by geographical differences in industry and institutional structure. Regional fixed-effects help to explain why, for certain regions, real wages appear lower regardless of the unemployment rate.[19] The regional unemployment rate is an appropriate measure for wage adjustment when individuals reside and work within the same regional domain. However, highly mobile individuals who commute outside of their region of residence present a problem to this analysis. Workers who reside in high unemployment areas but commute to work in a high wage area, for example, generate a spurious positive relationship between the regional unemployment rate and regional pay. Fortunately, the BHPS contains information concerning both the location of work and the amount of time the individual usually spends travelling to work each day. We include a dummy variable therefore if the individual's travel time is greater than 45 minutes. This should help capture movement across regional boundaries and reduce potential underestimation of the unemployment effect brought about by movement from high unemployment regions to regions of high pay. Time dummies and the natural logarithm of the ratio of regional to national consumer prices are additionally included to capture cyclical effects on wages and the impact of regional price variations.[20,21]

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[18] A positive association between wages and firm size is well established. See Brown & Medoff (1985) and Green *et al* (1996) for details.

[19] Regional unemployment is drawn from NOMIS and is matched to the data at the level of the standard region by month and year of interview.

[20] Blackaby et al (1991) show that the usual practise of calculating the real wage by simply deflating nominal wage rates by the national retail price index is inadequate where workers recognise regional price variations and act upon it in wage bargaining. They argue that, unless the national price index is all important, the omission of a relative regional to national price term is likely to seriously mis-specify the wage relationship and bias the coefficients of explanatory variables that capture other regionally varying factors. Since the unemployment term is one such variable in our wage equations, we include the natural logarithm of the ratio of regional to national prices in our analysis.

[21] Regional price information is provided by The Reward Group (2000).

The sample is selected on the basis that the individual is aged 16 to retirement age and has a current status of employee. Retired and self-employed 'workers', the unemployed, individuals working on government schemes and 'inactive' sections of the working-age population are thus excluded. Individuals who have missing relevant information or who are not interviewed at a particular wave are also excluded. Individuals who enter and exit the sample across the panel are, however, allowed. Whilst this results in an unbalanced panel in our econometric analysis, it does serve to minimise potential attrition biases and yields a greater numbers of observations in the panel when controlling for fixed effects.

We estimate our wage equations separately for men and women.[22] In addition, to alleviate potential biases from serious over or under estimation of earnings, we symmetrically trim the male and female samples and omit the 0.5% of observations with both the highest and lowest real hourly wages. These additional restrictions result in a male sample of 17,080 data points (4,224 individuals) and a female sample of 17,421 (4,286 individuals). The gender distribution across the panel is presented in Table A1 of the Appendix. Table A2 details the total number of waves for which each individual is observed. Data definitions and summary statistics are presented in Tables A3 and A4.

[22] The problems of measuring the labour market experiences of married women are well recognised. Concerns regarding gender differences in the rates of return to educational attainment are also acknowledged.

4.5 Methodology

We use an econometric technique that takes into account the panel nature of the data and estimate a fixed-effects model where unobserved individual-specific heterogeneity is assumed to be time-invariant but correlated with explanatory variables.

The basic framework is a regression model of the form:

$$\ln w_{it} = \alpha_i + \beta x_{it} + v_{it} \qquad i=1,\ldots,N, \quad t=1,\ldots,T, \tag{4.1}$$

where $\ln w_{it}$ is the natural logarithm of the real hourly wage of worker *i* at time *t*, α_i is an individual-specific component of wages reflecting observed time-invariant individual heterogeneity such as gender and race, and v_{it} is a random error term independently and identically distributed over *i* and *t*.

Assuming unobserved individual-specific heterogeneity to be time-invariant, the error term v_{it} can be decomposed as:

$$v_{it} = u_i + e_{it} \tag{4.2}$$

where u_i denotes the individual-specific unobserved effect and e_{it} denotes the remainder disturbance.

Equation (4.1) may now be written:

$$\ln w_{it} = \alpha_i + \beta x_{it} + u_i + e_{it} \tag{4.3}$$

Averaging over time gives:

$$\ln \overline{w}_{i.} = \alpha_i + \beta \overline{x}_{i.} + u_i + \overline{e}_{i.} \tag{4.4}$$

Subtracting equation (4.4) from (4.3) thus yields:

$$\ln w_{it} - \ln \overline{w}_{i.} = \beta\left(x_{it} - \overline{x}_{i.}\right) + \left(e_{it} - \overline{e}_{i.}\right) \tag{4.5}$$

This is the fixed-effects (or within) estimator. The within estimator produces consistent and efficient estimates of the identifiable parameters when the time-invariant effects are assumed correlated with x_{it}.

4.6 Empirical Results

Table 2 reports results for alternative specifications of log earnings equations for UK males 1991-1998. Column 1 adopts a semi-logarithmic specification that relates the log of real hourly wages to the level of unemployment implying the wage–unemployment relationship is exponential. The reported coefficient is significant and provides an estimated elasticity of -0.14 evaluated at the mean. This elasticity is significantly different from -0.1 but lies within the rough band of zero to –0.15 proposed by Blanchflower & Oswald (1994b). The existence of a well-defined unemployment effect for UK males is thus supported.

Column 3 replaces the semi-logarithmic specification with a double-log specification. The estimated elasticity is again significant but is approximately -0.05. This result is surprising and contrasts with Blanchflower & Oswald (1990, 1994a) and Blackaby *et al* (1991) both of whom find little to choose statistically between the log of unemployment and the unemployment level. The double-log specification is often preferred on the basis of expositional ease: the reported coefficient may be immediately interpreted as the elasticity in question. It imposes, however, significant constraints on the data. A double-log specification considers the relationship between wages and unemployment to be log-linear across the whole range of observed data. This implies a constant unemployment elasticity of wages. It also implies, in the levels, that the relationship between wages and unemployment is either increasing or decreasing without limit. The semi-logarithmic equation, by contrast, is not so restrictive. It also has desirable features in terms of interpretation in that the estimated function will be asymptotic. A negative sign on unemployment implies a downward sloping locus in wage-unemployment space. This locus will, however, never reach the x-axis. In reality, wages will never equal zero. For this purpose, the semi-logarithmic specification is our preferred equation.

Table 2

Estimates of the UK Wage Curve: Males 1991-1998

Dependent Variable: log real hourly wage				
Unemployment	**1**	**2**	**3**	**4**
U	-0.0188 (3.43)†	-0.0133 (1.77)*		
U^2		-0.0004 (1.04)		
Log U			-0.0489 (2.08)**	-0.0040 (0.14)
Log U^3				-0.0108 (2.51)**
ε	-0.14	-0.14	-0.05	-0.13
Diagnostics				
F	30.94	30.60	30.83	30.56
R^2	0.9323	0.9324	0.9323	0.9323
Specification Test	-0.0100 [0.488]	-0.0102 [0.490]	-0.0094 [0.508]	-0.0099 [0.494]
NT	17,080	17,080	17,080	17,080

Notes

1. All specifications control for unobserved individual heterogeneity and include the following controls: 7 segment piecewise linear spline for age and dummies for marital status (3), highest qualification (7), registered disabled, health limits work, head of household, own children in household, age of children in household (3), recent labour market experience (2), region (11), occupation (9), industry (9), firm size (8), full-time work, temporary work, contract work, employment sector (8), union recognition, union member, manager, supervisor, shift worker, bonus in pay, annual increments in pay, travel to work time greater than 45 minutes, time (8 waves).
2. Estimations by Intercooled Stata 6.0. Coefficient t-values in parentheses. Significance levels: †(0.01), **(0.05), *(0.10); p-values of diagnostics in [].
3. The Hausman test for random-effects models is rejected for all specifications.
4. The specification test is due to Pregibon (1980). Similar to a standard RESET test in time series analysis, it is distributed as standard normal under the null hypothesis of no misspecification: 5% critical value N(0,1)=±1.96.

Non-linearities provide a recurring theme in the wage curve literature. Evidence from Blanchflower and Oswald is, however, mixed. Blanchflower and Oswald (1990) find different polynomial structures to fit the data well. Though hard to interpret economically, they find, for example, that the inclusion of a cubic term for the logarithm of unemployment improves their estimates. Later evidence, by contrast, rejects the inclusion of such higher order unemployment terms.[23] We test for non-linearities by adding cubic or squared terms of unemployment in logs and levels.[24] Column 2 imposes a quadratic on the unemployment-log-wage relationship. The estimated unemployment elasticity of pay is identical to that of the semi-logarithmic specification. The inclusion of a square term for unemployment fails, however, to improve the performance of the original equation and its coefficient is insignificantly different from zero. Column 4 adopts a specification including the natural logarithm of unemployment and its cube. Again, there is evidence of a well-defined unemployment effect. The cubic term in unemployment is highly significant, although the coefficient on the log of unemployment becomes small and insignificantly different from zero. This evidence, illustrated in Figure 1, suggests that the previous literature may be wrong to assume a double-log specification as the appropriate functional form for estimation of the UK wage curve. We test this assumption further and utilise a J test to select between the semi-logarithmic and double-log specifications of unemployment.[25] The test rejects the double-log specification against the semi-logarithmic specification and accepts the semi-logarithmic specification against the double-log specification at conventional levels. Thus, the semi-logarithmic specification is statistically preferred and our original preference for the level of unemployment is supported.

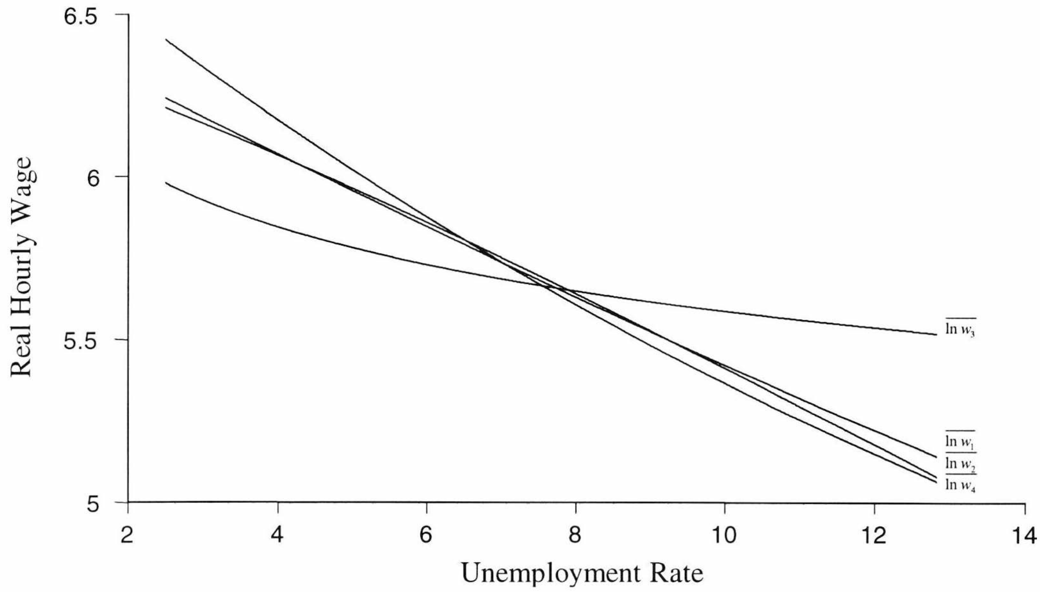
[23] See Blanchflower & Oswald (1994a).

[24] We also estimated our wage equations using the inverse of unemployment, and the inverse of unemployment and its square. Neither of these specifications identified a significant unemployment effect nor added to the overall fit of the equation. Thus, these additional results are not reported.

[25] See Davidson & MacKinnon (1981) for details.

Figure 1

Alternative Specifications of the UK Wage Curve: Males 1991-1998



Notes.

$\overline{\ln w_1} = \alpha + \hat{\beta}\bar{u}$, $\overline{\ln w_2} = \alpha + \hat{\beta}\bar{u} + \hat{\gamma}\bar{u}^2$, $\overline{\ln w_3} = \alpha + \hat{\beta}\overline{\ln u}$, $\overline{\ln w_4} = \alpha + \hat{\beta}\overline{\ln u} + \hat{\gamma}\overline{\ln u}^3$.

Table 3 presents equivalent estimates for the female sample.[26] The main finding is that there is no evidence of a significant wage curve for women. The estimated elasticity of pay for our preferred equation is identical to that of Blanchflower and Oswald (1994b).[27] The coefficients for alternative specifications of unemployment are, however, either small or insignificantly different from zero. This result is consistent with the

[26] Given the focus of this chapter, we do not report the coefficients on other controls variables utilised in estimation across both the male and female samples. Full results for the semi-logarithmic specification are, however, reported in Table A5 of the appendix. These results, consistent with those obtained for alternative specifications of the unemployment-wage relationship, reveal two significant and interesting findings. First, the inclusion of individual fixed effects enables our wage equations to explain over 90% of the total variation in wages. Thus, observed and *unobserved* differences between workers perhaps reflecting innate ability or other characteristics of individuals not captured by observed data perform a vital role in the wage determination process. Second, the estimated wage equations appear to be both meaningful and appropriate in that they are consistent with a large previous literature on wage determination. Thus, for example, *ceteris paribus*, age-earnings profiles are concave (although earnings increase over any individual's lifetime); households with children depress female earnings; there are significant private returns to college qualifications (e.g. degree or teaching certificate) though the effect is greater for women than for men; seasonal or temporary workers earn less than their permanent counterparts; workers in large firms earn more than those in smaller enterprises; unionised workers enjoy a wage premium over their non-unionised colleagues; recent periods of unemployment or inactivity have a detrimental effect on earnings; workers are compensated for long travel-to-work times; and wages are higher in the south of Britain.

panel findings of both Janssens & Konings (1997) and Pannenberg & Schwarze (1998). The lack of a significant wage curve for women may indicate that the female labour market is more competitive than the male labour market. It might also indicate problems concerning non-employment (unemployment) and/or non-participation. Simultaneity bias due to the endogeneity of local unemployment provides another likely cause.[28] We do not test for endogeneity in this chapter. Recent work by Baltagi & Blien (1998) suggests, however, accounting for endogeneity to be an important task for future work.

Table 3

Estimates of the UK Wage Curve: Females 1991-1998

Dependent Variable: log real hourly wage				
Unemployment	**1**	**2**	**3**	**4**
U	-0.0090 (1.61)	-0.0056 (0.72)		
U^2		-0.0002 (0.60)		
Log U			-0.0143 (0.59)	0.0177 (0.57)
Log U^3				-0.0075 (1.70)*
ε	-0.07	-0.05	-0.01	-0.05
Diagnostics				
F	27.55	27.23	27.52	27.24
R^2	0.9189	0.9189	0.9189	0.9189
Specification Test	-0.0024 [0.734]	-0.0024 [0.744]	-0.0025 [0.731]	-0.0024 [0.739]
NT	17,421	17,421	17,421	17,421

Notes
See notes to Table 2.

Previous studies for the UK report the addition of regional fixed effects as having little impact on estimated wage curve elasticities.[29] Pencavel (1994) argues that this may reflect a greater degree of permanence in the geographical distribution of unemployment. Permanence in unemployment rates is certainly reflected in UK data for the 1980's. Unemployment rates for the 1990's, however, exhibit a significant

[27] Blanchflower & Oswald report a significant unemployment elasticity of pay for UK women of –0.07.

[28] The fixed effects estimator does not control for simultaneity bias due to the endogeneity of local unemployment unless local unemployment is only correlated with time and/or region effects.

[29] This contrasts with studies for US data where the omission of regional dummies exerts an upward bias on estimated elasticities and in some instances turns them positive.

downward trend with marked changes regarding both structure and composition. We test the above hypothesis, therefore, and re-estimate our wage equations on the original male sample excluding regional fixed effects. The results are reported in Table 4. The exclusion of regional fixed effects reduces the absolute size of the coefficients for the unemployment terms for all specifications. There is, however, comparatively little difference to the findings reported earlier in Table 2. Estimated elasticities of pay are biased upwards but remain within close proximity of –0.1. The coefficient for the level of the unemployment rate in our preferred equation also remains significant at conventional levels. The robustness of these results suggests the inclusion of regional fixed effects to not be necessary in identifying a significant negative locus in wage-unemployment space. In this context, permanence in UK unemployment rates is again supported.[30]

Table 4

The UK Wage Curve: Males 1991-1998 Excluding Regional Fixed Effects

Dependent Variable: log real hourly wage				
Unemployment	1	2	3	4
U	-0.0143 (3.28)†	-0.0090 (1.29)		
U^2		-0.0004 (0.99)		
Log U			-0.0480 (2.26)**	-0.0034 (0.11)
Log U^3				-0.0083 (2.19)**
ε	-0.11	-0.08	-0.05	-0.10
Diagnostics				
F	34.79	34.35	34.70	34.32
R^2	0.9323	0.9323	0.9322	0.9323
Specification Test	-0.0107 [0.463]	-0.0109 [0.463]	-0.0099 [0.487]	-0.0106 [0.467]
NT	17,080	17,080	17,080	17,080

Notes
See notes to Table 2.

[30] The inclusion of regional fixed effects eliminates the 'permanent' components of unemployment from the wage-unemployment relationship. Thus, similarity across estimates when regional fixed effects are excluded suggests that the dominant component of the estimated unemployment effect is largely permanent in nature.

Many studies estimate the wage curve on the basis of *weekly*, *monthly* or *annual earnings*. To test the robustness of our results we therefore re-estimate male earnings equations using two alternative specifications for the dependent variable. Table 5 reports results using the log of real monthly pay as the dependent variable. In contrast, Table 6 presents estimates when the real hourly wage is derived using usual hours of work (i.e. excluding overtime). The issue of hours worked is complex. Blanchflower and Oswald (1994b) and others, for example, define wages as annual earnings. This is

Table 5

The UK Wage Curve: Males 1991-1998

Dependent Variable: log real monthly pay				
Unemployment	**1**	**2**	**3**	**4**
U	-0.0190 (3.72)†	-0.0154 (2.18)**		
U^2		-0.0003 (0.74)		
Log U			-0.0526 (2.40)**	-0.0083 (0.30)
Log U^3				-0.0107 (2.66)†
ε	-0.14	-0.12	-0.05	-0.13
Diagnostics				
F	95.58	94.50	95.43	94.47
R^2	0.9415	0.9415	0.9414	0.9415
Specification Test	-0.0214 [0.000]	-0.0217 [0.000]	-0.0207 [0.000]	-0.0212 [0.000]
NT	17,080	17,080	17,080	17,080

Notes
Controls are as those reported for Table 2. However, the log of hours worked is additionally included.

often due to the lack of a more appropriate measure. Card (1995) indicates, however, that this may be inappropriate and asserts that part of the negative relationship between annual earnings and local unemployment may be caused by a response in hours worked.[31] Evidence to support this criticism is mixed. Blanchflower and Oswald (1994a, 1994b) report similar elasticities for both annual and/or weekly earnings and hourly wages. Card, in contrast, reports an unemployment elasticity of pay for annual earnings twice that of the estimated elasticity for hourly wages. Such results are surprising. They are, however, indicative of the problems faced by labour economists in the use of retrospective data and reported hours of work.[32]

Table 6

The UK Wage Curve: Males 1991-1998

	Dependent Variable: log real hourly wage excluding overtime			
Unemployment	**1**	**2**	**3**	**4**
U	-0.0192 (3.46)†	-0.0153 (2.00)**		
U^2		-0.0003 (0.73)		
Log U			-0.0533 (2.24)**	-0.0089 (0.30)
Log U^3				-0.0107 (2.45)**
ε	-0.14	-0.12	-0.05	-0.13
Diagnostics				
F	35.34	35.13	35.44	35.11
R^2	0.9308	0.9308	0.9308	0.9308
Specification Test	-0.0009 [0.860]	-0.0010 [0.853]	-0.0008 [0.880]	-0.0008 [0.879]
NT	17,080	17,080	17,080	17,080

Notes
See notes to Table 2.

The results for the UK wage curve utilising alternative measures of the dependent variable are remarkably similar to those reported in Table 2. The semi-logarithmic equation is again preferred to the double-log specification. Estimated elasticities also remain virtually identical with both the unemployment level and the logarithm and its cube, delivering an unemployment elasticity of pay significantly different from –0.1. Such robustness would appear to suggest that the wage curve is largely insensitive to demand shocks and the adjustment of individuals' working hours. It also indicates that switching from an hourly wage to monthly pay variable has no impact on the main conclusions of the chapter.

[31] Card argues that since annual earnings are the product of annual hours and hourly wages, and annual hours are highly correlated with contemporaneous unemployment, the wage curve may in fact reflect an 'hours curve'.

[32] See Hamermesh (1998) for discussion of this data and the misapplication of standard econometric techniques in labormetric research.

To confirm the generality and robustness of our results, a number of additional specifications were examined. First, to test that the results were not heavily influenced by a few outliers, we adopt the approach of Miles (1997) and re-estimate the preferred equation with the weight on observation *i* the reciprocal of its squared residual. This technique provides a good test for heteroscedasticity since a lower weight is attached to large residuals. Neither the parameter estimates nor their statistical significance are substantially different from the original estimates. This suggests that heteroscedasticity is not a significant problem in the data.[33] Normality of the residuals' distribution was additionally checked by residual histograms. Again, there is no evidence of non-normality though the distribution reveals weak leptokurtosis.[34]

Second, we investigate the sensitivity of our results to the fact that our sample is an unbalanced panel of individuals, some of whom were only interviewed on relatively few occasions (see Table A2). The results obtained from re-estimating the male earnings equations using only the balanced panel (and thus only individuals who were observed in all 8 waves) are reported in Table 7.[35] Again, there is evidence of a negatively sloped relationship in wage-unemployment space. However, this relationship is neither statistically significant nor well-defined. Insignificance of the coefficients may indicate a problem concerning estimation.[36] Nonetheless, sample selection provides a more

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[33] Accordingly, these weighted regressions are not reported.

[34] Kurtosis measures the degree of peakedness of a probability function near the mode. The normal distribution is said to be *mesokurtic*, one less peaked is said to be *platykurtic*, and one more peaked is said to be *leptokurtic*.

[35] These results additionally utilise the longitudinal respondent weights provided with the BHPS data to correct for the sample design and non-response rates. Technically, these individual weights should be used in any analysis utilising the BHPS to ensure that the marginal distributions in the data match the known distribution in the population.

[36] Card (1995) points out that the local unemployment rate does not vary across individuals. The 'degrees of freedom' in estimation of the wage curve is thus equal to the number of regions times the number of time periods. This chapter uses data for eleven standard regions across eight waves of data. Individual interviews take place between August and May each wave. The actual 'degrees of freedom' for our data is thus 543.

likely reason. Balanced panels are often preferred when sample selection issues brought about by attrition are considered to be important. Selecting observations for those individuals who report earnings across all eight waves, however, raises significant issues of its own. The main effect of this selection criterion is to considerably reduce the sample size and thus information by which an unemployment effect may be identified. Another significant effect concerns the selection of those individuals for whom unemployment may *not* serve as an appropriate disciplining device. Balanced panels, observed over the business cycle, suppress compositional change in the labour market brought about by changes in the experience and composition of unemployment.[37] Recognising the nature of sample restrictions is thus of critical importance.

Table 7

The UK Wage Curve: Male Balanced Panel 1991-1998

Dependent Variable: log real hourly wage				
Unemployment	**1**	**2**	**3**	**4**
U	-0.0041 (0.57)	-0.0038 (0.39)		
U^2		-0.0001 (0.05)		
Log U			-0.0245 (0.81)	-0.0286 (0.76)
Log U^3				-0.0010 (0.18)
ε	-0.03	-0.03	-0.03	-0.04
Diagnostics				
F	13.58	13.42	13.58	35.11
R^2	0.9200	0.9200	0.9200	0.9308
NT	6,368	6,368	6,368	6,368

Notes
See notes to Table 2.

Finally, we estimate the UK wage curve utilising a non-parametric approach. The estimates in Tables 2-7 impose assumptions regarding the functional form of unemployment. Table 8 adopts the approach of Blanchflower and Oswald (1994a, 1994b) and reports results utilising an unrestricted specification where the distribution

[37] Gregg *et al* (1999) present recent evidence that suggests that the cost of job loss for an average worker following involuntary unemployment is approximately 9 percent of previous earnings.

of unemployment is split into 5% segments of approximately equal size, each segment being replaced by an unemployment dummy.[38] Taking the first interval as the reference

Table 8

5% Disaggregations: UK males 1991-1998

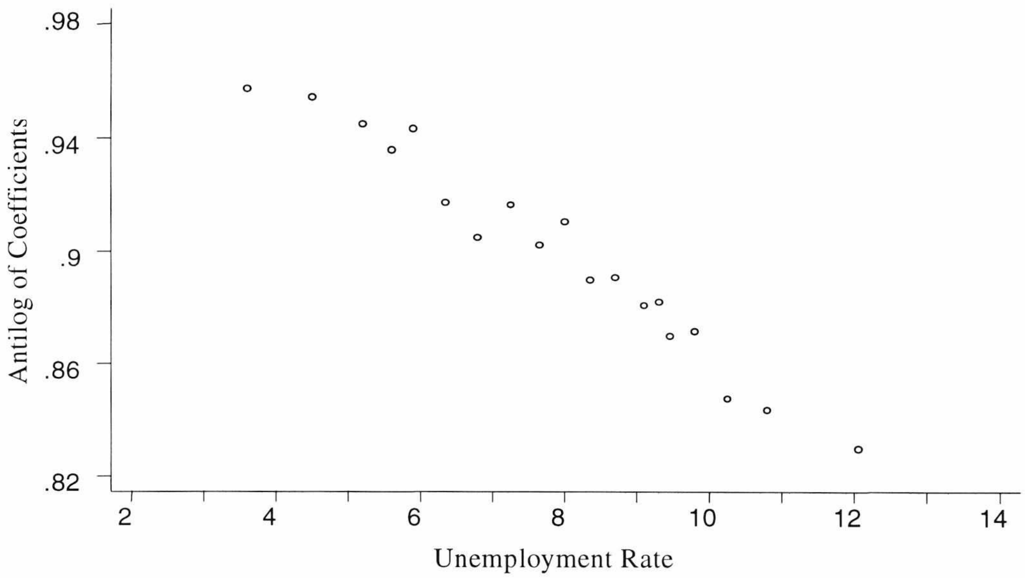
Unemployment (%)	Coefficient	Unemployment (%)	Coefficient
2.5-3.1	- -	8.5-8.9	-0.1158 (3.62)†
3.2-4.0	-0.0437 (2.74)†	9.0-9.2	-0.1271 (3.91)†
4.1-4.9	-0.0468 (3.01)†	9.3	-0.1256 (3.55)†
5.0-5.4	-0.0564 (3.08)†	9.4-9.5	-0.1395 (3.98)†
5.5-5.7	-0.0660 (3.68)†	9.6-10.0	-0.1375 (3.78)†
5.8-6.0	-0.0582 (2.88)†	10.1-10.4	-0.1652 (4.27)†
6.1-6.6	-0.0859 (4.12)†	10.5-11.1	-0.1700 (4.30)†
6.7-6.9	-0.0995 (4.10)†	11.2-12.9	-0.1863 (4.12)†
7.0-7.5	-0.0869 (3.42)†		
7.6-7.7	-0.1026 (3.78)†	F	25.84
7.8-8.2	-0.0933 (3.41)†	R^2	0.9325
8.3-8.4	-0.1169 (4.17)†	NT	17,080

Notes: The dependent variable is log real hourly wage.

group, all nineteen dummies are negative and statistically significant at conventional levels. The absolute size of the coefficients also increases as the unemployment rate rises. Figure 2 plots the antilogs of the coefficients against the mid-point of the

Figure 2

Unrestricted Estimates for UK Males 1991-1998



[38] Each dummy identifies between two and ten regions depending on the number of observations.

unemployment range for each dummy. There is clear evidence for a downward sloping locus in wage-unemployment space. A curve linking the antilogged coefficients additionally suggests this locus to be broadly linear. Rejection of higher order polynomial terms for unemployment earlier in the chapter is thus clearly supported.

4.7 Conclusion

This chapter has investigated the empirical evidence for a UK wage curve using longitudinal micro data drawn from the first eight waves of the British Household Panel Survey. The main finding is that there is evidence of a negative relationship in wage-unemployment space. This finding is robust to alterations in the nature of the dependent variable and the exclusion of regional fixed effects. It is, however, sensitive to sample selection and indicates distinct differences across identifiable labour market groups. The estimated unemployment elasticity of pay for UK males is approximately equal to –0.14. There is no evidence of a female wage curve. These findings are consistent with the panel studies reported for other countries. They contrast with previous studies for the UK, however, in that they reject the inclusion of higher order polynomial terms for unemployment. The main findings of the chapter, therefore, are that the wage-unemployment relationship is robust but not as non-linear as has been previously thought.

APPENDIX

Table A1

Distribution of Observations for BHPS Waves 1-8

Wave of interview	*Males*	*Females*	*Total*
Wave 1	2280	2278	4558
Wave 2	2068	2087	4155
Wave 3	1967	2043	4010
Wave 4	1986	2075	4061
Wave 5	1978	2051	4029
Wave 6	2084	2144	4228
Wave 7	2320	2319	4639
Wave 8	2397	2424	4821
Total	17,080	17,421	34,501

Table A2

Distribution of Individuals for BHPS Waves 1-8

No. of waves individual is observed	*Males*	*Females*	*Total*
1 wave	1055	1014	2069
2 waves	699	713	1412
3 waves	408	413	821
4 waves	330	348	678
5 waves	275	327	602
6 waves	287	317	604
7 waves	374	419	793
8 waves	796	735	1231
Total	4,224	4,286	8,510

Table A3: Data Definitions

Variable	*Definition and Description*
Dependent Variable:	
Log of real hourly wage	Log of real hourly wage
Independent Variables:	
Age	Age of individual at December of interview
Race	
White	(1,0) if white
Black	(1,0) if black ethnic origin
Other non-white	(1,0) if other ethnic origin
Marital Status	
Never Married	(1,0) if never married
Married or Living as a Couple	(1,0) if married or living as a couple
Widowed/Separated/Divorced	(1,0) if widowed, separated or divorced
Highest Qualification	
Higher or First Degree, Teaching	(1,0) qualification dummy
Other Higher Education	(1,0) qualification dummy
GCE A-level	(1,0) qualification dummy
GCE O-level	(1,0) qualification dummy
CSE Grade1-5	(1,0) qualification dummy
Apprenticeship, Nursing, Other	(1,0) qualification dummy
No Qualification	(1,0) qualification dummy
Health	
Registered Disabled	(1,0) if registered disabled
Limits types of work	(1,0) if health limits type or amount of work
Other Personal Controls	
Head of Household	(1,0) if head of household
Own Children	(1,0) if own children in household
Children aged 0-4 Years	(1,0) if children aged <5 years in household
Children aged 5-11 Years	(1,0) if children aged 5-11 years in household
Children aged 12-15 Years	(1,0) if children aged 12-15 years in household
Unemployed in Past Year	(1,0) if unemployment spell(s) in past year
Non-Participant in Past Year	(1,0) if non-participation spell(s) in past year
Size of Establishment	
<10 Employees	(1,0) if <10 employees
10-24 Employees	(1,0) if 10-24 employees
25-49 Employees	(1,0) if 25-49 employees
50-99 Employees	(1,0) if 50-99 employees
100-199 Employees	(1,0) if 100-199 employees
200-499 Employees	(1,0) if 200-499 employees
500-999 Employees	(1,0) if 500-999 employees
>1000 Employees	(1,0) if >1000 employees
Workplace and Other Controls	
Full-time	(1,0) if work >30 hours per week
Seasonal or Temporary Work	(1,0) if job seasonal or temporary
Fixed time or Contract Work	(1,0) if job fixed time or contract
Promotion Opportunities	(1,0) if job has promotion opportunities
Bonuses or Profit	(1,0) if pay includes bonuses or profits
Annual Increments	(1,0) if pay includes annual increments
Union or Staff Association	(1,0) if union or staff association at workplace
Member of Union	(1,0) if member of workplace union
Member of Other Union	(1,0) if member of non-workplace union
Rotating Shifts	(1,0) if work involves rotating shifts
Manager	(1,0) if manager
Supervisor	(1,0) if supervisor
Travel ≥45 Minutes	(1,0) if travel to work time ≥45 Minutes
Regional Unemployment	NOMIS Unemployment by Standard Region

Employing Organisation	
Private	(1,0) if private sector
Civil Service	(1.0) if civil service
Local Govt.	(1,0) if local government
NHS or Hospital	(1,0) if NHS or hospital
Nationalised Industry	(1,0) if nationalised Industry
Non-profit organisation	(1,0) if non-profit organisation
Armed Forces	(1,0) if armed forces
Other	(1,0) if other sector
Occupation Major Groups	
Managers and Administrators	(1,0) occupation dummy
Professional Occupations	(1,0) occupation dummy
Associate Professionals & Technical	(1,0) occupation dummy
Clerical and Secretarial	(1,0) occupation dummy
Craft and Related	(1,0) occupation dummy
Personal and Protective Services	(1,0) occupation dummy
Sales	(1,0) occupation dummy
Plant and Machine Operatives	(1,0) occupation dummy
Other Occupations	(1,0) occupation dummy
1-digit industry groups	
Agriculture, forestry and fishing	(1,0) industry dummy
Energy and water supplies	(1,0) industry dummy
Minerals, metal manufacture & chemicals	(1,0) industry dummy
Metal goods, engineering and vehicles	(1,0) industry dummy
Other manufacturing	(1,0) industry dummy
Construction	(1,0) industry dummy
Distribution, hotels and catering	(1,0) industry dummy
Transport and communication	(1,0) industry dummy
Banking, finance, insurance & business services	(1,0) industry dummy
Other services	(1,0) industry dummy
Regions of the UK	
Greater London	(1,0) regional dummy
Rest of South	(1,0) regional dummy
East Anglia	(1,0) regional dummy
South West	(1,0) regional dummy
West Midlands	(1,0) regional dummy
East Midlands	(1,0) regional dummy
Yorkshire	(1,0) regional dummy
North West	(1,0) regional dummy
North	(1,0) regional dummy
Wales	(1,0) regional dummy
Scotland	(1,0) regional dummy

Table A4: Summary Statistics

Variable	Males		Females	
	Mean	*SD*	*Mean*	*SD*
Dependent Variable:				
Log of real hourly wage	1.737	0.482	1.464	0.464
Independent Variables:				
Age	37.13	11.54	37.09	10.86
Race				
White (reference)	0.967		0.968	
Black	0.008		0.012	
Other non-white	0.025		0.020	
Marital Status				
Never Married (reference)	0.231		0.176	
Married or Living as a Couple	0.721		0.724	
Widowed/Separated/Divorced	0.048		0.010	
Highest Qualification				
Higher or First Degree, Teaching	0.164		0.152	
Other Higher Education	0.244		0.154	
GCE A-level	0.148		0.116	
GCE O-level (reference)	0.202		0.269	
CSE Grade1-5	0.055		0.041	
Apprenticeship, Nursing, Other	0.037		0.099	
No Qualification	0.150		0.169	
Health				
Registered Disabled	0.010		0.007	
Limits types of work	0.063		0.082	
Other Personal Controls				
Head of Household	0.773		0.219	
Own Children	0.354		0.366	
Children aged 0-4 Years	0.145		0.102	
Children aged 5-11 Years	0.190		0.204	
Children aged 12-15 Years	0.115		0.151	
Unemployed in Past Year	0.070		0.047	
Non-Participant in Past Year	0.035		0.084	
Size of Establishment				
<10 Employees (reference)	0.142		0.198	
10-24 Employees	0.138		0.184	
25-49 Employees	0.134		0.160	
50-99 Employees	0.128		0.108	
100-199 Employees	0.118		0.098	
200-499 Employees	0.154		0.111	
500-999 Employees	0.080		0.054	
>1000 Employees	0.106		0.087	
Workplace and Other Controls				
Full-time	0.973		0.656	
Seasonal or Temporary Work	0.025		0.043	
Fixed time or Contract Work	0.030		0.032	
Promotion Opportunities	0.562		0.445	
Bonuses or Profit	0.370		0.229	
Annual Increments	0.433		0.484	
Union or Staff Association	0.500		0.500	
Member of Union	0.348		0.304	
Rotating Shifts	0.133		0.072	
Manager	0.242		0.140	
Supervisor	0.179		0.166	
Travel ≥45 Minutes	0.156		0.107	
Regional Unemployment	7.496	2.378	7.519	2.356

Employing Organisation				
Private (reference)	0.773		0.612	
Civil Service	0.048		0.039	
Local Govt.	0.092		0.186	
NHS or Hospital	0.035		0.108	
Nationalised Industry	0.021		0.004	
Non-profit organisation	0.017		0.038	
Armed Forces	0.008		0.001	
Other	0.006		0.012	
Occupation Major Groups				
Managers and Administrators	0.168		0.087	
Professional Occupations	0.106		0.097	
Associate Professionals & Tech	0.102		0.113	
Clerical and Secretarial (female reference)	0.099		0.300	
Craft and Related (male reference)	0.191		0.027	
Personal and Protective Services	0.067		0.148	
Sales	0.045		0.099	
Plant and Machine Operatives	0.156		0.045	
Other Occupations	0.066		0.084	
1-digit industry groups				
Agriculture, forestry and fishing	0.016		0.006	
Energy and water supplies	0.032		0.008	
Minerals, metal manufacture & chemicals	0.051		0.018	
Metal goods, engineering and vehicles	0.153		0.045	
Other manufacturing	0.125		0.073	
Construction	0.054		0.007	
Distribution, hotels and catering	0.154		0.223	
Transport and communication	0.088		0.034	
Banking, finance, insurance & business services	0.124		0.133	
Other services (reference)	0.203		0.453	
Regions of the UK				
Greater London	0.096		0.105	
Rest of South (reference)	0.195		0.201	
East Anglia	0.039		0.036	
South West	0.094		0.083	
West Midlands	0.091		0.089	
East Midlands	0.086		0.079	
Yorkshire	0.094		0.093	
North West	0.104		0.103	
North	0.067		0.064	
Wales	0.049		0.046	
Scotland	0.085		0.101	
NT	17,080		17,421	

Table A5: Earnings Equations using BHPS 1991-1998

Dependent Variable: log real hourly wage	Males: Table 2 Column 1		Females: Table 3 Column 1	
Unemployment	-0.019	(3.43)†	-0.009	(1.61)
Log of Regional to National Price Deflator	0.117	(0.69)	-0.065	(0.37)
Personal Controls				
Males Age 16-24 / Females Age 16-24	0.111	(0.83)	0.191	(0.82)
Age 24-29 / Age 24-29	0.078	(0.58)	0.145	(0.63)
Age 29-34 / Age 29-34	0.065	(0.49)	0.138	(0.59)
Age 34-39 / Age 34-39	0.051	(0.39)	0.129	(0.56)
Age 39-44 / Age 39-45	0.049	(0.37)	0.133	(0.57)
Age 44-51 / Age 45-50	0.046	(0.35)	0.126	(0.54)
Age 51-64 / Age 50-59	0.032	(0.24)	0.127	(0.55)
Married or Living as a Couple	0.002	(0.17)	0.030	(2.49)*
Widowed, Separated or Divorced	-0.022	(1.15)	0.022	(1.24)
Higher or First Degree, Teaching	0.096	(3.15)†	0.119	(3.92)†
Other Higher Education	0.038	(2.30)	0.037	(2.28)*
GCE A-level	0.054	(2.82)†	0.037	(1.78)
CSE Grade1-5	-0.038	(1.09)	0.033	(0.80)
Apprenticeship, Nursing, Other	0.087	(1.63)	0.036	(1.48)
Other Qualification	0.045	(1.58)	0.013	(0.47)
Registered Disabled	-0.007	(0.22)	-0.069	(1.65)
Health Limits types of work	-0.031	(3.12)†	-0.035	(3.84)†
Head of Household	-0.001	(0.03)	0.012	(1.32)
Own Children	-0.007	(0.63)	0.015	(1.19)
Children aged 0-4 Years	0.009	(0.99)	-0.033	(3.13)†
Children aged 5-11 Years	0.014	(1.67)*	-0.028	(3.00)†
Children aged 12-15 Years	0.011	(1.07)	-0.014	(1.45)
Unemployed in past year	-0.041	(4.76)†	-0.019	(1.91)
Non-participant in past year	-0.074	(5.83)†	-0.056	(6.89)†
Workplace Controls				
10-24 Employees	0.032	(3.59)†	0.035	(4.33)†
25-49 Employees	0.032	(3.42)†	0.056	(6.31)†
50-99 Employees	0.052	(5.29)†	0.068	(6.74)†
100-199 Employees	0.052	(5.12)†	0.065	(6.23)†
200-499 Employees	0.071	(7.07)†	0.069	(6.50)†
500-999 Employees	0.081	(6.94)†	0.068	(5.46)†
>1000 Employees	0.094	(7.99)†	0.069	(5.56)†
Full-time Employment	-0.154	(9.44)†	-0.101	(13.58)†
Seasonal/Temporary Work	-0.072	(4.62)†	-0.027	(2.27)**
Contract Work	-0.020	(1.54)	0.006	(0.43)
Promotion Opportunities	0.003	(0.51)	0.006	(1.04)
Bonuses or Profit	0.032	(6.38)†	0.026	(4.19)†
Annual Increments	0.012	(2.45)†	0.016	(3.01)†
Union or Staff Association	0.017	(2.09)**	0.058	(6.85)†
Member of Union	0.080	(8.57)†	0.035	(3.93)†
Rotating Shifts	0.027	(2.97)†	0.009	(0.80)
Manager	0.040	(4.71)†	0.038	(4.08)†
Supervisor	0.023	(3.66)†	0.029	(4.48)†
Travel 45+ Minutes	0.022	(3.05)†	0.025	(2.99)†

Employing Organisation				
Civil Service	0.013	(0.70)	0.044	(2.04)**
Local Govt.	0.037	(2.08)**	0.055	(4.14)†
NHS or Hospital	-0.034	(1.44)	0.030	(2.00)**
Nationalised Industry	0.047	(2.55)**	0.057	(1.47)
Non-profit organisation	-0.022	(0.92)	0.022	(1.32)
Armed Forces	0.096	(2.59)†	0.083	(1.16)
Other	-0.068	(2.33)**	0.035	(1.42)
Occupation Major Groups				
Managers and Administrators	0.015	(1.24)	0.026	(2.24)**
Professional Occupations	0.026	(1.91)*	0.051	(3.23)†
Associate Professionals and Technical	0.014	(1.12)	0.051	(4.14)†
Clerical & Secretarial	-0.031	(2.59)†	-	-
Craft and Related	-	-	-0.051	(2.16)*
Personal and Protective Services	-0.076	(4.62)†	-0.070	(5.61)†
Sales	-0.018	(1.18)	-0.095	(7.92)†
Plant and Machine Operatives	-0.033	(3.22)†	-0.029	(1.51)
Other Occupations	-0.080	(5.72)†	-0.098	(6.47)†
Industry Classes (1-digit)				
Agriculture, forestry and fishing	0.019	(0.65)	-0.003	(0.08)
Energy and water supplies	0.076	(3.20)†	0.157	(4.50)†
Minerals, metal manufacture and chemicals	0.031	(1.66)*	0.032	(1.23)
Metal goods, engineering and vehicles	0.016	(1.07)	0.088	(4.77)†
Other manufacturing	0.026	(1.72)*	-0.001	(0.09)
Construction	0.016	(0.94)	0.093	(2.82)†
Distribution, hotels and catering	-0.031	(2.17)**	-0.030	(2.71)†
Transport and communication	-0.001	(0.01)	-0.017	(0.84)
Banking, finance, insurance & business services	0.038	(2.68)†	0.032	(2.51)**
Region Dummies				
Greater London	0.079	(2.38)**	0.048	(1.55)
East Anglia	-0.018	(0.42)	0.005	(0.09)
South West	0.027	(0.71)	-0.108	(2.93)†
West Midlands	-0.037	(0.84)	-0.134	(3.12)†
East Midlands	0.012	(0.32)	-0.023	(0.55)
Yorkshire	-0.022	(0.43)	0.001	(0.01)
North West	-0.031	(0.69)	0.020	(0.41)
North	0.001	(0.01)	0.077	(1.18)
Wales	0.088	(1.71)*	-0.203	(3.00)†
Scotland	0.024	(0.43)	-0.022	(0.44)
Time Dummies				
Wave 2	-0.002	(0.02)	-0.092	(0.40)
Wave 3	-0.048	(0.18)	-0.213	(0.46)
Wave 4	-0.111	(0.28)	-0.348	(0.50)
Wave 5	-0.185	(0.35)	-0.471	(0.51)
Wave 6	-0.229	(0.34)	-0.596	(0.51)
Wave 7	-0.300	(0.38)	-0.737	(0.53)
Wave 8	-0.337	(0.36)	-0.850	(0.52)
Constant	-1.949	(0.43)	-4.161	(0.53)
Diagnostics				
F	30.94 [0.000]		27.55 [0.000]	
R^2	0.9323		0.9189	
NT	17,080		17,421	

Notes: t-ratios in parentheses. Significance levels: †(0.01), **(0.05), *(0.10); p-values in [].

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Chapter 5 - Regional Unemployment and Individual Heterogeneity

5.1 Introduction

The last twenty years has witnessed unprecedented growth in the analysis of labour force dynamics and the transition of individuals between alternative labour market states. Part of this expansion invariably lies in the development of the new economics of information and the resurgence of neoclassical principles within the microeconomic foundations of modern macroeconomics.[1] The remainder rests in the development and application of econometric techniques and the increased availability of good, reliable microeconomic data.[2] The Theory of Job Search provides the theoretical basis for the analysis of labour market transitions via the process of worker separations. The timing of these separations also provides the conceptual framework for the analysis of unemployment spell lengths. Viewed as the consequence of a sequence of single stage decisions, differences in the duration and frequency of unemployment appear to arise because of worker heterogeneity and variation in local labour market conditions. The frequency and average duration of unemployment provide information on the distribution of unemployment across individuals. They also inform how and when labour market transitions take place. Determining the nature of such transitions is critical. Increased duration of unemployment depreciates human capital and increases the inequality of employment opportunities and income distribution. The potential impact on economic development is thus great. Failure to tackle persistent unemployment significantly reduces the value of a nation's current and future output and results in misery for those concerned.[3]

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[1] Phelps (1970) provides the seminal contribution in this regard.
[2] See Lancaster (1990) for a survey of this literature.
[3] See Oswald (1997) for an analysis of the happiness of unemployed workers.

Job search theory emphasises flows into and out of unemployment, rather than the level of unemployment at any one time: the equilibrium or 'natural' rate of unemployment is asserted to be unaffected by the distribution of workers across labour market states or the distribution in any period. In particular, the theory focuses on the outflow rate from unemployment; the flow is interpreted as being equivalent to the probability that an unemployed individual finds work. Viewing the unemployed as a pool of workers with an inflow and an outflow allows observed changes in unemployment to be expressed as an excess of one over the other. It also allows the unemployment rate to be expressed, in a steady-state, as the inflow into unemployment multiplied by the average time spent there (average duration is defined as the inverse of the outflow rate).[4] Such a link is of critical importance. First, it provides a suggestive framework where aggregate unemployment may be investigated.[5] Second, it provides a method of identifying groups of workers with potentially low re-employment probabilities. This latter aspect yields significant policy implications: it permits discussion of flows to be applied to the analysis of variation in unemployment rates among groups of workers with different characteristics. Identifying the relative importance of workers' characteristics may result in the formulation of policy that alters the pattern of flows among groups. This, in turn, may yield desired alterations to the unemployment rate at both the national and regional level.

The empirical literature on unemployment duration is vast and encompasses a variety of themes. Most of these studies utilise the hazard approach to the analysis of unemployment and use individual data to estimate models that specify the conditional probability of exiting unemployment for a completed unemployment spell rather than

[4] See Layard *et al* (1991) for details.

[5] This decomposition has been utilised extensively by Jackman *et al* (1989) to show that changes in UK unemployment between the 1960's and 1980's can be attributed to changes in duration that arise from a marked downward trend in the outflow rate from unemployment.

focus on those determinants that directly affect the unemployment spell itself. Many of these studies evaluate the effect of the level and duration of unemployment benefit on the duration of unemployment, or the time-dependence of unemployment when controlling for competing risks.[6] Several studies, however, emphasise the importance of the arrival rate of job offers and the role of personal and demographic characteristics in the unemployment process. Jones (1988) and van der Berg (1990) reveal that individual heterogeneity and variation in the arrival rate of offers is at least as important as the reservation wage in determining unemployment duration. Local labour market conditions undoubtedly contribute to variation in the arrival rate of job offers. So too does an individual's method (and intensity) of job search. Assessing the relative importance of such factors is vital to understanding the role of individual decisions in the determination of unemployment spell lengths. The identification of such factors yields important implications for both individual welfare and regional development. Regional disparities reduce output and raise inflationary pressure. They also constrain opportunities for unemployed workers in depressed areas and impose significant negative welfare effects where selective out migration of highly skilled workers causes low rates of economic activity to persist.

This chapter investigates the relative importance of unemployed individuals' decisions and local labour market conditions in determining unemployment spell lengths utilising a regional survey of individual job seekers for the English County of Kent. The data is taken from the Kent Employment Survey 1992, a representative random sample of currently unemployed job seekers that contains personal and background information alongside the local labour market within which they reside. An advantage of this data is that it provides responses concerning the individual's minimum acceptance

[6] See Devine & Kiefer (1991) for a survey of this empirical literature.

(reservation) wage and method of search utilised in the job searching process. We utilise these features of the data to assess the relative importance of such factors in the determination of unemployment duration. There are extremely few duration studies that contain responses concerning individual reservation wages and search methods for the UK. In addition, we are unaware of any such analyses undertaken at the regional level.[7] Thus, the ability to investigate such facets provides a unique contribution to an otherwise extensive literature.

The remainder of the chapter proceeds as follows. Section 5.2 presents a brief overview of the job search approach and evidence regarding those factors deemed to affect unemployment duration. Section 5.3 discusses the data and considers descriptive evidence of the role of socio-demographic characteristics in determining unemployment duration. Section 5.4 presents an empirical model of unemployment duration based on job search theory. Section 5.5 outlines the methodology utilised in the estimation of the econometric model. Empirical results and discussion are reported in Section 5.6. Section 5.7 concludes.

5.2 The Job Search Approach: A Brief Overview

Job search theory asserts that the hazard rate or transition probability out of unemployment depends on two factors: first, the probability that the worker receives a job offer; and second, the probability that the job offer is acceptable. An acceptable job offer is a random offer drawn from the wage distribution that exceeds the worker's

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[7] Blackaby & Manning (1990a, 1990b, 1992) analyse the duration of regional unemployment to investigate the determination of regional earnings differentials. Jones & Manning (1992) consider the importance of the long-term unemployed in identifying hysteresis in the unemployment-vacancy relationship across the ten standard regions of the UK There are, however, no previous studies that directly estimate the determinants of individual unemployment duration at the regional level.

reservation or minimum acceptance wage. The reservation wage represents an equality between the marginal costs and marginal benefits of search activity where the worker is indifferent between accepting an offer and continuing to search. In a stationary framework, this wage is constant and inversely related to search and opportunity costs. A job that offers a wage higher than the reservation wage is thus an acceptable wage and provides an optimal route into employment.[8]

The empirical literature on unemployment duration is vast. Most of this literature focuses on the hazard rate out of unemployment rather than the underlying components themselves. Modelling the hazard does, however, indirectly provide information about those factors that are likely to affect an individual's unemployment duration. The probability that a worker receives a job offer is determined by their personal characteristics and local labour market conditions. Labour market tightness and demographic characteristics invariably influence the rate at which job offers arrive. They also influence whether an offer is deemed acceptable. Individual characteristics such as age, gender, human capital and family situation play a vital role in determining individual preferences and hence, the formulation of an appropriate reservation wage. The importance of these characteristics has long been identified in empirical analyses of unemployment duration.[9] Such identification has, until recently however, been typically secondary in nature and derived only as sample groups are stratified or cross-examined.

Many empirical models of job search investigate the issues of state-dependence and unemployment benefits in the determination of unemployment spell lengths.[10] Theoretical models of job search assert that unemployment benefits lower the costs of

[8] In this framework, the job is completely characterised by the wage.

[9] See Atkinson *et al* (1984) for an examination of the sensitivity of the hazard across workers.

[10] The issue of state dependence provides the focus of the next chapter.

search thereby raising individual reservation wages and the length of an unemployment spell. Empirically, a small positive benefit effect is agreed upon.[11] The effect proves sensitive, however, to local labour market conditions, elapsed duration, age and other worker characteristics. Narendranathan and Stewart (1993) suggest that the benefit effect declines with unemployment spell length. They report a steady decline in the effect of unemployment benefit on the hazard out of unemployment up to the twentieth week of a spell. Meyer (1990), in contrast, observes the hazard rate to rise dramatically just prior to when unemployment benefits expire. Furthermore, where benefit duration is extended, the hazard rate is found to be high in the week that benefits were previously expected to cease. The source of this increase is not identified: the competing risks of employment and labour market non-participation are not controlled for. However, the sensitivity of unemployment spell lengths to both worker characteristics and the duration of benefit is clearly revealed. This sensitivity suggests that individual heterogeneity may be substantial. Thus, identifying individual heterogeneity is crucial to determining the role of 'choice or chance' in unemployment duration.[12] Individual heterogeneity contributes to the determination of individuals' reservation wages and provides an important source of variation in the arrival rate of job offers.

The arrival rate of job offers will be dependent on the level of demand in the labour market within which an unemployed individual resides. It will also be dependent on the individual's characteristics and the attractiveness of the individual to the employer and vice versa. Educational attainment, previous occupation and the reason for leaving one's job are all likely to influence the arrival rate of job offers and the wage offer distribution that the individual faces. Personal characteristics such as age, gender, race and the

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[11] See Atkinson & Micklewright (1992) for a critical review of this branch of the empirical literature.
[12] See Mortensen & Neumann (1984) for details.

individual's willingness to search should operate similarly. The intensity and method of search utilised to escape unemployment varies across individuals. This variation may reflect variability in unemployment benefit receipt. Wadsworth (1991), for example, finds that the receipt of unemployment benefit yields a positive and significant effect on search effort. Thus, benefits claimants search more extensively than non-claimants. Schmitt & Wadsworth (1993), in contrast, reveal that the level of benefit exerts little influence on overall search activity.[13]

Unobserved heterogeneity provides a more likely source of variation in the method and intensity of search across individuals. Jones (1988) suggests unobserved heterogeneity in the offer distribution and arrival rate to be substantial. He reveals that regional dummies or local unemployment rates used to capture the effect of local labour market conditions are often insignificant once individual heterogeneity is controlled for. The method and intensity of job search provide an important source of heterogeneity in this regard. Search activity generates information about alternative job offers. Such information may be derived via formal methods such as the use of state or private employment agencies, direct approaches to employers, and responses to advertisements in newspapers and journals. It may also be derived from informal methods such as the use of friends or relatives and ports of access to internal labour markets. Recent studies reveal that the choice of search method exhibits strong variation across individuals in similar socio-economic groups. The lack of an obvious explanation as to why individuals adopt differing search methods may indicate that the choice of search method employed can be used to proxy for unobserved heterogeneity. This assumption suggests that individuals utilise alternative methods to signal their potential productivity

[13] The authors conclude that earlier results indicating high levels of search effort amongst benefit recipients relative to non-recipients probably reflect participatory factors brought about by selectivity bias in the estimation procedure.

relative to similarly skilled workers. The motivation and potential effect of utilising such methods may, however, vary across different socio-economic groups. Atkinson *et al* (1996) and Alpin and Shackleton (1997), for example, report that a large number of the employed obtain their jobs using informal search methods. Informal networks appear thus to provide an important role in the exit from unemployment. Urwin & Shackleton (1998), in contrast, report that the use of informal search methods by the unemployed has a significant negative effect on the hazard out of unemployment. Thus, the effect of alternative search methods may have a differential role.

The extent to which increased job search may lead to an increase in the arrival rate of offers is well recognized. The effect that an increase in the offer arrival rate has on the hazard out of unemployment is, however, potentially ambiguous. First, there is a positive effect reflecting an increase in the expected number of occasions where the individual is presented with an opportunity to exit unemployment. Second, there is a negative effect reflecting the increased selectivity of the searcher who now faces a greater opportunity to leave the current state. Such ambiguity raises questions as to the appropriate sign to expect on variables utilised in a reduced form specification that are deemed to capture such effects. Direct evidence on offer arrival rates is limited. There is, however, strong evidence to suggest that unemployed job seekers receive and reject very few job offers. Jones (1989) reports that over 85 percent of a cross-section of unemployed British workers in 1982 had never received a job offer. Holzer (1988), van der Berg (1990) and Erens & Hedges (1990) report likewise for a range of different countries. These results indicate that individuals remain unemployed primarily because they receive very few job offers not because they reject many.[14] Further credence for

[14] Jones (1988) points out that offer rejections are typically rare because the rejection of an offer may mean disqualification from insurance payments.

this view is provided by indirect evidence based on wage and duration data. Wolpin (1987) reveals that variation in acceptance probabilities is generally small. Furthermore, the acceptance probability itself appears high. Variation in unemployment duration appears thus to arise primarily from variation in the arrival rate of offers. Gorter & Gorter (1993) confirm this result. They conclude that neither the level of unemployment benefit nor the individual's reservation wage are important in ending a spell of unemployment. Instead, the offer arrival rate and those factors deemed to influence it provide the dominant means of escape.

This chapter explicitly addresses the role of those factors deemed to be important in determining the duration of unemployment. We utilise cross-section data drawn from a regional survey of the stock of individual job seekers in the County of Kent at October 1992 to investigate the relative importance of unemployed individuals' decisions and local labour market conditions in the unemployment process. The dataset provides a rich source of information concerning personal and demographic factors alongside individuals' reservation wages and method of job search. This information is extremely rare in unemployment data and consequently provides a unique opportunity to investigate the role of such factors further.

5.3 Data

We estimate individuals' unemployment durations utilising cross-section micro data drawn from a representative random survey of 5,392 interviews taken from Kent Employment Service records at October 1992. Designed as a joint survey by the Kent Employment Service and Kent County Council Planning Department, the survey accords well with Department of Employment records and accounts for 8 percent of the unemployed in Kent at that time. The principal concern of the survey was that it be representative of the unemployed in Kent. Accordingly, the survey was collated by drawing on a proportionately stratified sample of the unemployed by district. For each district, this sampling strategy ensures that the same proportions of persons are represented in the survey as for NOMIS. In addition, it ensures that the distribution of the county's unemployed be representative by age, gender and unemployment duration.[15,16,17]

We restrict analysis to those individuals in the survey who provide valid responses to all of the questions that we utilise in an econometric model that appears well informed by job search theory.[18,19] In addition, to alleviate potential biases in the reservation wage data, we symmetrically trim the data and omit the one percent of those individuals with both the highest and lowest reservation wages. These restrictions result in a final sample of 4,872 individuals. Tables A1 to A3 of the Appendix report the distribution of unemployment duration by age, qualifications and district for this sample. Table A4 presents data definitions and summary statistics.

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[15] The data is available from the Kent Employment Service and the Economic Policy and Research Group of the Kent County Council Planning Department upon request.

[16] NOMIS records for October 1992 reveal that 78% of Kent's unemployed constituted men with 22% women. This proportion is represented in the survey sample of 5,392 persons of which 76% are men and 24% are women.

[17] The survey slightly under-represents persons unemployed between 0 and 3 months, and 12 months & over. Similarly, persons unemployed between 3 and 12 months are slightly over-represented.

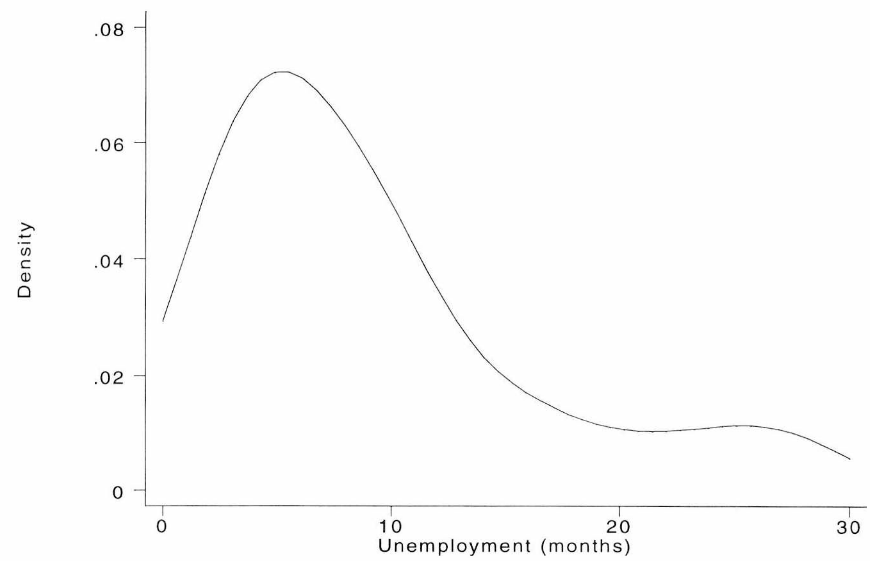
[18] One exception to this is that we include those individuals who either fail to report the wage earned from their previous employment or have a missing response to the question on the basis that they have not previously worked. For these individuals, the previous wage is imputed from existing data.

[19] We presume that the incidence of invalid responses is independent of the nature of other responses. Data mining provides credence here. Extensive cross-tabulations reveal that the estimable sample is representative of the survey design. Hence, selected individuals appear to be a fairly random draw.

The duration of unemployment is measured as months of registered unemployment in interval form. Figure 1 plots the distribution of unemployment durations. The distribution is positively skewed with 56 percent of the sample having unemployment duration of six months or less, and 7 percent having duration in excess of two years.[20]

Figure 1

The Distribution of Unemployment Duration



The distribution of unemployment duration by gender is reported in Table 1. This reveals that the final sample is consistent with the stratified sample for the survey as a whole. The proportion of women who are short-term unemployed is a little over 86 percent. For men the proportion is just over 77 percent. This suggests that unemployment duration is dependent upon gender and that men are more likely to remain unemployed. This pattern of unemployment may reflect a greater probability of exit to non-participation for women as duration increases. Competing risks in the analysis of unemployment is thus clearly inferred.

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[20] The distribution is estimated using kernel density estimation and constraining the upper bound of unemployment duration to 30 months.

Table 1

Unemployment Duration by Gender

	Male		Female		Total	
Duration Unemployed (months)	Persons	%	Persons	%	Persons	%
0-3	1,074	29.0	411	35.0	1,485	30.5
3-6	920	24.9	312	26.5	1,232	25.3
6-12	868	23.5	294	25.0	1,162	23.8
12-18	348	9.4	76	6.5	424	8.7
18-24	198	5.4	40	3.4	238	4.9
24+	289	7.8	42	3.6	331	6.8
Total	3,697	100	1,175	100	4,872	100

The survey provides a rich source of socio-economic information at the individual level. The richness of the data permits a variety of personal characteristics alongside identification of the district within which individuals reside. Personal characteristics have an important role in the determination of individual reservation wages. They also help to explain significant variation in the rate at which job offers arrive.

Individual attributes available in the data include gender, marital status, educational attainment and previous occupation. Additional information regarding an individual's age, health, literacy and labour market mobility are also included. Educational attainment, age and previous occupation are important considerations in the analysis of unemployment. Younger workers typically face a higher incidence of unemployment than older workers. Their durations are, however, on average much shorter. Similarly, individuals with no qualifications are likely to experience longer durations of unemployment, as are those individuals who were previously employed in industries experiencing sectoral decline. Marital status and gender are important because of the strong link with labour force participation and family dependency. Increased dependency should exert a negative effect on unemployment duration. For men, this is likely to result in the transition to employment. For women, however, there is an increased likelihood of exit to non-participation.[21] Individual exit rates are also likely to be influenced by labour market mobility. The greater the distance and prospective travel time an individual is willing to consider, the greater is the perceived wage offer distribution and the probability that an acceptable job offer arrives. Table 2 reports that prospective travel time exerts a significant impact on the distribution of unemployment duration. Gender and marital status are important considerations in this regard, as is having access to one's own transport. [22] Descriptive analysis of the data reveals that having one's own transport exerts a positive effect on travel time. Thus, a widening of the individual's job search area should be expected. Potential impacts here appear to be significant. 75 percent of individuals with their own transport are identified in that data as being unemployed for less than 6 months; 95 percent are observed as being unemployed for less than 1 year. This contrasts with 44 percent and 70 percent respectively for those without such access.

Table 2

Unemployment Duration and Travel to Work Time

	Travel Time (minutes)					
Duration Unemployed (months)	0 to 15	15-30	30-45	45-60	60+	Total
0-3	92	334	272	214	573	1,485
3-6	76	287	245	181	443	1,232
6-12	117	276	239	157	373	1,162
12-18	47	99	94	60	124	424
18-24	41	47	40	49	61	238
24+	63	93	47	47	81	331
Total	436	1,136	937	708	1,655	4,872

Reservation wages are derived from responses regarding the minimum weekly wage unemployed individuals would be prepared to accept in order to gain employment. Job search theory imparts that the reservation wage should be less than or equal to the

[21] This is particularly evident for married women who often consider employment in order to provide households with a secondary income.

[22] The data reveals that 53 percent of all women are prepared to commute up to half an hour, with 17 percent prepared to commute for an hour or more. This contrasts with 26 percent and 40 percent of all men respectively. Marital status is an important factor here: married women are the group identified as being least likely to commute as travel time increases.

workers acceptance wage and more than the individual's benefit entitlement. Lack of available data prevents this analysis. Reported reservation wages may, however, be tested using previous wages. The data reveals that 72 percent of unemployed respondents report a reservation wage less than or equal to their previous wage. This statistic appears meaningful given that the majority of worker separations occur as an exogenous process (i.e. they do not leave their jobs voluntarily). There is, however, significant variation in reservation wages. Reservation wages appear to increase with age. They are also markedly higher for men. The mean reported reservation wage for men is £192 per week; for women it is £134.[23] These differentials are highlighted in the construction of a variable that reflects the ratio of reservation wages to previous earnings. This ratio has a mean of 1.051 in the sample and is quite dispersed around this value with a standard deviation of 0.678 and a median of 0.999.

Search activity is captured in the data by a categorical variable that distinguishes between alternative methods of job search. The distribution of search activity across the range of unemployment duration is reported in Table 3. This reveals that 72 percent of individuals utilise job centres as the main method of search activity.[24] Newspapers and journals account for 18 percent of individuals, 7 percent is attributed to speculative inquiries and the remaining 3 percent to private employment agencies and other methods. The proportion of individuals using speculative inquiries is relatively constant across the duration of unemployment. The use of newspapers and journals, private employment agencies and other search methods are, however, dominated by the short-term unemployed. The use of job centres by the long-term unemployed is significant in

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[23] This disparity in expected earnings across gender highlights the importance of industry and occupation structure: women dominate lower paid professions.

[24] This partially reflects the nature of the benefit administration scheme in the UK.

Table 3

Unemployment Duration and Search Activity

Duration Unemployed (months)	Job centre	Newspaper	Private Agency	Speculative Inquiry	Other	Total
0-3	1,036	284	40	110	15	1,485
3-6	882	237	15	85	13	1,232
6-12	828	223	25	81	5	1,162
12-18	335	68	5	15	1	424
18-24	187	35	2	14	0	238
24+	279	32	1	18	1	331
Total	3,547	879	88	323	35	4,872

this regard. 70 percent of those unemployed for less than 12 months report using job centres as their chosen job search method. This proportion rises to 78 percent for those with duration between 1 and 2 years, and 84 percent for those experiencing duration of 2 years or more. This pattern may reflect a discouraged worker effect. It could, however, equally indicate the success of alternative search methods in reducing the individual's probability of remaining unemployed.

Finally, geographical variation in job offer arrival rates is captured by a set of district dummies. These help to capture those effects brought about by institutional and industrial differences that are inherent in determining the occupational structure of a region and local labour demand. The data reports significant variation in the experience of unemployment across the county's districts. Identifying such variation should help to capture variation in the arrival rate of offers across the county. It should also help in determining appropriate policy formation. The data reveals regional impacts of unemployment in Kent as severe. East and North Kent account for 81% of the county's unemployment problem. Identifying the true extent of geographical variations is thus of critical importance.

5.4 The Empirical Model

The standard job search model implies that both the reservation wage and hazard rate out of unemployment should remain constant over the length of an unemployment spell. The hazard or instantaneous probability of exiting unemployment is equal to the probability that a job offer is received, and the conditional probability that the offer is accepted by the unemployed individual. An acceptable offer is an offer whose wage is greater than the individual's reservation wage.[25]

The hazard rate may be formally derived as:

$$\tau = \delta\pi(1 - F(w^r)) \tag{5.1}$$

where τ is the hazard rate, δ is the job offer arrival rate, w^r is the reservation wage and $F(w)$ is the cumulative distribution of wage offers. If the hazard rate (τ) is independent of elapsed duration, the implied distribution of completed unemployment spells T will be exponential:

$$g(T) = \tau e^{-\tau T} \tag{5.2}$$

The data described in the previous section contains cross-section information for a stock of currently unemployed individuals. Thus, we are interested in the distribution of incomplete spells of unemployment rather than completed spells. The probability of observing an individual's incomplete spell of length t, is the probability of a spell lasting t. This probability is given by the survivor function:

$$S(t) = 1 - G(t) = e\{-\tau t\} \tag{5.3}$$

where G(t) is the cumulative distribution function for the density function g(t):

$$g(t) = \tau\, e(-\tau t) \tag{5.4}$$

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[25] The empirical methodology developed here is identical to that of Jones (1988).

The distribution of incomplete spells for an individual will be the normalised survivor function:

$$p(t) = \frac{1 - G(t)}{\int_0^{\infty} (1 - G(s))ds} \tag{5.5}$$

Integrating equation (5.2) over T to obtain G(t) and substituting into equation (5.5), the normalised survivor function may also be written:

$$p(t) = \tau e^{-\tau t} \tag{5.6}$$

Progression from equation (5.6) to an estimable model necessitates that additional structure be imposed. First, an assumption must be made regarding the wage offer distribution. The most common and tractable assumption in this regard is that wage offers are drawn from a Pareto distribution. In this instance, the probability that a wage offer is acceptable and exceeds the reservation wage may be expressed as:

$$1 - F(wr) = (A \mid w^r)^{\alpha} \tag{5.7}$$

$$\Rightarrow \tau = \delta(A \mid w^r)^{\alpha}$$

where A is the origin of the Pareto distribution and α is a scale parameter that may be interpreted as the constant elasticity of the hazard with respect to the reservation wage. Second, an assumption must be made regarding the functional form of the probability of receiving and accepting a job not accounted for by the reservation wage. For simplicity, an exponential function of the individual's characteristics, X_i is assumed:

$$\delta A^{\alpha} = e(k + X_i{}'\beta + u_i) \tag{5.8}$$

where k is a constant, X_i a vector of non-stochastic regressors, β a vector of unknown parameters, and u_i an independently identically normally distributed random variable with zero mean and variance σ^2. Sections 5.2 and 5.3 outlined the types of explanatory variables that X_i may represent. These are included to capture the effect of variation in the arrival rate of offers and the acceptance of such offers.

The expected log of incomplete unemployment duration ignoring variation in individuals can be expressed as:

$$E(\log t \mid \tau) = \int_0^\infty \log(s)p(s)ds \tag{5.9}$$

$$= \int_0^\infty \log(s)\tau e^{-\tau s}ds$$

$$= -c - \log(\tau)$$

where c is Euler's constant. The expected log of incomplete unemployment duration conditional on individual characteristics may thus be written:

$$E(\log t \mid w^r, X_i) = -(c+k) + \alpha \log(w^r) - X_i{}'\beta - E(u_i \mid w^r, X_i) \tag{5.10}$$

Renewal theory asserts that, if the flow into unemployment is constant over time, equation (5.10) may be treated as a regression model where the individuals used for estimation are a cross-section of unemployed people with incomplete durations at a particular point in time.[26] If the above assumptions are acceptable, the parameters of this model can be traced directly to job search theory and the model can be considered a structural model. If the assumptions are not acceptable, then equation (5.10) provides a valid reduced form regression from which the theory of job search provides guidance as to the types of explanatory variables to include.

Endogeneity provides a concern in the above analysis. The structural interpretation of equation (5.10) holds only if the conditional expectation of the error term in equation

[26] See Lancaster (1990) for details.

(5.10) is zero. If reservation wages are correlated with omitted variables, the conditional expectation of the error term will be non-zero. In this instance, the use of instrumental variables (IV) will be necessary to avoid potential simultaneity bias and ensure that parameter estimates are consistent. The choice of instruments used to obtain predicted values of the reservation wage must be restricted to variables that affect the reservation wage and are correlated with but do not affect the arrival rate of job offers and the wage offer distribution. Gorter and Gorter (1993) and Jones (1989) utilise the level of unemployment benefits as an appropriate instrument. Information concerning benefit eligibility and benefit levels is not available in our data. Thus, we utilise individuals' last reported wages and whether they were previously self-employed. These instruments should exert significant impacts on individual reservation wages but are unlikely to yield significant effects on the arrival rate of offers or the wage offer distribution.[27]

5.5 Methodology

Interval data presents a problem when utilised as a dependent variable in the estimation of an econometric model. Assigning the midpoint to observations in any given group may provide one method of undertaking. Assigning values to open ended groups is, however, an ad hoc process that additionally fails to produce consistent parameter estimates. We overcome this problem by adopting the approach of Stewart (1983), an approach which recognises that the upper and lower bounds of the observed intervals provide important information for consistent estimation of an econometric model.

[27] State dependence in the reservation wage also yields concerns for the estimation of equation (5.10). In general, state dependence entails that progression from equation (5.1) to equation (5.2) will no longer be valid. In this instance, the duration of unemployment and individuals' reservation wages may be considered as two endogenous variables in a simultaneous system. Lancaster (1985) demonstrates that under certain assumptions, a tractable expression for the reservation wage in a simultaneous system may be derived where the duration specification remains as in equation (5.10). This specification again warrants the use of instrumental variables to deal with the potential endogeneity bias outlined above. See Heath & Swan (1999) for additional details.

The latent structure of equation (5.10) is given by:

$$y_i = X_i'\beta + u_i \qquad i = 1, \ldots, n \tag{5.11}$$

where y_i is the unobserved dependent variable (log of unemployment duration), X_i a vector of non-stochastic regressors and β a vector of unknown parameters. The u_i are assumed to be independently identically normally distributed random variables with zero mean and variance σ^2. This yields the distribution of the unobserved dependent variable as:

$$y_i \sim N(X_i'\beta, \sigma^2) \qquad (i = 1, \ldots, n) \tag{5.12}$$

The observed information concerning the dependent variable is that it falls into a certain range on the real line. Let A_k be the upper boundary of the k^{th} range. Then, the information on the log of unemployment duration is:

$$A_{k-1} < y_i \leq A_k \tag{5.13}$$

The lower bound of unemployment duration is closed at zero but the upper bound is open ended. Thus, in logarithmic form, both end ranges are open ended such that $A_0 = -\infty$ and $A_k = +\infty$ where K is the number of groups.

The log likelihood of the above model is given by:

$$\log L = \Sigma_{k=1}^{K} \Sigma_{i \in k} \log \left\{ F\left[\left(\frac{A_k - X_i'\beta}{\sigma}\right)\right] - F\left[\left(\frac{A_{k-1} - X_i'\beta}{\sigma}\right)\right] \right\} \tag{5.14}$$

$$= \Sigma_i \log\{F_k - F_{k-1}\}$$

where F is the cumulative distribution of the standard normal. Consistent estimates of β and σ are obtained by Maximum Likelihood Estimation (MLE).

5.6 Empirical Results

Maximum likelihood estimates for the log of unemployment duration are reported in Table 4. Column 1 presents the parameter estimates for the log of unemployment duration when the regression equation is interpreted as a structural model of job search theory. The remaining columns, in contrast, present parameter estimates consistent with the reduced form interpretation of the econometric model. Column 2 reports the first stage of the IV procedure and presents estimates of the log of the reservation wage when explanatory variables and instruments are utilised in the estimation. Second stage estimates for the log of unemployment duration are reported in column 3.

Column 2 reveals that parameter estimates for the log reservation wage equation appear to be both meaningful and appropriate in that they are consistent with what would be expected *a priori*. Reservation wages are significantly greater for older workers, married workers, qualified workers and workers in professional occupations. They are also greater for workers who have their own transport and those who are prepared to travel for longer. Workers who are prepared to travel for between 30 and 60 minutes have reservations wages 9 to 10 percent higher than the reference category. For workers prepared to travel for one hour or more, the increase in the reservation wage is 16 percent. Female reservation wages are 11 percent lower than those for men.[28] This is consistent with the pattern of reservation wages described earlier. It is also consistent with observed wage differentials in the empirical literature of wage determination for individuals who are employed.

Residential location has a significant impact on the reservation wage. Residing in the Thanet district depresses the reservation wage by just under 10 percent. For Canterbury

[28] Percentage differentials are calculated as $100\times(e^{\beta_i}-1)$ - see Halvorsen & Palmquist (1980).

and Dover the reduction is between 3 and 4 percent. Lower reservation wages may reflect the latent employment structure of the region and the lack of good quality opportunities therein. Average weekly wages are significantly lower in East Kent than other parts of the County. Lower reservation wages may thus reflect reduced expectations by workers and an optimal response to the environment that they work and reside in. They could, however, equally reflect the skill distribution across the county. The data reveals that East Kent districts have a disproportionately high number of workers without any qualifications. Less qualified workers can expect to acquire less remuneration for their human capital. Thus, a negative effect for such districts may also be consistent.

The choice of job search method also yields a significant impact on the reservation wage. Individuals who make speculative inquiries or use newspapers and journals as their chosen search method have reservation wages 8 percent higher than those who report using job centres. For individuals using private employment agencies, the increase in the reservation wage is some 13 percent. Hence, individuals who utilise alternative search methods expect to earn higher wages. This result may indicate that workers expect to be compensated for any additional costs incurred in the search process. It could, however, reflect the characteristics of the workers involved. Qualified workers disproportionately represent individuals who report using such methods. These workers have higher reservation wages: they expect to earn wages that reflect their higher marginal productivity. Thus, a positive association between reservation wages and alternative search methods may be expected.

Column 3 reveals that the signs of parameter estimates for socio-demographic covariates on the log of unemployment duration are also as we would expect *a priori*.

Table 4

Estimation Results for Full Sample

	MLE		Instrumental Variables First Stage		Instrumental Variables Second Stage	
Dependent Variable	Log Duration		Log w^r		Log Duration	
Personal Characteristics						
Age 16-19	-0.314	(5.29)†	-0.066	(4.16)†	-0.337	(5.45)†
30-39	0.121	(2.97)†	0.063	(5.79)†	0.133	(3.18)†
40-49	0.181	(3.97)†	0.075	(6.16)†	0.194	(4.16)†
50+	0.123	(2.46)**	0.031	(2.34)†	0.131	(2.61)†
Gender	-0.208	(5.28)†	-0.118	(11.33)†	-0.235	(5.29)†
Married or Living as a Couple	0.010	(0.27)	0.087	(8.97)†	0.027	(0.70)
Separated, Divorced or Widowed	0.001	(0.01)	0.033	(2.53)**	0.009	(0.18)
Health problem	-0.038	(0.76)	-0.014	(1.04)	-0.044	(0.87)
Literacy problem	0.026	(0.30)	-0.005	(0.20)	0.016	(0.19)
Have own transport	-0.653	(20.91)†	0.023	(2.82)†	-0.647	(20.56)†
Want to work part-time	-0.070	(0.46)	-0.201	(4.98)†	-0.106	(0.68)
Educational Attainment						
First or Higher Degree, HND or HNC	-0.076	(1.05)	0.046	(2.35)**	-0.067	(0.92)
GCE A-level	-0.048	(0.72)	0.041	(2.33)**	-0.042	(0.63)
City & Guilds	-0.086	(1.82)*	0.027	(2.12)**	-0.079	(1.67)*
GCE O-level or equivalent	-0.153	(3.97)†	0.022	(2.14)**	-0.150	(3.86)†
NVQ	-0.261	(2.23)**	0.069	(2.19)**	-0.247	(2.09)**
Other Qualification	0.040	(0.61)	0.031	(1.76)*	0.046	(0.69)
Search Activity						
Newspapers & Journals	-0.020	(0.51)	0.075	(7.31)†	-0.006	(0.14)
Private Employment Agency	-0.018	(0.16)	0.125	(4.39)†	0.008	(0.07)
Speculative Inquiry	-0.022	(0.37)	0.078	(4.98)†	-0.008	(0.13)
Other	-0.407	(2.37)**	0.045	(1.02)	-0.398	(2.32)**
Travel Time (minutes)						
15-30	-0.151	(2.72)†	0.039	(2.64)†	-0.144	(2.60)†
30-45	-0.094	(1.60)	0.092	(5.82)†	-0.079	(1.32)
45-60	-0.097	(1.57)	0.083	(5.04)†	-0.081	(1.30)
60+	-0.181	(3.10)†	0.151	(9.61)†	-0.153	(2.46)**
Previous Job						
Managers and Administrators	-0.032	(0.49)	0.020	(1.12)	-0.023	(0.35)
Professional Occupations	-0.060	(0.64)	0.002	(0.07)	-0.058	(0.62)
Associate Professionals and Technical	-0.114	(1.47)	-0.002	(0.11)	-0.113	(1.46)
Clerical and Secretarial	-0.114	(1.95)**	-0.079	(5.05)†	-0.127	(2.15)**
Personal and Protective Services	-0.082	(1.32)	-0.103	(6.21)†	-0.106	(1.64)*
Sales	-0.184	(3.09)†	-0.071	(4.46)†	-0.205	(3.33)†
Plant and Machine Operatives	0.106	(2.05)**	-0.058	(4.10)†	0.094	(1.79)*
Other Occupations	0.030	(0.65)	-0.070	(5.66)†	0.014	(0.30)
No previous job	0.090	(1.31)	-0.143	(7.80)†	0.071	(1.02)
District						
Ashford	0.164	(2.22)**	-0.012	(0.60)	0.164	(2.22)**
Canterbury	0.450	(6.70)†	-0.039	(2.14)**	0.442	(6.55)†
Dartford	0.158	(2.23)**	0.055	(2.91)†	0.168	(2.35)**
Dover	-0.543	(7.59)†	-0.033	(1.78)*	-0.549	(7.65)†
Gillingham	0.261	(3.78)†	0.011	(0.57)	0.265	(3.82)†
Gravesham	-0.285	(3.38)†	0.042	(1.92)*	-0.277	(3.28)†
Rochester	0.097	(1.50)	0.053	(3.06)†	0.107	(1.64)*
Sevenoaks	-0.207	(1.67)*	0.047	(1.44)	-0.200	(1.61)
Shepway	0.101	(1.45)	0.001	(0.05)	0.103	(1.48)
Swale	-0.058	(0.84)	0.001	(0.06)	-0.058	(0.85)
Thanet	-0.382	(5.67)†	-0.091	(5.10)†	-0.400	(5.82)†
Tonbridge & Malling	0.057	(0.85)	0.003	(0.16)	0.060	(0.90)
Tunbridge Wells	-0.008	(0.06)	-0.013	(0.31)	-0.007	(0.05)
Constant	2.418	(9.64)†	3.418	(70.06)†	3.040	(5.73)†

Table 4 Continued

	Structural MLE	Instrumental Variables First Stage	Second Stage
Dependent Variable	Log Duration	Log w^r	Log Duration
Log Reservation Wage (w^r)	-0.061 (1.26)	-	-0.187 (1.75)*
Instruments			
Previously Self Employed	-	0.059 (5.63)†	-
Log Previous Wage	-	0.300 (34.31)†	-
Diagnostics			
F	-	132.48 [0.00]	-
LR χ^2	1156.77	-	1158.27
R^2	-	0.5738	-
Log Likelihood	-7191.5637	-	-7190.8152
N	4,872	4,872	4,872

Notes

1. Estimations by Intercooled Stata 6.0. Coefficient t-values in parentheses. Significance levels: †(0.01), **(0.05), *(0.10); p-values of diagnostics in [].
2. The Hausman test accepts the null hypothesis of no misspecification. $\chi^2(48)=1.62[1.00]$.

Age and gender have highly statistically significant effects on the probability of remaining unemployed. Women can expect to experience far shorter spells of unemployment than men. Younger workers can expect likewise. Workers aged between 16 and 19 years experience unemployment durations 29 percent shorter than those in the reference category. Workers aged 30 years or more, in contrast, can expect unemployment durations between 12 and 20 percent longer.

Longer durations may also be expected for workers without qualifications. Negative parameter estimates regarding educational attainment are consistent with human capital theory. Statistically significant estimates for 'O'-level or equivalent qualifications, and more vocational qualifications such as City and Guilds and NVQs, additionally suggest that broad based qualifications have a critical role in determining labour market experience. Broad based qualifications act as an entry-level screening device for both employers and academic institutions alike. The lack of such qualifications can thus be expected to have adverse consequences for individuals (re)employment probabilities.

The insignificant parameter estimates for marital status and health are somewhat surprising. The lack of statistical significance for marital status may reflect differences in experience by gender. In contrast, the lack of significance regarding health problems may reflect sampling bias in the unemployment register.[29] Labour market mobility and previous occupation are significant determinants of unemployment duration. Workers previously employed in semi-skilled occupations can expect shorter unemployment durations than the reference group of craft and related occupations. Individuals willing to travel for longer than 15 minutes can expect similarly. Significantly, workers with their own transport experience significantly shorter durations of unemployment regardless of travel time. This result is highly significant and suggests that lack of mobility may present a serious constraint on policies aimed at reducing the unemployment problem in Kent. The use of informal networks and 'other' search activity may help in this regard. Individuals who report using such methods experience unemployment spells 33 percent shorter than those who adopt more formal methods.

Geographical variations also yield significant impacts on the length of time individuals' can expect to remain unemployed. Individuals residing in the East and North Kent districts of Ashford, Dartford, and Rochester can expect unemployment durations between 11 and 18 percent longer than those residing in the Mid-Kent district of Maidstone. For Canterbury and Gillingham, the expected increase in unemployment duration is 56 percent and 30 percent respectively. The districts with significantly lower durations are the East and North Kent districts that report both the highest incidence of unemployment and the lowest proportions of long-term unemployed. This result is

[29] Disney & Webb (1991) reveal that there has been a significant upward trend in the receipt of long-term sickness benefits. This trend appears to be positively correlated with higher unemployment but insensitive to reductions in the aggregate unemployment rate. They tentatively suggest that this discrepancy may be due to asymmetry in the relationship between unemployment and sickness benefits. It could, however, also reflect changing eligibility conditions for other benefits (such as unemployment benefit).

somewhat surprising. However, as previously reported, these districts disproportionately represent unskilled workers. A high incidence of unemployment together with short unemployment durations suggests churning in these labour markets to be considerable. This is consistent with the earlier hypothesis that these districts may consist of relatively poor employment opportunities. It also provides confirmation that variation in the arrival rate of job offers due to local demand conditions is a significant determinant of unemployment duration.

The socio-economic and demographic parameter estimates reported in the IV specification of column 3 are not systematically different from the structural estimates reported in column1. The role of the log reservation wage on the log of unemployment duration also holds in this regard. Both specifications report a perverse negative sign on the log reservation wage with neither parameter estimate statistically significant at conventional levels. A negative sign on the log reservation wage implies that higher reservation wages reduce the probability of remaining unemployed. Thus, unemployment duration should be shorter. This result is at odds with job search theory. It may, however, reflect the static nature of cross-section data. Cross-section data entails that the focus of explanatory variables is on the incomplete duration of unemployment at a point in time. We have already reported that qualified workers, mobile workers, and workers who utilise alternative search methods have shorter durations of unemployment. These workers also report significantly higher reservation wages. Thus, a negative coefficient for the log reservation wage in the estimation of the log of unemployment duration may reflect strong correlation between such factors.

The reduced form specification for the log of unemployment duration is appropriate if reservation wages are correlated with omitted variables. If there are omitted variables, parameter estimates for the IV specification will be consistent and unbiased, but the parameter estimate of the log of reservation wages in the structural specification will be biased. This bias can be tested formally using a Hausman test.[30] The null hypothesis of the Hausman test is that the IV and structural estimates have no measurement error. Under the null hypothesis, both estimators are consistent estimators, although the IV estimator is inefficient. The Hausman test accepts the null hypothesis of no misspecification. Thus, the structural equation is the appropriate method of estimation and the reservation wage is not statistically significant in the determination of unemployment duration.[31]

In order to confirm the generality and robustness of our results, two additional experiments were performed. First, we investigated the validity of the instruments utilised in the first stage of the IV procedure. A good instrument for our econometric model is one that is correlated with the log reservation wage but not significantly correlated with the log of unemployment duration. The first-stage IV estimates reported in column 2 of Table 4 indicate that, of our two chosen instruments, the log of previous earnings has a more significant correlation with the log reservation wage than whether the individual was previously self-employed. Since we have two instruments but only one variable to instrument, we can test the validity of one instrument by assuming the validity of the other. Thus, we test the validity of the log of previous earnings by including it in the second-stage duration equation where the self-employed variable is used as the sole instrument in the first-stage. The parameter estimate for the log of previous earnings is positive but insignificant with a t-ratio of 0.53. This suggests that

[30] See Hausman (1978).
[31] This result is consistent with Gorter and Gorter (1993) but contrasts with Dolton & O'Neil (1995) and Warren (1999), both of whom report the reservation wage as having a significant positive effect on the unemployment experience of the long-term unemployed.

the over-identifying restriction that the log of previous earnings is a valid instrument is accepted.

Second, we estimate our wage and duration equations separately for men and women. The full sample reveals that women experience significantly shorter unemployment durations than men. This contrast in the experience of unemployment is likely to reflect gender differences in the exit probability into non-participation. The inability to control for competing risks by gender may yield potential biases in parameter estimates when covariates are estimated over the full sample. Thus, re-estimating the econometric specifications for men and women separately should test whether our conclusions hold *a fortiori*.

The results of estimating separate equations for men and women are reported in Tables A5 and A6 of the appendix. These show important differences in the determinants of unemployment duration. Regardless of gender, older workers have both higher reservation wages and unemployment durations. Qualifications significantly increase the reservation wages of men and women. Significant reductions in the probability of remaining unemployed are, however, only observed for men. Willingness to travel yields similar impacts. Reservation wages are significantly higher for all persons willing to travel for longer. A negative impact on unemployment duration is, however, again only observed for men. Marital status and health are important determinants of male reservation wages but have no significant effect on unemployment duration. Previous occupation and residential district, in contrast, yield significant impacts on the reservation wages and unemployment duration of both genders. Thus, our main finding that variation in the arrival rate of job offers has a significant impact on individuals' unemployment experiences is unaffected by this dichotomisation of the data.

5.6 Conclusion

This chapter has investigated the impact of individual heterogeneity and local labour market characteristics on unemployment duration using a unique regional dataset for the English County of Kent. Utilising an econometric model tied closely to job search theory, our results reveal that variation in the arrival rate of job offers is an important factor in determining unemployment spell length. Individual 'choice' characteristics such as educational attainment, labour market mobility and method of job search exercise significant and important effects on the duration of unemployment. These results are robust across both male and female unemployment spells. They are also consistent with a number of previous studies that recognise the importance of individual characteristics in determining the risks associated with unemployment and unemployment duration (Nickell (1980), Jones (1988), Gorter and Gorter (1993)). Interestingly, the sign on parameter estimates for the reservation wage are inconsistent with job search theory. This result is, however, only statistically significant for women. We take this result to indicate a shortcoming in cross-section data when applied to the analysis of unemployment duration and other lifetime events.

APPENDIX

Table A1

Unemployment Duration and Age

	Unemployment Duration (months)						
Age of Individual	0 to 3	3-6	6-12	12-18	18-24	24+	Total
16-19	129	124	96	24	7	2	382
20-29	584	468	439	157	74	114	1,839
30-39	310	236	251	100	69	74	1,040
40-49	243	241	200	83	56	67	890
50+	219	163	176	60	32	71	721
Total	1,485	1,232	1,162	424	238	331	4,872

Table A2

Unemployment Duration and Qualifications

	Unemployment Duration (months)						
Highest Qualification	0 to 3	3-6	6-12	12-18	18-24	24+	Total
Degree, HND/HNC	88	70	70	24	11	13	276
A-level	110	62	61	20	14	15	282
City & Guilds	211	152	164	57	29	34	647
O-level or equivalent	478	362	313	78	42	44	1,317
NVQ	22	21	16	5	4	3	71
Other qualifications	61	62	60	33	10	17	243
No qualification	515	503	478	207	128	205	2,036
Total	1,485	1,232	1,162	424	238	331	4,872

Table A3

Unemployment Duration and District

	Unemployment Duration (months)						
District	0 to 3	3-6	6-12	12-18	18-24	24+	Total
Ashford	73	72	70	32	17	30	294
Canterbury	82	66	117	57	46	60	428
Dartford	106	62	75	47	39	36	365
Dover	194	124	76	1	0	0	395
Gillingham	75	85	105	56	33	47	401
Gravesham	94	51	37	13	5	6	206
Maidstone	123	100	129	28	12	21	413
Rochester	126	115	127	54	24	34	480
Sevenoaks	27	22	17	6	1	0	73
Shepway	116	70	80	54	27	47	394
Swale	131	115	107	24	14	24	415
Thanet	205	219	115	5	1	2	547
Tonbridge & Malling	119	120	95	44	17	22	417
Tunbridge Wells	14	11	12	3	2	2	44
Total	1,485	1,232	1,162	424	238	331	4,872

Table A4

Data Definitions & Summary Statistics

Variable	All Persons Mean	All Persons SD	Males Mean	Males SD	Females Mean	Females SD
Dependent Variables:						
Log of unemployment duration						
Log of reservation wage	5.086	0.389	5.170	0.367	4.823	0.339
Independent Variables:						
Gender (1,0 if female)	0.241		-		-	
Age	34.10	12.23	34.84	12.28	31.80	11.78
Marital Status						
Never Married (reference)	0.463		0.460		0.472	
Married or Living as a Couple	0.399		0.414		0.352	
Separated, Divorced or Widowed	0.138		0.126		0.176	
Highest Qualification						
First or Higher Degree, HND or HNC	0.057		0.057		0.054	
GCE A-level	0.058		0.053		0.074	
City & Guilds	0.133		0.156		0.060	
GCE O-level or equivalent	0.270		0.230		0.396	
NVQ	0.015		0.013		0.019	
Other Qualification	0.050		0.053		0.041	
No Qualification (reference)	0.417		0.438		0.356	
Search Methods						
Job Centre (reference)	0.728		0.718		0.760	
Newspapers & Journals	0.180		0.178		0.189	
Private Employment Agency	0.018		0.017		0.022	
Speculative Inquiry	0.067		0.079		0.026	
Other	0.007		0.008		0.003	
Travel Time						
0-15 Mins. (reference)	0.090		0.073		0.141	
15-30 Mins.	0.233		0.185		0.386	
30-45 Mins.	0.192		0.188		0.205	
45-60 Mins.	0.145		0.158		0.106	
60+ Mins.	0.340		0.396		0.162	
Previous Occupation						
Managers and Administrators	0.066		0.071		0.049	
Professional Occupations	0.031		0.032		0.026	
Associate Professionals and Technical	0.043		0.045		0.040	
Clerical and Secretarial	0.108		0.062		0.252	
Craft and Related (reference)	0.218		0.276		0.036	
Personal and Protective Services	0.078		0.052		0.161	
Sales	0.090		0.062		0.180	
Plant and Machine Operatives	0.113		0.134		0.045	
Other Occupations	0.188		0.210		0.117	
No previous job	0.065		0.056		0.094	
Other Personal Controls						
Health problem	0.088		0.087		0.092	
Literacy problem	0.028		0.031		0.019	
Have own transport	0.385		0.407		0.313	
Want to work part-time	0.009		0.004		0.023	
Previously self-employed	0.184		0.234		0.028	
Log of last wage	5.134	0.553	5.247	0.511	4.782	0.534
District						
Ashford	0.060		0.061		0.057	
Canterbury	0.088		0.094		0.070	
Dartford	0.075		0.074		0.079	
Dover	0.081		0.082		0.078	

Gillingham	0.082		0.081		0.086	
Gravesham	0.042		0.041		0.045	
Maidstone (reference)	0.085		0.085		0.083	
Rochester	0.099		0.102		0.089	
Sevenoaks	0.015		0.012		0.026	
Shepway	0.081		0.087		0.062	
Swale	0.085		0.078		0.107	
Thanet	0.112		0.114		0.106	
Tonbridge & Malling	0.086		0.081		0.101	
Tunbridge Wells	0.009		0.008		0.011	

Table A5

Estimation Results for Male Sample

	MLE		Instrumental Variables IV First Stage		Instrumental Variables IV Second Stage	
Dependent Variable	Log Duration		Log w^r		Log Duration	
Log Reservation Wage (w^r)	-0.029	(1.63)	-	-	-0.234	(1.94)*
Instruments						
Previously Self Employed	-	-	0.048	(4.58)†	-	-
Log Previous Wage	-	-	0.313	(31.20)†	-	-
Personal Characteristics						
Age 16-19	-0.373	(5.09)†	-0.101	(5.34)†	-0.423	(5.46)†
30-39	0.129	(2.79)†	0.067	(5.60)†	0.151	(3.17)†
40-49	0.207	(3.94)†	0.085	(6.20)†	0.233	(4.31)†
50+	0.086	(1.50)	0.021	(1.39)	0.100	(1.74)*
Married or Living as a Couple	0.007	(0.17)	0.107	(9.74)†	0.041	(0.89)
Separated, Divorced or Widowed	-0.064	(1.14)	0.032	(2.21)**	-0.050	(0.88)
Health problem	-0.040	(0.67)	-0.033	(2.18)**	-0.054	(0.91)
Literacy problem	0.026	(0.29)	-0.003	(0.10)	-0.042	(0.45)
Have own transport	-0.722	(20.25)†	0.025	(2.68)†	-0.713	(19.83)†
Want to work part-time	-0.049	(0.19)	-0.154	(2.34)**	-0.104	(0.40)
Educational Attainment						
First or Higher Degree, HND or HNC	-0.028	(0.34)	0.028	(1.31)	-0.013	(0.16)
GCE A-level	-0.010	(0.13)	0.033	(1.65)*	-0.003	(0.03)
City & Guilds	-0.100	(1.97)**	0.014	(1.06)	-0.091	(1.78)*
GCE O-level or equivalent	-0.153	(3.38)†	0.006	(0.53)	-0.151	(3.33)†
NVQ	-0.337	(2.38)**	0.050	(1.36)	-0.320	(2.26)**
Other Qualification	0.039	(0.53)	0.024	(1.23)	0.046	(0.62)
Search Activity						
Newspapers & Journals	-0.039	(0.85)	0.077	(6.60)†	-0.012	(0.26)
Private Employment Agency	-0.015	(0.11)	0.104	(3.12)†	0.026	(0.20)
Speculative Inquiry	-0.033	(0.52)	0.089	(5.51)†	-0.004	(0.07)
Other	-0.292	(1.63)	0.022	(0.47)	-0.279	(1.55)
Travel Time (minutes)						
15-30	-0.193	(2.75)†	0.041	(2.22)**	-0.182	(2.58)†
30-45	-0.175	(2.41)**	0.088	(4.64)†	-0.150	(2.05)**
45-60	-0.126	(1.71)*	0.073	(3.81)†	-0.101	(1.36)
60+	-0.238	(3.40)†	0.136	(7.45)†	-0.193	(2.62)†
Previous Job						
Managers and Administrators	-0.006	(0.09)	0.016	(0.83)	0.065	(0.09)
Professional Occupations	-0.002	(0.18)	-0.004	(0.14)	-0.001	(0.00)
Associate Professionals and Technical	-0.201	(2.31)**	-0.010	(0.47)	-0.201	(2.31)
Clerical and Secretarial	-0.099	(1.32)	-0.081	(4.15)†	-0.127	(1.66)*
Personal and Protective Services	-0.090	(1.14)	-0.106	(5.16)†	-0.130	(1.60)
Sales	-0.231	(3.10)†	-0.070	(3.66)†	-0.267	(3.48)†
Plant and Machine Operatives	0.140	(2.55)**	-0.052	(3.58)†	0.121	(2.18)**
Other Occupations	0.027	(0.55)	-0.061	(4.79)†	0.004	(0.09)
No previous job	0.117	(1.44)	-0.154	(7.32)†	0.085	(1.03)
District						
Ashford	0.187	(2.20)**	0.008	(0.38)	0.191	(2.25)**
Canterbury	0.430	(5.63)†	-0.037	(1.84)*	0.417	(5.44)†
Dartford	0.182	(2.22)**	0.082	(3.83)†	0.205	(2.47)**
Dover	-0.552	(6.69)†	-0.025	(1.19)	-0.559	(6.78)†
Gillingham	0.269	(3.35)†	0.052	(2.47)**	0.284	(3.53)†
Gravesham	-0.324	(3.30)†	0.075	(2.99)†	-0.303	(3.07)†
Rochester	0.157	(2.12)**	0.076	(3.95)†	0.180	(2.41)**
Sevenoaks	-0.220	(1.38)	0.027	(0.66)	-0.218	(1.36)
Shepway	0.095	(1.20)	0.014	(0.67)	0.101	(1.27)
Swale	-0.015	(0.19)	0.008	(0.39)	-0.012	(0.16)

Thanet	-0.363 (4.72)†	-0.078 (3.92)†	-0.391 (5.01)†
Tonbridge & Malling	0.107 (1.38)	0.027 (1.31)	0.117 (1.50)
Tunbridge Wells	0.011 (0.06)	-0.029 (0.61)	0.008 (0.04)
Constant	2.284 (7.80)†	3.443 (60.05)†	3.332 (5.57)†
Diagnostics			
F	-	90.63 [0.00]	-
LR χ^2	960.61	-	964.25
R^2	-	0.5439	-
Log Likelihood	-5524.5598	-	-5522.7392
N	3,697	3,697	3,697

Notes

1. See notes to Table 4.
2. The Hausman test accepts the null hypothesis of no misspecification. $\chi^2(47)=3.59[1.00]$.

Table A6

Estimation Results for Female Sample

	MLE		Instrumental Variables: IV First Stage		Instrumental Variables: IV Second Stage	
Dependent Variable	Log Duration		Log w^r		Log Duration	
Log Reservation Wage (w^r)	-0.267	(2.80)	-	-	-0.085	(0.34)
Instruments						
Previously Self Employed	-	-	0.075	(1.55)	-	-
Log Previous Wage	-	-	0.245	(13.84)†	-	-
Personal Characteristics						
Age 16-19	-0.142	(1.43)	-0.024	(0.84)	-0.126	(1.23)
30-39	0.131	(1.58)	0.046	(1.94)*	0.119	(1.40)
40-49	0.059	(0.64)	0.050	(1.88)*	0.045	(0.48)
50+	0.279	(2.66)†	0.056	(1.81)*	0.264	(2.48)**
Married or Living as a Couple	0.024	(0.33)	0.020	(0.97)	0.017	(0.23)
Separated, Divorced or Widowed	0.164	(1.77)*	0.033	(1.27)	0.157	(1.68)*
Health problem	-0.051	(0.52)	0.029	(1.04)	-0.054	(0.55)
Literacy problem	0.244	(1.23)	0.006	(0.11)	0.249	(1.26)
Have own transport	-0.375	(5.89)†	0.020	(1.11)	-0.382	(5.92)†
Want to work part-time	-0.144	(0.77)	-0.220	(4.16)†	-0.096	(0.49)
Educational Attainment						
First or Higher Degree, HND or HNC	-0.189	(1.23)	0.113	(2.58)†	-0.212	(1.36)
GCE A-level	-0.139	(1.16)	0.072	(2.09)**	-0.155	(1.27)
City & Guilds	-0.007	(0.05)	0.094	(2.56)**	-0.027	(0.21)
GCE O-level or equivalent	-0.128	(1.72)*	0.078	(3.65)†	-0.146	(1.88)*
NVQ	-0.071	(0.34)	0.127	(2.14)**	-0.109	(0.52)
Other Qualification	0.084	(0.59)	0.040	(0.96)	0.071	(0.50)
Search Activity						
Newspapers & Journals	0.044	(0.59)	0.061	(2.89)†	0.030	(0.39)
Private Employment Agency	0.007	(0.03)	0.141	(2.58)†	-0.023	(0.11)
Speculative Inquiry	0.099	(0.56)	-0.042	(0.84)	0.113	(0.64)
Other	-	-	0.175	(1.32)	-	-
Travel Time (minutes)						
15-30	-0.046	(0.52)†	0.041	(1.59)	-0.054	(0.61)
30-45	0.075	(0.76)	0.074	(2.57)†	0.059	(0.58)
45-60	-0.097	(0.81)	0.060	(1.75)*	-0.109	(0.90)
60+	-0.105	(0.90)	0.147	(4.42)†	-0.139	(1.11)
Previous Job						
Managers and Administrators	-0.336	(1.78)*	0.069	(1.25)	-0.366	(1.89)*
Professional Occupations	-0.494	(2.05)**	0.088	(1.27)	-0.520	(2.12)**
Associate Professionals and Technical	-0.001	(0.00)	0.094	(1.61)	-0.120	(0.10)
Clerical and Secretarial	-0.335	(2.19)**	-0.021	(0.46)	-0.331	(2.16)**
Personal and Protective Services	-0.294	(1.89)*	-0.091	(1.98)**	-0.263	(1.64)
Sales	-0.331	(2.15)**	-0.047	(1.04)	-0.308	(1.97)*
Plant and Machine Operatives	-0.329	(1.75)*	-0.104	(1.89)*	-0.309	(1.62)
Other Occupations	-0.185	(1.15)	-0.095	(1.99)**	-0.152	(0.92)
No previous job	-0.198	(1.17)	-0.103	(2.06)**	-0.173	(1.01)
District						
Ashford	0.003	(0.02)	-0.075	(1.75)*	0.013	(0.09)
Canterbury	0.539	(3.92)†	-0.011	(0.27)	0.544	(3.93)†
Dartford	0.041	(0.30)	-0.011	(0.28)	0.040	(0.29)
Dover	-0.502	(3.55)†	-0.033	(0.82)	-0.495	(3.49)†
Gillingham	0.152	(1.14)	-0.105	(2.70)†	0.173	(1.27)
Gravesham	-0.215	(1.35)	-0.047	(1.03)	-0.213	(1.33)
Rochester	-0.122	(0.95)	-0.016	(0.43)	0.121	(0.94)
Sevenoaks	-0.206	(1.07)	0.045	(0.81)	-0.221	(1.13)
Shepway	0.102	(0.70)	-0.045	(1.06)	0.104	(0.71)
Swale	-0.172	(1.35)	-0.008	(0.23)	-0.165	(1.30)

Thanet	-0.411 (2.98)†	-0.106 (2.71)†	-0.387 (2.72)†
Tonbridge & Malling	-0.083 (0.66)	-0.061 (1.65)*	-0.075 (0.59)
Tunbridge Wells	-0.180 (0.65)	0.001 (0.01)	-0.196 (0.71)
Constant	-3.249 (6.62)†	3.572 (35.12)	2.389 (1.99)**
Diagnostics			
F	-	17.53 [0.00]	-
LR χ^2	228.54	-	220.82
R^2	-	0.4276	-
Log Likelihood	-1625.1663	-	-1.629.0303
N	1,175	1,175	1,175

Notes

1. See notes to Table 4.
2. Stata 6.0 drops 'other' search method from estimation of unemployment duration on the basis that observations are only recorded for women experiencing an unemployment spell of between 0 and 3 months.
3. The Hausman test accepts the null hypothesis of no misspecification. $\chi^2(46)=2.44[1.00]$.

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Chapter 6 - Unemployment Duration, State Dependence and Individual Heterogeneity in the UK

6.1 Introduction

Event history analysis has come to occupy a great deal of interest in empirical labour research over the last 20 years.[1] Part of this interest invariably reflects a growing dissatisfaction with orthodox econometric analysis and the lack of qualitative information in traditional cross-section and time-series data. The remainder, in many regards, marks an acknowledgment by the profession of the limitations of viewing unemployment as a stock concept and instead recognising it as the consequence of the transition of individuals across alternative labour market states. The passage of people across alternative states has generated a great deal of interest in identifying what determines the nature of such flows. Particular interest, in this regard, has been devoted to identifying those factors deemed important in determining the probability of an unemployed individual exiting a spell of unemployment. This interest arises from the realisation that the welfare of the unemployed is likely to be closely related to unemployment duration. Aggregate unemployment rates conceal the distribution of unemployment across individuals over time: no information is provided as to whether the same individuals experience unemployment each year or whether individual experiences of unemployment are distributed randomly across the labour force. Unemployment duration, in contrast, is much more revealing. The distribution of unemployment duration provides important information regarding the dispersion of unemployment across individuals. It also permits the recognition of individual

[1] The methodology for the analysis of the "failure" time of an individual originates from biostatistics and much of the terminology has been transferred to other disciplines. Kalbfleisch and Prentice (1980), Lawless (1982), Cox and Oakes (1984) and Lancaster (1990) provide the standard references for this statistical analysis.

heterogeneity in determining the nature of such transitions. Identifying individual heterogeneity has significant implications for individual welfare. Recognising those characteristics that are associated with prolonged spells of unemployment enables policy makers to recognise unemployed individuals with potentially low re-employment probabilities and, thus, those who are most likely to be at risk of long-term unemployment. Perhaps of more significance, it additionally allows one to assess what affect the duration of unemployment has on determining the exit probability of an existing spell. The idea that past unemployment experience may help determine current unemployment is recognised as 'state dependence' in the statistical literature and 'scarring' in the economics literature. The issue of state dependence has attracted considerable attention in recent years. Understanding the origins and magnitude of this effect remains, however, to be resolved.

A number of studies document the influence of personal characteristics and unemployment spell length on the probability of exiting unemployment using British data for the 1970's and 1980's. Many of these studies evaluate the effect of the level of unemployment benefit on unemployment duration (Atkinson *et al*, 1984; Narendranathan *et al*, 1985; Arulampalam and Stewart, 1995).[2] The impact of targeted assistance schemes has also been examined.[3] This chapter sets out to investigate the determinants of unemployment duration and state dependence in unemployment for men and women in the 1990's, drawn from the first eight waves of the British Household Panel Survey (BHPS). The BHPS is a nationally representative sample of more than 5,000 households (approximately 10,000 individual interviews) and provides a rich source of socio-economic information for issues concerning household

[2] Related studies examine the impact of unemployment benefit receipt on individuals search intensity. See Wadsworth (1991) and Schmidt and Wadsworth (1993) for details.

[3] Dolton and O'Neill (1995) analyse the impact of the RESTART scheme in reducing the unemployment duration of the long-term unemployed.

organisation, labour market activity, income and wealth, housing, health and education amongst others. It also provides extensive information on individual labour market activity both during the panel and retrospectively from labour market entry. This information enables a complete labour market status history for almost every individual in the survey. Thus, the chapter provides a representative framework for analysis during the 1990's, a period where the level and structural composition of unemployment has witnessed a marked change from the preceding decades.

The remainder of the chapter proceeds as follows. Section 6.2 presents a brief overview of the standard framework adopted in the empirical literature for the analysis of unemployment spells. The hazard approach to modelling unemployment duration is explored and issues regarding the sensitivity of parameter estimates to econometric (mis)specification additionally revealed. Section 6.3 outlines the empirical framework used to assess the determinants of unemployment duration and the impact of duration in determining 'state' dependence in unemployment over the distribution of completed unemployment spells. Section 6.4 discusses the data and provides descriptive statistics therein. Empirical results are reported in section 6.5. Section 6.6 concludes.

6.2 Job Search Theory: The Empirical Framework

The usual framework for the empirical analysis of unemployment duration is the theory of job search. Job search theory asserts that the hazard rate or transition probability out of unemployment is equal to the product of the probability that a job offer is received, and the conditional probability that the offer is accepted by the unemployed individual. An acceptable job offer is a random offer drawn from the wage distribution that exceeds the worker's reservation or minimum acceptance wage. The reservation wage represents an equality between the marginal costs and marginal benefits of search activity where the worker is indifferent between accepting an offer and continuing to search. A job that offers a wage higher than the reservation wage is thus an acceptable wage and provides an optimal route into employment.

The job search framework allows a variety of estimation techniques to be adopted in empirical work. Most empirical studies, however, utilise transition data and adopt the hazard function approach.[4] This approach models the duration of unemployment by specifying the conditional probability of leaving unemployment: the probability of leaving unemployment at time t conditional on not having exited up to that time. Many of these studies examine the impact of individual characteristics, and the level and duration of unemployment benefits on the probability of an unemployment spell ending.[5] Numerous studies, however, explore the issue of state or duration dependence and examine whether the experience of unemployment contributes to the probability of an unemployment spell ending. Hazard functions provide a convenient interpretation in this regard. An increasing hazard function implies positive state dependence; that is, the conditional probability of leaving unemployment increases with spell length. A decreasing hazard function, in contrast, implies negative state dependence; the conditional probability of exit falls the longer the individual remains unemployed.

Economic theory is not informative as to the appropriate shape of the hazard function. The basic search model predicts that the probability of exiting unemployment is independent of unemployment duration. Thus, the distribution of completed

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[4] See, for example, Lancaster (1990), Devine and Kiefer (1991) and Wolpin (1995).

[5] The issue of state benefits on unemployment duration is now largely resolved. See Atkinson and Micklewright (1992) for a critical review.

unemployment spells is exponential.[6] Empirically, the exponential distribution is convenient to interpret and is an adequate model for duration data that does not exhibit much variation. The existence of time varying processes may alter this result. Declining reservation wages or exhaustive benefit entitlement in the search environment could cause the conditional probability of exiting unemployment to rise with unemployment duration. Conversely, a fall in the arrival rate of job offers due to the depreciation of human capital, or signalling by employers could cause the hazard rate to fall. Such non-stationarity necessitates that an alternative specification for the distribution of unemployment spells be considered. Many distributional specifications exist in this regard. Common examples include the Weibull, exponential, Gamma and log-normal distributions. Less common are the inverse-Gaussian, truncated Gaussian, Gompertz, log-logistic, Box-Cox and the generalised Gamma. Selecting between competing models is, however, a difficult task. The choice among the alternatives may be theoretical arising from known properties of the distributions, data related via the shape of empirical representations of the hazard, or on the basis of goodness of fit statistics. Mathematical convenience and complexity of calculation provide less robust criteria. They are, however, utilised extensively and probably help explain the dominance of the Exponential and its generalisation, the Weibull distribution in the empirical literature.[7]

The empirical evidence on state dependence is mixed. Having controlled for observed individual characteristics, Moffitt (1985) and Meyer (1990) reveal positive state dependence consistent with an increase in the hazard as unemployment benefits

[6] The exponential distribution is often termed *memoryless* because the hazard function is constant and uniquely characterises the distribution as having no duration dependence.

[7] Any specification of the hazard has a mathematically equivalent specification in terms of a probability distribution. The hazard function specification emphasises conditional probabilities. In contrast, the specification in terms of a probability distribution emphasises unconditional probabilities. These two specifications involve the same parameters. Thus, each specification represents a different way of describing the same set of probabilities.

approach exhaustion. Several studies, however, report strong negative state dependence (Nickel, 1979; Atkinson *et al*, 1984; van der Berg and van Ours, 1994). The analysis of state dependence is complicated by the presence of unobserved individual heterogeneity. Unmeasured or unobserved characteristics bias the estimated hazard function toward spurious negative state dependence. Intuitively, this arises if some unobserved characteristics intensify the transition of workers into reemployment. In this instance, individuals with higher reemployment probabilities leave the sample first leaving behind those individuals who do not possess those unobserved characteristics. Over time, these less employable individuals will come to dominate the sample thus inducing a systematic bias toward stronger negative state dependence than actually exists. To avoid this bias, unobserved heterogeneity must be accounted for. Separating 'true state dependence' from that which is 'spurious' is, however, a difficult task. The typical approach in the empirical literature has been to write the hazard as conditional upon those unobserved characteristics in the same manner as the observed characteristics (regressors) in the model, and to integrate out over some assumed functional form. This approach is simple to apply and appears intuitively sensible. However, the problem of identification arises immediately. A variety of distributions may be selected for the structural hazard and unobserved heterogeneity. Numerous combinations of these distributions may adequately represent the data. Estimating a reduced form hazard that arises from an erroneous specification of the structural hazard and heterogeneity mixing distribution will, however, yield very misleading and biased estimates of the structural hazard coefficients.

The correct strategy for measuring state dependence necessitates that both the baseline hazard function (the duration distribution) and the unobserved heterogeneity distribution be correctly identified (the baseline hazard will capture 'true' state dependence). By definition, the distribution of unobserved heterogeneity is unknown. Therefore, a parsimonious specification must be imposed. Heckman and Singer (1984) show that misspecifying the heterogeneity distribution yields serious consequences for the parameter estimates capturing time-varying covariates and inferences regarding state dependence. They estimate a Weibull hazard together with Standard Normal, log-normal and Gamma mixing distributions to capture the effects of individual heterogeneity using a subset of the Kiefer and Neumann (1981) unemployment duration data. The reported results provide very different structural estimates and range from insignificant to strongly significant negative state dependence according to the mixing distribution imposed. The impact of the 'observed' explanatory variables is also reported to reveal variation across the three models. This result suggests that the specification of the mixing distribution is of vital importance in determining consistent and unbiased parameter estimates of the structural hazard. Other studies, however, suggest that the choice of functional form for the baseline hazard may, in general, be more important.

The most commonly used specifications of the hazard function are parametric. Parametric specifications of the hazard function are relatively simple to apply to duration data. They are, however, unduly restrictive in identifying the nature of state dependence. The Weibull model, for example, allows only for hazard rates that monotonically increase or decrease with duration (or remain constant - it nests the exponential distribution). If variation in the hazard is not monotonic, this parametric misspecification will violate the 'true' distribution of unemployment spells and parameter estimates will be biased. Inferences concerning state dependence will also be contaminated. Several studies suggest that parameter estimates are more sensitive to misspecification of the baseline hazard than potential misspecification of the mixing distribution used to capture unobserved heterogeneity. Ridder (1987) indicates that in the presence of a flexible specification of the duration distribution, unobserved individual heterogeneity may be adequately accounted for via a simple parameterisation of the heterogeneity distribution. This result suggests that the sensitivity of parameter estimates reported by Heckman and Singer to alternative specifications of the mixing distributions for unobserved heterogeneity may be due to the inappropriateness of the Weibull model. This conclusion is given further credence by Han and Hausman (1990). They find that commonly used parametric specifications of the baseline hazard are unduly restrictive and, more often than not, too simple for observed data. In addition, the inclusion of unobserved heterogeneity has only a minor effect on reported results once a flexible parameter specification of the baseline hazard is adopted. Related work by Meyer (1990), Narendranathan and Stewart (1993) and Dolton and van der Klaauw (1995) confirms these findings. A recent study by Addison and Portugal (1997) reports likewise. The authors report a non-monotonic hazard that is more or less inversely U-shaped. They additionally conclude that the inclusion of unobserved individual has no significant impact on regression parameter estimates or state dependence once a flexible parametric specification of the baseline hazard is used.

Identifying true state dependence from that which is spurious has significant implications for labour market policy. Negative state dependence or 'scarring' as it has become known in the economics literature implies that the long-term unemployed may be stigmatised by their unemployment experience. This stigma may occur on the demand or the supply side of the economy. Supply side considerations emphasise loss of skill (Sinfield, 1981) and worker demoralisation (Pissarides, 1985). Demand side considerations, in contrast, stress the importance of firms' hiring functions and the associated roles of discrimination (Harrison, 1976) and screening (Lockwood, 1991;

Pissarides, 1992). The precise nature of each remains to be identified. Implications regarding aggregate unemployment, by contrast, do not. If the long-term unemployed search less actively or are less desirable than the short-term unemployed, then the higher the proportion of long-term unemployment, the weaker is the effective competition for vacancies. Weaker competition for vacancies imparts that aggregate unemployment will be less effective at holding down aggregate wages. This process naturally entails hysteresis (the effects of a change in short-run unemployment are greater than those of a change in long-term unemployment).[8] It also ensures long-run concavity in the relationship between wages and unemployment (downward pressure on wages increases less than proportionally to unemployment). Both of these yield significant impacts on the long-term structure and performance of the labour market. Thus, identifying the true nature of state dependence is an important concern.

This chapter explicitly addresses the issue of state dependence and the role of individual heterogeneity in the determination of unemployment spell lengths. We take account of the potential bias on parameter estimates of time varying covariates and the underlying shape of the baseline hazard imposed by restrictive parametric specifications of the hazard rate and estimate the probability of leaving unemployment using a discrete time proportional hazards framework. We utilise this framework to examine the sensitivity of estimations to alternative specifications of the hazard and to test the role of unobserved individual heterogeneity in the unemployment process. Economic policy necessitates the correct identification of those factors that are important in determining the probability of exit from unemployment. Thus, controlling for the potential bias of omitted heterogeneity and spurious state dependence is of considerable importance for individual welfare.

[8] See Nickell (1987) for details.

6.3 The Econometric Model

We estimate the instantaneous probability of exit from unemployment at time t, conditional on survival to time t, utilizing a discrete time framework with parametric and non-parametric baseline hazards. The discrete time proportional hazard model enables us to overcome two potential weaknesses observed in the empirical literature. First, following Meyer (1990) and Narendranathan and Stewart (1993), it allows us to estimate the underlying hazard non-parametrically. This generates a very flexible baseline hazard that can circumvent the bias that arises from misspecifying the underlying hazard. Second, evidence suggests that spurious state dependence arising from unobserved heterogeneity in duration models can also be mitigated if a sufficiently flexible baseline hazard is employed (Han and Hausman, 1990; Dolton and van der Klaauw, 1995).

The probability of a spell being completed by time t+1 given that it was still continuing at time t, is the discrete time (or grouped) proportional hazard (Prentice and Gloeckler, 1978) given by:

$$h_i(t) = 1 - \exp\{-\exp[x_i(t)'\beta + \theta(t)]\} \tag{6.1}$$

where $x_i(t)$ is a set of covariates associated with the risk of exiting unemployment, β are the coefficients to be estimated, and $\theta(t)$ is some functional form for the underlying or baseline hazard at time t.

We adopt two specifications for the underlying hazard $\theta(t)$. First, we consider the discrete time equivalent of the Weibull specification for the baseline hazard such that $\theta(t) = \alpha t^{\alpha-1}$. The model is estimated by including the log of the unemployment duration in the set of covariates. A positive sign on this coefficient implies positive state dependence with a monotonically increasing hazard. A negative sign, in contrast, implies that the hazard is decreasing monotonically with negative state dependence. The Weibull model is a common specification for state dependence in the unemployment literature. This specification has, however, been rejected by Han and Hausman (1990) and Narendranathan and Stewart (1993) as being too restrictive which can lead to severe bias in the estimated parameters. Thus, the Weibull model provides a useful point of reference for the remainder of our analysis.

Our second specification adopts the approach of Meyer (1990) and specifies a fully flexible specification of the baseline hazard with an interval specific parameter $\gamma(t)$ where $\gamma(t) = \ln\left[\int_t^{t+1} \lambda(u)du\right]$ and is interpreted as the logarithm of the integral of the baseline hazard for each completed interval. A fully flexible non-parametric specification of the baseline hazard removes the restriction of monotonic state dependence and allows for non-linear variations. This should limit the potential bias in parameter estimates that arises from misspecification of the baseline hazard. The potential impact of unobserved heterogeneity on the hazard is, however, not identified. We thus follow the approach of Meyer (1990) and extend both of the above specifications by introducing a random variable that is independent of the covariates associated with the risk of exiting unemployment. A convenient distribution to assume for this variable is the gamma with mean one (as a normalization) and variance σ^2.[9] Thus, the corresponding discrete hazard is given by:

$$h_i(t) = 1 - \exp\{-\exp[x_i(t)'\beta + \theta(t) + \log(\epsilon_i)]\} \tag{6.2}$$

[9] See Meyer (1990) for details.

Incorporating unobserved heterogeneity is important in accounting for unobserved differences between individuals that help to explain variation in the probability of exiting unemployment. As previously discussed, several studies indicate that the inclusion of unobserved heterogeneity has only a minor effect on reported results once a flexible parameter specification of the baseline hazard is adopted. The inclusion of unobserved heterogeneity in our specifications of the baseline hazard will provide an additional test to the existent literature.

6.4 Data

We estimate the determinants of UK unemployment duration and the issue of state dependence using longitudinal micro data drawn from the first eight waves of the British Household Panel Survey (BHPS), a nationally representative survey of households randomly selected south of the Caledonian Canal.[10] The BHPS was designed as an annual survey of each adult member (age 16 or over) from a nationally representative sample of more than 5,000 households, providing a total of approximately 10,000 individual interviews. The first wave of the BHPS was conducted from September 1991 to January 1992, subsequent waves have been collected annually thereafter.[11,12]

The BHPS collects extensive information on respondents' labour market status at the time of interview at each wave of the panel, through the period between 1 September a year prior to the interview date, and retrospectively from leaving full-time education.

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[10] The very north of Scotland is thus excluded.
[11] From Wave Seven the BHPS has incorporated a sub-sample of the original United Kingdom European Community Household Panel (UKECHP), including all households still responding in Northern Ireland. For consistency purposes across the panel, these new sample members are excluded from analysis
[12] See Taylor (1998) for details.

The collection of such information imposes considerable organisational complexity in the manipulation of such data.[13] This complexity is a necessary and inevitable aspect of longitudinal surveys. It does, however, inhibit the use of the work-life history information. For this purpose, a set of 'reconciled' labour market history files has recently been released.[14] We utilise the second release of this set of files and restrict our analysis to those individuals who experience unemployment and provide complete responses to interviews across all eight waves of the panel.[15] We use the survey definition of unemployment, viz. out of work and looking for employment. All unemployment spells that commence prior to the Wave 1 interview are discarded. To each remaining spell, we attach a vector of socio-demographic characteristics as determined at the previous date of interview.[16] The survey provides a rich source of socio-economic information at the individual level. The information used in the analysis is selected on the basis that it is assumed to impact on the exit or transition probability from unemployment. Job search theory asserts that the transition probability out of unemployment depends on two factors: first, the probability that a job offer is received; and second, the probability that a job offer is accepted. Thus, those characteristics that are deemed to be important in determining either of these regards provide the focus of our analysis.

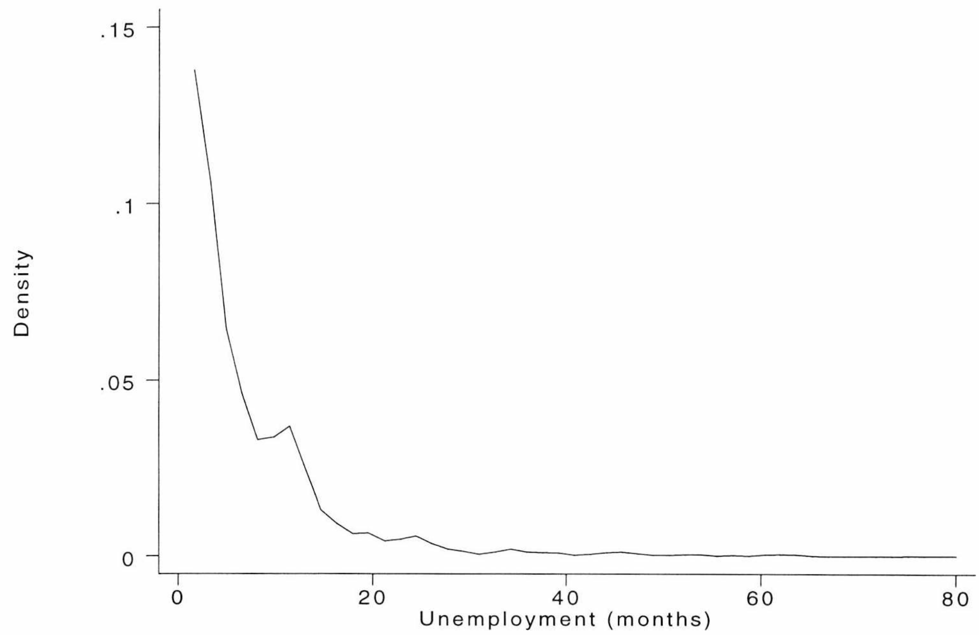
The resulting sample available from the BHPS work-life histories consists of 1,896 spells, of which, 1,792 are completed spells of unemployment. Thus, right-censored

[13] Life-time employment history is collected at Wave 2 while life-time occupational history is collected at Wave 3. This longitudinal component of respondents' labour market activity results in four different types of labour-market history information in twelve different files in the BHPS database.
[14] See Halpin (1997) for details.
[15] Individuals are additionally excluded from analysis when they reach state retirement age. These sample criteria may appear restrictive. They ensure, however, that all individuals were at risk of experiencing unemployment.
[16] Thus, the vector of individual characteristics is considered exogenous to unemployment spell length.

spells account for a little over 5 percent of the data.[17] Unemployment spell length is measured as months in unemployment. The distribution of completed unemployment spells is illustrated in Figure 1.[18] The distribution is positively skewed with a mean duration of 7.5 months and a median duration about one half the mean. Table 1 decomposes these unemployment spells by gender.[19] Table 2 provides an additional breakdown by spell length. The majority of spells are experienced by men (1,130 spells or 59.6%). The mean duration for men is 8.3 months, for women it is 6.3 months. Two thirds of male unemployment spells are completed in less than 9 months while 78.5 percent are completed within a year. For women, two thirds of spells last less than 7 months while 84.9 percent last less than a year. This confirms that women typically experience shorter unemployment spells. The reason for such exit patterns is, however, not identified.

Figure 1

The Distribution of Unemployment Spells



[17] Right-censored spells are observed when the survey interrupts spells still in progress.
[18] The distribution is estimated using kernel density estimation.
[19] We focus on spells of unemployment rather than individuals. While we have data on 1,836 spells, these spells comprise 1,149 individuals (645 men and 504 women).

The richness of the BHPS data permits a variety of personal controls. These controls include age, gender, race, health, marital status, educational attainment, housing tenure, head of household indicator, and the number of children in the household and their age profile. Additional information regarding whether the respondent has a source of non-labour income, regular use of a car, and a spouse in employment are also included. These factors can all be considered as potentially important determinants of unemployment spell length. Demographic characteristics affect marginal productivity and search intensity. These, in turn help to explain individuals' reservation wages and variation in the arrival rate of job offers. The reservation wage and job offer arrival rate determine whether an unemployment spell will end. Residential location is also important in this regard. The risk of unemployment varies with geography: inflow and outflow rates to and from unemployment vary across regions. Part of this variation invariable reflects the business cycle. Regional fixed-effects may account for the remainder.[20] Thus, we include a set of regional dummies to capture such effects. Table A1 of the Appendix provides data definitions and summary statistics for the data. Table A2 presents the means of covariates utilised in the econometric estimation.

6.5 Empirical Results

Table 3 presents the results of the discrete time hazard models when the instantaneous probability of exit is estimated by pooling unemployment spells across both men and women. Figure 2 plots the underlying baseline hazards.[21] Panel (A) reports the estimated coefficients when the baseline hazard, $\theta(t)$, is assumed to be monotonic (the

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[20] Regional fixed-effects help to explain why the incidence and structure of unemployment vary with location.

[21] The underlying baseline hazards are scaled to the characteristics of the mean or 'average' sample member. Given that we estimate proportional hazard models, changing the characteristics of the respondent has no impact on the shape of the underlying hazard. See Table A2 for details.

discrete time equivalent of the Weibull specification). The coefficient on Log(t) is negative and significant, indicating negative state dependence and a decreasing probability of exit over time. The negative state dependence bias that arises from the failure to incorporate unobserved heterogeneity is clearly revealed in a comparison of columns (1) and (2). Column (2) allows for gamma "frailty" in the Weibull specification. The unobserved heterogeneity parameter, $\sigma^2(\gamma)$, reveals that there is indeed significant unobserved heterogeneity.[22] In addition, the inclusion of $\sigma^2(\gamma)$ renders the coefficient on Log (t) insignificantly different from zero. Thus, the negative state dependence of column (1) appears to be almost entirely spurious in nature.

Panel B reports the results when the baseline hazard is estimated non-parametrically. Column (1) presents the estimates from the model with the non-parametric baseline hazard while column (2) reports the results for the extended model with gamma "frailty". A test for the statistical significance of the underlying hazard is reported in the 'Baseline hazard' row of Table 3. This reveals that the baseline hazard is not constant. The baseline hazard coefficients for column (1) reveal negative state dependence over the distribution of unemployment spells as shown in Figure 2. However, the hazard rate rises significantly between 8 and 12 months. A similar pattern is observed for the model with heterogeneity in column (2). The hazard rate is again fairly volatile. In addition, the peak hazard rate at 12 months is approximately 350 percent higher than that observed at month 8. These 'peaks' in the hazard rates are difficult to explain and may indicate reporting or measurement error. Nonetheless, it is worth noting that the baseline hazard for the model without heterogeneity in column (1) lies below that of the model with heterogeneity reported in column (2). This confirms the empirical finding

[22] A test of column (1) against column (2) rejects the specification of column (1) as shown in the diagnostics at the bottom of the table.

that the omission of unobserved heterogeneity significantly biases the impact of covariates on the hazard towards negative state dependence and the estimated variance of gamma frailty remains statistically significant. A test of model (1) *vs* model (2) rejects model (1). Thus, the flexible specification of the baseline hazard is not sufficient to mitigate the impact of unobserved heterogeneity.

The determinants of unemployment duration are largely as expected, and the effects and significance of parameter estimates remain similar across all four columns.[23] Workers over the age of 30 have a significantly lower probability of exit from unemployment. Parameter estimates for the Meyer model indicate that workers aged over 40 have a hazard rate approximately 40 percent lower than the reference category of those aged under 25.[24] This result is an established finding of the literature and highlights the disparity between the incidence and duration of unemployment across socio-demographic groups reported in official statistics. Health is not significant in determining the exit from unemployment. Gender and Marital status are, however, significant. Workers who are separated, divorced or widowed have a 20 percent lower probability of exit than workers who are married or living as a couple. Being female, in contrast, increases the conditional exit probability by a pproximately 25 percent.

Post 'O'-level education significantly increases the instantaneous probability of exit from unemployment. Workers with 'A'-level qualifications have a 28 percent higher probability of exiting unemployment than those without formal qualifications. Those with higher education qualifications have a 42 percent higher chance of exit. There is evidence that household composition has an effect on the exit rate from unemployment.

[23] The proportionate impact of covariates on the hazard can be calculated by taking the exponent of reported parameter estimates.

[24] Percentage differentials are calculated as $100 \times (e^{\beta} - 1)$ - see Halvorsen and Palmquist (1980).

Workers with a spouse in employment have an exit probability approximately 30 percent higher than those who do not. This result suggests that there may be interdependence in household labour supply decisions. It is also consistent with the general upward trend of dual working households through the 1990's. Children under the age of 5 significantly reduce the probability of exit from unemployment by approximately 25 percent. A lower probability of exit is consistent with increased choosiness of workers looking for flexibility in employment. It may, additionally, represent higher reservation wages to cover the costs of childcare. These effects are borne out by the remaining parameter estimates regarding family composition: the impact of children over the age of 5 is insignificantly different from zero.

Non-labour income significantly reduces the probability of exit from unemployment. This result is consistent with job search theory. In a stationary framework, the reservation wage is constant and inversely related to search and opportunity costs. Non-labour income reduces the costs of search and thus induces longer spells of unemployment.[25] The effects of housing tenure are also consistent with what would be expected *a priori*. Local authority tenants have a significantly lower hazard rate than homeowners. This concurs with recent evidence that local authority tenants are more likely to be persistently unemployed and only move short distances (Boheim and Taylor, 1999). Finally, workers in the North of England have a 40 percent lower probability of exit from unemployment than equivalent workers in the South East. Workers with regular access to a car, however, have a 12 percent higher probability of exit regardless of their residential location.

[25] This result can also be derived from orthodox neoclassical analysis – a rise in non-labour income reduces the opportunity cost of leisure thereby reducing the relative attractiveness of work.

A flexible specification of the baseline hazard commonly mitigates the impact of unobserved heterogeneity (Han and Hausman, 1990; Narendranathan and Stewart, 1993). The statistical significance of gamma frailty in Panel B column (2) indicates, however, that a fully flexible specification of the baseline hazard is not sufficient for our data. One possible reason for this result may be that a pooled specification for both men and women is not appropriate. The parameter estimates across the various specifications indicate that gender is highly significant in determining unemployment spell length. Empirical labour research identifies complex relationships in the female participation decision. Unobserved heterogeneity may be correlated with these factors. Thus, we re-estimate the discrete time proportional hazard models separately by gender.

Table 4 reports the determinants of unemployment duration for men only. Table 5 reports the equivalent results for women. The results indicate significant variation in the determinants of unemployment spell length across gender groups. Fewer variables are significantly different from zero for women than for men. Education, housing tenure, household composition and labour market mobility are not significant determinants of the female hazard. Such factors are, however, significant determinants for men. Age, marital status, non-labour income and the presence of a spouse in work are statistically significant for both groups of workers. Residential location proves likewise. Men who reside in Greater London, the North of England, and Wales have significantly lower hazard rates than those from the South East. Women in the West Midlands experience likewise. Interestingly, ethnicity is important for women. Non-white nor Afro-Caribbean women have an exit probability between 35 and 50 percent lower than the reference category. This result is surprising and may reflect greater participation in the labour market (and thus risk of unemployment) than other ethnic groups. Alternatively, it may indicate measurement error if the survey definition of unemployment is not strictly adhered too.

Variation in the determinants of unemployment duration is reflected in the underlying hazards for men and women. The coefficient on Log(t) in the Weibull model is negative and statistically significant for both men and women. Estimation allowing for gamma frailty reveals that this negative state dependence is again entirely spurious. The inclusion of $\sigma^2(\gamma)$ renders the coefficient on Log (t) insignificantly different from zero in both cases. A specification test of model (1) *vs* model (2) confirms that the simple Weibull specification should indeed be rejected.

Figures 3 and 4 plot the baseline hazards for men and women respectively. The negative state dependence bias that arises from the failure to incorporate unobserved heterogeneity is again revealed. Non-monotonic variation in the non-parametric specifications of the hazard additionally indicates that the prior decision to reject the Weibull model is also vindicated. The general feature of the non-parametric baseline hazard is a decreasing risk of exit for men. The hazard declines steadily up to 8 months. However, there is a marked rise in the hazard between 10 and 12 months. The hazard declines in a series of peaks and troughs from 12 months onward. This increase in the hazard appears odd and may again indicate measurement error in the data. It could, alternatively, reflect the relative success of targeted assistance schemes for specific groups of workers who have been *registered* as unemployed for longer than 6 months.[26] The inclusion of gamma frailty has little impact on the underlying shape of the non-parametric hazard. Hazard rates for the model with heterogeneity are again consistently

[26] Dolton and O'Neill (1996) report that targeted assistance schemes for individuals who have been unemployed for greater than 6 months significantly reduce the duration of unemployment when compared to individuals omitted from such schemes.

higher than those for the model without. The impact of $\sigma^2(\gamma)$ is not, however, statistically significant, and a test of model (1) *vs* model (2) cannot reject model (1) at conventional levels.

Figure 4 reveals considerable non-parametric variation in the underlying baseline hazard for women. The exclusion of unobserved heterogeneity in the Weibull model again induces a bias towards negative state dependence. A test of model (1) *vs* model (2) (reported in Panel A of Table 5) rejects model (1). The general feature of the non-parametric model is a decline in the hazard rate up to 8 months. As for men, the hazard then rises dramatically between 8 and 12 months. A decline in the hazard is again observed thereafter in the model without heterogeneity. However, the inclusion of gamma frailty has a distinct effect on the underlying baseline hazard. The inclusion of $\sigma^2(\gamma)$ is statistically significant and a test of model (1) *vs* model (2) rejects model (1) at conventional levels [p=0.00]. From 8 months onward the hazard diverges rapidly and becomes volatile with a series of peaks and troughs. Such variation cannot be captured in monotonic specifications of the baseline hazard and confirms our earlier finding that the Weibull model is indeed too restrictive. It also indicates that unobserved heterogeneity is a significant contributor to exit rates for women for longer unemployment durations.

The volatility of non-parametric baseline hazards for longer spells of unemployment may indicate important variation in exit rates that arise from competing risks. We estimate discrete time proportional hazard models for the single risk of exit from unemployment. However, individuals can exit to a variety of alternative labour market states. The determinants of exit from unemployment are likely to differ across states and by gender. They may also vary with unemployment duration. Descriptive analysis of the data supports this view. 70 percent of female unemployment spells last less than 8 months. Of these, 81 percent exit to employment. In contrast, of the 30 percent of spells that survive past 8 months, 58 percent exit to a state of inactivity.[27] Such variation in the distribution of unemployment by exit state suggests accounting for competing risks to be important. Recent work by Boheim and Taylor (2000) supports this premise. They estimate a discrete time independent competing risks framework with flexible baseline hazards using the Prentice-Gloeckler model on the first seven waves of the BHPS. Their results confirm that covariates have differential impacts depending on the competing risk under consideration. They also reveal significantly different underlying baseline hazards for each risk.

The above results suggest controlling for competing risks to be an important task for our work. The inclusion of unobserved heterogeneity in an independent competing risks framework necessitates, however, that strong assumptions be made regarding the correlation between the error terms across the hazards for each risk. One common assumption is to assume independence across the error terms. The inclusion of an independent error term in a competing risks framework has, however, been criticized by Narendranathan and Stewart (1993).[28] For this reason, we do not extend our analysis to an independent competing risks framework. Whilst this may bias the results (the parameter estimates are the weighted average of exit across alternative labour market states), it does allow us to examine the impact of unobserved heterogeneity across parametric and non-parametric specifications of the underlying baseline hazard.

[27] 70 percent of male unemployment spells are also completed within 8 months. However, the equivalent proportions that exit to employment and inactivity are 85 percent and 43 percent respectively.

[28] The authors argue that possible misspecifications of the unobserved heterogeneity term may bias the results of interest. In addition, this bias may be more serious than that caused by ignoring the issue of unobserved heterogeneity altogether.

Our focus on spells rather than individuals is problematic if there is correlation between the spells experienced by one person. Therefore, to test the robustness of our results we re-estimate our equations using the first unemployment spell observed in the sample for each individual. Estimates for these single spell analyses are qualitatively identical, and qualitatively very similar to those presented and discussed above. Thus, our main findings of non-monotonicity in the hazard and a downward bias toward negative state dependence in the absence of unobserved heterogeneity are not sensitive to this dichotomisation of the data.

6.6 Conclusion

This chapter has investigated the determinants of unemployment duration and state dependence in unemployment for men and women in the 1990's, drawn from the first eight waves of the British Household Panel Survey (BHPS). We use discrete time proportional hazard models to estimate parametric and non-parametric specifications of the baseline hazard. In addition, both specifications were extended to incorporate the impact of unobserved individual heterogeneity. The results reveal that a parametric specification of the baseline hazard is unduly restrictive and induces significant spurious negative state dependence. The inclusion of unobserved individual heterogeneity lessens this bias; it is, however, unable to capture the true shape of the hazard as revealed in a non-parametric specification. The flexible baseline hazard mitigates the impact of unobserved individual heterogeneity for men. This impact is, however, statistically significant for women. It also reveals a fairly volatile baseline hazard that exhibits significant positive state dependence, particularly for longer spells of unemployment. We take this to represent variation in alternative exit states associated with the time-spent unemployed. Recent work suggests that identifying alternative labour market states is an important task for the econometric analysis of the conditional probability of exiting unemployment. Strong assumptions are required to overcome the inclusion of unobserved individual heterogeneity in an independent competing risks framework. We leave this development as an avenue for future research work.

Table 1

Number and Duration of Unemployment Spells

Unemployment (months)	All Persons	Males	Females
Number of Spells	1,896	1,130	766
Mean Duration	7.487	8.308	6.277
Median Duration	4.000	4.000	4.000
Standard Deviation	9.382	10.75	6.702

Notes
1. Includes Right Censored Spells.

Table 2

The Distribution of Unemployment Duration (Grouped Spells)

	All Persons		Males		Females	
Unemployment Duration (months)	*Frequency*	*%*	*Frequency*	*%*	*Frequency*	*%*
1	349	18.41	202	17.88	147	19.19
2	258	13.61	150	13.27	108	14.10
3	213	11.23	125	11.06	88	11.49
4	135	7.12	77	6.81	58	7.57
5	102	5.38	58	5.13	44	5.74
6	91	4.80	51	4.51	40	5.22
7	82	4.32	44	3.89	38	4.96
8	44	2.32	34	3.01	10	1.31
9	60	3.16	36	3.19	24	3.13
10	57	3.01	29	2.57	28	3.66
11	73	3.85	45	3.98	28	3.66
12	73	3.85	36	3.19	37	4.83
13-15	85	4.48	45	3.98	40	5.22
16-18	43	2.27	28	2.48	15	1.96
19-21	30	1.58	25	2.21	5	0.65
22-24	30	1.58	23	2.04	7	0.91
25-30	24	1.27	17	1.50	7	0.91
31-36	13	0.69	10	0.88	3	0.39
37-48	18	0.95	17	1.50	1	0.13
48+	12	0.63	9	0.80	3	0.39
Right Censored Spells	104	5.49	69	6.11	35	4.57
Total	1,896	100.0	1,130	100.0	766	100.0

Table 3

Conditional Probability (Hazard) of Exit from Unemployment (full sample)

	(A) Weibull Model		(B) Non-Parametric Model	
Variable	**(1) Without Heterogeneity**	**(2) With Heterogeneity**	**(1) Without Heterogeneity**	**(2) With Heterogeneity**
Personal Characteristics				
Age 26-30	-0.100 (1.16)	-0.108 (1.03)	-0.092 (1.07)	-0.108 (0.95)
31-40	-0.298 (3.36)†	-0.379 (3.44)†	-0.293 (3.29)†	-0.409 (3.34)†
41-50	-0.400 (4.20)†	-0.483 (4.09)†	-0.395 (4.16)†	-0.513 (3.93)†
50+	-0.378 (3.49)†	-0.510 (3.76)†	-0.387 (3.57)†	-0.564 (3.67)†
Black Ethnic Origin	-0.130 (0.50)	-0.216 (0.71)	-0.151 (0.58)	-0.278 (0.84)
Other Ethnic Origin	-0.173 (1.27)	-0.247 (1.51)	-0.194 (1.43)	-0.276 (1.55)
Gender	0.231 (4.14)†	0.244 (3.63)†	0.217 (3.88)†	0.250 (3.43)†
Separated, Divorced or Widowed	-0.208 (1.92)*	-0.254 (1.96)**	-0.201 (1.87)*	-0.267 (1.89)*
Never Married	-0.036 (0.38)	-0.056 (0.48)	-0.025 (0.26)	-0.037 (0.29)
Higher or First Degree, Teaching	0.234 (2.39)**	0.324 (2.68)†	0.231 (2.35)**	0.352 (2.65)†
Other Higher Education	0.334 (4.11)†	0.361 (3.63)†	0.307 (3.77)†	0.368 (3.39)†
'A'-Levels or Equivalent	0.251 (2.86)†	0.250 (2.34)**	0.232 (2.64)†	0.244 (2.10)**
'O'-Levels or Equivalent	0.117 (1.48)	0.112 (1.18)	0.100 (1.27)	0.112 (1.08)
CSE Grade 1-5	0.042 (0.35)	0.056 (0.37)	0.046 (0.38)	0.071 (0.44)
Apprenticeship, Nursing, Other	0.166 (1.55)	0.166 (1.28)	0.149 (1.39)	0.170 (1.20)
Health Limits Types of Work	-0.051 (0.71)	-0.102 (1.17)	-0.059 (0.82)	-0.123 (1.27)
Head of Household	-0.052 (0.86)	-0.051 (0.71)	-0.055 (0.90)	-0.047 (0.60)
Spouse has Job	0.276 (3.54)†	0.352 (3.65)†	0.292 (3.73)†	0.406 (3.72)†
Have Children	0.037 (0.39)	0.017 (0.15)	0.043 (0.45)	0.015 (0.13)
Have Children Aged Under 5	-0.224 (2.24)**	-0.288 (2.38)**	-0.222 (2.21)**	-0.299 (2.28)**
Have Children Aged 5 to 11	0.026 (0.28)	0.000 (0.00)	0.011 (0.12)	0.021 (0.18)
Local Authority Tenant	-0.166 (2.57)†	-0.204 (2.59)†	-0.165 (2.56)**	-0.224 (2.57)†
Private Tenant	0.041 (0.51)	0.056 (0.57)	0.042 (0.53)	0.065 (0.62)
Have Non-labour income	-0.140 (2.54)**	-0.183 (2.66)†	-0.134 (2.42)**	-0.197 (2.56)†
Have Use of a Car	0.100 (1.80)*	0.130 (1.92)*	0.102 (1.83)*	0.147 (1.97)**
Regional Dummies				
Greater London	-0.122 (1.26)	-0.156 (1.32)	-0.128 (1.32)	-0.178 (1.38)
East Anglia	-0.012 (0.08)	-0.088 (0.53)	-0.022 (0.16)	-0.128 (0.70)
South West	0.003 (0.04)	-0.012 (0.10)	-0.005 (0.05)	-0.015 (0.12)
West Midlands	-0.107 (1.04)	-0.145 (1.17)	-0.112 (1.09)	-0.177 (1.29)
East Midlands	-0.113 (1.16)	-0.157 (1.31)	-0.110 (1.12)	-0.173 (1.32)
Yorkshire	-0.017 (0.18)	-0.049 (0.44)	-0.030 (0.33)	-0.064 (0.52)
North West	-0.104 (1.03)	-0.142 (1.14)	-0.114 (1.12)	-0.163 (1.20)
North	-0.366 (3.19)†	-0.457 (3.25)†	-0.366 (3.19)†	-0.499 (3.19)†
Wales	-0.131 (1.07)	-0.171 (1.15)	-0.131 (1.07)	-0.185 (1.15)
Scotland	-0.113 (1.14)	-0.183 (1.36)	-0.120 (1.21)	-0.192 (1.44)
Constant	-1.499 (10.50)†	-1.471 (8.59)†	-	-
Baseline Hazard	Log(t) -0.225 (9.61)†	Log(t) -0.006 (0.10)	Non-Parametric $\chi^2(20)=333.70$ [0.00]	Non-Parametric $\chi^2(20)=145.41$ [0.00]
$\sigma^2(\gamma)$	- -	0.260 (3.29)	- -	0.395 (2.46)
	Diagnostics		Diagnostics	
Log Likelihood	-5192.3387	-5184.9996	-5149.9376	-5145.4181
Model χ^2	$\chi^2(36)=380.491$	$\chi^2(37)=395.169$	$\chi^2(55)=465.294$	$\chi^2(56)=474.332$
Model (1) *vs* (2)	$\chi^2(1)=14.678$ [0.00]		$\chi^2(1)=9.039$ [0.00]	
No. of Spells	1,896		1,896	
No. of Person months	14,196		14,196	

Notes to Table 3

1. Estimations by Intercooled Stata 6.0 using the pgmhaz function of Jenkins (1997) Coefficient t-values in parentheses. Significance levels: †(0.01), **(0.05), *(0.10); p-values of diagnostics in [].
2. The "Baseline Hazard" row indicates the functional form selected for the underlying hazard – monotonic ('Weibull') or non-parametric. The reported statistics are the coefficients (t-ratios) of the coefficient on Log(t) and a test for the joint significance of the duration specific intercepts for the non-parametric hazard.
3. The significance test for the heterogeneity parameter, $\sigma^2(\gamma)$, is a one tailed test since $\sigma^2>0$.
4. Model χ^2 is a likelihood ratio test for the joint significance of the parameters.

Table 4

Conditional Probability (Hazard) of Exit from Unemployment (male sample)

	(A) Weibull Model		(B) Non-Parametric Model	
Variable	**(1) Without Heterogeneity**	**(2) With Heterogeneity**	**(1) Without Heterogeneity**	**(2) With Heterogeneity**
Personal Characteristics				
Age 26-30	-0.086 (0.76)	-0.125 (0.89)	-0.091 (0.80)	-0.130 (0.90)
31-40	-0.401 (3.33)†	-0.507 (3.30)†	-0.398 (3.30)†	-0.518 (3.10)†
41-50	-0.512 (3.87)†	-0.582 (3.49)†	-0.505 (3.81)†	-0.585 (3.37)†
50+	-0.377 (2.63)†	-0.502 (2.76)†	-0.382 (2.67)†	-0.514 (2.63)†
Black Ethnic Origin	-0.021 (0.05)	-0.147 (0.29)	-0.056 (0.13)	-0.193 (0.37)
Other Ethnic Origin	0.037 (0.19)	-0.015 (0.07)	0.028 (0.15)	-0.022 (0.10)
Gender	-	-	-	-
Separated, Divorced or Widowed	-0.211 (1.37)	-0.258 (1.37)	-0.203 (1.32)	-0.259 (1.34)
Never Married	-0.159 (1.19)	-0.174 (1.06)	-0.141 (1.05)	-0.160 (0.95)
Higher or First Degree, Teaching	0.262 (1.97)**	0.325 (2.00)**	0.259 (1.95)*	0.331 (1.96)**
Other Higher Education	0.431 (4.19)†	0.440 (3.51)†	0.410 (3.97)†	0.441 (3.42)†
'A'-Levels or Equivalent	0.264 (2.39)**	0.255 (1.88)*	0.244 (2.20)**	0.250 (1.81)*
'O'-Levels or Equivalent	0.301 (2.90)†	0.330 (2.59)†	0.283 (2.72)†	0.333 (2.53)**
CSE Grade 1-5	0.104 (0.70)	0.152 (0.82)	0.104 (0.70)	0.163 (0.85)
Apprenticeship, Nursing, Other	0.095 (0.59)	0.023 (0.12)	0.065 (0.40)	0.012 (0.06)
Health Limits Types of Work	-0.084 (0.89)	-0.135 (1.18)	-0.090 (0.96)	-0.135 (1.15)
Head of Household	-0.179 (1.96)*	-0.182 (1.66)*	-0.173 (1.91)*	-0.176 (1.58)
Spouse has Job	0.285 (2.95)†	0.349 (2.88)†	0.297 (3.06)†	0.366 (2.85)†
Have Children	0.035 (0.27)	0.074 (0.46)	0.042 (0.31)	0.084 (0.50)
Have Children Aged Under 5	-0.233 (1.70)*	-0.279 (1.67)*	-0.227 (1.65)*	-0.274 (1.61)
Have Children Aged 5 to 11	0.021 (0.16)	-0.033 (0.21)	0.013 (0.10)	-0.048 (0.30)
Local Authority Tenant	-0.245 (2.84)†	-0.330 (2.97)†	-0.239 (2.78)†	-0.335 (2.71)†
Private Tenant	0.086 (0.80)	0.148 (1.09)	0.102 (0.95)	0.164 (1.18)
Have Non-labour income	-0.130 (1.88)*	-0.176 (2.02)**	-0.128 (1.86)*	-0.181 (2.85)†
Have Use of a Car	0.180 (2.36)**	0.221 (2.35)**	0.182 (2.38)**	0.224 (2.29)**
Regional Dummies				
Greater London	-0.286 (2.20)**	-0.343 (2.15)**	-0.294 (2.26)**	-0.354 (2.15)**
East Anglia	-0.060 (0.31)	-0.109 (0.46)	-0.079 (0.41)	-0.129 (0.53)
South West	-0.089 (0.75)	-0.126 (0.85)	-0.093 (0.78)	-0.129 (0.85)
West Midlands	-0.045 (0.33)	-0.087 (0.52)	-0.057 (0.42)	-0.098 (0.58)
East Midlands	-0.162 (1.29)	-0.242 (1.54)	-0.176 (1.39)	-0.252 (1.55)
Yorkshire	-0.098 (0.82)	-0.131 (0.90)	-0.108 (0.91)	-0.136 (0.92)
North West	-0.168 (1.24)	-0.235 (1.40)	-0.169 (1.25)	-0.240 (1.38)
North	-0.516 (3.41)†	-0.628 (3.34)†	-0.515 (3.40)†	-0.647 (3.22)†
Wales	-0.382 (2.33)**	-0.462 (2.30)**	-0.380 (2.32)**	-0.465 (2.23)**
Scotland	-0.234 (1.76)*	-0.277 (1.68)*	-0.242 (1.82)*	-0.290 (1.71)*
Constant	-1.319 (6.87)†	-1.271 (5.42)†	-	-
Baseline Hazard	Log(t) -0.254 (8.55)†	Log(t) -0.039 (0.41)	Non-Parametric $\chi^2(20)$=181.62 [0.00]	Non-Parametric $\chi^2(20)$=64.70 [0.00]
$\sigma^2(\gamma)$	- -	0.277 (2.29)	- -	0.310 (1.51)
	Diagnostics		Diagnostics	
Log Likelihood	-3160.1055	-3156.9664	-3141.5129	-3140.1569
Model χ^2	$\chi^2(35)$=303.514	$\chi^2(36)$=309.721	$\chi^2(54)$=340.700	$\chi^2(55)$=343.412
Model (1) *vs* (2)	$\chi^2(1)$=6.278 [0.01]		$\chi^2(1)$=2.712 [0.10]	
No. of Spells	1,130		1,130	
No. of Person months	9,388		9,388	

Notes

1. See notes to Table 3.

Table 5

Conditional Probability (Hazard) of Exit from Unemployment (female sample)

	(A) Weibull Model		(B) Non-Parametric Model	
Variable	**(1) Without Heterogeneity**	**(2) With Heterogeneity**	**(1) Without Heterogeneity**	**(2) With Heterogeneity**
Personal Characteristics				
Age 26-30	-0.039 (0.28)	-0.018 (0.11)	-0.003 (0.02)	-0.000 (0.00)
31-40	-0.069 (0.48)	-0.117 (0.71)	-0.057 (0.40)	-0.169 (0.81)
41-50	-0.262 (1.82)*	-0.327 (1.94)*	-0.259 (1.80)*	-0.451 (2.08)**
50+	-0.475 (2.74)†	-0.591 (2.85)†	-0.492 (2.83)†	-0.827 (3.04)†
Black Ethnic Origin	-0.278 (0.82)	-0.344 (0.91)	-0.261 (0.77)	-0.479 (1.02)
Other Ethnic Origin	-0.429 (2.13)**	-0.529 (2.26)**	-0.461 (2.29)**	-0.717 (2.32)**
Gender	-	-	-	-
Separated, Divorced or Widowed	-0.426 (2.39)**	-0.502 (2.45)**	-0.433 (2.45)**	-0.651 (2.40)**
Never Married	-0.043 (0.27)	-0.095 (0.52)	-0.059 (0.37)	-0.138 (0.59)
Higher or First Degree, Teaching	0.054 (0.34)	0.125 (0.68)	0.057 (0.36)	0.189 (0.82)
Other Higher Education	0.132 (0.94)	0.177 (1.07)	0.109 (0.77)	0.222 (1.05)
'A'-Levels or Equivalent	0.242 (1.59)	0.240 (1.37)	0.238 (1.56)	0.188 (0.84)
'O'-Levels or Equivalent	-0.146 (1.17)	-0.183 (1.27)	-0.143 (1.14)	-0.270 (1.46)
CSE Grade 1-5	-0.215 (0.95)	-0.229 (0.89)	-0.217 (0.95)	-0.339 (1.04)
Apprenticeship, Nursing, Other	0.089 (0.59)	0.128 (0.72)	0.110 (0.73)	0.189 (0.84)
Health Limits Types of Work	-0.079 (0.67)	-0.091 (0.67)	-0.069 (0.56)	-0.153 (0.88)
Head of Household	0.025 (0.23)	0.016 (0.13)	0.018 (0.16)	0.019 (0.12)
Spouse has Job	0.261 (1.83)*	0.294 (1.79)*	0.264 (1.85)*	0.379 (1.82)*
Have Children	-0.056 (0.39)	-0.088 (0.54)	-0.057 (0.40)	-0.136 (0.65)
Have Children Aged Under 5	-0.112 (0.72)	-0.177 (1.00)	-0.104 (0.67)*	-0.252 (1.13)
Have Children Aged 5 to 11	0.063 (0.46)	0.046 (0.30)	0.060 (0.44)	0.025 (0.13)
Local Authority Tenant	-0.113 (1.09)	-0.114 (0.95)	-0.126 (1.20)	-0.124 (0.81)
Private Tenant	0.053 (0.42)	0.034 (0.24)	0.023 (0.19)	0.011 (0.06)
Have Non-labour income	-0.133 (1.29)	-0.186 (1.52)	-0.130 (1.25)	-0.249 (1.61)
Have Use of a Car	-0.017 (0.20)	0.001 (0.01)	-0.017 (0.20)	0.052 (0.42)
Regional Dummies				
Greater London	0.086 (0.57)	0.067 (0.38)	0.069 (0.46)	-0.021 (0.09)
East Anglia	0.093 (0.46)	0.029 (0.13)	0.101 (0.50)	-0.087 (0.30)
South West	0.062 (0.40)	0.056 (0.31)	0.034 (0.22)	0.076 (0.32)
West Midlands	-0.270 (1.68)*	-0.298 (1.61)	-0.267 (1.66)*	-0.472 (1.87)*
East Midlands	-0.152 (0.94)	-0.128 (0.69)	-0.113 (0.70)	-0.172 (0.72)
Yorkshire	-0.005 (0.03)	-0.056 (0.31)	-0.019 (0.12)	-0.167 (0.72)
North West	-0.162 (1.00)	-0.179 (0.96)	-0.175 (1.08)	-0.228 (0.94)
North	-0.136 (0.74)	-0.188 (0.89)	-0.147 (0.79)	-0.273 (1.00)
Wales	0.277 (1.45)	0.262 (1.21)	0.262 (1.37)	0.172 (0.62)
Scotland	0.004 (0.02)	-0.040 (0.22)	-0.006 (0.04)	-0.149 (0.63)
Constant	-1.351 (5.74)†	-1.289 (4.79)†	-	-
Baseline Hazard	Log(t) -0.089 (2.20)*	Log(t) 0.080 (0.88)	Non-Parametric $\chi^2(20)=65.54$ [0.00]	Non-Parametric $\chi^2(20)=77.40$ [0.00]
$\sigma^2(\gamma)$	- -	0.177 (1.94)	- -	0.611 (2.59)
	Diagnostics		Diagnostics	
Log Likelihood	-1997.7172	-1995.3884	-1961.6808	-1955.7805
Model χ^2	$\chi^2(35)=103.178$	$\chi^2(36)=107.836$	$\chi^2(54)=175.251$	$\chi^2(55)=187.052$
Model (1) *vs* (2)	$\chi^2(1)=4.658$ [0.03]		$\chi^2(1)=11.801$ [0.00]	
No. of Spells	766		766	
No. of Person months	4,808		4,808	

Notes

1. See notes to Table 3.

Figure 2

Baseline Hazards from Discrete-Time Proportional Hazards Models (Full Sample)

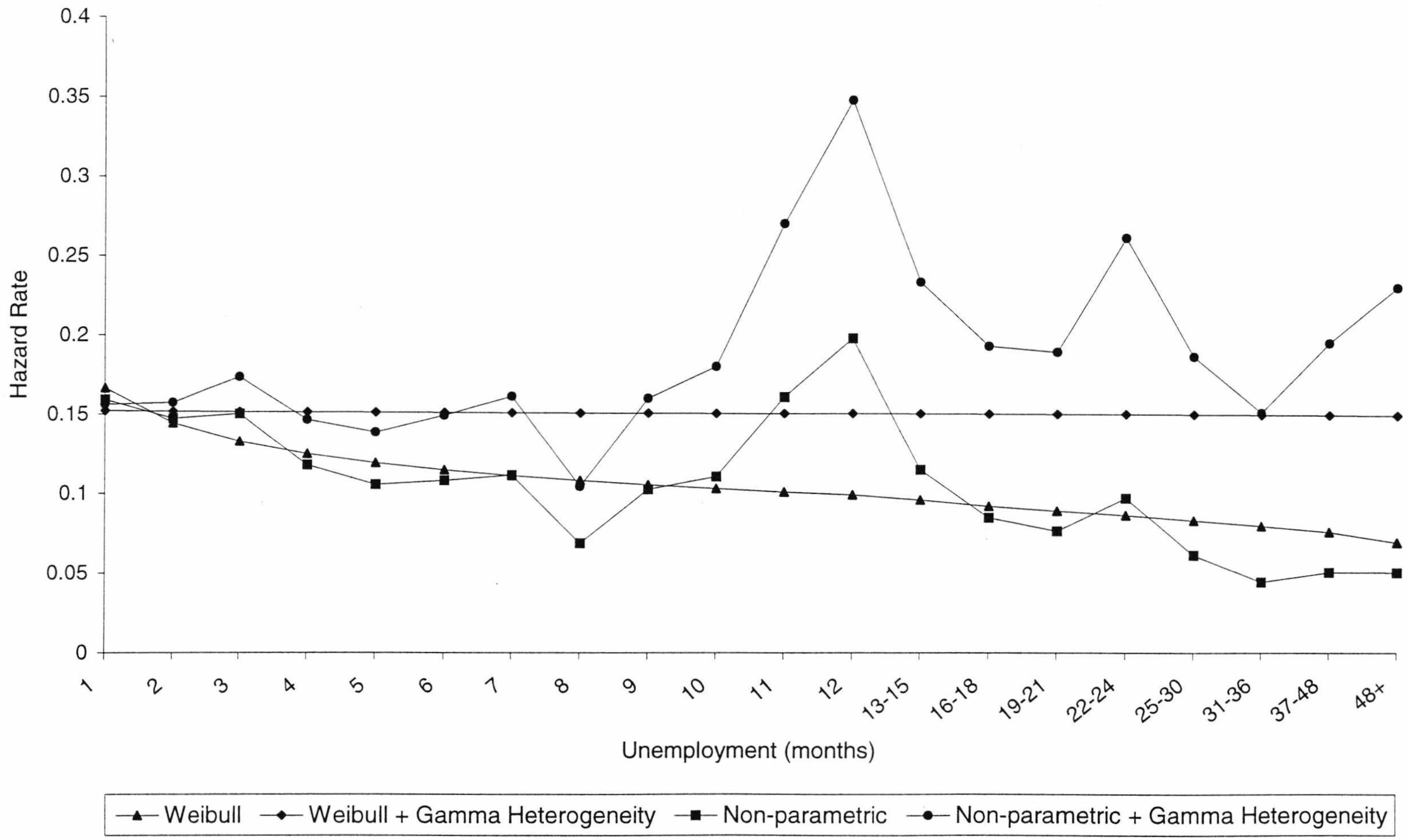


Figure 3

Baseline Hazards from Discrete-Time Proportional Hazards Models (Male Sample)

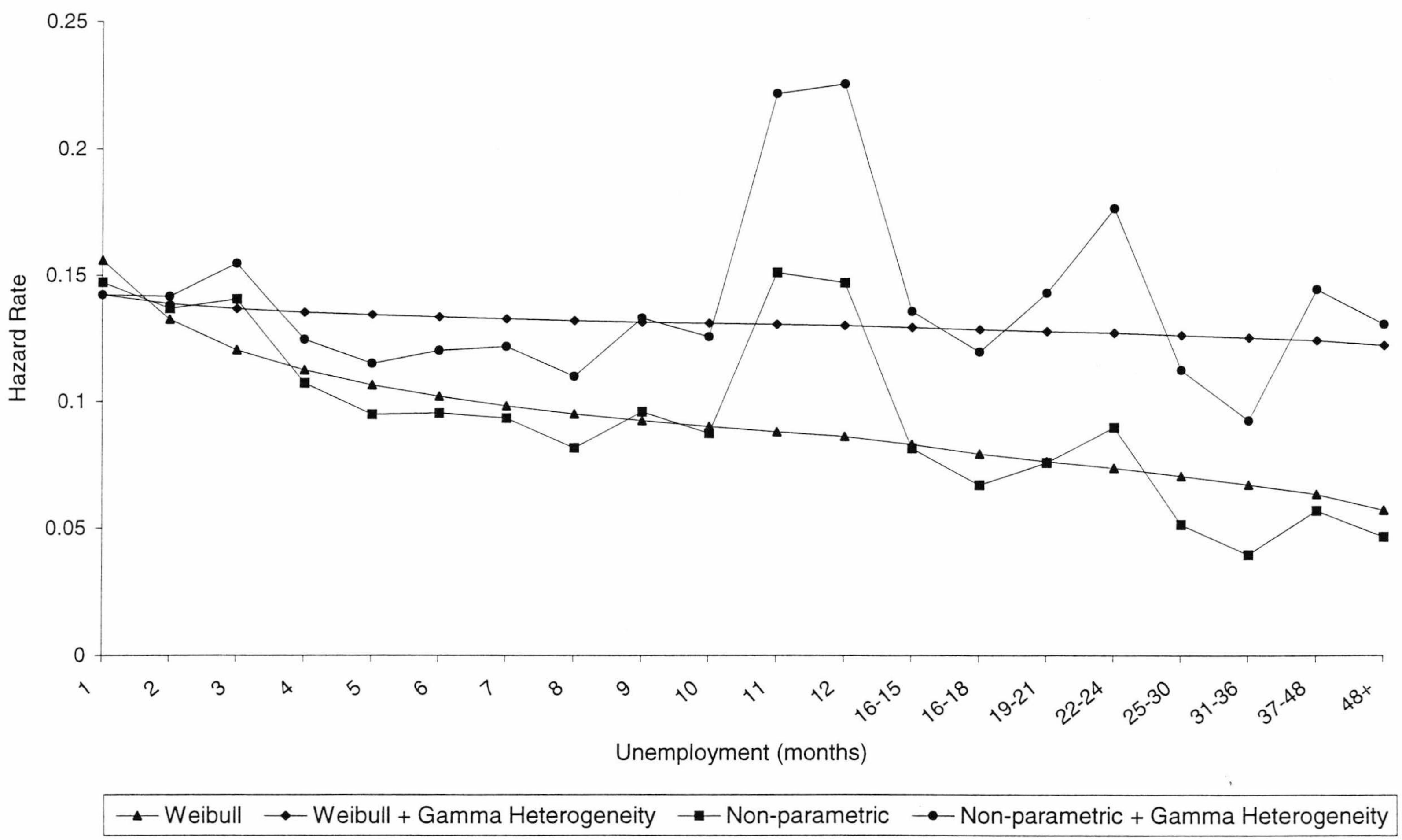
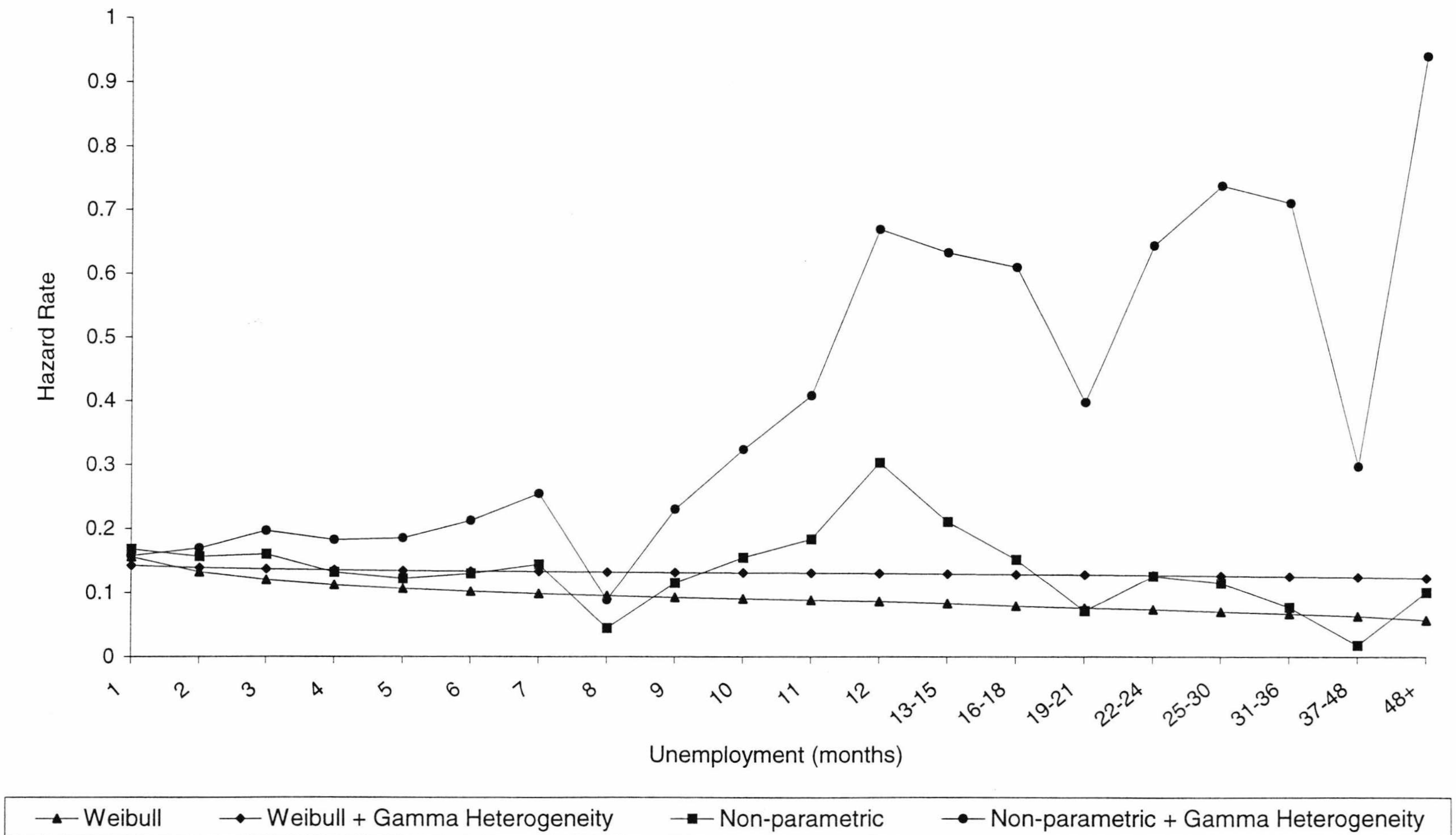


Figure 4

Baseline Hazards from Discrete-Time Proportional Hazards Models (Female Sample)



APPENDIX

Table A1

Data Definitions and Summary Statistics

Variable	All Persons		Males		Females	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Dependent Variable:						
Duration of Current Spell	7.487	9.382	8.308	10.754	6.277	6.702
Independent Variables:						
Age Under 25 (reference)	0.315		0.332		0.290	
26-30	0.139		0.133		0.148	
31-40	0.217		0.203		0.236	
41-50	0.191		0.182		0.205	
50+	0.138		0.150		0.121	
Gender (1,0 if female)	0.404		-	-	-	-
Race						
White (reference)	0.955		0.961		0.948	
Black Ethnic Origin	0.010		0.006		0.014	
Other Ethnic Origin	0.035		0.033		0.038	
Marital Status						
Married (reference)	0.557		0.557		0.556	
Separated, Divorced or Widowed	0.091		0.067		0.127	
Never Married	0.352		0.376		0.317	
Highest Qualification						
Higher or First Degree, Teaching	0.110		0.097		0.129	
Other Higher Education	0.184		0.212		0.144	
'A'-Levels or Equivalent	0.156		0.173		0.130	
'O'-Levels or Equivalent	0.219		0.196		0.253	
CSE Grade 1-5	0.056		0.066		0.041	
Apprenticeship, Nursing, Other	0.065		0.045		0.094	
No Qualification (reference)	0.210		0.211		0.209	
Other Personal Controls						
Head of Household	0.497		0.612		0.329	
Spouse has Job	0.391		0.348		0.454	
Own Children	0.324		0.305		0.351	
Children Aged 0-4 Years	0.125		0.127		0.123	
Children Aged 5 to 11 Years	0.193		0.187		0.201	
Health Limits Types of Work	0.140		0.148		0.128	
Have Non-labour income	0.726		0.681		0.791	
Have Use of a Car	0.611		0.671		0.522	
Housing Tenure						
Home Owner (reference)	0.615		0.641		0.577	
Local Authority Tenant	0.259		0.245		0.279	
Private Tenant	0.126		0.114		0.144	
Regional Dummies						
Greater London	0.108		0.103		0.115	
Rest of the South East (reference)	0.171		0.166		0.179	
East Anglia	0.037		0.031		0.046	
South West	0.104		0.111		0.094	
West Midlands	0.083		0.081		0.085	
East Midlands	0.093		0.099		0.085	
Yorkshire	0.117		0.131		0.096	
North West	0.082		0.078		0.089	
North	0.062		0.066		0.057	
Wales	0.052		0.051		0.052	
Scotland	0.091		0.083		0.102	
N	1,896		1,130		766	

Table A2

Means of Covariates

Variable	All Persons		Males		Females	
	Mean	*SD*	*Mean*	*SD*	*Mean*	*SD*
Duration Dummies						
1 month	0.133		0.120		0.159	
2 months	0.109		0.098		0.128	
3 months	0.090		0.082		0.105	
4 months	0.074		0.068		0.086	
5 months	0.064		0.059		0.073	
6 months	0.056		0.053		0.064	
7 months	0.050		0.047		0.055	
8 months	0.044		0.042		0.047	
9 months	0.040		0.039		0.045	
10 months	0.036		0.035		0.039	
11 months	0.032		0.031		0.034	
12 months	0.026		0.026		0.027	
13-15 months	0.053		0.058		0.042	
16-18 months	0.038		0.045		0.024	
19-21 months	0.030		0.036		0.017	
22-24 months	0.024		0.029		0.014	
25-30 months	0.031		0.039		0.014	
31-36 months	0.023		0.030		0.009	
37-48 months	0.027		0.035		0.012	
48+ months	0.020		0.028		0.006	
Personal Characteristics						
Age Under 25	-	-	-	-	-	-
26-30	0.122		0.111		0.143	
31-40	0.237		0.238		0.235	
41-50	0.209		0.213		0.199	
50+	0.160		0.160		0.159	
Gender	0.339			-	-	-
Race						
White	-	-	-	-	-	-
Black Ethnic Origin	0.014		0.012		0.017	
Other Ethnic Origin	0.031		0.024		0.046	
Marital Status						
Married	-	-	-	-	-	-
Separated, Divorced or Widowed	0.127		0.094		0.191	
Never Married	0.339		0.355		0.307	
Highest Qualification						
Higher or First Degree, Teaching	0.099		0.094		0.109	
Other Higher Education	0.148		0.158		0.126	
'A'-Levels or Equivalent	0.131		0.148		0.101	
'O'-Levels or Equivalent	0.207		0.164		0.291	
CSE Grade 1-5	0.067		0.077		0.047	
Apprenticeship, Nursing, Other	0.064		0.051		0.089	
No Qualification	-	-	-	-	-	-
Other Personal Controls						
Head of Household	0.558		0.652		0.374	
Spouse has Job	0.321		0.290		0.381	
Own Children	0.340		0.329		0.362	
Children Aged 0-4 Years	0.140		0.145		0.130	
Children Aged 5 to 11 Years	0.204		0.206		0.200	
Health Limits Types of Work	0.155		0.157		0.152	
Have Non-labour income	0.752		0.715		0.823	
Have Use of a Car	0.577		0.626		0.482	

Housing Tenure			
Home Owner	- -	- -	- -
Local Authority Tenant	0.335	0.337	0.331
Private Tenant	0.108	0.094	0.134
Regional Dummies			
Greater London	0.115	0.121	0.103
Rest of the South East	- -	- -	- -
East Anglia	0.033	0.136	0.162
South West	0.099	0.032	0.036
West Midlands	0.084	0.105	0.088
East Midlands	0.096	0.069	0.112
Yorkshire	0.104	0.096	0.096
North West	0.087	0.112	0.088
North	0.080	0.080	0.101
Wales	0.057	0.091	0.061
Scotland	0.099	0.063	0.046
No. of Person Months	14,196	9,388	4,808

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Chapter 7 - Conclusions

7.1 Summary and Concluding Remarks

This thesis has examined the role of individual heterogeneity in the determination of both wages and (un)employment. Utilising UK longitudinal data in the form of the British Household Panel Survey (BHPS), our results indicate that unobserved individual heterogeneity has a significant impact in the explanation of observed labour market behaviour. Our findings suggest that the failure to incorporate such heterogeneity results in the significant bias of econometric estimates and an understating of the 'true' importance of orthodox competitive theory. The failure to fully incorporate individual heterogeneity in empirical labour research has provided the basis of support for an array of non-competitive explanations of the labour market. Our substantive results suggest that these models may be less important than is currently thought and that the malign of standard competitive theory has been overstated.

The first part of the thesis examines the industry wage structure and the role of regional unemployment in wage determination. Chapter 3 investigates inter-industry wage differentials and tests the relevance of competing and non-competing labour market models as an explanation for the observed wage dispersion. Two well-established findings are apparent in the analyses of individual wage determination. First, standard cross-section wage equations rarely account for more than half of the total variance in earnings across individuals. Second, there are large and persistent inter-industry wage differentials. Chapter 3 explores these two empirical regularities using cross-section, pooled and panel data drawn from the first eight waves of the British Household Panel Survey. Though difficult to explain, inter-industry wage differentials are frequently attributed to non-competitive forces in wage determination. We show that around 90 percent of the variation in individual earnings can be explained by observed and *unobserved* individual characteristics, perhaps reflecting innate ability or other individual qualities not captured by observed data. Moreover, our results show that accounting for these characteristics substantially reduces the dispersion of inter-industry wages. However, small but statistically significant industry wage premia do remain, and there is also minor role for a rich set of job and workplace controls perhaps reflecting compensating differentials.

Chapter 4 assesses the existence of a UK 'Wage Curve' to explore the role of regional unemployment in the determination of individual pay. Recent empirical research adheres to the existence of a new empirical law of economics, a stable inverse non-linear relationship between individual pay and the local unemployment rate. Critiques of this research emphasise issues concerning choice of econometric technique and potential bias that arise from the use of time-series and cross-section data. This chapter estimates the UK wage curve using longitudinal micro data drawn from the first eight waves of the British Household Panel Survey. We use an econometric model that controls for observed and unobserved individual-specific heterogeneity, and find evidence of a significant negative relationship in wage-unemployment space. Our results indicate that the estimated unemployment elasticity of pay for UK males is approximately –0.14, and this elasticity is robust to a number of alternative specifications. There is no evidence of a significant Wage Curve for women. These findings are consistent with panel studies reported for other countries. They contrast with previous studies for the UK, however, in that they reject the inclusion of higher order polynomial terms for unemployment. Thus, the wage-unemployment relationship is robust but not as non-linear as has been previously thought.

The second part of the thesis examines the role of individual heterogeneity in determining unemployment duration. We utilise unique regional data and BHPS work-life history files to estimate duration models for regional and UK unemployment. The duration of unemployment is a far more revealing indicator of economic welfare than the incidence of unemployment. Aggregate unemployment rates conceal the distribution of unemployment across individuals over time. Unemployment duration, in contrast, provides information regarding the dispersion of unemployment across individuals and identifies those socio-demographic groups who are most likely to experience prolonged effects with regard to their own individual welfare.

Chapter 5 investigates the impact of individual heterogeneity and local labour market conditions on unemployment duration. Recent empirical literature for the analysis of unemployment durations indicates that individual heterogeneity is far more important in determining unemployment spell lengths than had previously been thought. We utilise a unique regional dataset for a statistically representative sample of individuals registered as unemployed in October 1992 to investigate this issue. Our results indicate that demographic characteristics have an important role in the distribution of incomplete spells of unemployment. Age, gender, educational attainment, travel to work time, mobility and method of job search all yield significant impacts on the probability of remaining unemployed. Variation in local labour market conditions is also found to be important. In contrast, individuals' reservation wages are not as important as theory suggests. This result is somewhat surprising given the central role of the reservation wage in the theory of job search. This result is, however, consistent with similar findings reported elsewhere.

Chapter 6 investigates the impact of individual heterogeneity and state dependence in unemployment for UK men and women in the 1990's. We use discrete-time proportional hazard models on BHPS work-life histories to estimate parametric and non-parametric specifications of the conditional exit from unemployment, and examine the impact of unobserved individual heterogeneity on the parameter estimates for the determinants of unemployment durations and state dependence in unemployment. Our results indicate that observed and unobserved individual characteristics have an important role in determining the distribution of completed unemployment spells. We find that age, gender, household composition, educational attainment, housing tenure and mobility have significant effects on the conditional probability of exit from unemployment. In addition, the omission of unobserved heterogeneity results in spurious negative state dependence. Having controlled for observed and unobserved individual heterogeneity, we indicate that the conditional probability of exit from unemployment is approximately constant for unemployment durations less than eight months. Longer spells of unemployment exhibit fairly volatile hazards. We take this to indicate the importance of alternative exit states which should be modelled in a competing risks framework. This is a potential avenue for further research work.

The central conclusion of the thesis is that empirical work which is not founded on techniques which utilise panel data can give rise to seriously misleading conclusions regarding the operation of labour markets, and, in particular, the nature of the wage determination process and the likelihood of exit from unemployment.